MULTI-OBJECTIVE OPTIMIZATION FOR A COMBINED LOCATION-ROUTING-INVENTORY SYSTEM CONSIDERING CARBON-CAPPED DIFFERENCES

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(Communicated by Changzhi Wu)

Abstract. A combined location-routing-inventory system (CLRIS) in a three-echelon supply chain network is studied with environmental considerations. Specifically, a bi-objective mixed integer programming model is formulated for the CLRIS to deal with the trade-offs between the total cost and the carbon-capped difference (CCD). A multi-objective particle swarm optimization (MOPSO) heuristic solution procedure is developed and implemented to solve the bi-objective mixed integer programming problem. The bi-objective mixed integer programming model and the MOPSO heuristic procedure are applied to a real-life problem as an illustrative example. The approximate nondominated frontier formed by solutions not dominated by others can be used for the decision makers to make trade-offs between the total cost and the CCD. Sensitivity analyses are conducted, and the relationship among the carbon cap, CCD, the total cost and the carbon prices are examined, and relevant managerial insights are provided. Comparisons with other existing algorithms show that the MSPSO heuristic procedure has very good performance.

2020 Mathematics Subject Classification. Primary: 65K05; Secondary: 90C08.
Key words and phrases. Location-routing-inventory, Carbon emissions, Carbon-capped difference, MOPSO heuristic procedure, Nondominated frontier.

This research was supported by National Science Foundation of China [grant numbers 71572031, 71971049 and 71702112].
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1. **Introduction.** Air quality becomes a major concern and a hot topic in politics, the general public and the research community because it directly relates to the public health and life quality. Governments all over the world have started making great effort in reducing pollution by continuously providing financial, land and policy supports to strategic projects. These supports show the determination of the governments to control pollution. The environmental damage caused by business activities leads to governmental legislations and environmentally conscious consumers [56]. Hence, consumers and the governments put pressures on business firms to mitigate the environmental impact from production and processes [9].

At the same time, with the rapid development of the global economy, the growing commodity consumption brings rapid circulations of goods in the worldwide supply chains. The operations of supply chains that consist of production, transportation, inventory and consumption make great impact on the environment and cause serious problems. The operations of comprehensive supply chain networks involve complex combined location-routing-inventory systems (CLRISs). Consumers now pay increasing attentions to environmental impact. The pressures from the governments and consumers motivate business firms to reduce carbon emissions in CLRISs. The environmental policies and regulations of the governments and the cooperative relationships among enterprises have created positive incentives in the development of low carbon CLRISs [47]. Consequently, eco-friendly supply chains involving CLRIS design become significant issues and attract attentions from many researchers. Three measures, including imposed regulations by the governments, improved techniques and operation process optimization, have been used to reduce carbon, i.e., CO2, emissions in supply chains. This study focuses on reducing carbon emissions by the third measure, i.e., optimizing the operations of the CLRISs. The operations of supply chains are a most important part in current economic activities as they are the vital tools for business firms to improve their competitiveness [1]. Hence, optimizing the operations in supply chain is equally vital to the environment and the economy.

The design of a CLRIS considering carbon-capped difference (CCD) is obviously complex, because the locations, capacities, inventory levels of the regional distribution centers (DCs), and the distribution routes need to be determined. When designing a CLRIS, the locations of the regional DCs need to be determined, the retailers need to be allocated to vehicles, the order quantities of the DCs need to be determined, and the routings of the vehicles need to be decided. A few studies dealing with the problem of carbon emissions have appeared in the literature, but none of them explicitly considered the environmental issues in the design of a CLRIS. The trade-offs between carbon emissions and costs of a CLRIS are generally formulated as optimization models with a single objective function. Because the problem involves different incompatible objectives, a multi-objective model is more appropriate and closer to reality in modeling the problem.

In this study, the concept of CCD is introduced and a bi-objective mixed integer programming model, in which both the total cost and the CCD are simultaneously minimized in a CLRIS, is presented. A multi-objective particle swarm optimization (MOPSO) heuristic procedure is developed to obtain nondominated solutions for this problem. The model and the MOPSO heuristic procedure are applied to a real-life problem in the petrochemical industry to show their relevance, effectiveness and conformity with practical applications. Furthermore, the performances of the
bi-objective mixed integer programming model and the MOPSO heuristic procedure are compared with those of other widely used procedures. The formulation of the petrochemical comprehensive supply chain network as a CLRIS considering the CCD is particularly suitable due to the following reasons. On the one hand, plants, DCs and retailers often belong to the same company in the petrochemical industry, which favors collaboration. On the other hand, a petrochemical company considers carbon emissions as quite a significant factor in its supply chain network, since reducing carbon emissions is not only a government requirement but also a responsibility of the company. Indeed, the operations of the comprehensive supply chain network involve complex CLRISs for this real-life petrochemical company, which motivated this work to focus on the design of its CLRIS with CCD consideration.

The main contributions of this study are as follows. First, a bi-objective mixed integer programming model is formulated for the CLRIS, which incorporates cost and environmental issues. The model explicitly minimizes the cost and the CCD. Second, an MOPSO heuristic procedure is developed to solve the bi-objective mixed integer programming problem for the CLRIS. The MOPSO heuristic procedure incorporates an infeasibility degree threshold to drive the infeasible trial solutions in the swarm to the feasible region in the search process. Being evolutionary algorithm based, the MOPSO heuristic procedure can handle both continuous and binary variables and can find a set of nondominated solutions. Third, the bi-objective mixed integer programming model and the MOPSO heuristic procedure are applied to a real-life problem in the petrochemical industry to demonstrate their applicability. The numerical results characterize the nondominated frontier and show their sensitivities to different parameters in the model. Some important managerial insights are drawn from the results.

The rest of the paper is organized as follows. Section 2 reviews the relevant literature. Section 3 introduces the problem in details and Section 4 describes some vital measures of carbon emissions. In Section 5, the bi-objective mixed integer programming model is formulated. The solution method is described in Section 6. The real-life problem is described and the results are given in Section 7. Finally, Section 8 summarizes the main findings and provides directions for further work.

2. Previous and related works. A low carbon CLRIS needs to deal with two issues, i.e., total carbon emission minimization and total cost minimization. Several researchers integrated these issues into a single objective function in their models given the high dependency between them. A taxonomy of some of the relevant studies focusing on low carbon supply chain networks and CLRISs is given in Table 1. These publications are categorized based on the major approaches used by these studies. In the following, literature is reviewed in low carbon supply chains, distribution networks in supply chains, and CLRISs considering carbon emissions. Finally, literature is briefly discussed in particle swarm optimization (PSO) and MOPSO.

Due to the increasing concerns on environmental issues, changes are foreseen in the future in supply chain operations, regardless of whether business firms are voluntarily or are forced by new legislations to reduce carbon emissions (Hoen et al. [17]; Xin et al. [51]; Zhang et al. [56]). Many publications have appeared in the literature in recent years focusing on low carbon supply chains. Jaber et al. [7] formulated a model for a two-echelon supply chain with a coordination mechanism.
Table 1. Summary of relevant literature for low carbon supply chains

| Literature category                                      | Issues considered                                      | Related publications                                                                 |
|----------------------------------------------------------|--------------------------------------------------------|--------------------------------------------------------------------------------------|
| Translating carbon emissions into cost                   | Carbon cost; carbon price; pollution cost; cap-and-trade; emissions trading scheme | Tseng and Hung [44]; Treitl et al. [43]; Alhaj et al. [1]; Bai et al. [5]; Wang, Tao and Shi [50]. |
| Treating carbon emissions as a constraint in supply chain models | Carbon footprints; carbon-constrained                   | Benjaafar et al. [8]; Xu et al. [53]; Lam and Gu [23]; Martí et al. [26].              |
| Policies for carbon emission reduction                  | Carbon trading; carbon tax                              | Bazan et al. [7]; Wang et al. [47]; Wang, Zhao and Herty [49]; Saxena et al. [34]; Xin et al. [51]; Huang et al. [18]; Samuel et al. [33]. |
| Multiple objectives with carbon emissions               | Trade-offs between cost and environment                 | Paksoy et al. [30]; Masavi and Bozorgi-Amiri [29]; Daryanto et al. [16].               |
| Carbon emission reduction with coordination mechanisms   | Green production; green purchasing; coordination mechanism; life cycle assessment | Palmer [31]; Jaber et al. [19]; Du et al. [13]; Xu et al. [52]; Zhang et al. [56].       |
| Supply chain network design                             | Location; routing; inventory                           | Min et al. [27]; Wang, Tao and Shi [50]; Javid and Azad [20]; Farahani et al. [15]; Tang et al. [42]; Zhalechian et al. [55]. |

The emission schemes considered include carbon tax, emission penalty, emission allowance trading and combinations of them. Samuel et al. [33] formulated a robust model for a closed-loop supply chain design with carbon emissions. The emission policies including emission carbon cap and carbon cap-and-trade are considered. Tseng and Hung [44] developed a mixed integer nonlinear programming model in which the operation cost and the carbon emission cost are considered to achieve a sustainable supply chain network. As pointed out by Martí et al. [26], the supply chain approaches aiming to ensure effective carbon management should make the environmental and operational trade-offs in the various processes, including purchasing, transportation and inventory. The regulations and policies on low carbon emissions play an important role in the low carbon supply chain management (Xin et al. [51]; Zhang et al. [56]). Saxena et al. [34] established a tactical planning model for a tyre remanufacturing supply chain considering the carbon emission cost. Meanwhile, reducing carbon emissions in a CLRIS is an important problem to study. The measure of carbon footprint is a fundamental research step. Wang, Zhao and Herty [49] proposed a carbon trading mechanism for a supply chain of fresh food considering the carbon emission permits. The works mentioned above indicate the possibility to reduce carbon emissions by proper operations of the supply chain.

A key driver in a supply chain is the distribution network, from which most of the carbon emissions are generated. There are three major components in the operations of a supply chain network, i.e., location-allocation, vehicle routing and inventory control. Javid and Azad [20] is the first to formulate a model that optimizes location, routing, and inventory decisions in a supply chain network. Ghorbani and Jokar [16] studied a location-routing-inventory problem for location-allocation, routing and inventory management in a three-echelon supply chain. Wang and Lim [48] proposed a multi-objective optimization model for an integrated location-routing-inventory problem that optimizes locations of the warehouses, inventories of products and distribution routings. The objectives to be minimized are the total
cost, total distance travelled by the fleet and total traveling cost. Some researchers reviewed the works in the area of location-routing-inventory. For example, Min et al. [27] surveyed the works in inventory-routing problems, Wang, Tao and Shi [50] reviewed the works for location-routing problems, and Farahani et al. [15] surveyed the works in location-inventory problems. Obviously, studying the CLRIS is an effective approach of studying the supply chain network giving considerations to carbon emissions.

Some works have been done related to sustainable or green supply chain networks and CLRISs considering carbon emissions. Ansari and Kant [3] provided a comprehensive survey for the green supply chain management for 15 years before 2016. There are a few works incorporating carbon emissions into the CLRISs. Zhalechian et al. [55] introduced a closed-loop CLRIS that considers carbon emissions and wasted energy and formulated the problem as a stochastic-possibilistic programming model. Tang et al. [42] integrated consumer environmental behavior into a CLRIS and established a multi-objective optimization model minimizing the cost and carbon emissions. Some studies on green and sustainable supply chain network considering carbon emissions have appeared recently. Lam and Gu [23] developed a tactical planning decision support model to provide practical trade-offs among cost, transportation time and the carbon emission restrictions. Their study focused on the container assignment, routing and transportation modes in the context of an intermodal transportation network. Wang, Tao and Shi [50] studied a green location-routing problem considering carbon emissions, and found that considering carbon emissions and realizing sustainable logistics are increasing necessities although that will increase the total cost. Alhaj et al. [1] focused on a joint location-inventory problem with one plant, several DCs and retailers, and extended the problem to include the reduction of carbon emissions. However, none of these earlier works comprehensively considered CLRIS optimization under carbon emissions.

The sustainable supply chain network problem is often formulated as, or transformed into, an optimization problem with a single objective. For example, Tseng and Hung [44] considered the CO2 emission cost alongside purchasing cost, production cost and transportation cost of materials. Treitl et al. [43] studied an inventory routing problem considering the carbon emissions from the warehousing activities and the transportation processes, and formulated an inventory routing model considering the transportation cost and carbon emissions in a single objective function to obtain cost-saving and environment friendly solutions.

A few general approaches have been used in the study of carbon emissions in supply chains as shown in Table 1. Bai et al. [5] introduced a perishable product supply chain considering the cap-and-trade regulation of carbon emissions. Xu et al. [52] used the carbon emission capacity regulation to reveal its effects on supply chain decisions. Benjaaifar et al. [8] used the carbon cap as a constraint in optimization models. Huang et al. [18] applied the carbon tax and trade-and-cap mechanism to reduce CO2 emissions in supply chain networks. Musavi and Bozorgi-Amiri [29] proposed a multi-objective mixed integer linear programming model for a perishable food supply chain, capturing the trade-offs among the transportation cost, delivery time and the total carbon emissions. They concentrated on the environmental investment in the location and routing phase and thus did not include decisions in inventory. Paksoy et al. [30] studied the environmental factor of a closed-loop supply chain network aiming to reduce CO2 emissions and promote recyclable products to
customers. They also considered different transportation choices between echelons in the supply chain network according to CO2 emissions. However, some special facilities need to be set up to handle recycling in a closed-loop supply chain network.

Kennedy and Eberhart [22] introduced PSO the first time as a population-based metaheuristic procedure. The particles are initialized with a population consisting of randomly generated solutions, and each of the particles can track a trajectory of a series of trial solutions. The population is called a swarm. The metaheuristic procedure can be tailored to different difficult problems by taking advantage of the specific problem structures. Several modifications in the PSO heuristic procedure have been made by researchers to solve different problems. Some recent developments can be found in Shi and Eberhart [36], Mousavi et al. [28], Yu et al. [54], Artale et al. [4], among others. As Sierra and Colleo [37] pointed out, the effectiveness of the PSO heuristic has been reflected by its wide applications in solving many problems with single objectives. They showed that the PSO procedures with modifications are also effective in solving multi-objective optimization problems and proposed an MOPSO heuristic procedure based on dominance relations. Experiments suggested that MOPSO has high competitiveness among some of the state-of-the-art solution procedures. Obtaining proper global best and individual best solutions to move the particles within the search space is crucial in MOPSO. Generally, an effective MOPSO heuristic procedure should have the capability to obtain solutions with good diversity and convergence in the nondominated frontier [25]. However, not many modified versions of the PSO procedures have been designed and used to solve multi-objective optimization problems in supply chain networks. Validi et al. [45] developed a MOPSO procedure to deal with a multi-objective product distribution supply chain optimization model with trade-offs among total cost, carbon emissions and the distance of the vehicles traveled, and the results showed that this procedure could provide a set of nondominated solutions. In Venkatesan and Kumanan [46], a multi-objective discrete PSO procedure was designed to solve a supply chain network problem in which the objectives were to minimize the supply chain cost, minimize the demand fulfillment lead time and maximize the volume flexibility. To solve bi-objective programming problems with both continuous and binary variables, Shankar et al. [35] designed a multi-objective hybrid PSO procedure and the result showed that the hybrid PSO procedure was efficient and effective.

3. The CLRIS problem.

3.1. Problem description and a real-life example. This study focuses on CLRISs with consideration of carbon emissions. A real-life illustrative example in the petrochemical industry is analyzed. To improve its competitiveness, Liaoning Shenyang Sales Branch of the China National Petroleum Corporation (CNPC) aims at optimizing the operations in its CLRIS so as to reduce the total cost and the CCD. The three-echelon supply chain network studied consists of three types of facilities, i.e., plants, potential regional DCs and retailers. For a general CLRIS, the index sets of the plants, DCs and retailers are represented by $I$, $J$ and $K$, respectively. Each plant $i \in I$ is assumed to have a known capacity and each potential DC $j \in J$ is also assumed to have a known capacity. The number and the index set of vehicles are represented by $n_v$ and $V$, respectively. A three-echelon supply chain network is graphically depicted in Figure 1.

As shown in Figure 1, the locations of the plants and the retailers are fixed but the DCs are not established. A DC may or may not be built at a potential site,
Figure 1. A three-echelon supply chain network

and a site \( j \in J \) is open if a DC is built and is closed otherwise. Costs are incurred and carbon is emitted in the CLRIS at the open DCs through the transportation of the products from the plants to the DCs and/or from the DCs to the retailers, and through the handling of inventory in the supply chain. When convenient, plants, DCs and customers are all called nodes in the supply chain network.

3.2. Assumptions. (a) Each plant \( i \in I \) has a known capacity \( G_i \) at a fixed location, which is a common assumption in CLRIS.

(b) The yearly demand of each retailer \( k \in K \) is a random variable following a \( N(\mu_k, \sigma_k) \) distribution and is independent of those of the other retailers.

(c) The inventory of each DC \( j \in J \) is supplied by a single plant, and the demand of each retailer \( k \in K \) is satisfied by a single DC.

(d) The total carbon emission from operating the CLRIS is \( E_{emit} \), the carbon cap of the CLRIS allocated by the governmental agency is \( E_{cap} \), and the CCD of the CLRIS is \( E_{ccd} = E_{emit} - E_{cap} \). A smaller value of CCD is better for promoting the low-carbon CLRIS. An \( E_{ccd} > 0 \) indicates that the CLRIS emits more carbon than permitted, and measures should be taken to reduce carbon emissions or the firm should buy carbon credit to increase \( E_{cap} \). Otherwise, an \( E_{ccd} \leq 0 \) indicates that the CLRIS meets the carbon emission restrictions.

(e) All the vehicles from the plants to the DCs are the same with unlimited capacity and the same fixed and variable costs. All the vehicles from the DCs to the retailers and from the retailers to the other retailers are the same with the same capacity \( V_d \) and the same fixed and variable costs. However, the vehicles used from plants to the DCs are different from those used from the DCs to the retailers and also from the retailers to the other retailers.

3.3. Parameters and notations. The solution of the bi-objective mixed integer programming model should determine (a) the potential DCs to open; (b) the assignment of the open DCs to the plants; (c) the economic order quantity of each DC; and (d) the assignment of the retailers to the open DCs. Furthermore, the routings of the vehicles should also be specified. The following parameters and notations are used in the model.

(a) Costs: \( f_j \) represents the fixed operating cost of DC \( j \) per time period; \( h_o^j \) represents the ordering cost of DC \( j \) per order; and \( h_j \) represents the inventory holding cost per unit of product per time period at DC \( j \). The fixed transportation cost from a plant to a DC per trip is represented by \( F_p \) and the variable transportation cost from a plant to a DC per unit of product per unit of distance is represented
by \( p_t \). The fixed transportation cost from a DC to a retailer or from a retailer to another retailer per trip is represented by \( F^d \) and the variable transportation cost per unit of product per unit of distance from a DC to a retailer or from a retailer to another retailer is represented by \( p_d \).

(b) Carbon caps: the carbon caps of plant \( i \), DC \( j \) and retailer \( k \) are represented by \( E_{\text{cap}i}, E_{\text{cap}j} \) and \( E_{\text{cap}k} \), respectively.

(c) Capacities: the capacities of plant \( i \) and DC \( j \) are represented by \( G_i \) and \( U_j \), respectively; the capacities of vehicles from DCs to retailers and from retailers to the other retailers are represented by \( V^d \); and the expected value and the standard deviation of the yearly demand of retailer \( k \) are represented by \( \mu_k \) and \( \sigma_k \), respectively.

(d) Distances: the distance between two nodes \( i \) and \( j \) is represented by \( d_{ij} \) for \( i \in I \) and \( j \in J \), for \( i \in J \) and \( j \in K \), or for \( i \in K \) and \( j \in K \).

(e) Lead time and service level: the lead time of DC \( j \) is represented by \( L_j \); and the service level, i.e., the expected percentage of orders being satisfied from inventory by the retailers during lead time, is represented by \( \alpha \).

3.4. Decision variables. The following decision variables are used in the bi-objective mixed integer programming model.

\[
y_j = \begin{cases} 1, & \text{if } DC \text{ is open} \\ 0, & \text{otherwise} \end{cases}, \quad \text{for } j \in J,
\]

\[
x_{ij}^p = \begin{cases} 1, & \text{if } DC \text{ is assigned to plant } i \\ 0, & \text{otherwise} \end{cases}, \quad \text{for } i \in I \text{ and } j \in J,
\]

\[
x_{jk}^d = \begin{cases} 1, & \text{if retailer } k \text{ is assigned to DC } j \\ 0, & \text{otherwise} \end{cases}, \quad \text{for } j \in J \text{ and } k \in K,
\]

\[
x_{wkv} = \begin{cases} 1, & \text{if } w \text{ precedes } k \text{ in the route of vehicle } v \\ 0, & \text{otherwise} \end{cases}, \quad \text{for } w \in (J \cup K) \text{ and } k \in K,
\]

\[
Q_j: \text{Order quantity of DC } j \text{ for } j \in J,
\]

\[
R_{kv}: \text{Auxiliary variable defined for retailer } k \text{ for subtour elimination in the route of vehicle } v, \quad \text{for } k \in K \text{ and } v \in V.
\]

4. Measurement of carbon emissions. The carbon emissions are measured by the weight of CO2 generated by different business activities in a CLRIS. The activities controllable through the decisions in the CLRIS include the locations of the DCs, the routing of the vehicles and the quantities of inventories.

4.1. Carbon emissions at facilities. The primary carbon emissions of the locations are originated from opening and operating the DCs. The carbon emissions of a DC are assumed to be directly related to the energy consumption but depends on the specific type of energy used. Given a set of activities \( S \), the carbon emissions of a location, represented by \( \prod_{L(g)} \), can be expressed as (1) in the following

\[
\prod_{L(g)} = \sum_{s \in S} \lambda_s E_s, \quad (1)
\]

where \( \lambda_s \) and \( E_s \) denote the carbon emission factor and the energy consumption of activity \( s \), which refers to the construction, maintenances and operations of the DC. However, the energy consumption and the related carbon emission factors are hard to acquire in practice. Because of the lack of data, the carbon emissions at the facilities are computed using an average carbon emission factor and the area
occupied or the volume possessed by the facilities. Hence, the carbon emissions of the DCs can be expressed as \( E_L \) in (2) in the following

\[
E_L = \lambda \sum_{j \in J} A_j y_j,
\]

where \( \lambda \) denotes the average carbon emission per \( \text{m}^2 \) (\( \text{m}^3 \)) and \( A_j \) denotes the area (volume) of DC \( j \) in \( \text{m}^2 \) (\( \text{m}^3 \)). The value of \( \lambda \) is obtained from the data in the China Statistical Yearbook which gives the actual carbon emissions of facilities of different industries.

4.2. Carbon emissions from routing. It is difficult to measure the exact carbon emissions from routing since they are determined by vehicle speeds, congestions, kerb weights, etc. However, carbon emissions have a direct relationship with fuel consumption. Therefore, fuel consumption from transportation/distribution can be used to deduce carbon emissions. Fuel consumption is measured in liters of gasoline or diesel. Similar to that in [31], a factor \( \theta \) in kgs of CO2 per liter of fuel is used to convert fuel consumption into carbon emissions. The value of \( \theta \) depends on the fuel products used. The carbon emissions from routing can be computed using (3) in the following

\[
E_R = \theta F,
\]

where \( F \) denotes the fuel consumption from routing and can be computed as

\[
F = \beta \sum_{i \in I} \sum_{j \in J} d_{ij} x_{ij}^p + \gamma \sum_{v \in V} \sum_{w \in (J \cup K)} \sum_{k \in K} d_{wk} x_{wkv}^r,
\]

where \( \beta \) represents the fuel consumption per unit of distance from a plant to a DC, and \( \gamma \) represents the fuel consumption per unit of distance from a DC to a retailer or from a retailer to another retailer. The values of \( \beta \) and \( \gamma \) depend on the road type. Hence, the carbon emissions from routing can be represented by \( E_R \) as shown in (5) in the following

\[
E_R = \theta \left( \beta \sum_{i \in I} \sum_{j \in J} d_{ij} x_{ij}^p + \gamma \sum_{v \in V} \sum_{w \in (J \cup K)} \sum_{k \in K} d_{wk} x_{wkv}^r \right).
\]

4.3. Carbon emissions from inventories. Assume carbon emissions from inventories positively correlate to the inventory levels and let \( \xi \) represent the carbon emissions per unit of inventory. Hence, the total carbon emissions from inventories within a planning time period can be calculated using (6) as follows

\[
\prod_{t \in (g)} = \xi \sum_{j \in J} \int_0^T s_j(\tau) d\tau,
\]

where \( s_j(\tau) \) represents the actual inventory level including the expected inventory and safety inventory at time \( \tau \) and \( T \) represents the length of a planning time period. However, because \( s_j(\tau) \) is not a continuous function of \( \tau \) at a DC in practice, the accurate value of \( \int_0^T s_j(\tau) d\tau \) is hard to obtain. Moreover, numerical integration is not suitable for real-world applications due to the scale of the problems and the lack of data. Since the search process of the MOPSO does not depend on the accurate values of the objective functions [21], the search can be guided by approximate
search directions. Therefore, the carbon emissions from inventories $\prod_{I(y)}$ in (6) can be approximated by $E_l$ in (7) in the following

$$E_l = \xi \sum_{j \in J} \left( \frac{Q_j}{2} + \sqrt{L_j \sum_{k \in K} \sigma_k^2 x_{jk}^d} \right),$$

where $\frac{Q_j}{2} + \sqrt{L_j \sum_{k \in K} \sigma_k^2 x_{jk}^d}$ is the average or expected, including safety, inventory at DC $j$.

5. The bi-objective mixed integer programming model.

5.1. The cost of the CLRIS. The total cost of the CLRIS includes the location cost, routing cost and inventory cost as follows:

(a) The fixed cost of operating the DCs, given by $\sum_{j \in J} f_j y_j$.

(b) The transportation costs from the plants to the DCs, given by $\sum_{i \in I} \sum_{j \in J} (F_P + p_t d_{ij}) p_{ij}$, and from the DCs to the retailers as well as from the retailers to the other retailers, given by $\sum_{j \in J} \sum_{k \in K} (F_D + \sum_{w \in (j \cup K)} p_d d_{wk} x_{jk}^d) x_{jk}^r$.

(c) The inventory cost consisting of two parts, i.e., the costs of expected inventory and of the safety inventory. Specially, the cost of the expected inventory includes ordering cost and holding cost, given by $\sum_{j \in J} (h_{o_j} Q_j / 2) \sum_{k \in K} \mu_k x_{jk}^d + \frac{1}{2} \sum_{j \in J} \sum_{k \in K} h_j Q_j$, where the first term is the ordering cost and the second term is the holding cost. The cost of safety inventory is given by $\sum_{j \in J} h_j \alpha \sqrt{L_j \sum_{k \in K} \sigma_k^2 x_{jk}^d}$, where $\alpha$ is the $\alpha$-percentile for the standard normal random variable $\phi$, i.e., $P(\phi \leq \alpha) = \alpha$.

5.2. The components of the CCD. The CCD is composed of two parts, i.e., the carbon cap of the CLRIS and the carbon emissions from the CLRIS. The carbon cap is given by the governmental agency.

The carbon emissions are from the operations of the CLRIS. According to (2), (5) and (7), the total carbon emissions of the CLRIS is given by $E_{emit} = E_L + E_R + E_I$, i.e.,

$$E_{emit} = \lambda \sum_{j \in J} A_j y_j + \theta \left( \sum_{k \in K} \sum_{j \in J} \beta_{d_{kj}} x_{kj}^p + \sum_{v \in V} \sum_{w \in (j \cup K)} \sum_{k \in K} \gamma_{d_{wk}} x_{wkv}^r \right) + \xi \sum_{j \in J} Q_j / 2. \quad (8)$$

The carbon cap of the CLRIS can be obtained by summing the different carbon caps from the governmental agency. The total carbon cap of the plants, the DCs and the retailers relevant to the decisions of the CLRIS can be summarized as

$$E_{cap} = \eta_1 \sum_{i \in I} E_{cap_i} + \sum_{j \in J} E_{cap_j} y_j + \eta_2 \sum_{k \in K} E_{cap_k}, \quad (9)$$

where $0 < \eta_1 < 1$ is the proportion of the carbon caps of the plants assigned to the transportation of the product from the plants to the DCs, and $0 < \eta_2 < 1$ is the proportion of the carbon caps of the retailers assigned to the transportation of the product from the DCs to the retailers. The carbon caps of the plants are not only used to offset the carbon emissions from transportation from plants to the DCs, but also used to offset the carbon emissions from production and other activities. The carbon caps of the retailers are also not only used to offset carbon emissions
from transportation from the DCs to the retailers, but also used to offset carbon emissions from other activities, such as distribution and inventory, among others.

5.3. Formulation of the model. According to the above analysis and discussion, the bi-objective mixed integer programming model is constructed as shown in (10)-(23) in the following.

\[
\begin{align*}
\min \ z_1 &= f_1(x) = \sum_{j \in J} f_j y_j + \sum_{j \in J} \left( \frac{h_j}{2} \sum_{k \in K} \mu_k x_{jk}^d \right) + h_j \frac{Q_j}{2} + h_j \varphi_\alpha \left( L_j \sum_{k \in K} \sigma_k^2 x_{jk}^d \right) \\
&+ \sum_{i \in I} \sum_{j \in J} \left( F_p + p_d d_{ij} \right) x_{ij}^p + \sum_{j \in J} \sum_{k \in K} \left( F_D + \sum_{w \in (J \cup K)} p_d d_{wv} x_{wkv}^d \right) x_{wkv}^r \\
\text{s.t.} \quad &\sum_{j \in J} Q_j x_{ij}^p \leq G_i \quad \forall i \in I \\
&Q_j + \varphi_\alpha \sqrt{L_j \sum_{k \in K} \sigma_k^2 x_{jk}^d} \leq U_j \quad \forall j \in J \\
&\sum_{k \in K} \sum_{w \in (J \cup K)} \mu_k x_{wkv}^r \leq V^d \quad \forall w \in (J \cup K) \\
&\sum_{v \in V} \sum_{w \in (J \cup K)} x_{wkv}^r = 1 \quad \forall k \in K \\
&\sum_{j \in J} \sum_{k \in K} x_{jkv}^r \leq 1 \quad \forall v \in V \\
&\sum_{w \in (J \cup K)} x_{wkv}^r - \sum_{w \in (J \cup K)} x_{wkv}^r = 0 \quad \forall k \in K, \forall w \in (J \cup K), \forall v \in V \\
&Q_j + \varphi_\alpha \sqrt{L_j \sum_{k \in K} \sigma_k^2 x_{jk}^d} \geq \sum_{k \in K, w \in (K \cup J)} \mu_k x_{wkv}^r \quad \forall j \in J \\
&R_{kv} - R_{wv} + (n_v \times x_{wkv}^r) \leq n_v - 1 \quad \forall k \in K, \forall w \in (J \cup K), \forall v \in V \\
&y_j = \{0, 1\} \quad \forall j \in J, \forall n \in U_j \\
x_{ij}^p = \{0, 1\} \quad \forall i \in I, \forall j \in J \\
x_{jk}^d = \{0, 1\} \quad \forall j \in J, \forall k \in K \\
x_{wkv}^r = \{0, 1\} \quad \forall w \in (J \cup K), \forall k \in K, \forall v \in V
\end{align*}
\]
The objective function (10) minimizes the total cost in the CLRIS in which the first term is the fixed cost of the CDs, the second term is the inventory cost, and the sum of the third and fourth terms is the routing cost. The objective function (11) minimizes the total CCD of the CLRIS. A \( E_{ccd} > 0 \) means that the carbon emissions of the CLRIS are larger than the carbon caps allocated by the governmental agency and the CLRIS should buy carbon credit from the carbon trade market or pay for the carbon penalty. A \( E_{ccd} = 0 \) indicates that the carbon emissions of the CLRIS just balance the carbon caps allocated by the governmental agency. A \( E_{ccd} < 0 \) means the CLRIS has carbon surplus and can get carbon credit. The carbon credit can be saved in the carbon bank for future use when needed or can be traded on the carbon market.

A constraint in (12) restricts the inventory at a plant to be within its capacity. A constraint in (13) restricts the inventory at a DC to be within its capacity. A constraint in (14) restricts the load of each vehicle from a DC to a retailer and from a retailer to another retailer to be within its capacity. A constraint in (15) guarantees that one and only one vehicle serves one retailer. A constraint in (16) indicates each vehicle serves no more than one DC. Constraints (17) are the conservation of flow constraints ensuring the vehicle that has entered any node must leave this node to guarantee the routes circular. A constraint in (18) ensures the capacity of a DC can satisfy the demands of the retailers it serves. A constraint (19) is a subtour elimination constraint that ensures that a tour includes a DC from which the tour starts and some retailers [12]. Constraints (20)-(23) restrict the decision variables to be in their respective domains.

For notational convenience in the following discussions, \( x \in \mathbb{R}^n \) is used to represent a solution for the optimization problem in the decision space where \( n \) represents the total number of decision variables in the model, and \( z \in \mathbb{R}^2 \), such that \( z = f(x) \), is used to represent a solution in criterion space, where \( f(x) \) is the vector of objective functions. Let \( X \subset \mathbb{R}^n \) and \( Z \subset \mathbb{R}^2 \) represent the feasible region in decision space and criterion space, respectively, of the model in (10)-(23). Usually, a \( z \in Z \) is called the criterion vector of an \( x \in X \) if \( z = f(x) \). For \( z^1 \in Z \) and \( z^2 \in Z \), \( z^1 \) dominates \( z^2 \) if \( z^1 \leq z^2 \) and \( z^1 \neq z^2 \). If and only if there is no \( z \in Z \) that dominates \( \tilde{z} \), then the criterion vector \( \tilde{z} \in Z \) is a nondominated criterion vector. The nondominated frontier is the set of all nondominated solutions. The nondominated solution which is most preferred by the decision maker is the optimal solution. Many, mostly interactive, solution methods have been proposed to identify an optimal solution for a multi-objective optimization problem [38, 41]. The purpose of this study is to find a large set of representative nondominated solutions to serve as the candidates for the final optimal solution. An ideal solution \( z^* \) is defined as \( z^* = \min \{ z_i | z \in Z \} \) for \( i = 1, 2 \). For most multi-objective programming problems, \( z^* \) is infeasible, that is, \( z^* \notin Z \).

By minimizing the two objective functions separately when finding the ideal solution \( z^* \), the endpoints of the nondominated frontier are obtained. These endpoints are also referred to as the extreme solutions. The final solutions obtained by a heuristic procedure are not necessarily nondominated but are not dominated by any other solutions in the set of the final solutions. Hence, the set of final solutions forms an approximation of the nondominated frontier. Furthermore, the extreme solutions are not necessarily in the final solutions. Among all the final solutions, the ones with the smallest value of one objective function and the largest value of the other objective function are the boundary solutions.
6. The solution method. In this section, an MOPSO solution method is developed and is described in details. Because of the existence of $\sqrt{x_{jk}^d}$ in (10), (11), (13) and (18), the bi-objective mixed integer programming model in (10)-(23) is nonlinear. However, $\sqrt{x_{jk}^d} = x_{jk}^d$ because $x_{jk}^d$ is binary. Therefore, each $\sqrt{x_{jk}^d}$ can be replaced with $x_{jk}^d$ and the model in (10)-(23) can be linearized.

6.1. An MOPSO heuristic procedure. Finding a set of nondominated solutions for the model in (10)-(23) is not an easy task because the problem is NP-hard. A heuristic procedure, specifically an MOPSO, is developed to solve this problem. The PSO metaheuristic has become a very popular optimization method for its simplicity for implementation and its ability of quickly converging to good solutions [35].

The PSO is inspired by the social behavior of birds flocking and fish schooling [35], and is based on the natural process in which swarms of particles share their individual and collective knowledge. A PSO procedure uses a swarm of particles, i.e., vectors, moving around to find the optimal or near optimal solutions in the search space. A particle has two properties, i.e., velocity and position. The velocity represents the speed and direction that the particle moves and the position represents the location and tracks the trajectory of the particle in the search space. The swarm of particles is retained during the search process. A specific trajectory is followed by each particle within the search space. A trial solution is then determined by each step of the particle. The quality of a trial solution is measured by its fitness.

A particle can utilize information of its previous best experience as well as the global best experience among the entire swarm. The best solution found so far by particle $p$ is called the individual best solution and is represented by $x_{pbest}^d$, and the best solution found by all the particles in the swarm is called the global best solution and is represented by $x_{gbest}^d$. The velocity and the position of particle $p$ at iteration (time) $t$ in dimension $d$ are represented by $v_{pd}^d(t)$ and $x_{pd}^d(t)$, respectively. The iteration $t$ also represents the number of evolutionary generation. By updating the velocity and the position of each particle in the search process, a set of approximately nondominated solutions satisfying the termination condition will be obtained.

Each particle $p$ updates its velocity along each dimension $d$ at iteration $t$ according to (24) in the following [22]

$$v_{pd}^d(t) = \omega_p v_{pd}^d(t-1) + c_1 r_1(t)(x_{pbest}^d - x_{pd}^d(t)) + c_2 r_2(t)(x_{gbest}^d - x_{pd}^d(t)), \quad (24)$$

where $\omega_p$ represents the inertia weight of particle $p$ usually with a value in the interval from 0.2 to 0.6, $c_1$ and $c_2$ are the cognitive rate and the social learning rate, and $r_1(t)$ and $r_2(t)$ are uniform random numbers with $r_1(t) \in [0, 1)$ and $r_2(t) \in [0, 1)$. The position of particle $p$ is then updated according to (25) in the following

$$x_{pd}^d(t) = x_{pd}^d(t-1) + v_{pd}^d(t). \quad (25)$$

The MOPSO heuristic procedure obtains a set of solutions not dominated by others. The nondominated solutions form a nondominated frontier [37, 38, 39]. The particles move toward the nondominated frontier during the search process [35]. The visited solutions not dominated by others are stored and those dominated by others are discarded. Finally, a set of solutions not dominated by others and close to the nondominated frontier can be obtained. These solutions form an approximation of the nondominated frontier and are also called the nondominated frontier for
notational simplicity. In the search process, visited solutions not dominated by others are saved into a file, called the external file [24].

The solution for bi-objective optimization problems differs from the solution for single objective optimization problems. For a single objective optimization problem, $x_{pbest}$ and $x_{gbest}$ are easy to recognize since only one criterion is used to measure them. Unlike the single objective optimization problems, two criteria need to be considered at the same time for the bi-objective optimization problems. Criterion vectors of the solutions represented by the particles usually do not dominate each other and the measurement method for single objective optimization problems is not applicable to bi-objective optimization problems. Therefore, picking proper particles as $x_{pbest}$ and $x_{gbest}$ is crucial because the position of each particle is updated iteration after iteration when the particle moves to the nondominated frontier [35].

Compared with $x_{gbest}$, the selection of $x_{pbest}$ is relatively simple. In this study, the Prandom method [14] is adopted for each particle in the search process to keep a single $x_{pbest}$. In each iteration, a new solution will replace $x_{pbest}$ when the criterion vector of the new solution dominates that of the current $x_{pbest}$. Otherwise, if the criterion vectors of the new solution and $x_{pbest}$ do not dominate each other, they will have the same chance to be selected as the new $x_{pbest}$ and only one of them will be randomly selected.

For the selection of $x_{gbest}$, a method similar to that in Sun [39, 40] is used in this MOPSO heuristic procedure. The fitness of any $x$ with a criterion vector $z = (z_1, z_2)$ is given by the Euclidian distance $L$ between $z^*$ and $z$ given by $L = \sqrt{(z_1 - z_1^*)^2 + (z_2 - z_2^*)^2}$. The fitness of $x_{pbest}$ is denoted by $L_p$, the fitness of the current $x_{gbest}$ is denoted by $L_g$, and the average fitness of all current solutions not dominated by others is denoted by $L_{avg}$. Hence, a newly determined $x_{pbest}$ becomes the new $x_{gbest}$ if $L_p < L_{avg}$.

In PSO, the inertia weight $\omega_p$ is an important parameter which is used to provide trade-offs between the exploration and the exploitation processes [2, 6]. The inertia weight $\omega_p$ determines the impact of the previous velocity on the current velocity of particle $p$. Since the introduction of the inertia weight in PSO, some researchers proposed variations of its updating strategies and Amoshahy et al. [2] provided a relatively comprehensive review of these strategies. Inspired by these updating strategies, this work presents a new updating mechanism of the inertia weight $\omega_p$.

The value of the inertia weight $\omega_p$ in the proposed MOPSO heuristic procedure is adaptively updated. The minimum and the maximum values of $\omega_p$ are represented by $\omega_{min}$ and $\omega_{max}$, respectively, for all $p$. During the search process, the value of $\omega_p$ updates but stays within the interval between $\omega_{min}$ and $\omega_{max}$. A $L_p < L_{avg}$ means the criterion vector of the solution represented by particle $p$ is closer to $z^*$ than that of an average solution. Thus, a larger value of the inertia weight should be given to particle $p$ to enhance its local optimization ability. In this case, $\omega_p$ is updated according to (26) in the following

$$\omega_p = \omega_{max} - (\omega_{max} - \omega_{min}) \frac{L_p - L_{avg}}{L_g - L_{avg}}$$  \hspace{1cm} (26)$$

On the other hand, a $L_p > L_{avg}$ means the criterion vector of the solution represented by particle $p$ is farther away from $z^*$ than that of an average solution. A smaller value of the inertia weight should be given to particle $p$ so that it can move faster to the nondominated frontier. In this case, $\omega_p$ is updated according to
(27) in the following
\[ \omega_p = \omega_{\text{min}} + \frac{1}{2}(\omega_{\text{max}} - \omega_{\text{min}}) \left( 1 + \cos \frac{t - 1}{\text{Gen} - 1} \pi \right), \]
where Gen represents the total number of generations made by the particles. Using such an updating mechanism, the MOPSO heuristic procedure balances the exploration and exploitation processes.

6.2. Modifications and enhancements. The MOPSO heuristic procedure described above works for bi-objective programming problems with continuous variables. Some modifications and enhancements are introduced to the MOPSO heuristic procedure to handle binary variables and to improve searching performance.

6.2.1. Mutation operator. The traditional PSO heuristic procedure does not have a mutation operation, which makes it easy to fall into local optima. To help the particles move from their current positions to new positions and improve the diversity of the population, a mutation operator is introduced in the MOPSO heuristic procedure. Let \( p_u \) be the mutation probability. Then, the mutation operator for each particle along each dimension \( d \) is given in (28) in the following
\[ x_{pd}(t) = \begin{cases} x_{\text{min},d} + r' (x_{\text{max},d} - x_{\text{min},d}), & \text{if } r'' \leq p_u \\ x_{pd}(t), & \text{otherwise} \end{cases}, \]
where \( x_{\text{min},d} \) and \( x_{\text{max},d} \) are the minimum and maximum values of dimension \( d \), i.e., \( x_d \), among all visited solutions by all particles, and \( r' \) and \( r'' \) are uniform random numbers with \( r' \in [0,1) \) and \( r'' \in [0,1) \).

6.2.2. Relaxation for infeasibility. To improve the searching performance of the MOPSO heuristic procedure in the feasible region and obtain global nondominated solutions in the search space, some infeasible solutions near the feasible region are kept in the swarm during the early phase of the search process. Thereby, some constraints are relaxed, and other constraints are added to limit the infeasibility of the constraints. However, all the solutions represented by the particles in the swarm must be feasible at the end of the search process. Therefore, the particles representing infeasible solutions will be gradually moved to the feasible region as the search progresses so as to guarantee the feasibility of the final nondominated solutions [24]. For the purpose of controlling the infeasible solutions, a dynamic self-adapting process similar to that in [42] is adopted. Without loss of generality, the right hand sides of all constraints are assumed to be 0. The infeasibility of solution \( \mathbf{x} \) can be calculated as
\[ C(\mathbf{x}) = \sum_o \max\{g_o(\mathbf{x}), 0\} + \sum_{o'} \max\{|h_{o'}(\mathbf{x}) - \delta|, 0\}, \]
where \( g_o(\mathbf{x}) \leq 0 \) is the \( o \)th inequality constraint, \( h_{o'}(\mathbf{x}) - \delta = 0 \) is the \( o' \)th equality constraint, and \( \delta \) with \( \delta > 0 \) is a very small permissible deviation. If \( \mathbf{x} \in \mathcal{X} \), then \( C(\mathbf{x}) = 0 \).

A dynamic infeasibility threshold \( \varepsilon \) is used to guarantee the feasibility of the final solutions. Let \( \varepsilon_0 \) be the initial permitted deviation for all the constraints. Then, \( \varepsilon \) is computed and updated as
\[ \varepsilon = \begin{cases} \varepsilon_0 \times (1 - 5t/(4\text{Gen})), & \text{if } t \leq 0.8\text{Gen} \\ 0, & \text{if } t > 0.8\text{Gen} \end{cases}. \]
It is clear that $\varepsilon$ decreases when $t$ increases. The solution $x$ represented by a particle is retained if $C(x) \leq \varepsilon$ and is abandoned otherwise. If $x$ is abandoned, the velocity of the particle is recalculated and a new position of the particle representing a different solution is determined. This process is repeated until a solution $x$ with $C(x) \leq \varepsilon$ is found.

6.2.3. Modification for binary variables. Binary variables are in the proposed model in (10)-(23). The MOPSO heuristic procedure described above needs to be modified when used to solve a multi-objective programming problem with binary variables. Following Shankar et al. [35], the update of the velocity of dimension $d$ of particle $p$ in (24) is altered when $x_d$ is binary. The cognitive and social learning rates are set to $c_1 = 1$ and $c_2 = 1$, and the inertia weight is set to $\omega_p = 1$. The modified velocity in dimension $d$ is given in (31) in the following
\[
v_{pd}(t) = v_{pd}(t-1) + r_1(t)(x_{p_{b_{best, pd}}} - x_{pd}(t-1)) + r_2(t)(x_{g_{best, d}} - x_{pd}(t-1)), \tag{31}
\]
where $r_1(t)$ and $r_2(t)$, as in (24), are two uniform random numbers. Each particle $p$ updates its position along each dimension $d$ as shown in (32) below
\[
x_{pd}(t) = \begin{cases} 
0, & \text{if } \rho_{pd} < s(v_{pd}(t)) \\
1, & \text{if } \rho_{pd} \geq s(v_{pd}(t))
\end{cases}, \tag{32}
\]
where $\rho_{pd}$ is a uniform random number with $\rho_{pd} \in [0,1)$, and $s(v_{pd}(t))$ is the probability threshold given by $s(v_{pd}) = [1 + \exp(-v_{pd}(t))]^{-1}$.

The velocities and positions of the particles are updated according to (24) and (25), respectively, for continuous variables, and according to (31) and (32), respectively, for binary variables, in the MOPSO heuristic procedure.

6.3. The MOPSO heuristic procedure. Let $\Omega$ denote the set of obtained solutions not dominated by others found in the solution process stored in the external file, and let $M$ represent the number of particles, i.e., solutions, in the population or the swarm. Based on the work of Kennedy and Eberhart [22], a step-by-step description of the proposed MOPSO heuristic procedure is given in the following.

Step 1 Initialize the parameters in the procedure including $M$, $\text{Gen}$, $c_1$, $c_2$, $\omega_p$, for all $p$, $\omega_{\text{min}}$, $\omega_{\text{max}}$, $\varepsilon_0$ and $\rho_{\text{u}}$. Initialize the swarm of particles by randomly generating $M$ solutions not dominated by others. Each such solution is a particle and is represented by $x_p(0)$. For the problem in this study, an initial solution is generated randomly by try and error until the solution satisfies all the relaxed constraints. Let $t = 0$, $x_{p_{b_{\text{best, p}}}} = x_p(0)$ for all $p$ and $v_{pd}(0) = 0$ for all $p$ and $d$. Choose $x_{g_{\text{best, p}}}$ among all $x_{p_{b_{\text{best, p}}}}$ with the shortest Euclidian distance from its criterion vector to $z^*$.

Step 2 Make a mutation operation for each particle with the mutation probability $p_{\text{u}}$. Calculate the fitness for each new solution obtained. The new solutions not dominated by others are saved in $\Omega$, and those in $\Omega$ dominated by the new solutions are discarded.

Step 3 Adaptively tune the inertia weight $\omega_p$ according to (26) or (27).

Step 4 Update the velocities and positions in the population as in (24) and (25), respectively, for the continuous decision variables, and according to (31) and (32), respectively, for binary variables. Check the relaxation for infeasibility according to (29) and (30). Add the solutions not dominated by others to $\Omega$ and delete the ones dominated by others in $\Omega$. Update $x_{p_{b_{\text{best, p}}}}$ for all $p$ and update $x_{g_{\text{best, p}}}$ accordingly.

Step 5 If $t < \text{Gen}$, go to Step 2; otherwise Stop.
7. An illustrative example.

7.1. General information and data. The formulated model and the proposed MOPSO heuristic procedure are applied to a real-life problem in the petrochemical industry. Specifically, the operations of the Liaoning Shenyang Sales Branch of the CNPC are used in the illustrative example. However, the data used in the illustrative example are slightly modified because of business confidentiality. The task of CNPC supply chain network is to transport products, i.e., petrochemicals, from plants to retailers via DCs. Decisions for locations of DCs, routing of vehicles and inventory levels are made for the CLRIS. The transportation activities from the plants to the DCs, from the DCs to the retailers and from the retailers to the other retailers are carried out through centralized dispatching of the enterprise’s logistics department to achieve coordination.

The enterprise has 2 plants, 4 potential DCs and 34 retailers. Specifically, the two plants are at Fushun and Liaoyang, the four potential DCs are at Shenbei, Yuhong, Sujiajun and Dongling districts of the city, and the retailers are scattered all over the city as shown in Figure 2. For planning purpose, each time period is one month (30 days).

The fixed transportation cost is $F_p = 1000$ per trip from a plant to a DC and the ordering cost is $h_o = 500$ per order. The fixed transportation cost is $F_d = 200$ per trip, and the variable transportation cost is $p_d = 14$/ton/km from a DC to a retailer, or from a retailer to another retailer. There is no limit on the vehicle capacities from the plants to the DCs because oversized vehicles are used. The vehicles from the DCs to the retailers and from the retailers to the other retailers have a capacity of $V^d = 50$ tons. The demands of the retailers are random variables following a normal distribution with a mean $\mu_k = 34$ tons and a standard deviation $\sigma_k = 20$ tons. The diesel consumption from a plant to a DC is $\beta = 50$ liters and that from a DC to a retailer and from a retailer to another retailer is $\gamma = 20$ liters per hundred kilometers. The carbon emission factor for diesel is $\theta = 2.82$kg/L, while $\theta = 2.70$kg/L is used in [31]. The capacities of plants at Fushun and Liaoyang

![Figure 2. Locations of the Plants, the potential DCs and the Retailers](image)
are 500 tons and 400 tons, respectively. According to the actual conditions, the proportion of carbon caps of the plants and the retailers assigned to the CLRIS are \( \eta_1 = 0 \) and \( \eta_2 = 0.7 \), respectively. Thus, the carbon caps for a plant, a DC and a retailer are calculated to be 0, 500 and 50kg. The distances from the plants to the potential DCs in kms are given in Table 2, and distances from the potential DCs to the retailers and from the retailers to the other retailers are given in Tables A1 and A2, respectively, in the Appendices. These distances are obtained from Baidu Map according to the real transportation network. The other parameters are shown in Tables 3 and 4.

### Table 2. Distances from the plants to the potential DCs (km)

|          | Shenbei | Yuhong | Sujiatun | Dongling |
|----------|---------|--------|----------|----------|
| Pushun   | 77.5    | 71.1   | 64.6     | 36.5     |
| Liaoyang | 112.8   | 65.5   | 44.7     | 35.8     |

### Table 3. Parameters of the potential DCs

|          | Shenbei | Yuhong | Sujiatun | Dongling |
|----------|---------|--------|----------|----------|
| Lead time (days) | 3      | 2      | 3        | 4        |
| Service level   | 95%    | 95%    | 95%      | 95%      |

### Table 4. Areas and fixed costs of the potential DCs

|          | Capacity (ton) | Fixed cost per period ($) | Holding cost (/ton/day) | Areas (m²) |
|----------|----------------|---------------------------|-------------------------|-----------|
| Shenbei  | 340            | 20000                     | 0.20                    | 1100      |
| Yuhong   | 500            | 18000                     | 0.25                    | 1600      |
| Sujiatun | 310            | 11200                     | 0.20                    | 1000      |
| Dongling | 380            | 15600                     | 0.25                    | 1200      |

The values of the parameters of the proposed MOPSO are set as follows. The swarm size is \( M = 60 \); the cognitive and social learning rates are \( c_1 = 1.49445 \) and \( c_2 = 1.49445 \) for continuous variables and \( c_1 = 1 \) and \( c_2 = 1 \) for binary variables, respectively; the value of the inertia weight is \( \omega_p = 1 \) for binary variables and the initial value of the inertia weight is \( \omega_p = 0.2 \), with \( \omega_{\text{min}} = 0.2 \) and \( \omega_{\text{max}} = 0.6 \), for continuous variables; the mutation probability is \( p_u = 0.3 \); the maximum number of iterations is \( Gen = 300 \); and the initial allowable deviation is \( \varepsilon_0 = 0.2 \). The MOPSO heuristic procedure is implemented in Matlab 7. All the computations are conducted on a computer with an Intel® Core-i7 (3.4 GHz) processor and 16 GB of RAM.

### 7.2. Detailed results

Some detailed results obtained by the MOPSO heuristic procedure for the illustrative example are reported in the following. In addition to the model in (10)-(23), a model minimizing the carbon emissions of the CLRIS is also solved for this illustrative example. For this model, the second objective function minimizing the CCD (11) is replaced with the objective function minimizing the CO2 emissions in the CLRIS by dropping the terms of the carbon caps in (11).

The nondominated frontier of the model minimizing the CCD is plotted in Figure 3 and that minimizing the carbon emissions is plotted in Figure 4. A diagonal line, called reference line, linking the two endpoints is drawn for each figure for
comparison purpose. These figures show that the nondominated frontiers are convex in most parts but not completely. Some of the solutions on the nondominated frontiers are unsupported [38, 41].

**Figure 3.** The nondominated frontier of the CLRIS considering CCD

![Figure 3. The nondominated frontier of the CLRIS considering CCD](image)

**Figure 4.** The nondominated frontier of the CLRIS considering carbon emissions

![Figure 4. The nondominated frontier of the CLRIS considering carbon emissions](image)

Figure 3 shows the trade-offs between the cost and the CCD, and Figure 4 shows the trade-offs between the cost and carbon emissions. Given fixed carbon caps of the facilities, when CCD or carbon emissions increase, the cost of the CLRIS decreases. By making trade-offs, a decision maker should be able to select a solution from the nondominated frontier as the final optimal solution of the problem possibly with the help of some interactive multi-objective optimization procedures [38]. Moreover, the nondominated frontiers in Figures 3 and 4 show that the CCD and the carbon emissions can be reduced without much increase in the total cost.
The nondominated frontiers shown in Figures 3 and 4 are very similar but are not exactly the same. However, the dissimilitude is pivotal, which reflects the impact of the government policy. However, there is no significant difference in the total cost between the two models minimizing the CCD and minimizing the carbon emissions. Besides, the nondominated frontier of the model minimizing the CCD is closer to the reference line than that minimizing the carbon emissions. Obviously, the range of changes in the CCD is smaller than that in the carbon emissions within the same cost range. Based on these results, a reasonable conclusion is that considering the CCD as a separate objective in the CLRIS is reliable for helping the decision makers in finding a proper trade-off between the total cost and the carbon emissions. Although there has been an increasing amount of research in the trade-offs between carbon emissions and cost, none of these studies considered the difference with and without government interventions in the CLRIS. The majority of these previous studies only considered the carbon cap or the carbon tax as regulations to reduce carbon emissions when government intervention was involved.

The details of the some typical solutions from the nondominated frontier, including the DC status, i.e., whether a potential DC is open, and the total cost and CCD, are presented in Table 5. Solutions in Table 5 show that not all the potential DCs should be open implying that opening some instead of all the potential DCs can reduce cost and carbon emissions, demonstrating the rationality of the proposed model. Besides, the solutions in Table 5 further show that, in general, increasing the number of open DCs will result in a lower CCD but a higher total cost. More open DCs make the delivery to the retailers more convenient thus, increasing the opportunity of choosing a proper route for delivery so as to reduce the total transportation distance and the total carbon emissions. However, the increase of cost caused by opening more DCs will lead to the increase in total cost in the CLRIS, which is the main tradeoff between total cost and carbon emissions.

### Table 5. Details of some typical solutions on the nondominated frontier

| Solutions | Plants   | DC Status | Total cost | CCD    |
|-----------|----------|-----------|------------|--------|
|           | Fushun   | 1         | 80153.5    | 4451.7 |
|           | Liaoyang | 1         | 81875.5    | 3677.2 |
|           | Fushun   | 1         | 88125.9    | 3025.7 |
|           | Liaoyang | 1         | 93750.3    | 2418.4 |
|           | Fushun   | 1         | 88125.9    | 3025.7 |
|           | Liaoyang | 1         | 93750.3    | 2418.4 |
|           | Fushun   | 1         | 100104.9   | 1975.1 |
|           | Liaoyang | 1         | 110139.3   | 1575.7 |
|           | Fushun   | 1         | 117697.4   | 1273.5 |
|           | Liaoyang | 1         | 122385.8   | 968.1  |
|           | Fushun   | 1         | 134982.2   | 613.9  |

7.3. Sensitivity analysis and managerial insights. Sensitivity analysis is conducted to provide relevant managerial insights. The influences of the different carbon cap levels on the CLRIS decisions are examined through sensitivity analysis. Given $\eta_1 = 0$ in this illustrative example, the carbon cap of the CLRIS relevant to
the decisions is the total of the carbon caps of the DCs and the retailers. The levels of $E_{\text{cap}}$ are varied at an increment of 500 from 2500 to 4500 and a series of nondominated frontiers are obtained as shown in Figure 5. These nondominated frontiers move from left to right as the value of $E_{\text{cap}}$ decreases. With the same CCD, a larger carbon cap leads to a smaller cost. If $E_{\text{cap}}$ is large, the CLRIS can emit more CO2 without punishment. Given the same CCD, a larger carbon cap implies larger carbon emissions are allowed because of the relationship $E_{\text{ccd}} = E_{\text{emit}} - E_{\text{cap}}$ as discussed earlier. The CLRIS could have larger emissions to reduce cost when the carbon cap is large enough. Figure 5 illustrates that with a higher carbon cap, it is easier to reduce the CCD without significantly increasing the cost. All the curves become steeper as $E_{\text{ccd}}$ decreases. This shows that the carbon reduction is easier when the emission levels are high, and becomes increasingly harder as the emission levels reduce. While with the same cost, as expected, the CCD will almost monotonically decrease as the carbon cap increases. When the carbon caps increase, both the CCD and the total cost could decrease together.

![Figure 5. Nondominated frontiers of the model minimizing CCD by varying the carbon cap](image)

Note that a trade-and-cap mechanism is followed in the CLRIS. Specifically, if the carbon emissions are lower than $E_{\text{cap}}$, i.e., if $E_{\text{ccd}} < 0$, the CLRIS would sell the surplus carbon credit in the carbon market. Otherwise if $E_{\text{ccd}} > 0$, the CLRIS should buy carbon credit to offset its excessive carbon emissions. In fact, the carbon cap is a constant in terms of its impact on social welfare. The carbon price, represented by $P$, on the carbon market is a function of $E_{\text{cap}}$. The relationship between $P$ and $E_{\text{cap}}$ is assumed to be $P = C / E_{\text{cap}}$ on the basis of supply and demand theory, where $C$ is a constant. Hence, the value of $P$ decreases as $E_{\text{cap}}$ increases because the demand for carbon credit becomes lower. The effects of the carbon cap on cost and on $P$ are examined through sensitivity analysis. Besides, $E_{\text{ccd}}$ will also decrease with the increase in $E_{\text{cap}}$ because of the relationship $E_{\text{ccd}} = E_{\text{emit}} - E_{\text{cap}}$. This relationship shows that under the trade-and-cap mechanism, the larger the carbon cap, the lower the cost. When the carbon cap is sufficiently large, the bi-objective optimization model will become a single objective optimization model only minimizing total cost. Therefore, the regulations about carbon emissions made by the
governmental agency have important impacts on the total cost of the CLRIS and on environment protection. The governmental agency should allocate a small carbon cap if its policy emphasizes environment protection, or should allocate a large carbon cap for the CLRIS to reduce cost if its policy emphasizes economic development. Therefore, a proper government intervention is necessary in encouraging the CLRIS to make appropriate decisions [56].

7.4. Comparisons with other state-of-the-art algorithms. To evaluate its effectiveness, the performance of the proposed MOPSO is compared with those of two well-known state-of-the-art algorithms, i.e., the nondominated sorting multi-objective genetic algorithm (NSGAII) [11] and the multi-objective evolutionary algorithm based on decomposition (MOEA/D) [57]. NSGAII and MOEA/D have often been used as benchmarks to test the effectiveness of new algorithms in the existing literatures and have been treated as the most effective multi-objective evolutionary algorithms. The same parameter values used and reported in [11] and [57] are used for NSGAII and MOEA/D, respectively, in this study. For NSGAII, the population size is set to 200, the crossover probability is set to 0.7 and the mutation probability is set to 0.3. For MOEA/D, the population size is set to 100, the number of the closest weight vectors is set to 10. To guarantee fairness, the maximum number of iterations for NSGAII and MOEA/D is also set to $Gen = 300$.

To compare the performance of different algorithms, three multi-objective evaluation indicators adopted from the literature [25, 39] are used. Let $P_1$, $P_2$ and $P_3$ represent the sets of final solutions obtained by MOPSO, NSGAII and MOEA/D, respectively, and let $P = P_1 \cup P_2 \cup P_3$. As a caveat, although the final solutions obtained by each procedure do not dominate each other, some of the solutions may dominate the others in $P$. Furthermore, let $\bar{P}_1$, $\bar{P}_2$, $\bar{P}_3$ and $\bar{P}$ denote the set of solutions in $P_1$, $P_2$, $P_3$ and $P$, respectively, that are not dominated by any other solutions in $P$. These indicators are described as follows:

1) Convergence indicator. Let $D_{z,\tilde{z}}(P_l)$ be the shortest Euclidean distance from a solution $z \in P_l$ to any $\tilde{z} \in \bar{P}$. The convergence indicator is defined as $\sum_{z \in P_l} D_{z,\tilde{z}}(P_l)/|P_l|$.

2) Diversity indicator. Let $D_1(P_l)$ and $D_2(P_l)$ be the Euclidean distances from the boundary solutions in $P_l$ to the extreme solutions, $D_{z,\tilde{z}}(P_l)$ be the Euclidean distance between two consecutive solutions $z$ and $\tilde{z}$ in $P_l$, and $\bar{D}(P_l)$ be the average of all the $D_{z,\tilde{z}}(P_l)$. Then, the diversity indicator is defined as $[D_1(P_l) + D_2(P_l) + \sum_{z \neq \tilde{z} \in P_l} |D_{z,\tilde{z}}(P_l) - \bar{D}(P_l)|]/[D_1(P_l) + D_2(P_l) + (|P_l| - 1)\bar{D}(P_l)]$.

3) Dominance indicator. It is defined as the proportion of solutions in $P_l$ which are not dominated by any solution in $P$, i.e., $|P_l|/|P_l|$.

It is obvious that a smaller convergence indicator, a smaller diversity indicator, and a larger dominance indicator imply better performance of an algorithm. The Convergence indicator is borrowed from [11] with modifications. The convergence indicator in [11] was designed for test problems with known nondominated solutions. In this study, the solutions in $\bar{P}$ are used because a set of widely dispersed nondominated solutions is not available. The diversity indicator is also borrowed from [11]. The consecutive solutions are obtained by sorting the solutions in $P_l$ in the values of one objective function. The dominance indicator is borrowed from [32].

Each of the three algorithms runs 21 times independently, and the values of the three evaluation indicators are calculated for each iteration as given in Table 6. Box
plots of the results in Table 6 are given in Figure 6 to further show the performance of the proposed and the comparative procedures. Moreover, the respective non-dominated frontiers obtained by MOPSO, NSGAII and MOEA/D are plotted in Figure 7 to compare the results visually. These nondominated frontiers are plotted with the understanding that these solutions are not dominated by each other in the final set of solutions obtained with the respective heuristic procedure but may be actually dominated by solutions not found or found with other procedures.

Table 6 shows that MOPSO is superior to NSGAII and MOEA/D for most of the results in terms of the three performance indicators. Moreover, the box plots in Figure 6 show that the results found by MOPSO are more stable and reliable because they have less variations. The plots in Figure 7 show that the nondominated frontier obtained by MOPSO is better than the ones obtained by the other two procedures. These results demonstrate the effectiveness and applicability of the proposed MOPSO, and also verify the superiority of MOPSO to the other two procedures in solving the multi-objective mixed linear programming model for the CLRIS.

8. Conclusions. A CLRIS in a three-echelon supply chain network is studied considering the CCD. The trade-offs between the total cost and the CCD are handled through a bi-objective mixed integer programming model. This model integrates the environmental impacts and the total cost in a single model but explicitly considers the two objectives using multi-objective optimization techniques.

An MOPSO heuristic procedure is developed and implemented to find nondominated solutions for the bi-objective mixed integer programming model. The obtained nondominated solutions form an approximate nondominated frontier. In the MOPSO heuristic procedure, a dynamically decreasing infeasibility degree threshold is used to relax the constraints so as to search the solutions on the edges of the feasible region.
The proposed model and the implemented MOPSO heuristic procedure are applied to an illustrative example based on the operations of a petrochemical company in China. The results show that the MOPSO heuristic procedure outperforms existing evolutionary algorithms for multi-objective programming problems. The approximate nondominated frontier formed by the obtained solutions not dominated by others can be used for the decision makers to make trade-offs between the total cost and the CCD. The sensitivity analysis results demonstrate that the carbon cap...
has important impacts on the performance of the CLRIS both in its total cost and its carbon emissions. Hence, a proper carbon cap by the governmental agency is critical.

A direction of future study is to consider more factors in the trade-offs between cost and the impacts on the environment, especially the environmental aspect [56]. Consumer environment consciousness will be the focus of future studies. The effects of the governmental interventions will be further discussed in more depth. In addition, the development of more effective solution methods for the bi-objective programming model is also a direction of further research.

Table A1. Distances from the potential DCs to the retailers (km)

|   | Shenbei | Yabong | Dongling |
|---|---------|--------|----------|
| 1 | 82.6    | 47.7   | 55.6     |
| 2 | 80.1    | 47.0   | 37.3     |
| 3 | 80.5    | 27.9   | 54.2     |
| 4 | 64.5    | 35.7   | 42.3     |
| 5 | 62.3    | 40.0   | 47.3     |
| 6 | 64.6    | 49.8   | 15.7     |
| 7 | 61.2    | 55.6   | 7.0      |
| 8 | 58.2    | 45.0   | 27.3     |
| 9 | 64.2    | 36.1   | 49.1     |
| 10| 66.1    | 27.2   | 49.5     |
| 11| 66.0    | 12.0   | 50.0     |
| 12| 66.2    | 48.2   | 60.1     |
| 13| 63.8    | 60.6   | 12.0     |
| 14| 56.6    | 40.2   | 58.9     |
| 15| 55.2    | 35.2   | 67.1     |
| 16| 58.1    | 7.0    | 55.3     |
| 17| 62.1    | 54.2   | 42.0     |
| 18| 56.9    | 42.1   | 41.1     |
| 19| 50.3    | 38.4   | 47.9     |
| 20| 45.7    | 39.0   | 52.1     |
| 21| 50.1    | 32.2   | 50.0     |
| 22| 50.1    | 12.0   | 57.1     |
| 23| 40.1    | 36.1   | 37.0     |
| 24| 50.1    | 48.9   | 12.2     |
| 25| 30.2    | 45.9   | 52.1     |
| 26| 25.8    | 40.1   | 67.1     |
| 27| 32.1    | 40.2   | 55.3     |
| 28| 23.2    | 38.4   | 55.3     |
| 29| 25.8    | 42.6   | 65.1     |
| 30| 22.4    | 48.9   | 54.2     |
| 31| 20.5    | 52.6   | 62.1     |
| 32| 23.7    | 46.0   | 70.1     |
| 33| 7.0     | 55.6   | 66.2     |
| 34| 15.0    | 61.3   | 72.1     |

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Received July 2020; revised January 2021.

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|    | 1    | 2    | 3    | 4    | 5    | 6    | 7    | 8    | 9    | 10   | 11   | 12   | 13   | 14   | 15   | 16   | 17   | 18   | 19   | 20   | 21   | 22   | 23   | 24   | 25   | 26   | 27   | 28   | 29   | 30   | 31   | 32   | 33   | 34   |
|----|------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|
| 1  | 0.0  | 17.1 | 15.9 | 18.7 | 50.2 | 52.5 | 55.6 | 52.5 | 48.9 | 50.2 | 49.5  | 48.9  | 58.8  | 52.5  | 47.9  | 51.1  | 60.0  | 50.1  | 52.5  | 49.1  | 50.2  | 50.2  | 55.3  | 55.3  | 56.3  | 52.1  | 56.3  | 62.3  | 67.3  | 69.2  | 70.1  | 75.2  | 77.1  |
| 2  | 17.1 | 0.0  | 18.7 | 7.0  | 10.1  | 18.8 | 50.2 | 20.1 | 15.9 | 15.9 | 24.1  | 52.5  | 55.1  | 18.8  | 19.8  | 45.1  | 53.2  | 47.1  | 20.1  | 50.2  | 50.2  | 51.2  | 53.2  | 54.7  | 55.7  | 53.2  | 54.9  | 66.1  | 66.1  | 67.1  | 67.1  | 69.2  | 70.1  |
| 4  | 18.7 | 7.0  | 17.3 | 0.0  | 7.0  | 55.1 | 40.1 | 30.2 | 25.1 | 7.0  | 15.2  | 32.1  | 41.9  | 30.2  | 27.1  | 25.7  | 41.9  | 56.2  | 30.2  | 29.5  | 35.1  | 26.7  | 36.9  | 36.3  | 41.9  | 39.1  | 36.9  | 50.1  | 53.4  | 57.3  | 59.9  | 62.0  | 64.7  |
| 5  | 50.2 | 10.1 | 47.5 | 7.0  | 0.0  | 7.0  | 49.6 | 7.2  | 5.9  | 28.1 | 50.5  | 25.8  | 32.6  | 27.1  | 13.8  | 45.1  | 32.6  | 44.3  | 40.1  | 46.2  | 49.9  | 43.2  | 32.6  | 36.6  | 39.8  | 39.8  | 37.6  | 55.3  | 55.3  | 59.9  | 62.0  | 65.0  | 66.0  |
| 6  | 52.5 | 18.8 | 49.9 | 55.1 | 7.0  | 0.0  | 18.8 | 8.7  | 20.4 | 24.1 | 29.4  | 48.9  | 55.1  | 55.1  | 57.8  | 35.9  | 54.1  | 55.1  | 54.1  | 32.4  | 48.9  | 58.8  | 57.8  | 48.9  | 53.9  | 54.8  | 55.5  | 58.4  | 58.7  | 62.4  | 67.1  | 68.6  | 68.1  |
| 9  | 48.9 | 15.9 | 45.2 | 25.1 | 5.9  | 20.4 | 49.6 | 6.4  | 0.0  | 15.2 | 18.9  | 25.8  | 26.8  | 6.4  | 15.2  | 35.6 | 26.8  | 27.8  | 10.1  | 35.6  | 38.9  | 30.2  | 38.9  | 39.7  | 40.1  | 37.8  | 41.1  | 45.6  | 45.8  | 47.6  | 50.2  | 50.6  | 50.9  |
| 16 | 51.1 | 45.1 | 45.7 | 25.7 | 45.1 | 35.9 | 54.1 | 35.9 | 35.6 | 15.9 | 7.1  | 10.0  | 45.9  | 15.2  | 15.2  | 0.0  | 37.1  | 29.1  | 25.7  | 10.1  | 11.1  | 23.4  | 37.1  | 32.7  | 33.3  | 23.4  | 30.0  | 31.2  | 36.1  | 46.1  | 45.2  | 47.7  | 49.2  |
| 19 | 50.1 | 47.1 | 49.9 | 56.2 | 44.3 | 55.1 | 49.8 | 24.2 | 27.8 | 36.8 | 20.1 | 40.3  | 20.3  | 16.1  | 48.9  | 29.1  | 18.7 | 0.0  | 7.4  | 35.9 | 40.6  | 10.0  | 22.0  | 29.0  | 24.7  | 27.8  | 35.7  | 40.7  | 49.7  | 50.7  | 52.3  | 57.9  | 58.7  |
| 22 | 50.2 | 50.2 | 44.1 | 35.1 | 49.9 | 48.9 | 51.2 | 28.7 | 32.8 | 39.7 | 43.2 | 26.7 | 49.0  | 17.0  | 40.1  | 40.7  | 37.1 | 44.3  | 40.7 | 45.2  | 41.8  | 36.1  | 38.9  | 35.9  | 40.6  | 45.2  | 40.1  | 38.9  | 45.2  | 41.8  | 36.1  | 44.3  | 40.7  |
| 25 | 55.3 | 55.3 | 60.3 | 36.9 | 36.6 | 48.9 | 19.8 | 20.6 | 38.9 | 45.2 | 27.1 | 49.0  | 17.0  | 40.1  | 40.7  | 37.1 | 44.3  | 40.7 | 45.2  | 41.8  | 36.1  | 38.9  | 35.9  | 40.6  | 45.2  | 40.1  | 38.9  | 45.2  | 41.8  | 36.1  | 44.3  | 40.7  |
| 29 | 62.3 | 66.1 | 57.3 | 50.6 | 52.1 | 45.6 | 45.4 | 36.5 | 40.3 | 38.8 | 36.5 | 40.3  | 38.8  | 36.5 | 40.3  | 38.8  | 36.5 | 40.3  | 38.8  | 36.5 | 40.3  | 38.8  | 36.5 | 40.3  | 38.8  | 36.5 | 40.3  | 38.8  | 36.5 | 40.3  | 38.8  | 36.5 | 40.3  | 38.8  |

Table A2. Distances between the retailers (km)