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Sustainable design of a closed-loop location-routing-inventory supply chain network under mixed uncertainty

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ABSTRACT

Considering economic, environmental and social impacts, this paper presents a new sustainable closed-loop location-routing-inventory model under mixed uncertainty. The environmental impacts of CO_2 emissions, fuel consumption, wasted energy and the social impacts of created job opportunities and economic development are considered in this paper. The uncertain nature of the network is handled using a stochastic-possibilistic programming approach. Furthermore, for large-sized problems, a hybrid meta-heuristic algorithm and lower bounds are developed and discussed. Finally, a real case study is provided to demonstrate the applicability of the model in real-world applications, and several in-depth analyses are conducted to develop managerial implications.

1. Introduction

The traditional definition of supply chain management (SCM) is a process of planning, implementing and controlling the operations from a supplier to a set of customers based on efficiency (Zahiri et al., 2014). In the recent years, several important reasons highlighted the need for reverse logistics and designing closed-loop supply chains (CLSCs), including economic aspects, customers' expectations and government legislations such as the directive on Waste Electrical and Electronics Equipment (WEEE) (Melo et al., 2009). In contrast to the forward logistic, a reverse logistic starts from end users (i.e., consumers), where used products are collected, and then attempts to manage end-of-life products through different decisions such as remanufacturing, repairing and disposing (Govindan et al., 2015). The integration of traditional forward supply chain management and reverse logistic results in a CLSC, which has recently gained significant importance. In a CLSC, the distribution system forms a closed-loop where returned damaged products, unsold products or end-of-life products are remanufactured to refurbished products or sold as spare parts or new products to a secondary market (Diabat et al., 2015).

Recently, companies have noticed that the spare parts and after-sales service markets have a huge profit potential. These markets are worth more than $200 billion (Bacchetti and Saccani, 2012). A study of more than 80 multi-national companies in different industries reported that more than 50% of the total revenue of many high tech companies are gained through

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spare parts and after-sales services (Koudal, 2006). As a result, designing a CLSC with spare parts consideration can help meet the requirements and expectations of governments and customers as well as increase the total revenue of the supply chain.

In addition to the need to design a CLSC, incorporating operational decisions alongside the strategic decisions is of crucial importance in supply chain network design (SCND) (Govindan et al., 2014). In today's competitive business environment, companies should make operational decisions alongside strategic decisions to optimize and manage their logistic system more efficiently. Reducing costs and improving customer service are the two main challenges for each company in a competitive business environment. In the literature, there are two important operational decisions, vehicle routing and inventory management, which are known as the main tools for coping with such challenges (Govindan et al., 2014; Asl-Najafi et al., 2015). A vitally important operational decision concerns finding optimal vehicle routes to transfer the products through the network efficiently (Govindan et al., 2014). Although finding optimal vehicle routes can significantly reduce costs and improve customer service, many of the studies in the area of CLSC did not consider this important operational decision. Inventory management is another important operational decision that is known as one of the main tools for reducing costs and improving customer service (Asl-Najafi et al., 2015). Indeed, inventory decisions enable firms to offer improved responsiveness at lower cost (Daskin et al., 2002). There are a limited number of studies in SCND that are entirely incorporated in such operational planning levels of analysis. Traditionally, the three sets of decisions (i.e., location-allocation, vehicle routing and inventory management) are made at different levels of management and are generally analyzed separately. However, integrating these decisions leads to better network design because it enables a firm to efficiently manage their logistic system processes (Govindan et al., 2014; Gzara et al., 2014).

Regardless of the system's cost efficiency, sustainability is becoming a growing interest due to the concern about the environmental impacts (EIs) and social impacts (SIs) of business activities (Pagell and Wu, 2009). The World Summit of Sustainable Development (WSSD) defines sustainability as a balance between economic benefits, environmental protection and social developments. Following the WSSD, environmental impacts are a significant pillar of sustainability. Transportation networks have an important role in the design of a sustainable supply chain because they affect the environment through GHG emissions, particularly carbon dioxide (CO_2) (Dekker et al., 2012; Elhedhli and Merrick, 2012; Pan et al., 2013). In this respect, many countries, including both developed and developing countries have set national targets to reduce their CO_2 emissions in the near future. For instance, according to the ''Eleventh development plan of China,'' the country must reduce its carbon emissions by 10 percent (Wang et al., 2011).

Another pillar of sustainability is social responsibility (SR), which has rarely been addressed in the literature (Pagell and Wu, 2009). This aspect of sustainability is related to the force of Non-Governmental Organizations (NGOs) to take responsibility for the SIs of their actions. Because SR includes a wide variety of aspects, considering all of them in SCND would result in a non-optimal network (Pishvaee et al., 2014). Community involvement and development is considered as one of the main aspects of SR because researchers believe that the communities around the workplace should be respected and enhanced economically and socially (Dehghanian and Mansour, 2009; Pishvaee et al., 2012). Indeed, increasing employment opportunities and providing balanced economic development for local communities are the main goals of this aspect of SR. Recently, governments have paid significant attention to this aspect of SR, especially in developing countries (Lakin and Scheubel, 2010). For instance, according to the ''Fifth development plan of Islamic Republic of Iran,'' the issues of job creation and balanced economic development that belong to the community involvement and development aspect of SR have been significantly addressed. Therefore, developing a decision framework to design a sustainable supply chain considering employment opportunities and economic development alongside the environmental aspects of the designed network can be a great help in mitigating the worldwide concerns regarding sustainability.

Due to the dynamic nature of supply chain networks, different parameters such as demand, cost, distances and other relevant parameters may change due to the uncertain circumstances. Because it will greatly affect the design of the network, uncertainties must be addressed in the SCND (Snyder, 2006; Zahiri et al., 2014). To address the uncertainties, three types of modeling techniques have been introduced in the literature: stochastic programming, fuzzy programming and robust optimization; recently, researchers have attempted to combine these techniques to address uncertainties more efficiently (see Snyder, 2006; Mohammadi et al., 2014; Vahdani and Mohammadi, 2015).

This paper develops a sustainable CLSC model, in which routing and inventory decisions are integrated with location-allocation decisions in a multi-period, multi-product CLSC under mixed uncertainty. In this way, a new multi-objective, mixed-integer, nonlinear mathematical programming (MOMINLP) model is proposed to minimize the total investment cost, transportation cost, inventory cost and EIs of a transportation network. Additionally, the proposed mathematical programming model aims to maximize the positive SIs of designing a supply chain network. The main contributions of this paper that differentiate our efforts from related studies are as follows:

- designing a new sustainable multi-period, multi-product closed-loop supply chain that incorporates routing, inventory and location-allocation decisions and addresses the fluctuations in demand, costs, etc.;
- proposing a new environmental objective function to minimize the EIs of CO_2 emissions and fuel consumption (i.e., regarding different factors of vehicles, roads and air conditions) and wasted energy in the transportation network;
- utilizing an M/M/c queueing model to address the waiting time of vehicles in the remanufacturing facilities;
- applying SIs as an objective function to maximize the positive impacts of CLSC network design;
- applying a two-phase approach including an efficient stochastic-possibilistic programming method and a modified game theory approach to cope with the uncertainty;

- developing a new hybrid meta-heuristic algorithm to efficiently solve the large-sized instances;
- proposing a lower bound to evaluate the performance of the developed meta-heuristic algorithm; and
- applying the presented model in a case study.

The rest of the paper is organized as follows: Section 2 provides an overview of the related literature. The problem description and mathematical formulation are presented in Section 3. Section 4 elaborates the proposed stochastic-possibilistic programming method and the solution approach. In Section 5, the developed meta-heuristic algorithm and the new developed lower bound procedure are presented. Section 6 reports the results of the computational experiments, sensitivity analyses and the case study. Finally, Section 7 presents the conclusions and outlines future studies.

2. Literature

Focus on the current research can be classified into three main categories: inventory, routing and location decisions in the supply chain; sustainable supply chain; and queueing approach and uncertainty in the supply chain. We discuss each section in detail.

2.1. Inventory management, vehicle routing and facility location in the supply chain

As discussed earlier, inventory and routing decisions are two major operational decisions in SCND that can enable firms to manage their logistic system processes efficiently and to provide responsiveness at lower cost (Govindan et al., 2014; Gzara et al., 2014; Sedighy and Rezaei-Malek, 2015). The integration of location and inventory decisions is becoming an increasingly important issue and is addressed in some studies. In this area, the first idea was proposed by Baumol and Wolfe (1958); they considered a location problem with a fixed inventory cost. A Dantzig-Wolfe decomposition was used to solve the linear relaxation of the problem. Nozick and Turnquist (2001) presented a model to optimize inventory, transportation and customer responsiveness costs in a two-echelon network. A single-sourcing multi-period model considering inventory and transportation costs in a dynamic environment was introduced by Freling et al. (2003). Shu et al. (2005) studied the inventory-transportation network design problem in an uncertain environment with the assumption of keeping safety stock. In the study of Miranda and Garrido (2006), a nonlinear mixed-integer model was developed that simultaneously considered inventory and location decisions with the stochastic capacity constraint. They solved the presented model using a heuristic algorithm based on Lagrangian relaxation. Daskin et al. (2002) and Shen et al. (2003) introduced a new approach for integrating location and inventory decisions using (Q,r) policy. Daskin et al. (2002) introduced a distribution center (DC) location model in which a (Q,r) inventory control policy was considered. The authors used Lagrangian relaxation to solve the problem. Finally, Diabat et al. (2013) studied a multi-echelon location-inventory model and solved the model using Lagrangian relaxation.

The literature includes other studies in which the integration of routing and location decisions is addressed. It has been proven that solving the facility location problem and vehicle routing problem (VRP) separately generates sub-optimal results (Prins et al., 2006). Therefore, the significance of combining these two aspects (i.e., facility location and VRP), which is known as the location routing problem (LRP) has been highlighted in the literature. Watson-Gandy and Dohrn (1973) were probably the first authors that clearly addressed the LRP problem in their study. Afterward, several efforts were conducted in this field. Interested readers are referred to two comprehensive reviews in the literature for more details about LRPs (Nagy and Salhi, 2007; Prodhon and Prins, 2014).

The integration of location-routing-inventory (LRI) is also studied in several papers. A single product, multi-depot LRI problem was proposed by Liu and Lee (2003). Liu and Lin (2005) proposed a heuristic method that was a combination of tabu search and simulated annealing to solve the LRI problem. Moin et al. (2011) developed an inventory-routing many-to-one distribution network consisting of an assembly plant and a number of suppliers. They developed a hybrid genetic algorithm to obtain near-optimal solutions. Javid and Azad (2010) developed an LRI model and solved the LRI model using a heuristic method based on tabu search and simulated annealing algorithms. In their model, they integrated a VRP into the inventory-location model given in Daskin et al. (2002). Nekooghadirli et al. (2014) developed the model presented by Javid and Azad (2010) and proposed a multi-period, multi-product LRI model and solved the problem using four multi-objective meta-heuristic algorithms. Kumar et al. (2015) developed a mathematical model that considered production, the pollution routing problem and inventory decisions. A hybrid self-learning particle swarm optimization algorithm was developed to solve the presented model.

The next stream of related studies combined inventory or routing decisions in a CLSC network design. Due to the focus of many companies on devising a CLSC, several studies have been conducted in the field of CLSC. Fleischmann and Minner (2004) reviewed the inventory management issues related to the CLSC and concluded that there are significant advantages in integrating inventory decisions into CLSC networks. Chung et al. (2008) developed a CLSC inventory model to maximize the joint profits of the supplier. In their study, a multi-echelon inventory system with remanufacturing capability was proposed. Chung and Wee (2011) and Wee et al. (2011) addressed a supply chain inventory system for deteriorating items. Abdallah et al. (2012) considered a CLSC in which the remanufacturing centers (RCs) serve as the intermediary between the recovery of the products and their re-entry to the market as spare parts. In their study, a (Q,r) inventory control policy was used in the DCs and RCs. Diabat et al. (2015) proposed a two-stage Lagrangian relaxation algorithm to solve the location-inventory problem developed by Abdallah et al. (2012). They also conducted three case studies from the United States to show the applicability of their model. For future research, they suggested considering routing and capacity problems in the presented location-inventory model. Kaya and Urek (2016) presented a CLSC that addressed location, inventory and pricing decisions holistically in an MINLP model. They developed three hybrid meta-heuristic algorithms to solve the presented model. Recently Asl-Najafi et al. (2015), developed a dynamic closed-loop location-inventory problem under disruption risk, and they showed the applicability of their model via a real case study in the refrigerator industry. For future research, they again suggested considering the routing problem in the developed CLSC network. Despite the advantages of considering routing decisions alongside inventory decisions in SCND (Govindan et al., 2014; Gzara et al., 2014; Javid and Azad, 2010), none of the papers mentioned above considered both inventory and routing decisions in a CLSC network design.

2.2. Sustainable supply chain

The literature on sustainability can be classified into two main groups: (i) green SCND and (ii) SR SCND. There is extensive literature devoted to the EIs in the supply chain. Therefore, we introduce some of the recent papers in this area. Chaabane et al. (2012) presented a mixed-integer linear programming–based framework for sustainable SCND. Their model demonstrated that efficient carbon management strategies will help decision makers (DMs) achieve sustainability objectives. In the study of Wang et al. (2011), the environmental investment decision was addressed in an SCND problem. Chaabane et al. (2011) developed a multi-objective model to address carbon emissions and total logistic costs including suppliers, sub-contractor selection, technology acquisition and transportation modes. Elhedhli and Merrick (2012) studied an SCND in which emission costs are considered alongside fixed and variable location and production costs. They used a concave function to model the relationship between CO_2 emissions and vehicle weight. Fahimnia et al. (2013) developed an optimization model to evaluate the influence of forward and reverse supply chains on the carbon footprint. The developed model was implemented in an Australian case study. In another study, Fahimnia et al. (2015) proposed a tactical supply chain model to investigate the trade-off between cost and environmental degradation including carbon emissions, energy consumption and waste generation. They used a nested integrated cross-entropy method to solve the proposed model. Rezaee et al. (2015) presented a green supply chain in a carbon trading environment. They incorporated uncertainty in carbon price and product demand using a two-stage stochastic programming model. Govindan et al. (2015) developed a five-echelon SCND and simultaneously considered the EIs of all of the supply chain members, including the most harmful GHG emissions such as CO_2, CFC and NO_x. The study of Abdallah et al. (2012) is one of the rare studies in which inventory management and sustainability are addressed. In their study, carbon credits are allocated to companies implementing reverse logistics to ensure proper recovery of products. Another study that considered environmental concerns alongside inventory management is the study of Diabat and Al-Salem (2015). They developed a location-routing model accounting for the reduction of carbon emissions.

Other studies that belong to VRP address the environmental aspect of sustainability. Erdoğan and Miller-Hooks (2012) proposed a green vehicle routing model that aimed to minimize fuel consumption by minimizing the total distance traveled. Suzuki (2011) developed a VRP approach to minimize the fuel consumption and pollutant emissions. In this way, their model minimized the distance that a vehicle with a heavy payload must travel in a given tour. Bektaş and Laporte (2011) presented a pollution-routing problem as an extension of the classic VRP. In the presented model, more parameters related to vehicle features such as vehicle load, speed and total cost are considered to minimize the amount of GHG emissions. A robust optimization approach for a green pickup and delivery problem was introduced by Tajik et al. (2014). The presented model aims to minimize the total cost while considering the road's physical condition, weight of the vehicles, the load the vehicles carry and the penalty for tardiness and earliness in arrival time of pickup customers.

The scope of sustainability has been expanded in recent studies through considering SIs of an SCND alongside the EIs. Dehghanian and Mansour (2009) introduced a supply chain model to maximize the social responsibility and to minimize the total cost. They considered four factors of SR: employment, damage to workers, product risk and local development. Pishvaee et al. (2012) proposed a robust possibilistic approach to model a supply chain under epistemic uncertainty that considered social factors, including the number of potentially hazardous products, the number of lost days caused from work damage, the amount of produced waste and the number of created job opportunities. Mota et al. (2014) proposed a multi-objective mathematical model for the design of a supply chain. They addressed three pillars of sustainability, and they focused on created job opportunities as an SI of the designed supply chain. Similarly, Devika et al. (2014) simultaneously considered three pillars of sustainability in an SCND. As an SI of the designed network, they considered fixed and variable jobs that totally depend on the used capacity of the facility. In another study, Pishvaee et al. (2014) presented a sustainable medical supply chain network under uncertainty. In the proposed model, three conflicting objective functions including economic, environmental and SR were considered in the medical needle and syringe supply chain. Four factors of SR, including local development, created job opportunities, consumer risk and damage to workers, are addressed in their model. For more precise details, interested readers can refer to the review papers of Brandenburg et al. (2014), Eskandarpour et al. (2015) and Fahimnia et al. (2015).

2.3. Queueing approach and uncertainty in the supply chain

In supply chain networks, the difference between the arrival rate of the incoming flow and the processing rate of servers may lead to the formation of a queue in some facilities. In this way, there are a number of studies that use a queuing approach to reduce congestion in the supply chain and location-allocation problems. Lieckens and Vandaele (2007) developed a mathematical model in a reverse logistic and used queueing relationships to incorporate a product's cycle time and inventory holding cost. Zahiri et al. (2014) proposed a location-allocation model for the design of an organ transplant transportation network. They used an M/M/c queueing model with priority to minimize the waiting time in the queue for the transplant operation. Vahdani et al. (2012) proposed a reliable forward/reverse logistic network under uncertainty in the iron and steel industry. An M/M/c queueing model was used in a scrap processing facility to avoid congestion of arrival flows. Saeedi et al. (2015) presented a De Novo programming approach for a CLSC in which they utilized an M/M/1 queueing model to determine the capacity of recovery facilities in the reverse flow. Vahdani and Mohammadi (2015) developed a model to design a CLSC under uncertainty. They used a priority M/M/c queueing model to minimize the maximum waiting times in the queue of products. Recently, Mohammadi et al. (2014) used a queueing approach to reduce the EIs in a hub-and-spoke network for the first time. They tried to reduce the congestion at hubs to reduce the EIs of wasted energy in vehicles that may stay in queue to receive services (i.e., loading and unloading). They concluded that this approach can significantly reduce the EIs in the network. Because several studies in the literature of CLSC have shown the possibility of queue formation in some facilities, a similar strategy can be adopted to more comprehensively reduce the EIs in the CLSC.

The importance of addressing uncertainty in SCND is clearly emphasized in the literature (Snyder, 2006; Mousazadeh et al., 2014). Moreover, considering reverse logistic and sustainability can further increase the number of uncertain parameters in the designed supply chain, and, as a consequence, addressing uncertainty is of crucial importance in such networks (Mousazadeh et al., 2014). The literature includes a number of studies in the area of forward/reverse/closed-loop supply chains that address uncertainty via different approaches, including stochastic (Chatfield and Pritchard, 2013; Georgiadis, 2013; Li and Womer, 2015), robust (Saeedi et al., 2015; Hasani et al., 2015; Ramezani et al., 2013; Rezaei-Malek and Tavakkoli-Moghaddam, 2014), fuzzy and interval fuzzy (Dai and Zheng, 2015; Fallah et al., 2015). According to the comprehensive review of Govindan et al. (2015) in reverse logistic and CLSC, adopting new nondeterministic approaches to address the uncertainty in a more realistic way and regarding new uncertain parameters are two issues that should be addressed in new studies in the reverse logistic and CLSC area. The stochastic-possibilistic programming method is an efficient approach that is able to address both fuzzy and random-fuzzy uncertainties. This approach has successfully been used in numerous applications (Mohammadi et al., 2014; Liu et al., 2003; Mousavi et al., 2014). Therefore, adopting the stochastic-possibilistic approach and considering more uncertain parameters to address the uncertainty in a more realistic way is a contribution to the relevant literature.

The studies reviewed so far demonstrate several gaps in the area of CLSC. First, a clear gap is shown in the integration of inventory, routing and location-allocation decisions in a CLSC. As discussed previously, considering these decisions holistically enables firms to manage their logistic system processes efficiently, provides responsiveness at lower cost and avoids generating sub-optimal results (Govindan et al., 2014; Gzara et al., 2014; Javid and Azad, 2010). Therefore, we consider the inventory policies and vehicle routing problem in the considered CLSC network. Moreover, despite the importance of addressing sustainability concerns and operational decisions in SCND, there is no study that addresses both issues simultaneously. In this respect, using a queuing model to reduce the EIs can also be helpful for designing a sustainable supply chain more comprehensively. Furthermore, the relevant literature does not sufficiently address the uncertainty in the CLSC. Hence, our study targets another gap in the existing literature by considering different types of uncertain data (i.e., both fuzzy data and random fuzzy data). To overcome these shortcomings and fulfill these gaps, we develop a sustainable CLSC with routing and inventory decisions under mixed uncertainty. The presented model can be used to investigate trade-offs between cost, SIs and EIs of the designed network.

3. Problem description and mathematical modeling

3.1. Modeling framework

Fig. 1 shows a schematic view of the structure of the proposed CLSC network and the interaction between its chain members. In the forward logistic, multiple suppliers ship several types of products through DCs to different numbers of retailers.

The delivery of products from DCs to retailers is performed by vehicles through the existing routes. A vehicle must leave a DC, visit the retailers on its route and then return to its departing DC.

In this network, the responsibility of collecting and sorting the returned products from customers is given to the retailers. Hence, each retailer collects and sorts the returned products and then sends them to an RC. In the RC, the returned products are remanufactured as spare parts and then pushed back to the retailers through the forward supply chain. To eliminate shipping costs from RCs to DCs, an RC can only be opened when a DC is opened at the same site. Notably, the returned products do not influence the demand of the original products. In the reverse logistics, the products that have potential use as spare parts are transported from retailers to the remanufacturing facilities by vehicles. A normal distribution is a good approximation for sufficiently large demand values (Montgomery et al., 2009). Moreover, the normality assumption is

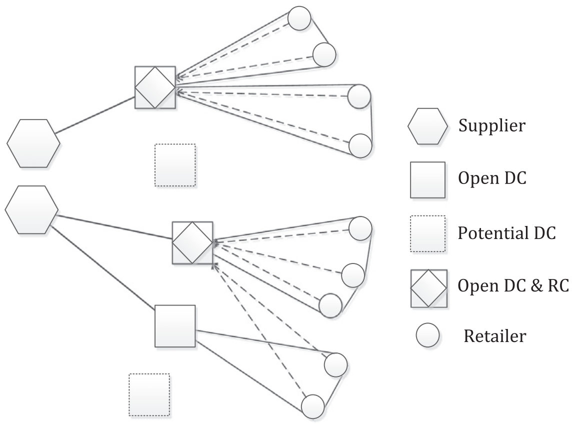


Fig. 1. The structure of proposed CLSC network.

widely invoked in literature of EOQ inventory models as it captures the essential features of demand uncertainty and is convenient for calculating the safety stock in EOQ inventory models (Diabat et al., 2015; Daskin et al., 2002; Shen et al., 2003; Abdallah et al., 2012; Ahmadi-Javid and Seddighi, 2013). Hence, in our model, the demand of the retailers and the return flows follow a normal distribution of $\left(\text{i.e., } R_{kpt} \sim N\left(\mu^t_{kp}, \sigma^{2,t}_{kp}\right)\right)$ and $\left(\text{i.e., } r_{kpt} \sim N\left(\gamma^t_{kp}, \rho^{2,t}_{kp}\right)\right)$, respectively, where $\gamma^t_{kp} = \delta_p \mu^t_{kp}$. More precisely, it is assumed that a certain share of previous demand quantity (δ_p) will return.

To integrate the inventory model into the CLSC, we consider a (Q, r) inventory model with type I service in the DCs and RCs. The working inventory cost at DCs is obvious and needs no explanation. Following Diabat et al. (2015), for the working inventory at the RCs, we assume that each product consists of $M + 1$ subassemblies in which one main subassembly is salvaged and M subassemblies are shipped from suppliers to the RC. To simplify the model, an aggregate subassembly is considered based on the dollar value of the M subassemblies. Hence, the holding cost of the aggregate subassembly is introduced as $q = \gamma h$, where $\gamma \in (0, 1)$ depends on the overall dollar value of the aggregate subassemblies regarding the overall dollar value of the main product.

The presented model focuses on three main issues in designing a comprehensive CLSC: (i) the establishment cost of DCs and RCs, the inventory cost in these facilities and transportation costs (ii) the environmental impacts of the designed network related to the CO_2 emissions, fuel consumption and wasted energy and (iii) the SIs of the designed network. The considered inventory model is explained in Section 3.2. The main focus of the proposed study is the logistical viewpoint of the supply chain and not the production process of a manufacturing company. From the logistical viewpoint of SCND, the transportation network has an important role in designing a sustainable supply chain because it is the largest source of environmental hazards, particularly carbon dioxide (CO_2), in the logistic system (Dekker et al., 2012; Elhedhli and Merrick, 2012; Pan et al., 2013). In calculating the CO_2 emitted through transportation activities, several factors such as the average vehicle acceleration, rolling resistance, vehicle front space, vehicle empty weight, air friction and the load that a vehicle can carry are considered. Despite the many studies that just consider simple concepts in calculating the CO_2 emissions, the proposed model also focuses on the EIs of wasted energy when vehicles wait for service in RCs. These EIs are calculated through a queue model and are explained in Section 3.3. In this network, establishing a DC or RC will have some SIs on the network. This establishment will create several job opportunities in the related region. Furthermore, the establishment of an DC or RC will also affect the economic development of the local community. Therefore, less developed areas will be given more importance to ensure balanced development. The main assumptions used to formulate the CLCS are the following:

- The locations of supplier and retailer zones are known, and each retailer has an uncertain demand that follows a normal distribution (i.e., the demand of retailers must be satisfied in each period).
- There are a set of J potential sites for locating DCs, each of which has a capacity cu^n_j and a fixed cost f^n_j for opening a DC.
- There are a set of M potential sites where RCs can be located. RCs can only be opened at locations where DCs exist. Each potential site has a capacity $cw^{n'}_m$ and fixed cost $l^{n'}_m$ for opening an RC in that location.
- A (Q, r) inventory model with type I service is considered for products available at DCs and subassemblies waiting remanufacturing at RCs.
- Different types of products are considered in the CLSC network.
- Received goods from suppliers in DCs must be transported to a set of retailers by vehicles with specific capacity levels. A vehicle must leave a DC, visit the retailers on its route and return to its departing DC.
- Returned products collected and sorted by retailers must be transported to RCs by vehicles.
- Vehicles entering an RC may wait to receive services.
- Different factors (i.e., vehicles, the vehicle load-carrying capacity, roads and air conditions) are considered in calculating the emission rate.

- Locating a DC or an RC in a region results in creating job opportunities and regional development.

3.2. Inventory model

In the (Q, r) inventory model, a recorder point (r) is pre-defined in the inventory model. Then, whenever the inventory position drops to the recorder point r, a replenishment order for quantity order Q is placed immediately. After a certain lead time, the order will be received. In our (Q, r) inventory model, the inventory costs in each period include fixed order cost, shipment cost and holding working inventory cost.

To present the inventory model, the following notations are introduced:

Sets:	
s	Index of suppliers, $s = \{1, \ldots, S\}$
j, j'	Index of DCs, $j = \{1, \ldots, J\}$, $j' = \{1, \ldots, J'\}$
k, l	Index of retailers, $k = \{1, \ldots, K\}, l = \{1, \ldots, L\}$
m	Index of potential RCs, $m = \{1, \ldots, M\}$
p	Index of products, $p = \{1, \ldots, P\}$
t	Index of time periods, $t = \{1, \ldots, T\}$
Parameters:	
I_{sj}	Fixed ordering cost placed to the supplier s by DC j
g_{sj}	Fixed cost of shipment from supplier s to DC j
a_{sjp}	Unit cost of shipment product p from supplier s to DC j
h^t_{jp}	Inventory holding cost related to product p at DC j in period t
γ_p	Constant coefficient related to reverse holding cost of product p
$\bar{L}^t_{sj}$	Lead time of DC j that is served by supplier s in period t
δ_p	Coefficient of expected return product p
θ	Weight of inventory cost
β	Weight of transportation cost
Decision variables:	
X_{sj}	1; if DC j is served by supplier s, 0; otherwise
Y_{jk}	1; if retailer k is served by DC j, 0; otherwise
Z_{km}	1; if returns from retailer k are collected by RC m, 0; otherwise
Q_j	Order size at DC j

Regarding the above notations, the inventory costs of DC j is calculated as:

$$\sum_s I_{sj}X_{sj}\frac{D_j}{Q_j} + \left(\sum_s g_{sj}X_{sj}\frac{D_j}{Q_j} + \sum_s a_{sj}X_{sj}D_j\right) + h_j\frac{Q_j}{2} \tag{1}$$

Following Daskin et al. (2002), the shipment cost between suppliers and DCs is a function of $v(x) = g + a(x)$, where g and a are the fixed and unit cost of a shipment, respectively.

Furthermore, it is assumed that the demand during the lead time is normally distributed with mean of $\bar{L}\sum_{k\in A_j}\mu_k$ and variance of $\bar{L}\sum_{k\in A_j}\sigma_k^2$. Then, the safety stock is calculated as $z_a\sqrt{\bar{L}\sum_{k\in A_j}\sigma_k^2}$, where A_j is a set of retailers assigned to a DC_j and z_a is a standard normal deviate (i.e., $P(z < z_a) = a$).

Adding the weights of inventory cost and transportation cost, replacing D_j by $\sum_k \mu_k Y_{jk}$ and considering the amount of safety stock we would have:

$$\left(\theta\sum_s I_{sj}X_{sj} + \beta\sum_s g_{sj}X_{sj}\right)\frac{\sum_k \mu_k Y_{jk}}{Q_j} + \beta a_{sj}\sum_k \mu_k Y_{jk} + \theta\frac{h_j Q_j}{2} + \theta h_j z_\alpha\sqrt{\sum_s \bar{L}_{sj}X_{sj}\sum_k \sigma_k^2 Y_{jk}} \tag{2}$$

Alternatively, the optimal value of decision variable Q_j can be obtained by taking the derivative of Eq. (2) in Q_j, giving:

$$Q_j^* = \sqrt{\frac{2\left(\theta\sum_s I_{sj}X_{sj} + \beta\sum_s g_{sj}X_{sj}\right)\sum_k \mu_k Y_{jk}}{\theta h_j}} \tag{3}$$

By substituting Eq. (3) in Eq. (2), the single-period, single-product inventory model for our forward logistic can be formulated as:

$$\sqrt{2\theta h_j\left(\theta\sum_s I_{sj}X_{sj} + \beta\sum_s g_{sj}X_{sj}\right)\sum_k \mu_k Y_{jk}} + \beta\sum_s a_{sj}X_{sj}\sum_k \mu_k Y_{jk} + \theta h_j Z_\alpha\sqrt{\sum_s \bar{L}_{sj}X_{sj}\sum_k \sigma_k^2 Y_{jk}} \tag{4}$$

Because the inventory model in our reverse logistic is similar to that of the forward one, the multi-period multi-product inventory model for our forward and reverse logistics can be obtained by Eqs. (5) and (6), respectively.

$$\sqrt{2\theta\sum_{k\in K}\sum_{p\in P}\sum_{t\in T}h_{jp}^{t}\left(\theta\sum_{s\in S}l_{sj}X_{sj}+\beta\sum_{s\in S}g_{sj}X_{sj}\right)\mu_{kp}^{t}Y_{jk}^{2}}+\beta\left(\sum_{p\in P}\sum_{t\in T}\sum_{s\in S}a_{sjp}X_{sj}\right)\sum_{k\in K}\mu_{kp}^{t}Y_{jk}^{2}+\theta\sum_{p\in P}\sum_{t\in T}h_{jp}^{t}z_{\alpha} \times\sqrt{\sum_{s\in S}\bar{L}_{sj}^{t}X_{sj}\sum_{k\in K}\sigma_{kp}^{2,t}Y_{jk}^{2}} \tag{5}$$

$$\sqrt{2\theta\sum_{k\in K}\sum_{p\in P}\sum_{t\in T}\gamma_{p}h_{mp}^{t}\left(\theta\sum_{s\in S}l_{sm}X_{sm}+\beta\sum_{s\in S}g_{sm}X_{sm}\right)\delta_{p}\mu_{kp}^{t}Z_{km}^{2}}+\beta\left(\sum_{p\in P}\sum_{t\in T}\sum_{s\in S}a_{smp}X_{sm}\right)\delta_{p}\sum_{k\in K}\mu_{kp}^{t}Z_{km}^{2} +\theta\sum_{p\in P}\sum_{t\in T}\gamma_{p}h_{mp}^{t}z_{\alpha}\sqrt{\sum_{s\in S}\bar{L}_{sm}^{t}X_{sm}\sum_{k\in K}\rho_{kp}^{2,t}Z_{km}^{2}} \tag{6}$$

3.3. M/M/c queueing system

In the proposed model, the EIs of wasted energy when vehicles wait to receive services (i.e., loading and unloading) in RCs are considered and minimized. Therefore, the environmental impact of total required watt (EITRW) for each vehicle staying in a queue at RCs needs to be calculated. To calculate EITRW, the waiting time of vehicles at RCs should be calculated using a queueing model.

Different types of queueing models are introduced in the literature. There are numerous studies in which a queue approach is used to calculate the waiting time or queue length at the queueing system. In this paper, because the returned products at retailers are transferred by vehicles, the number and frequency of vehicles entering the RCs is low. Moreover, there is a variation in the inter-arrival times of vehicles due to several factors such as environmental conditions, link disruptions, traffic jams etc. Therefore, a Poisson distribution is considered for modeling the waiting times of vehicles entering the RCs. By considering peak hours, we assume that the average arrival rate and service rate are both constant and follow a Poisson distribution. Applying the M/M/c queueing system as the development of mathematical models to study and analyze the waiting time and queue length in the network design problems has led to beneficial results (i.e., see Vahdani et al., 2012). Hence, an M/M/c queueing system is considered to model the queue formed by the vehicles.

To present the queuing system, the following notations are introduced:

Parameters:	
Ψ_m	Number of servers at RC m
τ_m^t	Service rate of RC m in period t
rw	Required watt per minute of vehicles
eiw	Environmental impact of used watt per minute
Decision variables:	
λ_m^t	Arrival rate of vehicles to RC m
NT_{km}^t	Number of vehicles sent from DC k to RC m in period t
WT_m^t	Waiting time at RC m in period t

According to Gross (2008), the waiting time at RC m is calculated by:

$$WT_m^t=\frac{\left(\frac{\lambda_m^t}{\tau_m^t}\right)^{\Psi_m}\tau_m^t}{(\Psi_m-1)!(\Psi_m\tau_m^t-\lambda_m^t)^2}\left\{1+\sum_{n=1}^{\Psi_n-1}\left(\frac{\lambda_m^t}{\tau_m^t}\right)^n\frac{1}{n!}+\left(\frac{\lambda_m^t}{\tau_m^t}\right)^{\Psi_m}\frac{1}{\Psi_m!}\times\frac{\lambda_m^t}{\tau_m^t-\lambda_m^t}\right\}^{-1} \tag{7}$$

where the arrival rate λ_m^t in our CLCS is calculated by:

$$\lambda_m^t=\sum_k NT_{km}^t \tag{8}$$

Finally, the EITRW for all entering vehicles at RC m is calculated by:

$$\mathrm{EITRW_m}=eiw\times rw\times\sum_k NT_{km}^t \times\frac{\left(\frac{\sum_k NT_{km}^t}{\tau_m^t}\right)^{\Psi_m}\boldsymbol{\tau}_m^t}{(\Psi_m-1)!(\Psi_m\boldsymbol{\tau}_m^t-\sum_k NT_{km}^t)^2}\left\{1+\sum_{n=1}^{\Psi_m-1}\left(\frac{\sum_k NT_{km}^t}{\boldsymbol{\tau}_m^t}\right)^n\frac{1}{n!}+\left(\frac{\sum_k NT_{km}^t}{\boldsymbol{\tau}_m^t}\right)^{\Psi_m}\frac{1}{\Psi_m!}\times\frac{\sum_k NT_{km}^t}{\boldsymbol{\tau}_m^t-\sum_k NT_{km}^t}\right\}^{-1} \tag{9}$$

3.4. Mathematical programming

Sets:	
n	Index of capacity level available for DCs $n = \{1, \ldots, N\}$
n'	Index of capacity level available for RCs $n' = \{1, \ldots, N'\}$
V	Index of vehicles $v = \{1, \ldots, V\}$
M'	Aggregate index of retailers and potential DCs $(k \cup j)$
Parameters:	
d_{kl}	Distance between node k to node l
Pr_v	Fixed cost of using vehicle v
c^t_{km}	Transportation cost between retailer k and RC m in period t
f^n_j	Fixed cost of establishing DC j with capacity level n
$l^{n'}_m$	Fixed cost of establishing RC m with capacity level n'
jcu^n_j	Number of created job opportunities if DC j is opened with capacity level n
$jcw^{n'}_m$	Number of created job opportunities if RC m is opened with capacity level n'
up_j	Unemployment rate at node j
evu^n_j	Economic value of opened DC j with capacity level n
$evw^{n'}_m$	Economic value of opened RC m with capacity level n'
rd_j	Regional development at node j
t_{kl}	Transportation time between node k and node l
ev_f	Environmental impact of fuel consumption
e	Environmental impact of CO_2 emissions
a_v	Average acceleration of vehicle v
c_r	Coefficient of rolling resistance
A_v	Front space of vehicle v
We_v	Empty weight of vehicle v
c_d	Coefficient of air friction
cs_s	Capacity of supplier s
cu^n_j	Capacity of DC j with level n
$cw^{n'}_m$	Capacity of RC m with level n'
cv_v	Capacity of vehicle v used for transportation between DCs and retailers
ct	Capacity of vehicles used for transportation between retailers and RCs
$\lvert B \rvert$	Number of retailers in set $K(B = \lvert K \rvert)$
E	A very large number
Decision variables:	
U^n_j	1; if DC j is opened with capacity level n; Otherwise, 0
$W^{n'}_m$	1; if RC m is opened with capacity level n'; Otherwise, 0
R^t_{klv}	1; if there is a route of vehicle v between node k and node l in period t; Otherwise, 0
Q^t_{klv}	Amounts of loads of products in vehicle v after passing node k, before arriving to node l in period t

3.4.1. Objective functions

Following the above notations, the objective functions of the proposed model are presented as follows:

$$\begin{aligned}
\text{Min } & \sum_{j\in J}\sum_{n\in N} f^n_j U^n_j + \sum_{m\in M}\sum_{n'\in N'} l^{n'}_m W^{n'}_m + \sum_{j\in J}\left(\sqrt{2\theta\sum_{k\in K}\sum_{p\in P}\sum_{t\in T} h^t_{jp}\left(\theta\sum_{s\in S} I_{sj}X_{sj} + \beta\sum_{s\in S} g_{sj}X_{sj}\right)\mu^t_{kp}Y_{jk}}\right. \\
& + \beta\sum_{p\in P}\sum_{t\in T}\sum_{s\in S}\left(a_{sjp}X_{sj}\sum_{k\in K}\mu^t_{kp}Y_{jk}\right) + \left.\theta\sum_{p\in P}\sum_{t\in T} h^t_{jp} z_\alpha \sqrt{\sum_{s\in S}\bar{L}^t_{sj}X_{sj}\sum_{k\in K}\sigma^{2,t}_{kp}Y_{jk}}\right) \\
& + \sum_{m\in M}\left(\sqrt{2\theta\sum_{k\in K}\sum_{p\in P}\sum_{t\in T}\gamma_{\mathrm{p}} h^t_{mp}\left(\theta\sum_{s\in S} I_{sm}X_{sm} + \beta\sum_{s\in S} g_{sm}X_{sm}\right)\delta_p\mu^t_{kp}Z_{km}} + \beta\sum_{p\in P}\sum_{t\in T}\sum_{s\in S}\left(a_{smp}X_{sm}\delta_p\sum_{k\in K}\mu^t_{kp}Z_{km}\right)\right. \\
& + \left.\theta\sum_{p\in P}\sum_{t\in T}\gamma_{\mathrm{p}} h^t_{mp} z_\alpha \sqrt{\sum_{s\in S}\bar{L}^t_{sm}X_{sm}\sum_{k\in K}\rho^{2,t}_{kp}Z_{km}}\right) + \beta q\left(\sum_{v\in V}\sum_{k\in M'}\sum_{l\in M'}\sum_{t\in T} d_{kl}R^t_{klv} + \sum_{j\in J}\sum_{l\in M'}\sum_{v\in V}\sum_{t\in T} Pr_v R^t_{jlv}\right) \\
& + \beta\sum_{k\in K}\sum_{m\in M}\sum_{t\in T} c^t_{km} NT^t_{km}
\end{aligned} \tag{10}$$

$$\text{Min} \sum_{v\in V}\sum_{k\in M'}\sum_{l\in M'}\sum_{t\in T}(ev_f+e)(a_v+(\sin(k,l)+c_r\cos(k,l))g)d_{kl}We_vR^t_{klv}+\sum_{v\in V}\sum_{k\in M'}\sum_{l\in M'}\sum_{t\in T}(ev_f+e)(a_v+(\sin(k,l)+c_r\cos(k,l))g)d_{kl}Q^t_{klv}+\sum_{v\in V}\sum_{k\in M'}\sum_{l\in M'}\sum_{t\in T}(ev_f+e)(1/2c_dA_v\rho)d_{kl}t_{kl}R^t_{klv}+\sum_{t\in T}\sum_{m\in M}eiw\times rw \times\left(\sum_{k\in K}NT^t_{km}\times\frac{\left(\frac{\sum_k NT^t_{km}}{\tau^t_m}\right)^{\Psi_m}\tau^t_m}{(\Psi_m-1)!\left(\Psi_m\tau^t_m-\sum_k NT^t_{km}\right)^2}\left\{1+\sum_{n=1}^{\Psi_m-1}\left(\frac{\sum_k NT^t_{km}}{\tau^t_m}\right)^n\frac{1}{n!}+\left(\frac{\sum_k NT^t_{km}}{\tau^t_m}\right)^{\Psi_m}\frac{1}{\Psi_m!}\times\frac{\sum_k NT^t_{km}}{\tau^t_m-\sum_k NT^t_{km}}\right\}^{-1}\right) \tag{11}$$

$$\text{Max } \omega_{jo}\left(\sum_{j\in J}\sum_{n\in N}U^n_j jcu^n_j up_j+\sum_{m\in M}\sum_{n'\in N'}W^{n'}_m jcw^{n'}_m up_m\right)+\omega_{be}\left(\sum_{j\in J}\sum_{n\in N}U^n_j evu^n_j(1-rd_j)+\sum_{m\in M}\sum_{n'\in N'}W^{n'}_m evw^{n'}_m(1-rd_m)\right) \tag{12}$$

The presented model consists of three objective functions. The first objective function (10) minimizes the total cost, including the fixed costs of establishing DCs and RCs, inventory costs and transportation costs. The first and second terms of objective function (10) are related to the fixed establishing costs of DCs and RCs. The third term is the total expected working inventory cost and safety stock inventory cost at DCs. Similarly, the fourth term is the total expected working inventory cost and safety stock inventory cost at RCs. The fifth term is the transportation costs between DCs and retailers. The sixth term is the transportation costs between retailers and RCs. The objective function (11) is related to the EIs of CO_2 emissions, fuel consumption and wasted energy. The first three components in the objective function (11) measure the EIs of CO_2 emissions and fuel consumption regarding the vehicle features, road and air conditions (i.e., surface, slope, air fraction etc.) and the load that vehicles carry. The fourth component calculates the EIs of wasted energy while vehicles wait for receiving services in RCs. The objective function (12) maximizes the positive SIs of the considered CLSC. The first term of objective function (12) aims to maximize the created job opportunities with respect to the unemployment rate. The second term aims to maximize the balanced economic development.

3.4.2. Constraints

$$\sum_{s\in S}X_{sj}=\sum_{n\in N}U^n_j \quad \forall j\in J \tag{13}$$

$$\sum_{k\in K}\sum_{j\in J}\sum_{p\in P}\mu^t_{kp}Y_{jk}X_{sj}\leqslant cs_s \quad \forall t\in T,\forall s\in S \tag{14}$$

$$\sum_{n\in N}U^n_j\leqslant 1 \quad \forall j\in J \tag{15}$$

$$\sum_{p\in P}\sum_{k\in K}\mu^t_{kp}Y_{jk}\leqslant\sum_{n\in N}cu^n_jU^n_j \quad \forall t\in T,\forall j\in J \tag{16}$$

$$\sum_{v\in V}\sum_{l\in M'}R^t_{klv}=1 \quad \forall t\in T,\forall k\in K \tag{17}$$

$$\sum_{p\in P}\sum_{l\in K}\mu^t_{lp}\sum_{k\in M'}R^t_{klv}\leqslant cv_v \quad \forall t\in T,\forall v\in V \tag{18}$$

$$M_{kvt}-M_{lvt}+\left(B\times R^t_{klv}\right)\leqslant B-1 \quad \forall t\in T,\forall k,l\in K,\forall v\in V \tag{19}$$

$$\sum_{l\in M'}R^t_{klv}-\sum_{l\in M'}R^t_{lkv}=0 \quad \forall t\in T,\forall k\in M',\forall v\in V \tag{20}$$

$$\sum_{j\in J}\sum_{k\in K}R^t_{jkv}\leqslant 1 \quad \forall t\in T,\forall v\in V \tag{21}$$

$$\sum_{l\in M'}R^t_{klv}+\sum_{l\in M'}R^t_{jlv}-Y_{jk}\leqslant 1 \quad \forall t\in T,\forall j\in J,\forall k\in K,\forall v\in V \tag{22}$$

$$R^t_{jj'v}=0 \quad \forall t\in T,\forall v\in V,\forall j,j'\in J \tag{23}$$

$$\sum_{k\in M'}\sum_{v\in V}Q^t_{klv} - \sum_{p}\mu^t_{lp} = \sum_{k\in M'}\sum_{v\in V}Q^t_{lkv} \quad \forall t\in T, \forall l\in K \tag{24}$$

$$Q^t_{klv} \leqslant ER^t_{klv} \quad \forall t\in T, \forall v\in V, \forall k,l\in M' \tag{25}$$

$$Q^t_{jkv} + E(1-R^t_{jkv}) \geqslant \sum_{k\in M'}\sum_{l\in L}\sum_{p\in P}\mu^t_{lp}R^t_{klv} \quad \forall t\in T, \forall v\in V, \forall j\in J, \forall k\in K \tag{26}$$

$$\sum_{n'\in N'}W^{n'}_m \leqslant 1 \quad \forall m\in M \tag{27}$$

$$\sum_{k\in K}\sum_{p\in P}\delta_p\mu^t_{kp}Z_{km} \leqslant \sum_{n'\in N'}cw^{n'}_m W^{n'}_m \quad \forall t\in T, \forall m\in M \tag{28}$$

$$\sum_{j\in J}Y_{jk} = 1 \quad \forall k\in K \tag{29}$$

$$\sum_{m\in M}Z_{km} = 1 \quad \forall k\in K \tag{30}$$

$$\sum_{n'\in N'}W^{n'}_m - \sum_{k\in K}Y_{km} \leqslant 0 \quad \forall m\in M \tag{31}$$

$$NT^t_{km} \geqslant \frac{\sum_{p\in P}\delta_p\mu^t_{kp}Z_{km}}{ct} \quad \forall t\in T, \forall k\in K, \forall m\in M \tag{32}$$

Eq. (13) indicates that each open DC must be assigned to one supplier. Constraint (14) is the capacity constraint associated with suppliers. Constraint (15) states that at most one capacity level must be selected for a DC. Constraint (16) guarantees that the flow entering a DC j does not exceed the capacity of DC j. Eq. (17) ensures that each retailer is placed on just one vehicle route. Constraint (18) is the capacity constraint associated with vehicles used for transportation between DCs and retailers. Constraint (19) is related to the sub-tour elimination. This constraint guarantees that each route contains one DC and some retailers. Eq. (20) is related to flow conservation and ensures that the routes remain circular and that whenever a vehicle visits a DC or retailer in a time period, the vehicle should leave the visited DC or retailer within that same time period. Constraint (21) makes sure that only one DC is in each route. Constraint (22) links the routing and allocation decision variables; if vehicle v starts its trip from DC j and serves retailer k during its trip, then retailer k should be assigned to DC j. Eq. (23) implies that there is not any route between DCs. Eq. (24) and constraints (25) and (26) calculate the load levels that each vehicle carries along the route. Eq. (24) describes the equilibrium of product flows, indicating that the loads that each vehicle carries only change when the vehicle meets a retailer in its route. Constraint (25) states that when a vehicle does not meet retailer l after retailer k, variable Q^t_{klv} should not take any value. Constraint (26) states that when a vehicle starts its trip from a DC, it should carry enough products to cover the demands of all of the retailers in its route. Constraint (27) assures that at most one capacity level must be selected for an RC. Constraint (28) states that the flow entering RC m

Table 1
Source of randomly generated parameters.

Parameters	values	parameters	values
d_{kl}	$Uniform(50,100)$	jcu^n_j	$Uniform(100,150)$
Pr_v	$1500{+}0.1\times cv_v$	$jcw^{n'}_m$	$Uniform(80,120)$
c_{kmt}	$Uniform(15,20)$	up_j	$Uniform(0,1)$
I_{sj}	$Uniform(15,20)$	evu^n_j	$Uniform(500,800)$
g_{sj}	$Uniform(12,16)$	$evw^{n'}_m$	$Uniform(300,600)$
a_{sjp}	$Uniform(6,12)$	rd_j	$Uniform(0,1)$
h^t_{jp}	$Uniform(5,10)$	t_{kl}	$Uniform(25,50)$
L^t_{sj}	$Uniform(6,12)$	ev_f	$Uniform(0.3,0.6)$
z_a	1.96	e	$Uniform(3.5,5)$
δ_p	$Uniform(0.05,0.2)$	a_v	$Uniform(0.8,2.8)$
μ^t_{kp}	$Uniform(400,800)$	A_v	$Uniform(1,3)$
$\sigma^{2,t}_{kp}$	$Uniform(5,10)$	c_d	$Uniform(0,1)$
$\rho^{2,t}_{kp}$	$Uniform(5,10)$	cs_s	$Uniform\left(\left[\frac{\sum_k\sum_p\sum_t\mu^t_{kp}}{\lvert S\rvert}\right], 2\left[\frac{\sum_k\sum_p\sum_t\mu^t_{kp}}{\lvert S\rvert}\right]\right)$
θ	$Uniform(0.2,0.6)$	cv_v	$Uniform\left(\left[\frac{\sum_k\sum_p\sum_t\mu^t_{kp}}{\lvert V\rvert}\right], 2\left[\frac{\sum_k\sum_p\sum_t\mu^t_{kp}}{\lvert V\rvert}\right]\right)$
β	$Uniform(0.002,0.02)$	ct	$Uniform(50,100)$

must not exceed its capacity. Eq. (29) ensures that each retailer is assigned to one DC. Eq. (30) indicates that each retailer must be assigned to exactly one RC. Constraint (31) implies that an RC can be opened when a DC has been opened at the same site. Constraint (32) calculates the number of vehicles needed to transfer return products from retailer k to RC m at period t.

By assuming three capacity levels for each DC and RC, the capacities of DCs and RCs are as follows:

$cu_j^1 = [cap(j)]$	$cu_j^2 = [1.75cap(j)]$	$cu_j^3 = [2.5cap(j)]$
$cw_m^1 = [cap(m)]$	$cw_m^2 = [1.75cap(m)]$	$cw_m^3 = [2.5cap(m)]$

where $(j) = c(j) \times \frac{\sum_k \sum_p \sum_t \mu_{kp}^t}{|J|}$, $cap(m) = c(m) \times \frac{\sum_k \sum_p \sum_t \delta_p \mu_{kp}^t}{|M|}$ and $c(j) \sim Uniform(0.8, 1.2)$. Alternatively, the establishment cost for DCs and RCs are considered as follows:

$f_j^1 = [0.7k(j)]$	$f_j^2 = [1.1k(j)]$	$f_j^3 = [1.5k(j)]$
$l_m^1 = [0.7\acute{k}(m)]$	$l_m^2 = [1.1\acute{k}(m)]$	$l_m^3 = [1.5\acute{k}(m)]$

where $k(j) \sim Uniform(3000, 4500)$ and $\acute{k}(m) \sim Uniform(2500, 3500)$.

3.5. Validation of the proposed model

To validate the proposed model, we considered a small-sized problem (i.e., $|S| \times |J| \times |K| \times |V| \times |P| \times |T| = 2 \times 4 \times 6 \times 3 \times 2 \times 2$) and solved the presented multi-objective model as three separate single-objective problems for the given problem. Each single objective problem was solved by the GAMS software using Baron Solver. Fig. 2a-c depict the result of the solved problem for each objective function. Due to the space limitation, we have just depicted the results of the model for $t = 1$. It should be noted that deterministic values, generated from probability distributions listed in Table 1, are used in this section.

In Fig. 2a-c the hexagon nodes refer to the suppliers, the dashed line squares indicate the unselected regions to establish DCs or RCs, the square-rhombic nodes refer to the selected regions to establish DCs and RCs and the circles indicate the retailers. In addition, the vehicle route to satisfy the demand of retailers and the allocation of retailers to RCs are shown in these figures. Regarding the obtained results, there is a conflict between three-objective functions.

Fig. 2a shows the optimal solution for the first objective function. In this problem, we just considered the cost of establishing a network. In this way, the solution is obtained regardless of other factors such as EIs and SIs. As a result, two candidate locations (i.e., 2 and 4) are selected as DCs and these selected locations are also selected as RCs. Furthermore, the demands of retailers 1, 2, 3 and 4 are assigned to DC 2, and the demands of retailers 5 and 6 are assigned to DC 4. The proposed model decided to establish this network to reduce four types of costs: (1) the fixed cost of establishing DCs and RCs, (2) the shipping and ordering cost between the suppliers and DCs, (3) the shipping cost between the DCs and retailers and (4)

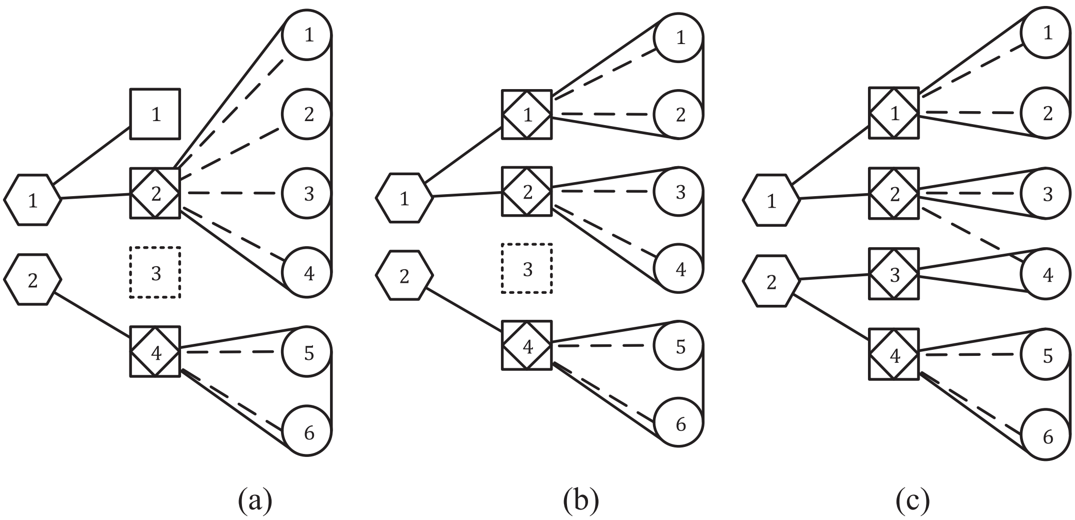


Fig. 2. (a) Optimal solution for the first objective function. (b) Optimal solution for the second objective function. (c) Optimal solution for the third objective function.

the shipping cost between the retailers and RCs. Fig. 2b illustrates the optimal solution for the second objective function. In this problem, the model focused on reducing the EIs of an established network. As a result, three candidate locations (i.e., 1, 2 and 4) are selected as DCs, and these selected locations are also selected as RCs. In addition, retailers 1 and 2 are covered by DC 1, retailers 3 and 4 are covered by DC 2 and retailers 5 and 6 are covered by DC 4. Because it aims to only reduce the EIs, the model desires to form more tours than the previous problem. When the model forms more tours, each DC will cover fewer retailers. As a result, the loads that vehicles carry in a route will be reduced, and, as a consequence, there will be fewer EIs in the designed network. Moreover, this solution has more established RCs than the previous solution. Therefore, each RC will cover the remanufacturing process of fewer retailers, leading to less congestion at RCs and therefore less EITRW. Fig. 2c shows the optimal solution for the third objective function. In this problem, the model tends to increase the positive SIs of an established network. Because establishing DCs and RCs will increase the job opportunities and economic development, the model decided to select all four candidate location as DCs and RCs. Notably, this model does not consider the establishing costs of DCs and RCs.

4. Crisp counterpart formulation

In this section, we first introduce the uncertain parameters of the proposed CLSC. Afterward, a stochastic-possibilistic programming is proposed to convert the model into its crisp counterpart.

4.1. Uncertain parameters

In real world applications, due to the dynamic nature of supply chain networks, different parameters such as demand, cost and distance should be considered as uncertain parameters. There is considerable variation in the costs considered in an SCND because they are dependent on a variety of factors (e.g., inflation rate and supply and demand of raw materials). Based on our observations and discussions with experts, estimation of certain demand and supply levels is difficult or sometimes impossible over the long term. Extensive parameters have been considered in calculating the EIs, some of which related to the vehicle driver, different types of vehicles used and climate. In this way, there is a need to consider them as uncertain parameters. In addition, because social parameters related to the created job opportunities and regional development depend on other factors, these parameters are also considered as uncertain parameters in the network. For instance, the number of created job opportunities depends on the opinion of different managers, and there is a possibility of increasing or decreasing the regional development due to the opening or closing of business activities in the region. Among different parameters, the capacities of facilities and vehicles are affected by other uncertain parameters such as demands, transportation times and distances. In this way, the capacity of DCs, the capacity of RCs and the capacity of vehicles used between DCs and retailers are considered random fuzzy numbers (i.e., fuzzy numbers with stochastic boundaries). The uncertain data are in triangular form.

The considered uncertain parameters in the proposed model are listed in Table 2.

4.2. Stochastic-possibilistic programming

In practical CLSC, some uncertainties can be declared as probability distribution functions (PDFs) or fuzzy membership functions, while others can be declared as random fuzzy membership functions (Mohammadi et al., 2014). Stochastic programming methods are the most often applied approaches to address the uncertainty in input data for which random variables with known probability distribution are often utilized (Mousazadeh et al., 2014). However, due to a lack of historical data in many cases, it is difficult or even impossible to fit a probability distribution for some objective-natured parameters; however, it is reasonable to fit a suitable possibilistic distribution for each parameter based on experts' subjective knowledge derived from past experiences and feelings (Mousazadeh et al., 2015).

Sometimes, uncertainties in input data are deeper and exist in the form of a random fuzzy membership function. For instance, the capacity of some facilities that are encountered with a higher level of uncertainty (i.e., the capacity is affected by other uncertain parameters) can be quantified as random fuzzy membership functions. It is impossible to estimate an exact boundary point for this type because of its random nature, but a PDF may be considered for coping with this deeper level of uncertainty (Mohammadi et al., 2014). Because our model contains both uncertainties, a mixed possibilistic-stochastic programming approach can be developed to cope with the randomness and fuzziness of the input data.

In this section, we have used the stochastic-possibilistic programming approach that was introduced by Liu et al. (2003). This approach resulted from combining the well-known chance-constrained programming and possibilistic programming. Consider the following general model that involves mixed uncertainty:

$$\text{Min } f = \widetilde{C}X \tag{33}$$

s.t.

$$\widetilde{A}X \leqslant \widetilde{B} \text{ with } \widetilde{B} = \left(b_1, b_2, \ldots, b_{m_1}, b_{m_1+1}^{(p_1)}, b_{m_1+2}^{(p_2)}, \ldots, b_m^{(p_{m-m_1})}\right) \tag{34}$$

$$x_j \geqslant 0, x_j \in X \quad j = 1, 2, \ldots, n \tag{35}$$

where some elements of vector $\widetilde{B}$ and all elements of vector $\widetilde{C}$ and $\widetilde{A}$ are treated as possibilistic data in the form of triangular fuzzy numbers according to their membership function, expected interval (EI) and expected value (EV) of the triangular fuzzy numbers. For instance, the membership function of the triangular fuzzy number $\tilde{a}_j$ is calculated as:

$$\mu_{\tilde{a}_j}(x) = \begin{cases} f_{a_j}(x) = \frac{x-a_j^p}{a_j^m-a_j^p} & \text{if } a_j^p \leqslant x \leqslant a_j^m \\ 1 & \text{if } x = a_j^m \\ g_{a_j}(x) = \frac{a_j^o-x}{a_j^o-a_j^m} & \text{if } a_j^p \leqslant x \leqslant a_j^o \\ 0 & \text{if } x \leqslant a_j^p \text{ or } x \geqslant a_j^p \end{cases} \tag{36}$$

Following Jiménez et al. (2007), the EI and EV of a fuzzy number $\tilde{a}_j$ can be obtained as follows:

$$EI(\tilde{a}_j) = \left[E_1^{a_j}, E_2^{a_j}\right] = \left[\int_0^1 f_{a_j}^{-1}(r)dr, \int_0^1 g_{a_j}^{-1}(r)dr\right] \tag{37}$$

$$EV(\tilde{a}_j) = \frac{E_1^{a_j} + E_2^{a_j}}{2} = a_j^e \tag{38}$$

where $E_1 = \left(\frac{a_j^p+a_j^m}{2}\right)$ and $E_2 = \left(\frac{a_j^m+a_j^o}{2}\right)$.

As mentioned previously, some elements of vector $\widetilde{B}$ involve random fuzzy numbers. To cope with some of these right-hand sides in constraints (34) that follow a probability distribution, these constraints can be replaced by 2 k precise inequalities as shown in Eqs. (39) and (40).

$$\sup(A^l) \leqslant \sup(B^l) \quad l = 1, 2, \ldots, k \tag{39}$$

$$\inf(A^l) \leqslant \inf(B^l) \quad l = 1, 2, \ldots, k \tag{40}$$

where k indicates the k levels of α - cut.

Finally, the general model with mixed uncertainty can be transformed into a conventional linear programming problem using the method presented in Liu et al. (2003) and Jiménez et al. (2007) as follows:

$$\text{Min } f = EV(\widetilde{C})X \tag{41}$$

s.t.

$$\overset{n}{\underset{j=1}{m}} \sup(a_{ij}^s) \leqslant \sup(B_i^s) \tag{42}$$

$$with \ \sup\left(B_i^s\right) = \begin{cases} \sup\left(b_i^s\right) & when \ i = 1, 2, \ldots, m_1; \ s = 1, 2, \ldots, k_1 \\ \sup\left(b_i^{s(p_i)}\right) & when \ i = m_1+1, m_1+2, \ldots, m; \ s = k_1+1, k_1+2, \ldots, k \end{cases} \tag{43}$$

$$\sum_{j=1}^{n} \inf(a_{ij}^s) \leqslant \inf(B_i^s) \tag{44}$$

$$with \ \inf\left(B_i^s\right) = \begin{cases} \inf\left(b_i^s\right) & when \ i = 1, 2, \ldots, m_1; \ s = 1, 2, \ldots, k_1 \\ \inf\left(b_i^{s(p_i)}\right) & when \ i = m_1+1, m_1+2, \ldots, m; \ s = k_1+1, k_1+2, \ldots, k \end{cases} \tag{45}$$

$$x_j \geqslant 0, x_j \in X \quad j = 1, 2, \ldots, n \tag{46}$$

Alternatively, the boundaries of fuzzy intervals under any α - cut for the stochastic-possibilistic constraints in (34) follow a normal distribution and can be expressed as:

$$p[sup(b_2(s))] = \frac{1}{\sqrt{2\pi sup(\sigma)}} exp\left\{-\frac{[sup(b_2(s)) - sup(\mu)]^2}{2sup(\sigma^2)}\right\} \tag{47}$$

$$p[inf(b_2(s))] = \frac{1}{\sqrt{2\pi inf(\sigma)}} exp\left\{-\frac{[inf(b_2(s)) - inf(\mu)]^2}{2inf(\sigma^2)}\right\} \tag{48}$$

where $\sup(\mu), \sup(\sigma^2)$ and $\inf(\mu), \inf(\sigma^2)$ are the expected values and variances of $\sup(b_2(s))$ and $\inf(b_2(s))$, respectively. In addition, p_i is the probability of violating constraint i.

Based on the above descriptions, the crisp equivalent of the proposed model can be formulated as follows:

$$
\begin{aligned}
\text{Min} & \sum_{j\in J}\sum_{n\in N} f_j^{n,e} U_j^n + \sum_{m\in M}\sum_{n'\in N'} l_m^{n',e} W_m^{n'} + \sum_{j\in J}\left(\sqrt{2\theta\sum_{k\in K}\sum_{p\in P}\sum_{t\in T} h_{jp}^{e,t}\left(\theta\sum_{s\in S} I_{sj}^e X_{sj} + \beta\sum_{s\in S} g_{sj}^e X_{sj}\right)\mu_{kp}^{t,e} Y_{jk}}\right.\\
& + \beta\sum_{p\in P}\sum_{t\in T}\sum_{s\in S}\left(a_{sjp}^e X_{sj}\sum_{k\in K}\mu_{kp}^{t,e} Y_{jk}\right) + \theta\sum_{p\in P}\sum_{t\in T} h_{jp}^{t,e} z_\alpha \left.\sqrt{\sum_{s\in S}\bar{L}_{sj}^{t,e} X_{sj}\sum_{k\in K}\sigma_{kp}^{2,t} Y_{jk}}\right)\\
& + \sum_{m\in M}\left(\sqrt{2\theta\sum_{k\in K}\sum_{p\in P}\sum_{t\in T}\gamma_{\mathrm{p}} h_{mp}^{t,e}\left(\theta\sum_{s\in S} I_{sm}^e X_{sm} + \beta\sum_{s\in S} g_{sm}^e X_{sm}\right)\delta_p \mu_{kp}^{t,e} Z_{km}} + \beta\sum_{p\in P}\sum_{t\in T}\sum_{s\in S}\left(a_{smp}^e X_{sm}\delta_p\sum_{k\in K}\mu_{kp}^{t,e} Z_{km}\right)\right.\\
& + \theta\sum_{p\in P}\sum_{t\in T}\gamma_{\mathrm{p}} h_{mp}^{t,e} z_\alpha \left.\sqrt{\sum_{s\in S}\bar{L}_{sm}^{t,e} X_{sm}\sum_{k\in K}\rho_{kp}^{2,t} Z_{km}}\right) + \beta q\left(\sum_{v\in V}\sum_{k\in M'}\sum_{l\in M'}\sum_{t\in T} d_{kl}^e R_{klv}^t + \sum_{j\in J}\sum_{l\in M'}\sum_{v\in V}\sum_{t\in T} Pr_v^e R_{jlv}^t\right)\\
& + \beta\sum_{k\in K}\sum_{m\in M}\sum_{t\in T} c_{km}^{t,e} NT_{km}^t
\end{aligned}
\tag{49}
$$

$$
\begin{aligned}
\text{Min} & \sum_{v\in V}\sum_{k\in M'}\sum_{l\in M'}\sum_{t\in T}\left(ev_f^e + e^e\right)\left(a_v^e + (sin(k,l) + c_r cos(k,l))g\right) d_{kl}^e We_v R_{klv}^t + \sum_{v\in V}\sum_{k\in M'}\sum_{l\in M'}\sum_{t\in T}\left(ev_f^e + e^e\right)\left(a_v^e + (\sin(k,l) + c_r\cos(k,l))g\right) d_{kl}^e Q_{klv}^t\\
& + \sum_{v\in V}\sum_{k\in M'}\sum_{l\in M'}\sum_{t\in T}\left(ev_f^e + e^e\right)\left(1/2c_d^e A_v^e \rho\right) d_{kl}^e t_{kl}^e R_{klv}^t\\
& + \sum_{t\in T}\sum_{m\in M}\left(eiw^e \times rw^e \times \sum_k NT_{km}^t \times \frac{\left(\frac{\sum_k NT_{km}^t}{\tau_{mt}}\right)^{\psi_m} \tau_{mt}}{(\psi_m - 1)!\left(\psi_m\tau_{mt} - \sum_k NT_{km}^t\right)^2}\left\{1 + \sum_{n=1}^{\psi_m - 1}\left(\frac{\sum_k NT_{km}^t}{\tau_m^t}\right)^n \frac{1}{n!} + \left(\frac{\sum_k NT_{km}^t}{\tau_m^t}\right)^{\psi_m}\frac{1}{\psi_m!} \times \frac{\sum_k NT_{km}^t}{\tau_m^t - \sum_k NT_{km}^t}\right\}^{-1}\right)
\end{aligned}
\tag{50}
$$

$$
\text{Max }\omega_{jo}\left(\sum_{j\in J}\sum_{n\in N} U_j^n jcu_j^{n,e} up_j^e + \sum_{m\in M}\sum_{n'\in N'} W_m^n jcw_m^{n',e} up_m^e\right) + \omega_{be}\left(\sum_{j\in J}\sum_{n\in N} U_j^n evu_j^{n,e}(1 - rd_j^e) + \sum_{m\in M}\sum_{n'\in N'} W_m^n evw_m^{n',e}(1 - rd_m^e)\right)
\tag{51}
$$

s.t.

$$
\sum_{k\in k}\sum_{j\in J}\sum_{p\in P}\left[\alpha\left(\frac{\mu_{kp}^{m,t} + \mu_{kp}^{o,t}}{2}\right) + (1-\alpha)\left(\frac{\mu_{kp}^{p,t} + \mu_{kp}^{m,t}}{2}\right)\right] Y_{jk} X_{sj} \leqslant cs_s \quad \forall t\in T, \forall s\in S
\tag{52}
$$

$$
\begin{aligned}
& \sum_{p\in P}\sum_{k\in K} sup\left[\left(\mu_{kp}^{o,t} - \alpha(\mu_{kp}^{o,t} - \mu_{kp}^{m,t})\right), \left(\mu_{kp}^{p,t} - \alpha(\mu_{kp}^{m,t} - \mu_{kp}^{p,t})\right)\right] Y_{jk}\\
& \leqslant \sum_{n\in N} sup\left[\left(cu_j^{n,o} - \alpha(cu_j^{n,o} - cu_j^{n,m})\right), \left(cu_j^{n,p} - \alpha(cu_j^{n,m} - cu_j^{n,p})\right)\right]^{p_i} U_j^n \quad \forall t\in T, \forall j\in J
\end{aligned}
\tag{53}
$$

$$
\begin{aligned}
& \sum_{p\in P}\sum_{k\in K} inf\left[\left(\mu_{kp}^{o,t} - \alpha(\mu_{kp}^{o,t} - \mu_{kp}^{m,t})\right), \left(\mu_{kp}^{p,t} - \alpha(\mu_{kp}^{m,t} - \mu_{kp}^{p,t})\right)\right] Y_{jk}\\
& \geqslant \sum_{n\in N} inf\left[\left(cu_j^{n,o} - \alpha(cu_j^{n,o} - cu_j^{n,m})\right), \left(cu_j^{n,p} - \alpha(cu_j^{n,m} - cu_j^{n,p})\right)\right]^{p_i} U_j^n \quad \forall t\in T, \forall j\in J
\end{aligned}
\tag{54}
$$

$$
\begin{aligned}
& \sum_{p\in P}\sum_{l\in K} sup\left[\left(\mu_{lp}^{o,t} - \alpha(\mu_{lp}^{o,t} - \mu_{lp}^{m,t})\right), \left(\mu_{lp}^{p,t} - \alpha(\mu_{lp}^{m,t} - \mu_{lp}^{p,t})\right)\right]\sum_{k\in M'} R_{klv}^t\\
& \leqslant sup\left[(cv_v^o - \alpha(cv_v^o - cv_v^m)), (cv_v^p - \alpha(cv_v^m - cv_v^p))\right]^{p_i} \quad \forall t\in T, \forall v\in V
\end{aligned}
\tag{55}
$$

$$
\begin{aligned}
& \sum_{p\in P}\sum_{l\in K} inf\left[\left(\mu_{lp}^{o,t} - \alpha(\mu_{lp}^{o,t} - \mu_{lp}^{m,t})\right), \left(\mu_{lp}^{p,t} - \alpha(\mu_{lp}^{m,t} - \mu_{lp}^{p,t})\right)\right]\sum_{k\in M'} R_{klv}^t\\
& \geqslant inf\left[(cv_v^o - \alpha(cv_v^o - cv_v^m)), (cv_v^p - \alpha(cv_v^m - cv_v^p))\right]^{p_i} \quad \forall t\in T, \forall v\in V
\end{aligned}
\tag{56}
$$

$$
\sum_{k\in M'}\sum_{v\in V} Q_{klv}^t - \sum_p\left[\alpha\left(\frac{\mu_{lp}^{m,t} + \mu_{lp}^{o,t}}{2}\right) + (1-\alpha)\left(\frac{\mu_{lp}^{p,t} + \mu_{lp}^{m,t}}{2}\right)\right] = \sum_{k\in M'}\sum_{v\in V} Q_{lkv}^t \quad \forall t\in T, \forall l\in K
\tag{57}
$$

$$Q_{jkv}^{t} + E(1 - R_{jkv}^{t}) \geqslant \sum_{k \in M'} \sum_{l \in K} \sum_{p} \left[\alpha \left(\frac{\mu_{lp}^{m,t} + \mu_{lp}^{o,t}}{2} \right) + (1-\alpha) \left(\frac{\mu_{lp}^{p,t} + \mu_{lp}^{m,t}}{2} \right) \right] R_{klv}^{t} \quad \forall t \in T, \forall v \in V, \forall j \in J, \forall k \in K \tag{58}$$

$$\begin{aligned} &\sum_{k} \sum_{p} sup\left[\left(\mu_{kp}^{o,t} - \alpha\left(\mu_{kp}^{o,t} - \mu_{kp}^{m,t} \right) \right), \left(\mu_{kp}^{p,t} - \alpha\left(\mu_{kp}^{m,t} - \mu_{kp}^{p,t} \right) \right) \right] Z_{km} \\ &\quad \leqslant \sum_{n' \in N'} sup\left[(cw_m^{n',o} - \alpha(cw_m^{n',o} - cw_m^{s,m})), (cw_m^{n',p} - \alpha(cw_m^{n',m} - cw_m^{n',p})) \right]^{p_i} W_m^{n'} \quad \forall t \in T, \forall m \in M \end{aligned} \tag{59}$$

$$\begin{aligned} &\sum_{p \in P} \sum_{k \in K} inf\left[\left(\mu_{kp}^{o,t} - \alpha(\mu_{kp}^{o,t} - \mu_{kp}^{m,t}) \right), \left(\mu_{kp}^{p,t} - \alpha(\mu_{kp}^{m,t} - \mu_{kp}^{p,t}) \right) \right] Z_{km} \\ &\quad \geqslant \sum_{n' \in N'} inf\left[(cw_m^{n',o} - \alpha(cw_m^{n',o} - cw_m^{n',m})), (cw_m^{n',p} - \alpha(cw_m^{n',m} - cw_m^{n',p})) \right]^{p_i} W_m^{n'} \quad \forall t \in T, \forall m \in M \end{aligned} \tag{60}$$

$$\begin{aligned} &\sum_{p \in P} sup\left[\left(\mu_{kp}^{o,t} - \alpha(\mu_{kp}^{o,t} - \mu_{kp}^{m,t}) \right), \left(\mu_{kp}^{p,t} - \alpha(\mu_{kp}^{m,t} - \mu_{kp}^{p,t}) \right) \right] Z_{km} \\ &\quad \leqslant sup[(ct^o - \alpha(ct^o - ct^m)), (ct^p - \alpha(ct^m - ct^p))] NT_{km}^{t} \quad \forall t \in T, \forall k \in K, \forall m \in M \end{aligned} \tag{61}$$

$$\begin{aligned} &\sum_{p \in P} inf\left[\left(\mu_{kp}^{o,t} - \alpha(\mu_{kp}^{o,t} - \mu_{kp}^{m,t}) \right), \left(\mu_{kp}^{p,t} - \alpha(\mu_{kp}^{m,t} - \mu_{kp}^{p,t}) \right) \right] Z_{km} \\ &\quad \geqslant inf[(ct^o - \alpha(ct^o - ct^m)), (ct^p - \alpha(ct^m - ct^p))] NT_{km}^{t} \quad \forall t \in T, \forall k \in K, \forall m \in M \end{aligned} \tag{62}$$

Constraints (13), (15), (17), (19)–(23), (25), (27), (29)–(31)

4.3. Proposed solution approach

In this section, a new hybrid two-stage approach is proposed to solve the presented mixed integer programming model. In the first stage, the presented stochastic-possibilistic programming in Section 4.2 is adopted to convert the model into its crisp counterpart. In the second stage, to accommodate three objective functions and to find a compromise solution, a modified game theory approach (MGT) is applied. The MGT approach is briefly explained in Section 4.3.1. Finally, the steps of the proposed hybrid two-stage approach are presented in Section 4.3.2.

4.3.1. Modified game theory approach

In the literature, various approaches have been introduced to solve the crisp multi-objective programming model (Mousazadeh et al., 2015; Azadeh et al., 2015). Among them, we have used a game theory–based approach that was proposed by Annamdas and Rao (2009).

There are two major groups of games in game theory: non-cooperative and cooperative games. In non-cooperative games, players make decisions independently. Conversely, in cooperative games, the players agree to cooperate with each other. This type of game is typically a competition between a coalition of players rather than individual players.

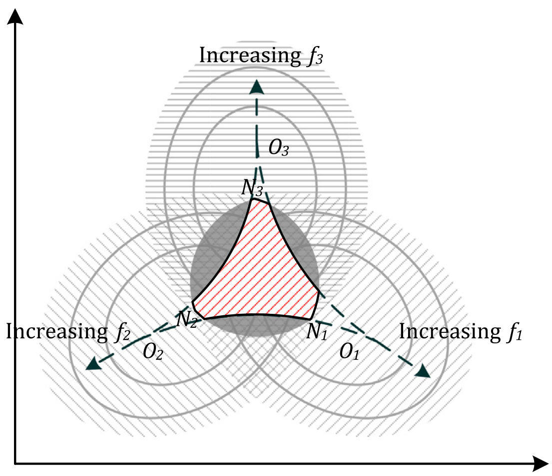


Fig. 3. Co-operative and non-co-operative game theory.

For the purpose of understanding game-based optimization approach, consider three objective functions f_1, f_2 and f_3, in which the value of them related to decision variables x_1 and x_2. In the game-based optimization approach, each objective function associated with a player. Hence, each player desires to minimize his/her own objective function. Fig. 3 shows the schematic view of a multi-objective optimization problem. In this figure, the contours of f_1, f_2 and f_3 are depicted. By assuming that the players do not co-operate with each other, nodes N_1, N_2 and N_3 (i.e., called the Nash equilibrium solutions) are the candidate for three-objective minimization problem. Despite the non-co-operative game in which players cannot deviate unilaterally form their Nash equilibrium point, in the co-operate game, players can improve their situation unilaterally. Subsequently, any player, can force the other players to play at the equilibrium of his/her own choice by choosing a proper value of his/her decision variable (Annamdas and Rao, 2009). In this way, any point in the shaded region in Fig. 3 will provide a better solution rather than their Nash equilibrium solutions for all of the objective functions. Since there is more than one solution in the shaded region, the concept of Pareto optimal solutions can be helpful to choose a compromise solution that is acceptable to all of the players in the game. Notably, the Pareto optimal solutions are shown as the nodes between boundaries of red region in Fig. 3.

4.3.2. Proposed hybrid approach

The steps of the hybrid approach are presented as follows:

Step 1: Identify all of the uncertain parameters and determine the associated distribution functions.
Step 2: Formulate the multi-objective stochastic-possibilistic programming model.
Step 3: Convert the imprecise parameters in the objective functions into their equivalent crisp functions given the expected value of the parameters.
Step 4: Convert the mixed stochastic-possibilistic constraints into their corresponding crisp contraints given the predetermined α and p_i.
Step 5: Determine the α-positive ideal solution $\left(Z_k^{\alpha-PIS}\right)$ and α-negative ideal solution $\left(Z_k^{\alpha-NIS}\right)$ for each objective function.
Step 6: Normalize each objective function to change its magnitude, and scale the function between zero and one as shown in Eq. (63) for the objective functions that should be minimized and as shown in Eq. (64) for the objective functions that should be maximized.

$$Z_{nk} = \frac{Z_{nk}^{\alpha-NIS} - Z_{nk}}{Z_{nk}^{\alpha-NIS} - Z_{nk}^{\alpha-PIS}} \tag{63}$$

$$Z_{nk} = \frac{Z_{nk} - Z_{nk}^{\alpha-NIS}}{Z_{nk}^{\alpha-PIS} - Z_{nk}^{\alpha-NIS}} \tag{64}$$

Step 7: The Pareto optimal solution set can be calculated as the following formulation:

$$FC = C_1 Z_{n1} + C_2 Z_{n2} + \ldots + C_{k-1} Z_{n(k-1)} + (1 - C_1 - C_2 - \ldots - C_{k-1}) Z_{nk} \tag{65}$$

where FC should be minimized under the stated constraints for all combination of weights vector $\left(\sum_{i=1}^{k} C_k = 1\right)$. To ensure that each of the normalized objective functions will be as far away as possible from their worst possible value, a super-criterion ζ is introduced as shown in Eq. (66).

$$\zeta = \prod_{i=1}^{k} (1 - Z_{ni}) \tag{66}$$

Therefore, Eq. (66) can be replaced by Eq. (67) to find the Pareto optimal solution that represents a compromise solution:

$$F(Y) = FC - \zeta = FC - \prod_{i=1}^{k} (1 - Z_{ni}) \tag{67}$$

where $Y = \{x_1, x_1, \ldots, x_n, C_1, C_2, \ldots, C_{k-1}\}$ and $0 \leqslant C_i \leqslant 1, i = 1, 2, \ldots, k = 1$.
Step 8: Minimize $F(Y)$ to find Y, which yields the best compromise solution of the multi-objective problem.

5. Lower bound procedure and meta-heuristic algorithm

The model presented in Section 3 is a mixed-integer nonlinear programming (MINLP) optimization model. Several optimization techniques such as branch-and-cut, branch-and-price and branch-and-bound have been developed in the literature to solve these problems. Solving such an MINLP problem is very computationally challenging for large-sized instances. To address this challenge, we developed a new hybrid meta-heuristic algorithm to solve large-sized problems. In addition, a new lower bound procedure was also developed to evaluate the performance of the developed meta-heuristic algorithm.

5.1. Proposed lower bound procedure

In this section, a lower bound procedure is presented to evaluate the efficiency of the developed meta-heuristic algorithm. In this way, the original problem P is divided into several sub-problems, and then each created sub-problem is relaxed under some assumptions. In the proposed procedure, a sub-problem of P can be created by dividing the set of DCs and RCs distinctly. It can be asserted that any sets of DC locations, Λ_γ and Λ_η are distinct if there is at least one DC $j \in \Lambda_\gamma$ and $j \notin \Lambda_\eta$. The RC locations are similar. Subsequently, there will be $C_i^{|J|} i = 1, 2, \ldots, |J|$ numbers of DC sets. Because RCs can only be opened at locations where DCs exist, there will be $C_k^{|SJ|} k = 1, 2, \ldots, |SJ|$. numbers of RC sets in which SJ is a selected set of DCs that locations of RCs must be located at. Now, we introduce Λ_p as a set of total sub-problems. Afterward, for a selected sub-problem from set Λ_p, the corresponding location variables DCs and RCs are fixed at 1. Therefore, the original problem P is then reduced to several sub-problems SP_ε over the binary decision variables related to the location of DCs and RCs. To relax each SP_ε, we consider that each DC and RC have only one capacity level; furthermore, following Ahmadi-Javid and Seddighi (2013), we assume that vehicle capacity is unlimited (i.e., each DC can serve all of its allocated retailers with only one route). Hence, binary variables related to the location of DCs and RCs, routing decisions and variables that indicate the loads that vehicles carry must be redefined. Furthermore, some additional constraints have been added to the model because we have eliminated constraints (19) and (22), which made the model very difficult to solve. The whole relaxed model used to find a lower bound for each sub-problem is given in Eqs. (68)–(87). Now, let $RP(SP_\varepsilon)$ be the partial relaxation of SP_ε, and let $\mathrm{OFV}_{RP(SP_\varepsilon)}$ be the optimal objective value of $RP(SP_\varepsilon)$. Finally, a lower bound for the original problem P is defined as $\mathrm{OFV}_{LB(P)}$ and calculated as the minimum value among $\mathrm{OFV}_{RP(SP_\varepsilon)}$ (i.e., $\mathrm{OFV}_{LB(P)} = \min_\varepsilon \mathrm{OFV}_{RP(SP_\varepsilon)}$).

U_j	1 if DC j is selected to be opened; Otherwise 0.
W_m	1 if RC m is selected to be opened; Otherwise 0.
R^t_{klj}	1 if node k precedes node l in the route starting at DC j in period t; Otherwise 0.
Q^t_{klj}	Amounts of loads of products in the route starting at DC j after passing node k, before arriving to node l in period t.

$$\text{Min} \sum_{j\in J} f_j U_j + \sum_{m\in M} l_m W_m + \text{Inventory decisions} + \beta q\left(\sum_{j\in J}\sum_{k\in M'}\sum_{l\in M'}\sum_{t\in T} d_{kl} R^t_{klj}\right) + \beta \sum_{k\in K}\sum_{m\in M}\sum_{t\in T} c^t_{km} NT^t_{km} \tag{68}$$

$$\begin{aligned}\text{Min} & \sum_{v\in V}\sum_{k\in M'}\sum_{l\in M'}\sum_{t\in T}(e v_f + e)(a_v + (\sin(k,l) + c_r\cos(k,l))g) d_{kl} We_v R^t_{klj} + \sum_{v\in V}\sum_{k\in M'}\sum_{l\in M'}\sum_{t\in T}(e v_f + e)(a_v + (\sin(k,l) + c_r \\ & \times \cos(k,l))g) d_{kl} Q^t_{klj} + \sum_{v\in V}\sum_{k\in M'}\sum_{l\in M'}\sum_{t\in T}(e v_f + e)(1/2 c_d A_v \rho) d_{kl} t_{kl} R^t_{klj} + EITRW\end{aligned} \tag{69}$$

$$\text{Max } \omega_{jo}\left(\sum_{j\in J} U_j jcu_j up_j + \sum_{m\in M} W_m jcw_m up_m\right) + \omega_{be}\left(\sum_{j\in J} U_j evu_j(1 - rd_j) + \sum_{m\in M} W_m evw_m(1 - rd_m)\right) \tag{70}$$

s.t.

$$\sum_{s\in S} X_{sj} = U_j \quad \forall j \in J \tag{71}$$

$$\sum_{k\in K}\sum_{j\in J}\sum_{p\in P} \mu^t_{kp} Y_{jk} X_{sj} \leqslant cs_s \quad \forall t \in T, \forall s \in S \tag{72}$$

$$\sum_{p\in P}\sum_{k\in K} \mu^t_{kp} Y_{jk} \leqslant cu_j U_j \quad \forall t \in T, \forall j \in J \tag{73}$$

$$\sum_{j\in J}\sum_{l\in M'} R^t_{klj} = 1 \quad \forall t \in T, \forall k \in K \tag{74}$$

$$\sum_{l\in M'} R^t_{klj} - \sum_{l\in M'} R^t_{lkj} = 0 \quad \forall t \in T, \forall k \in M', \forall j \in J \tag{75}$$

$$\sum_{k\in K} R^t_{jkj} = U_j \quad \forall t \in T, \forall j \in J \tag{76}$$

$$\sum_{l\in M'} R^t_{klj} \leqslant Y_{jk} \quad \forall t \in T, \forall j \in J, \forall k \in K \tag{77}$$

$$\sum_{k\in M'} R^t_{klj} \leqslant Y_{jl} \quad \forall t \in T, \forall j \in J, \forall l \in K \tag{78}$$

$$\sum_{k\in M'}\sum_{j\in J} Q^t_{klj} - \sum_{p\in P}\mu^t_{lp} = \sum_{k\in M'}\sum_{j\in J} Q^t_{lkj} \quad \forall t \in T, \forall l \in K \tag{79}$$

$$Q^t_{klj} \leqslant ER^t_{klj} \quad \forall t \in T, \forall j \in J, \forall k, l \in M' \tag{80}$$

$$Q^t_{jkj} + E(1 - R^t_{jkj}) \geqslant \sum_{k\in M'}\sum_{l\in K}\sum_{p\in P}\mu^t_{lp} R^t_{klj} \quad \forall t \in T, \forall j \in J, \forall k \in K \tag{81}$$

$$R^t_{kkj} = 0 \quad \forall t \in T, \forall k \in M', \forall j \in J \tag{82}$$

$$\sum_{j'\in J} R^t_{jj'j} = 0 \quad \forall t \in T, \forall j \in J \tag{83}$$

$$\sum_{l\in M'} R^t_{j'lj} = 0 \quad \forall t \in T, \forall j, j' \in J, j \neq j' \tag{84}$$

$$R^t_{klj} + R^t_{lkj} \leqslant 1 \quad \forall t \in T, \forall k \in K, \forall l \in K, \forall j \in J \tag{85}$$

$$\sum_{k\in K}\sum_{p\in P}\delta_p \mu^t_{kp} Z_{km} \leqslant cw_m W_m \quad \forall t \in T, \forall m \in M \tag{86}$$

$$W_m - \sum_{k\in K} Y_{km} \leqslant 0 \quad \forall m \in M \tag{87}$$

$$\text{Constraints } (29), (30), (32)$$

Eq. (76) indicates that routes can be constructed only for open DCs. Constraints (77) and (78) indicate that if there is a route between two retailers, they must be assigned to the same DC. Eq. (82) guarantees that a node cannot be connected to itself through a route. Eqs. (83) and (84) ensure that two open DCs are not placed on the same route. Constraint (85) eliminates a sub-tour that can be formed between two retailers.

Determining a valid lower bound for the original problem P requires finding a global optimal solution for each sub-problem $RP(SP_\varepsilon)$. To guarantee that the mixed integer nonlinear problem can be solved optimally, the convexity of objective functions (10) and (11) and the concavity of objective function (12) need to be approved. Because the nonlinear part of objective function (10) just includes binary variables and objective function (12) is linear, objective function (10) is convex and objective function (12) is concave. However, the convexity of objective function (11) needs to be verified.

Lemma 5.1.1. *Objective function (11) is convex in λ.*

Proof. To prove that objective function (11) is convex, we need to prove that the waiting time in Eq. (7) is convex in λ and also in NT, as λ is a linear function of NT. For the purpose of simplification, other parameters in Eq. (7) are considered constants. Therefore, Eq. (7) will be replaced by Eq. (88):

$$WT = \frac{A\lambda^B}{(\Psi\mu - \lambda)^2} \times \left\{1 + \Delta\lambda^E + \frac{Z\lambda^H}{\mu - \lambda}\right\}^{-1} \tag{88}$$

where A through Z are constants. For the first-order derivative, it can be shown that for $\lambda < \Psi\mu$:

$$\frac{dWT}{d\lambda} = \frac{A\lambda^B\left(\Delta E\lambda^{-1+E} + \frac{Z\lambda^H}{(\mu-\lambda)^2} + \frac{ZH\lambda^{-1+H}}{\mu-\lambda}\right)}{(\Psi\mu - \lambda)^2\left\{1 + \Delta\lambda^E + \frac{Z\lambda^H}{\mu-\lambda}\right\}^2} + \frac{AB\lambda^{-1+B}}{(\Psi\mu - \lambda)^2\left\{1 + \Delta\lambda^E + \frac{Z\lambda^H}{\mu-\lambda}\right\}} + \frac{2A\lambda^B}{(\Psi\mu - \lambda)^3\left\{1 + \Delta\lambda^E + \frac{Z\lambda^H}{\mu-\lambda}\right\}} > 0 \tag{89}$$

In addition, for the second-order derivative, it can be shown that $\frac{d^2WT}{d\lambda^2} > 0$. Both of the derivatives were verified in Mathematica software.

Lemma 5.1.2. *Objective function (11) is convex in NT.*

Proof. If a function $H(Y)$ is convex in Y and $g(X)$ is an affine function of X, then $H[g(X)]$ is convex in X (Bazaraa et al., 2013).

Because Eq. (7) is convex in λ, which is a linear function of X in $RP(SP_\varepsilon)$, it can be concluded that Eq. (7) is convex in X.

5.2. Developed meta-heuristic algorithm

The mathematical model proposed in Section 3.4 is NP-hard because it generalizes three well-known NP-hard problems: the capacitated facility location problem (CFLP), the capacitated vehicle routing problem (CVRP), and the multi-depot vehicle routing problem (MDVRP) (Escobar et al., 2013; Ho et al., 2008). To solve the large-sized instances, this section proposes an efficient hybrid meta-heuristic algorithm based on a new self-adaptive genetic algorithm (SGA) and variable neighborhood search (VNS) algorithm, namely the SGV algorithm. The genetic algorithm (GA) has been widely used in the literature to solve LRPs (for more details, please see Ho et al. (2008), Baker and Ayechew (2003), Derbel et al. (2012), Potvin and Bengio (1996), Tasan and Gen (2012) and the references therein).

Afterward, a detailed description of the proposed SGV algorithm is explained, including the whole algorithmic flow and various features borrowed from the GA and VNS algorithms.

5.2.1. Self-adaptive GA

In this section, we propose a new variant of GA, self-adaptive GA (SGA), to obtain near-optimal Pareto solutions based on the objective function (67) compared to pure GA.

In the SGA, a self-adaptive version of crossover and mutation operators is applied. In the literature, several crossover operators (e.g., one point, two points, three points, uniform, cycle crossover etc.) and mutation operators (e.g., Swap, insertion, reversion etc.) have been introduced; using all of the operators simultaneously in an algorithm significantly increases the computation time. Therefore, many studies have used just a few of them to search the solution space. In the proposed SGA, several crossover and mutation operators are simultaneously applied without increasing the computation time. Accordingly, the SGA includes an initialization phase where each crossover and mutation operator obtains a score compared to other operators based on whether it could be able to find a better solution at each iteration. At the end of the initialization phase, which is limited by a predefined number of iterations, a selection probability (*SP*) metric is calculated for each crossover and mutation operator by dividing the obtained score by the number of iterations, in which the sum of all of the selection probabilities is equal to 1. When the initialization phase is finished, the main phase of SGA begins, including searching the solution space using the self-adapted crossover and mutation operators and VNS algorithm. The crossover operators applied in this paper consist of one point, two points, three points, uniform and three parent crossover operators, and the mutation operators are the swap, insertion and reversion operators (Vahdani and Mohammadi, 2015; Mohammadi et al., 2013; Sivanandam and Deepa, 2008; Niakan et al., 2015; Mohammadi et al., 2015; Mohammadi et al., 2014; Mohammadi and Tavakkoli-Moghaddam, in press; Mohammadi et al., 2016; Mohammadi et al., 2016; Rahimi et al., 2015). The Pseudo code of the initialization phase of the proposed SGA is shown in Fig. 4.

5.2.2. SGA algorithm framework

The flowchart of the proposed SGV is depicted in Fig. 5. The optimization process begins with initializing the SGA based on Fig. 5. The initial population of the proposed SGV is randomly generated. After population initialization, each individual is evaluated by the value of objective function (67). Afterward, by adjusting the value of the weight vectors (i.e., *C*s) in objective function (67), Pareto solutions are archived. A set of genetic operators, including binary tournament selection, self-adapted crossover and self-adapted mutation, is then performed on the evaluated and ranked population. Next, the Pareto archive is updated. Thereafter, the Pareto solutions are considered for VNS initialization. The local search procedure of VNS (detailed in Section 5.2.2.1) is then applied to each individual in the Pareto frontier. Finally, the results from both SGA and VNS are combined and the final Pareto frontier is extracted. The evolution process is repeated until the stop criterion is met.

5.2.2.1. Intensification using VNS. It has been proven that genetic algorithms are generally very good at diversifying the solution space but fail to intensify the search in local regions (Črepinšek et al., 2013). However, hybridization with local search methods may strengthen this weakness and lead to a powerful search algorithm. Hence, VNS is hybridized with the proposed SGA to balance global exploration and local exploitation during the evolutionary process (Wen et al., 2011). The main steps of the proposed VNS are described in Fig. 6.

6. Computational results

In this section, the validity of the proposed model and stochastic-possibilistic programming method are first evaluated among several medium-sized test problems. The source of the randomly generated samples is listed after Table 1. Afterward, the performance of the developed meta-heuristic algorithm is evaluated using the lower bound procedure and the MGT approach. Finally, a real case study in Iran is studied. Notably, the proposed CLSC was coded in GAMS 22.9 software using BARON solver. The instances were solved on a laptop with a 2.6-GHz CPU and 4 GB of RAM.

6.1. Sensitivity analyses

In this section, the summary of results on a medium-sized test problem for different values of α (i.e., $\alpha = 0.1-0.9$) and values of p_i (i.e., $p_i = 0.1, 0.5, 0.9$) are reported in Tables 3 and 4, respectively. The weights vector of the objective functions was set according to the opinion of DM. However, there are numerous multiple attribute decision-making (MADM) methods that can be used to set the objective function weights vector more precisely.

Two significant parameters in the considered CLSC network are β and θ, which represent the weight of transportation cost and the weight of inventory cost, respectively. Figs. 7 and 8 show the effect of β on the number of established DCs and RCs and OFV_3. Similarly, the effect of θ on the number of established DCs and RCs and OFV_3 are shown in Figs. 9 and 10. Generally, increasing the value of β or θ will increase the total costs (i.e., first objective). As shown in Fig. 7, increasing the value of β resulted in establishing more DCs and RCs in the designed network because in this situation, establishing more DCs and RCs reduces the costs related to delivering the orders from suppliers to DCs and RCs, transportation between DCs and retailers and transportation between retailers and RCs. Because establishing each DC or RC will create a certain number of job opportunities and will also increase the economic development of the selected regions, increasing the value of β will increase the value of OFV_3. Conversely, increasing the value of θ will result in establishing fewer DCs or RCs in the designed network. Because increasing the value of θ will increase the total inventory cost, the model chooses to establish fewer DCs and RCs to prevent additional inventory costs in the established facilities. As discussed previously, a decrease in the number of DCs or RCs will decrease the value of OFV_3, as shown in Fig. 10.

Fig. 11 shows the changes in OFV_1 with changes in β and θ (i.e., weights of transportation cost and inventory cost). According to this figure, increasing the value of β and θ resulted in increasing the value of OFV_1. However, the slope of the blue line (ranging from 1.20E+7 to 4.80E+7), which is related to an increase in β, is significantly greater than the slope of the red line (ranging from 4.74E+6 to 5.13E+6), which is related to increase in θ. Moreover, an increase in the value of β will heavily increase the computation time required to solve the problem after a certain threshold. Therefore, the weight of transportation cost has a more significant role than the weight of inventory cost in designing our network. As a consequence, the DMs should pay special attention to selecting the proper value for this parameter.

Fig. 12 illustrates the changes in OFV_2 versus the changes of the total available number of vehicles between DCs and retailers. The increase in the value of $|V|$ between the interval $[2, 4]$ will significantly decrease the value of OFV_2 because the increase in the number of vehicles will decrease the loads carried by vehicles during the routes. Subsequently, the EIs of CO_2 emissions will decrease. However, increasing the value of $|V|$ beyond four would not decrease the total cost of the designed network due to the additional fixed usage cost of vehicles incurred in OFV_1. In this way, the model decided not to use all of the available vehicles and instead used only four vehicles. Alternatively, the value of OFV_2 will not significantly decrease in the interval of $[5, 7]$. The slight decrease in the interval $[5, 7]$ is because choosing another combination of four vehicles resulted in a lower cost.

Set the parameters ($PopSize$, $Max\ Iteration$)
$SXO(i) = 0$ ($i \in$ All Crossovers-XOs)
$SM(j) = 0$ ($j \in$ All Mutations-M)
$Iter = 0$
Create Initial Population
Calculate FC for each Solution (Equation (67))
While (Terminate=**false**) **do**

Self-adaptive Crossover
Choose Parents (Binary Tournament Selection)
Apply all Crossover Operators
a. One Point XO (No.1)
b. Two Point XO (No.2)
c. Three Point XO (No.3)
d. Uniform XO (No.4)
e. Three Parent XO (No.5)
Calculate FC of Obtained Solutions (Equation (67))
If $FC_{XO(i')}$ **Dominates** $XO(i), i' \neq i$ **then**
$SXO(i') = SXO(i') + 1$
EndIf

Self-adaptive Mutation
Choose a Sample Solution Randomly
Apply all Mutation Operators
a. Swap (No.1)
b. Insertion (No.2)
c. Reversion (No.3)
Calculate FC of Obtained Solutions (Equation (67))
If $FC_{XO(j')}$ **Dominates** $XO(i), j' \neq i$ **then**
$SM(j') = SM(j') + 1$
EndIf

If Iter ≥ Max Iteration **then**
Terminate = **True**
EndIf
Iter= Iter+1
EndWhile
Calculate Selection Probabilties $\left(SP_{(i)}^{XO} = \frac{SXO(i)}{\sum_i SXO(i)}, SP_{(j)}^{M} = \frac{SM(j)}{\sum_i SM(j)}\right)$

Fig. 4. Pseudo code of SGA's initialization phase.

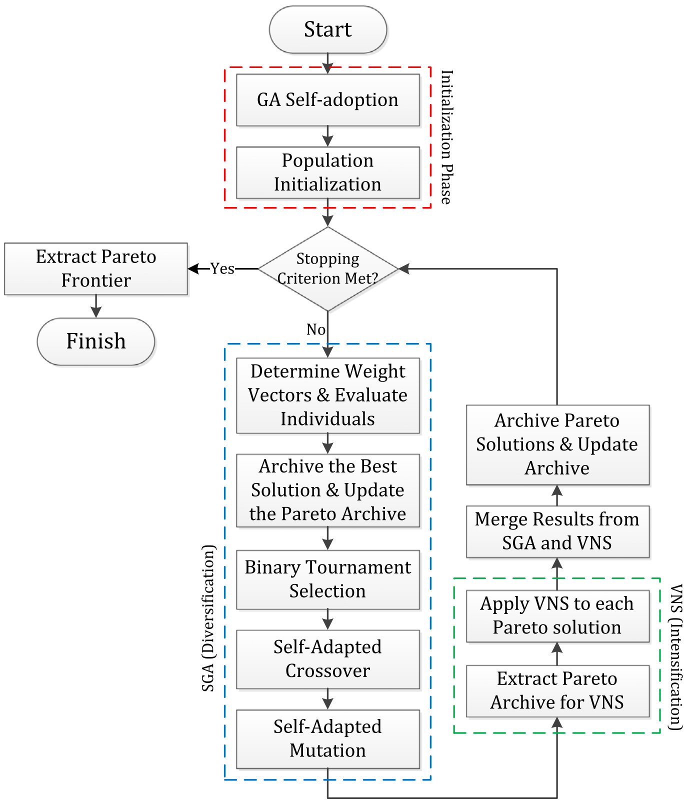


Fig. 5. Flowchart of the proposed SGV.

Extract the set of the Pareto solutions (*SPS*) obtained by SGA
Select a set of neighborhood structures $\mathbb{N}_h$ $(h = 1,2,\ldots,h_{max})$
For each individual x in the *SPS* **Do**
    $h = 1$
    While (Terminate = **false**) **do**
        Sub-optimality avoidance: Randomly generate a solution x' from the hth neighborhood of x
        Local search: Search x' locally to obtain possible better local optimum solution $\leftarrow x''$
        If x'' is better than x **Then**
            Substitute x by x'' $(x \leftarrow x'')$
            $h = 1$
        Else
            $h = h + 1$
        EndIf
        If $(h \geq h_{max})$ or (CPU time reaches a Max) **Then**
            Terminate = **True**
        EndIf
    EndWhile
EndFor

Fig. 6. Main steps of VNS in the SGV algorithm.

Fig. 13 shows the sensitivity analysis for different values of δ_p (i.e., the coefficient of expected return product p) for EITRW. To show the effectiveness of the M/M/c queueing system, two scenarios are generated. In the first scenario (red line), the queueing system is not considered, and in the second scenario (blue line), the queueing system is considered to minimize the EITRW. In this analysis, we considered δ_p to be the same for all of the products. In both scenarios, by increasing the value of δ_p, the waiting time in the queue increases, and, as a consequence, the EITRW will increase. The M/M/c queueing system is effective for minimizing the EITRW in the CLSC. The slope of the blue line is significantly less that the slope of the red line because the considered queueing system in the second scenario resulted in less EITRW than the first scenario.

In the proposed model, similar to the study of Diabat et al. (2015) and Abdallah et al. (2012), it is assumed that the reverse logistic in the CLSC is always a profitable business. In many industries, this can be a reasonable assumption; however, there are some industries where the assessment of the effect of the value of retuned products on the economic feasibility of the CLSC should be guaranteed. In this respect, for a test problem, we calculated the reverse logistic cost related to collecting and sorting, remanufacturing, reverse inventory and shipping. Then, the profit is calculated by subtracting the manufacturing cost from the reverse logistic cost. There is a relationship between the value of γ and the value of returned product, where a low value of γ corresponds to a high value for returned products (Abdallah et al., 2012). The production operation's costs needed to calculate the feasibility of the reverse logistic are shown in Table 5.

Fig. 14 shows the variations in remanufacturing profit with changes in the value of γ, when $\delta = 0.1$ and $p = 1$. As shown in the figure, for a low value of returned product (i.e., $\gamma = 0.9$), remanufacturing is economically infeasible, while for values of γ less than 0.9, remanufacturing is economically feasible. Generally, decreasing the value of γ resulted in increasing the profit gained from remanufacturing.

6.2. Benchmarking study

In this section, the performance of the developed meta-heuristic algorithm in terms of solution quality and computation time is addressed using some randomly generated data sets. Ranging from small-scale instances to large ones, the data sets contain 30 test problems with five different intervals of parameters each for better comparison. As a result, 150 problem instances were tested. The SGV parameters were tuned using the response surface methodology (RSM) (Zahiri et al., 2014; Niakan et al., 2015) and are shown in Table 6. The parameter settings were pre-tested over randomly selected problem instances prior to being used in the comparative study.

The percentage of relative gap (PRG) measure is used to compare SGV solutions with lower bound solutions and is calculated as $[100 \times (OFV_{LB} - OFV_{Meta})/OFV_{Meta}]$, where OFV_{LB} and OFV_{Meta} are the GT objective function value of the obtained solution over the lower bound approach and meta-heuristic algorithm, respectively. Because the objective function of GT is in the form of maximizing, OFV_{LB} is bigger than OFV_{Meta}. The calculation of OFV_{LB} is discussed in Section 5.1. Furthermore, to show the tightness of the lower bound approach, a comparison between OFV_{LB} and the optimal solutions based on the GT objective function is conducted using some small test problems (see Fig. 15). Based on the obtained results, the mean gap of the GT objective function between the lower bound and optimal solution is 1.6%. Therefore, compared to the optimal solutions, the tightness of the lower bound is approximately 1.6%.

The average percentage of relative gap (APRG) is computed and, along with the average computational times, reported in Tables 7 and 8. The column "Data set" shows different datasets generated based on Table 1. The column "Exact time" reports the CPU time required to find the optimal solution using the GAMS software. The column "Exact time" in Table 7 reveals that the CPU time required to find the optimal solution even for small-sized instances increased in an exponential manner. Moreover, the column "SGV" shows the gaps of five different replications, the mean gap and the CPU time required to find near-optimal solutions. The column "Exact time" in Table 8 reports that the exact solution can only be found up to test instance number 17, while finding optimal solutions for medium- and large-sized instances is impossible.

The minimum, average and maximum percentage of relative gap over all of the test problems for SGV is 0.048, 3.87 and 13.16%, respectively, showing the efficient performance of the SGV. The required computational times are also provided in the last columns of Tables 7 and 8. The computation time of SGV increases with the problem size but is relatively small.

Table 2
Uncertain parameters.

Fuzzy parameters	
$\tilde{d}_{kl} = (d^p_{kl}, d^m_{kl}, d^o_{kl})$	$\widetilde{evu}^n_j = (evu^{n,p}_j, evu^{n,m}_j, evu^{n,o}_j)$
$\widetilde{Pr}_v = (Pr^p_v, Pr^m_v, Pr^o_v)$	$\widetilde{evw}^{n'}_m = (evw^{n',p}_m, evw^{n',m}_m, evw^{n',o}_m)$
$\tilde{c}_{kmt} = (c^p_{kmt}, c^m_{kmt}, c^o_{kmt})$	$\widetilde{rd}_j = (rd^p_j, rd^m_j, rd^o_j)$
$\tilde{I}_{sj} = (I^p_{sj}, I^m_{sj}, I^o_{sj})$	$\tilde{t}_{kl} = (t^p_{kl}, t^m_{kl}, t^o_{kl})$
$\tilde{g}_{sj} = (g^p_{sj}, g^m_{sj}, g^o_{sj})$	$\widetilde{ev}_f = (ev^p_f, ev^m_f, ev^o_f)$
$\tilde{a}_{sjp} = (a^p_{sjp}, a^m_{sjp}, a^o_{sjp})$	$\tilde{e} = (e^p, e^m, e^o)$
$\tilde{L}^t_{sj} = (L^{p,t}_{sj}, L^{m,t}_{sj}, L^{o,t}_{sj})$	$\tilde{a}_v = (a^p_v, a^m_v, a^o_v)$
$\tilde{h}^t_{kp} = (h^{p,t}_{kp}, h^{m,t}_{kp}, h^{o,t}_{kp})$	$\tilde{A}_v = (A^p_v, A^m_v, A^o_v)$
$\tilde{f}^n_j = (f^{n,p}_j, f^{n,m}_j, f^{n,o}_j)$	$\tilde{c}_d = (c^p_d, c^m_d, c^o_d)$
$\tilde{I}^{n'}_m = (I^{n',p}_m, I^{n',m}_m, I^{n',o}_m)$	$eiw = (eiw^p, eiw^m, eiw^o)$
$\widetilde{jcu}^n_j = (jcu^{n,p}_j, jcu^{n,m}_j, jcu^{n,o}_j)$	$\widetilde{rw} = (rw^p, rw^m, rw^o)$
$jcw^{n'}_m = (jcw^{n',p}_m, jcw^{n',m}_m, jcw^{n',o}_m)$	$\tilde{\mu}^t_{kp} = (\mu^{p,t}_{kp}, \mu^{m,t}_{kp}, \mu^{o,t}_{kp})$
$\widetilde{up}_j = (up^p_j, up^m_j, up^o_j)$	$\widetilde{ct} = (ct^p, ct^m, ct^o)$
Random fuzzy parameters	
$\widetilde{cu}^{n,s'}_j = (cu^{n,p}_j, cu^{n,m}_j, cu^{n,o}_j)$	$\widetilde{cv}^{s'}_v = (cv^p_v, cv^m_v, cv^o_v)$
$\widetilde{cw}^{n',s'}_m = (cw^{n',p}_m, cw^{n',m}_m, cw^{n',o}_m)$	

Table 3
Objective functions vs. different values of $\boldsymbol{\alpha}$ based on ($\boldsymbol{p_i = 0.5}$).

Problem size	Uncertainty level α	Objective function values		
$\lvert S\rvert \times \lvert J\rvert \times \lvert K\rvert \times \lvert V\rvert \times \lvert P\rvert \times \lvert T\rvert$		OFV_1	OFV_2	OFV_3
$2 \times 5 \times 6 \times 3 \times 2 \times 2$	0.1	246592.247	9890.893	352.634
	0.2	246843.051	10247.131	321.961
	0.3	247266.039	13188.152	300.065
	0.4	247337.157	13207.541	206.451
	0.5	247875.042	13345.746	142.935
	0.6	247953.116	13664.591	105.341
	0.7	248228.056	13854.342	87.718
	0.8	248999.716	13940.308	82.091
	0.9	249084.399	13955.856	80.923

Table 4
Objective functions vs. different values of $\boldsymbol{p_i}$ based on ($\boldsymbol{\alpha = 0.4}$).

Problem size	Level of probability p_i	Objective function values		
$\lvert S\rvert \times \lvert J\rvert \times \lvert K\rvert \times \lvert V\rvert \times \lvert P\rvert \times \lvert T\rvert$		OFV_1	OFV_2	OFV_3
$2 \times 5 \times 6 \times 3 \times 2 \times 2$	0.1	248013.931	13402.844	197.401
	0.5	247337.157	13207.541	206.451
	0.9	247301.171	13187.257	221.389

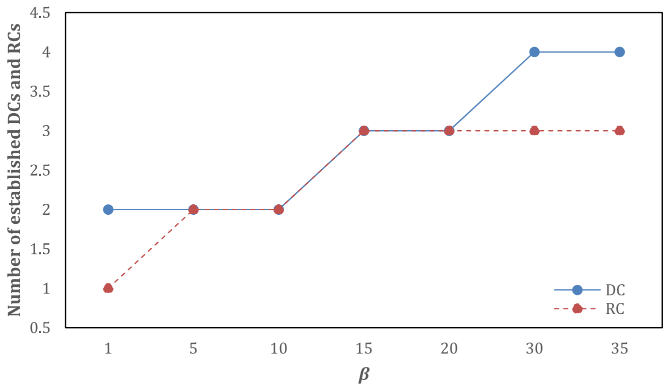


Fig. 7. Number of established DC and RC vs. wieght of transportation cost.

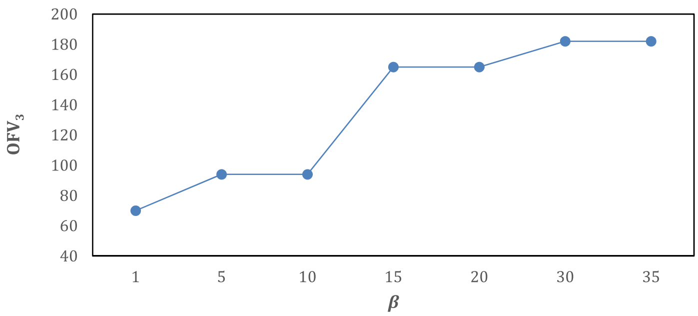


Fig. 8. OFV_3 vs. wieght of transportation cost.

Because the optimal solution is between the lower bound and SGV and because the relative gap between the lower bound and optimal solution is 1.6%, it can be concluded that the mean gap between SGV and the optimal solution are 2.27% (i.e., $(3.87 - 1.6)\%$). The obtained results indicate that our proposed meta-heuristic algorithm can find near-optimal solutions within a reasonable time.

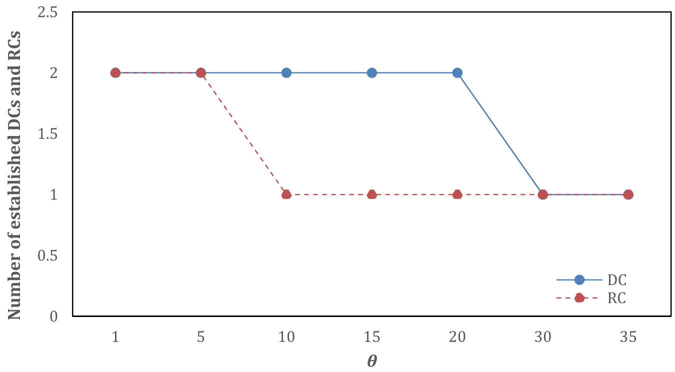


Fig. 9. Number of established DC and RC vs. wight of inventory cost.

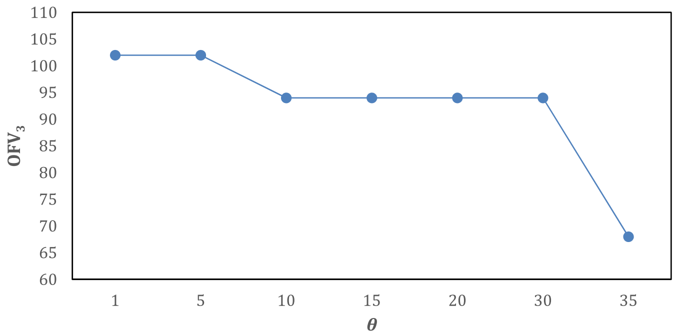


Fig. 10. OFV_3 vs. weight of invetory cost.

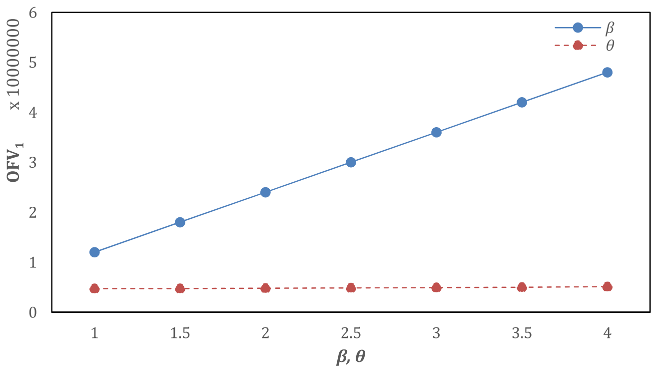


Fig. 11. OFV_1 vs. weights of transportaion cost and inventory cost.

To better track the reciprocal behavior of the data sets and computational times as well as APRG, Figs. 16 and 17 show the sensitivity analyses under these two measures.

Fig. 16 illustrates the CPU time required for finding both optimal (exact) and near optimal (SGV) solutions. It can be easily shown that the exact CPU time increased in an exponential manner by increasing the size of the problems.

6.3. Case study

This case study considers the supply chain of LCD and LED TVs. Currently, electronic devices play an increasingly important role in the daily life of people, among which TVs are considered one of the most popular devices. The replacement of early bulky, high-voltage cathode ray tube (CRT) screen displays with compact and energy-efficient technologies such as

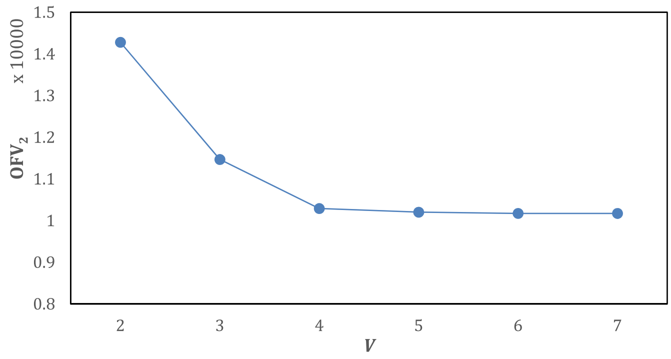


Fig. 12. OFV_2 vs. number of vehicles.

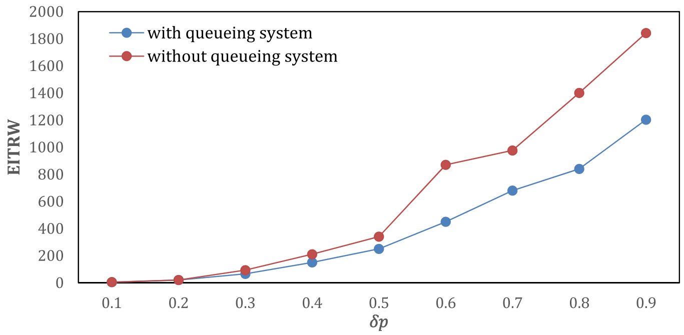


Fig. 13. EITRW vs. coefficient of expected return product *p*.

Table 5
Production operations' parameters.

Parameters	
sorting and collection cost per unit of product	5
manufacturing cost per unit product	100
remanufacturing cost per unit of product	$100^{*}\gamma$

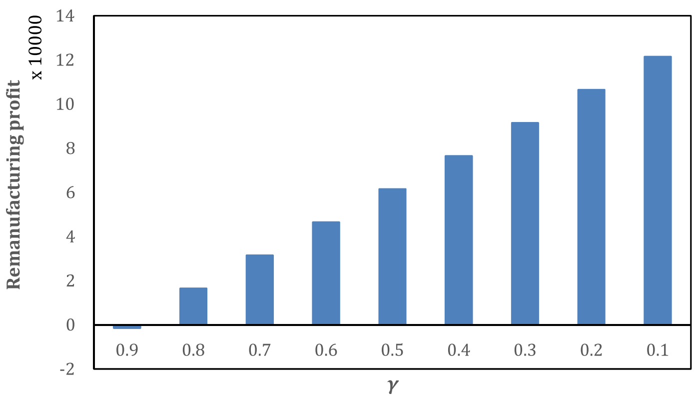


Fig. 14. Remanufacturing profit vs. γ.

LCD and LED has resulted in a huge increase in demand for these new types of TVs. This replacement occurred from 2010 to 2012 in most developed countries; in developing countries such as Iran, this huge increase in demand started in 2013 and is expected to continue until 2017. Therefore, considering the supply chain of the new generation of TVs is of great importance in Iran.

Table 6
SGV parameters settings.

Parameter	Settings
Population size	80S[a], 150M[a], 200L[a]
Number of iteration	150S, 250M, 500L
Selection operator	Binary tournament
Crossover rate	0.8
Mutation rate	0.2

[a] S: Small size; M: Medium size; L: Large size.

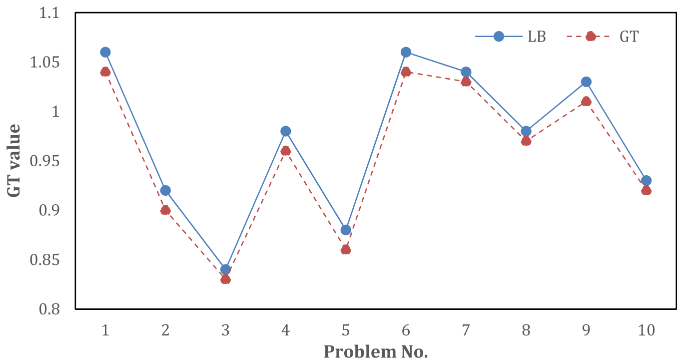


Fig. 15. Comparison between $\mathbb{Z}_{LB}$ and GT of the optimal solution.

Table 7
APRG and CPU time (in second) for small scaled instances.

Data set	Exact time (s)	SGV						
		Replications					Gap (%)	Time (s)
		1	2	3	4	5		
1	41	0.04	0.05	0.05	0.04	0.06	0.048	33
2	48	0.05	0.07	0.08	0.05	0.07	0.064	34
3	62	0.09	0.1	0.09	0.11	0.09	0.096	36
4	89	0.5	0.6	0.5	0.7	0.6	0.58	39
5	116	0.9	1	0.9	1	1.1	0.98	42
6	147	1.1	1.1	1	1.2	1	1.08	44
7	189	1.3	1	1.3	1.4	1.1	1.22	48
8	243	1.4	1.4	1.3	1.4	1.5	1.4	55
9	298	1.6	1.5	1.7	1.6	1.6	1.6	57
10	369	1.7	1.8	1.8	1.9	1.7	1.78	61
11	468	1.8	1.9	1.9	2	2	1.92	66
12	687	2.1	2	2.1	1.9	2.2	2.06	71
13	897	2.2	2.2	2.5	2.3	2.3	2.3	72
14	1432	2.4	2.4	2.5	2.6	2.3	2.44	79
15	1957	2.7	2.5	2.6	2.8	2.7	2.66	83

Among developing countries, we have chosen Iran for our case study. Designing an optimal supply chain to improve the shipment of commodities, providing a proper service level to costumers in both cost and time and considering sustainability aspects are the applications of the problem under study. Fig. 18 depicts the 20 considered cities in our study. According to the experts, the potential locations of DCs and RCs as well as the current two major suppliers are marked in Fig. 18.

Although obtaining all of the parameters used by the presented model is challenging, the associated parameters are obtained from different sources. In this way, traveling times and distances between the considered cities are estimated using Google maps. The demand of two considered products (i.e., LCD and LED TVs) and the fixed cost of establishing DCs and RCs are obtained from a feasibility study report for establishing a supply chain for TV products that was prepared by the Avicenna Research Institute. The unemployment rate in each city was taken from the Iranian Statistical Center (ISC). Some of the green parameters related to the physical conditions of vehicles were obtained regarding the considered vehicles.

Table 8
APRG and CPU time (in second) for medium and large scaled instances.

Data set	Exact time (s)	SGV						
		Replications					Gap (%)	Time (s)
		1	2	3	4	5		
16	2865	2.9	2.9	3.1	3	2.8	2.94	99
17	3897	3	3.1	3.3	3.2	3.1	3.14	102
18	–	3.5	3.3	3.3	3.5	3.4	3.4	111
19	–	3.6	3.7	3.7	3.9	3.8	3.74	121
20	–	4	4.1	4	3.9	4	4	128
21	–	4.5	4.7	4.4	4.6	4.5	4.54	134
22	–	4.9	4.8	5	4.9	4.9	4.9	136
23	–	5.2	5.1	5.3	5.3	5.2	5.22	141
24	–	6.3	6.5	6.4	6.6	6.4	6.44	150
25	–	6.9	7	7	7.3	7.1	7.06	158
26	–	7.7	7.8	7.6	7.5	7.5	7.62	173
27	–	8	8.1	8.3	8.1	8.1	8.12	192
28	–	9.8	10.2	10	9.9	10.2	10.02	220
29	–	11.5	11.9	11.7	11.4	11.6	11.62	245
30	–	13.1	12.9	13	13.5	13.3	13.16	288

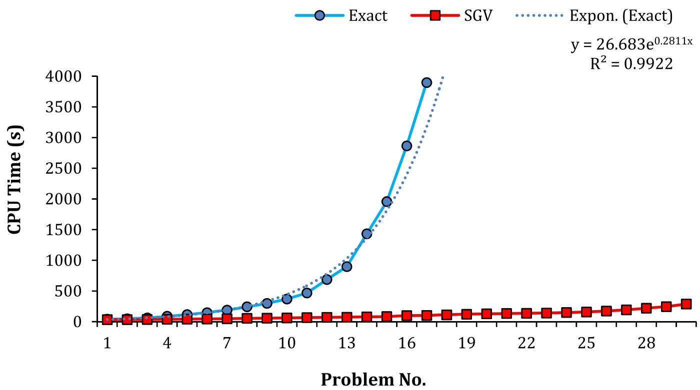


Fig. 16. CPU Time vs. the problem number.

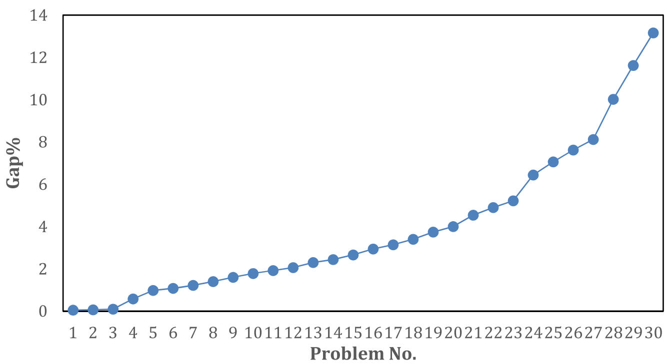
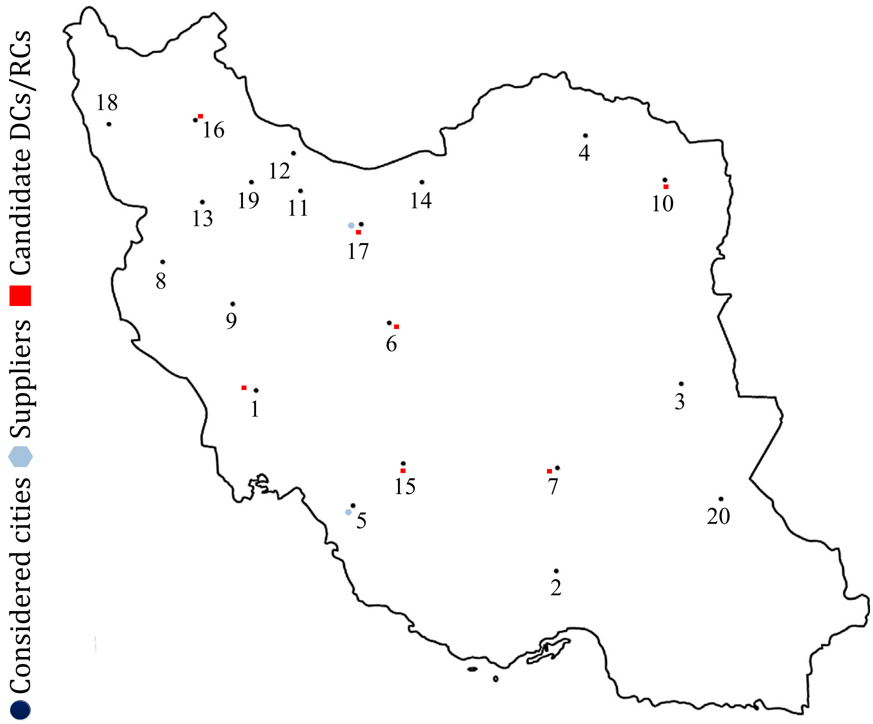


Fig. 17. Mean gap vs. problem number.

In this case, we extended the data set by defining three capacity levels for the potential DCs and RCs. Two scenarios were considered for the capacity levels of potential DCs and RCs: tight capacity and excess capacity.

To generate triangular fuzzy parameters, the most likely value of the parameter (ξ^m) is obtained from the data provided in the case. Then, using a uniform distribution, two random numbers (r_1, r_2) are generated between 0.2 and 0.8 by which the most pessimistic value (ξ^p) and the most optimistic value (ξ^o) are obtained as follows:

$$\xi^o = (1 + r_1)\xi^m \quad \text{and} \quad \xi^p = (1 - r_2)\xi^m$$



1	Ahwaz	6	Isfahan	11	Qazvin	16	Tabriz
2	Bandar Abbas	7	Kerman	12	Rasht	17	Tehran
3	Birjand	8	Kermanshah	13	Sanandaj	18	Urmia
4	Bojnord	9	Khorramabad	14	Sari	19	Zanjan
5	Bushehr	10	Mashhad	15	Shiraz	20	Zahedan

Fig. 18. Iran's map with considered cities in the case study.

Due to the large problem size of our case study, the proposed SGV meta-heuristic is used to obtain the near-optimal solution for our network. The parameters of the proposed SGV meta-heuristic were set according to Table 6.

After applying SGV, the obtained results are illustrated in Figs. 19 and 20.

As shown in Fig. 19, when a tight capacity is considered for DCs and RCs, three candidate locations (Tehran, Tabriz and Shiraz) are selected as DCs and two candidate locations (Tehran and Shiraz) are selected as RCs. Two fixed suppliers are located in Tehran and Bushehr. Reducing the shipping and ordering cost between the suppliers and DCs is a significant reason for selecting Tehran and Shiraz for the DCs. The model selected Tehran as a RC for remanufacturing the return products that come from the northwest and northeast of Iran. Regarding the ISC, Zahedan, Ahwaz and Shiraz are the cities with the highest unemployment rates in Iran. Because our model considered sustainability features such as unemployment rate, Shiraz seems to be a good choice as a DC in the south of Iran. Furthermore, Shiraz's strategic location at the map makes it a proper choice for covering the demands of middle and south Iran and also to be an RC in southeast Iran. In the second scenario (see Fig. 20), in which an excess capacity is considered for DCs and RCs, two candidate locations (Tehran and Shiraz) are selected as DCs and two candidate locations (Tehran and Shiraz) are selected as RCs. Because DCs and RCs can be open with more capacity in this scenario, Tabriz is not selected as a DC. Instead, a DC in Tehran covers all of the demands of northwest and northeast Iran.

Regarding Figs. 19 and 20, the model tries to use short routes to deliver the products to a set of customers. For instance, in the first scenario, a truck is assigned to a route to cover the demand of just one customer (i.e., Isfahan). There are two reasons for this assignment: the high demand of Isfahan for the considered products and the reduction of the environmental impact

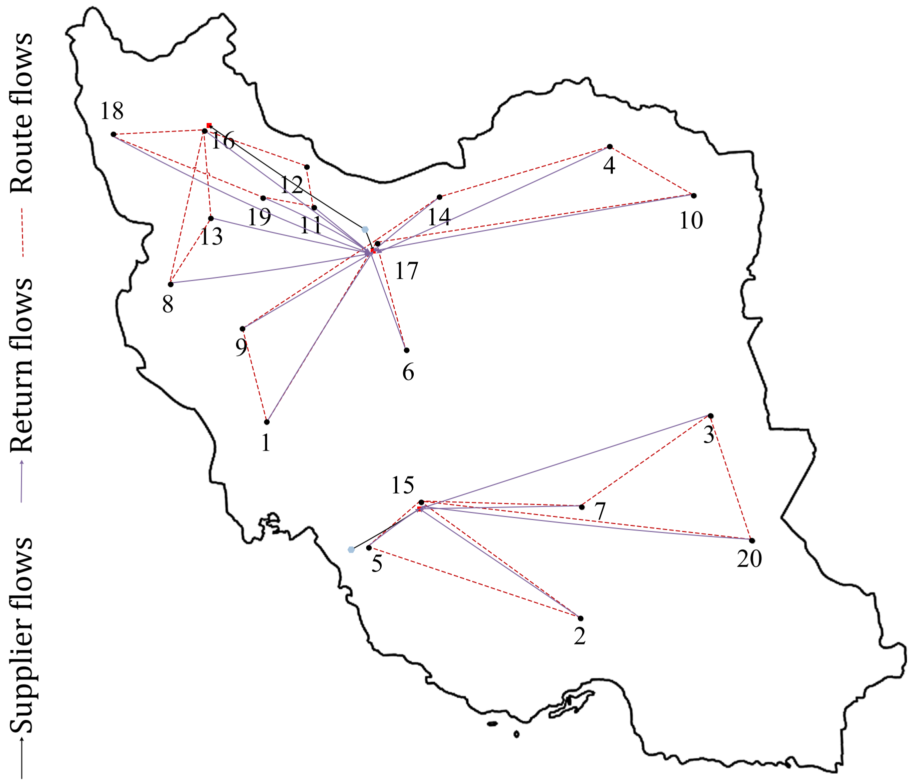


Fig. 19. Designed network and its interaction for tight capacity.

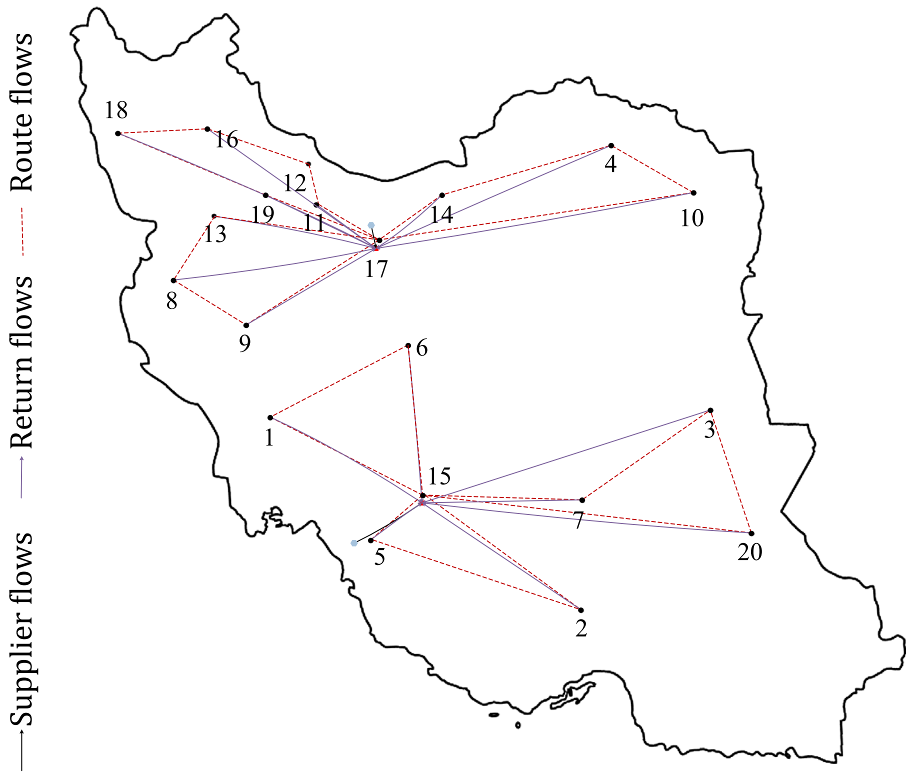


Fig. 20. Designed network and its interaction for excess capacity.

Table 9
Details of real case study.

Input	Output				
capacity	DC locations	RC locations	OFV_1	OFV_2	OFV_3
Tight	15, 16, 17	15, 17	5.67E+09	5.72E+08	4.90E+02
Excess	15, 17	15, 17	4.82E+09	6.31E+08	4.15E+02

of CO_2 emissions and fuel consumption (i.e., a vehicle with a heavy load will emit more CO_2 and consume more fuel). The detailed results of two scenarios are tabulated; the first column is the capacity strategy, the second and third columns are the location of the established DCs and RCs, and the fourth through sixth columns are the values of the objective functions (see Table 9).

7. Conclusions and future work

The main contributions of this paper to the literature are threefold: (i) proposing a new multi-objective mathematical programming model for the sustainable CLCS network to simultaneously address routing, inventory and location-allocation decisions; the proposed model considers location-routing-inventory, green factors (i.e., CO_2 emissions, fuel consumption and wasted energy due to the queue formation) and the SIs of a designed CLSC, (ii) proposing a new hybrid approach including an efficient stochastic-possibilistic programming method and a modified game theory approach to cope with the uncertainty and to address the multiple conflicting objectives of the proposed model and (iii) developing a new hybrid meta-heuristic algorithm with an efficient new lower bound procedure to solve large-sized problems. Furthermore, to validate the presented model, several sensitivity analyses have been conducted and managerial insights have been discussed. The presented model enables top managers to evaluate their strategic, tactical and operational decisions from both cost and sustainability perspectives. The results showed that the number of DCs and RCs and the positive SIs of the considered CLSC increased as the weight of the transportation cost increased and decreased as the weight of the inventory cost increased. Additionally, we found that the weight of the transportation cost has a more significant impact on the costs of the considered CLSC network than the weight of the inventory cost. Moreover, the appropriate number of transportation vehicles is discussed. Utilizing a queueing system can have a significant impact on reducing the EITRW. The analysis further assessed the feasibility of remanufacturing in reverse logistic for different values of returned products. Finally, a real case study in Iran was also studied to show an application of the proposed model.

Some extensions on the presented work could be addressed by future research. Considering other challenges such as facility disruption and pricing decisions in the designed CLCS network could be interesting topics for future research. In addition, developing other efficient meta-heuristic algorithms or using an efficient exact method such as the Lagrangian relaxation algorithm is also a good direction for future research.

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