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Article

A Multi-Objective Collection-Distribution Center Location and Allocation Problem in a Closed-Loop Supply Chain for the Chinese Beer Industry

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Abstract: Recycling waste products is an environmental-friendly activity that can bring benefits to accompany, saving manufacturing costs and improving economic efficiency. For the beer industry, recycling bottles can reduce manufacturing costs and reduce the industry's carbon footprint. This paper presents a model for a multi-objective collection-distribution center location and allocation problem in a closed loop supply chain for the beer industry, in which the objective is to minimize total costs and transportation pollution. Uncertainties in the form of randomness and fuzziness are jointly handled in this paper to ensure a more practical problem solution, for which returned bottle sand unusable bottles are considered fuzzy random variables. A heuristic algorithm based on priority-based global-local-neighbor particle swarm optimization (pb-glnPSO) is applied to ensure reliable solutions for this NP-hard problem. A case study on a beer operation company is conducted to illustrate the application of the proposed model and demonstrate the priority-based global-local-neighbor particle swarm optimization.

Keywords: collection-distribution center; closed loop supply chain; fuzzy random variable; particle swarm optimization

1. Introduction

Due to resource scarcity and environmental concerns, responsible companies are beginning to pay attention to the future of the planet and the global environment. Recycling used products for remanufacturing is, therefore, becoming of greater importance in supply chain management, a move that can dramatically reduce carbon emissions [1]. Closed loop supply chains (CLSC) combine the forward supply chain with a reverse supply chain that covers the whole life cycle of the products [2], with the manufacturing of new products and the transportation to customers via distribution centers and retailers as the forward supply chain and recycling, sorting, disposal and remanufacturing as the reverse supply chain. In recent years, the CLSC has received a great deal of academic and business attention because of the need to be socially responsible, environmental concerns and government legislation [3,4], which has motivated companies to pay more attention to recycling to reduce costs and lessen their carbon footprint.

Facility location and allocation problems (FLAP) have been widely studied. Subramanian [5] developed priority based simulated annealing to solve a CLSC network design problem, in which the distribution center (DC) and the centralized return center (CC) were set. Amin [6] presented a multi-objective facilities location model for manufacturing and remanufacturing plants and CLSC collection centers, which included demand and return uncertainties. Subulan [7] developed a multi-objective CLSC network design model for the lead/acid battery industry that considered both financial and collection objectives. CLSC network design in a competitive environment with price-dependent demand was examined by Rezapour [4], in which the DC and CC were built separately. Zeballos [8] proposed a model for a multi-period CLSC design and planning problem with demand uncertainty that had ten echelons in which the DC and CC were considered. Oh [9] developed a multi-objective model for profits and carbon emissions to determine optimal production, transportation and inventory quantities on a CLSC network in the fashion industry. Khatami [10] proposed a scenario-based stochastic mixed-integer linear programming model to solve a CLSC network design problem, in which the retailers' demand and the quantity of returned products were considered to be uncertain and the DC and CC were set. Vahdani [11] proposed capacitated bidirectional facilities to conduct distribution in a CLSC, in which a multi-priority queuing system was studied. Kim [12] designed a model to minimize the manufacturer's total cost to find the optimal solution to the supply of raw material, the quantity of products and materials to be recycled, the recycling facility scale and the potential benefits or downfalls of joining a recycling association. As a growing number of companies are now engaging in recycling activities due to economic and environmental concerns, distribution and collection activities using the same vehicle has been found to reduce carbon emissions and transportation costs because empty loads can be avoided. In this paper, we combine the distribution center (DC) with the collection center (CC) as a collection-distribution center (CDC), which can benefit company operations and reduce construction costs. In practice, as the recycled product owners are usually at the same location as the potential new product buyer [13], a DC/CC combination requires less construction and operating expense sand can significantly reduce environmental pollution.

Ramkumar [14] developed a multi echelon, multi period, multi product closed loop supply chain network model which was solved using a genetic algorithm with fixed variables. Kaya and Onur [13] presented a facilities location-inventory-pricing model without uncertainty to determine the optimal location for facilities. Barz [15] proposed an optimization model for a two-stage capacitated facilities location and allocation problem with the effects of additive manufacturing, in which all the variables were certain. Jindal [16] developed a multi-objective model for a CLSC network design problem that considered the economic and environmental factors as fuzzy uncertain and in which the DC and CC were separate. Ramezani [17] conducted research into a CLSC network design problem that only considered fuzzy variables. In recent years, uncertainty has attracted more research attention [18–20]. Stochastic programming, robust optimization, and fuzzy set theory are three applicable tools which can be used to present uncertainty in the FLAP [21,22]. Keyvanshokooh [23] proposed a novel hybrid robust-stochastic programming (HRSP) approach to simultaneously model two different types of uncertainties by including stochastic scenarios for transportation costs and polyhedral uncertainty sets for demands and returns. However, they considered the DC and the CC to be separate and the collection disposal rate was treated as a certain variable. Uncertainties exist in both the forward supply and reverse supply chains; however, the uncertainties in the reverse flow are higher than those in the forward supply chain [7,19], with the returned product quantity generally being considered uncertain [10,23]. Subjective uncertainties such as decision maker's choices and the environmental coefficients can be dealt with using fuzziness and objective uncertainties such as unit transportation costs, product prices and the quantity of unusable products can be dealt with using randomness. In this paper, the return rate and disposal rate are considered fuzzy random variables to reflect the problem. The random and fuzzy uncertainties are handled together and represented by triangular fuzzy numbers [7]. Based on the above consideration, the model is formulated to determine the proper number and location of the CDCs as well as the allocation strategy between the different kinds of facilities.

Because of their structure, facilities location and allocation problems are non-convex and non-differentiable and are strongly NP-hard problems. A collection and distribution center location and allocation problem (CDCLAP) in a closed loop supply chain under a fuzzy random environment, therefore, is even more complicated. Particle swarm optimization(PSO) has been shown to be effective in solving NP-hard problems [24–26]. However, after observation, when the local optimal solution is found, the particles' behavior in the basic PSO is directly influenced, which means that it frequently falls into a local optimum [27–29]. Different advanced PSOs have been used to solve supply chain management problems. Ai and Kachitvichyanukul [30] proposed a global-local-neighbor PSO which was more effective, based on which Xu [27] proposed a fuzzy

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random simulation-based bi-level global-local-neighbor particle swarm optimization (frs-bglnPSO). In this paper, a priority-based global-local-neighbor particle swarm optimization (pb-glnPSO) is applied to solve the CDCLAP.

In summary, this paper proposes a multi-objective model to solve a collection-distribution center location and allocation problem in a closed loop supply chain that considers the economic and environmental factors and includes fuzzy random variables for the return and disposal rates. The remainder of this paper is organized as follows: Section 2 presents the problem statement and model assumptions. A description of the model and its formulation are given in Section 3. The proposed hybrid solution based on the pb-glnPSO is described in Section 4. A case study is conducted to illustrate the model formulation and the proposed method in Section 5. Finally, Section 6 concludes this paper.

2. Research problem statement

In this paper, a company with factories at certain locations and several retailers at different customer zones are considered. The company is considering whereto set the integrated collection and distribution centers (CDC), at which both the collection network for used products and the distribution network for new products are jointly established [13]. CDCs reduce both construction and transportation costs because the same vehicles can be used for both distribution and recycling. Therefore, in this paper, only CDCs are considered.

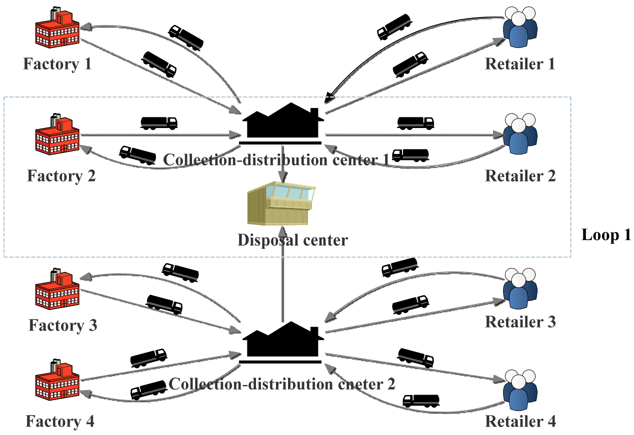

Figure 1. The closed loop supply chain network

A general illustration of the classical CDCLAP for a closed loop supply chain is shown in Fig 1, with the CLSC framework shown in loop1. The CLSC framework has four echelons: factories, CDCs, retailers and disposal centers [11]. The forward supply chain begins with new production. From the factories, the finished products are transported to the retailers via the CDCs. In the reverse supply chain, the returned products are collected and transported to the CDCs, where the recycled products are inspected, consolidated and sorted into those that are available for remanufacturing, which are sent to the factories, and those that are unsuitable for remanufacturing, which are transported to the disposal centers [23]. A CDC can supply products to multiple retailers and retailer demand is fulfilled by only one production site. A CDC can handle products from different factories and send the returned products to multiple factories for remanufacturing.

In this CLSC, the retailers' demand is estimated based on pre-orders; however, the return rate is considered fuzzy random as customers may not return the used product or the product may have broken. In consideration of the transportation costs and the carrying loss, the availability of recycled products is unsure. Transportation costs and transportation pollution are related to the distance

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between two facilities. Another fuzzy random variable considered in this paper is the returned product disposal rate, which is decided on after inspection and consolidation at the CDC.

Following are the assumptions in the proposed problem investigation: (1) Only one product one period is considered; (2) All alternative locations for the CDCs have been identified; (3) Recycling a used product costs less than manufacturing a new one [31]; (4) Considering uncapacitated facilities is an unrealistic assumption in many LAP problems. Many researchers assign a maximum capacity level to facilities to model more realistic decisions. The CDCs and the factories have a capability limit [32–34]; (5) The locations for the factories, retailers and disposal centers are known; (6) New product and returned product storage is allowed at the CDCs [22].

The initial problem is making a decision as to where to set the CDCs from the candidate sites and deciding on an allocation strategy at minimal total CDC costs; operating costs, transportation costs and transportation pollution cost; while also considering the flow constraints, capability limits and the retailers' demand.

3. Modelling

In this section, a mathematical description is given for the CDCLAP in the CLSC, including the notations, the research problem statement, and the mathematical formulation.

3.1. Notations

To facilitate the problem description, the notations are explained.

Sets

Ω: set of CDCs, $\Omega = \{1, 2, 3, ..., I\}$.
Ψ: set of factories, and $\Psi = \{1, 2, 3, ..., J\}$
Φ: set of retailers, and $\Phi = \{1, 2, 3, ..., K\}$
Υ: set of disposal centers, and $\Upsilon = \{1, 2, 3, ..., N\}$

Indices and parameters

i: alternative location position for the CDCs, $i \in \Omega = \{1, 2, 3, ..., I\}$.
j: known position of the factories, $j \in \Psi = \{1, 2, 3, ..., J\}$.
k: known position of the retailers, $k \in \Phi = \{1, 2, 3, ..., K\}$.
n: known disposal center, $n \in \Upsilon = \{1, 2, 3, ..., N\}$.
U: the upper limit of the CDCs.
D_k: the demand of retailer k.
α_i: the capability of CDC i.
γ_j: the capability of factory j.
P_{ji}: product quantity from factory j to CDC i.
Q_{ik}: product quantity from CDC i to retailer k.
$\tilde{\bar{a}}_k$: the product return rate from retailer k.
$\tilde{\bar{b}}_i$: the product disposal rate at CDC i.
F_i^c: the fixed costs of the CDC.
V_i^c: the variable cost of the CDC for a new product unit.
RV_i^c: the variable cost of the CDC triage for a returned product unit.
C_{ij}^p: unit transportation cost between CDC i and factory j.
C_{ik}^d: unit transportation cost between CDC i and retailer k.
C_{in}^w: unit transportation cost between CDC i and disposal center n.
β_{ij}: environmental impact of transportation between CDC I and factory j.
β_{ik}: environmental impact of transportation between CDC i and retailer k.
β_{in}: environmental impact of transportation between CDC i and disposal center n.

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Decision variables
x_i: a binary variable indicating whether point i is chosen. If point i is chosen, then $x_i = 1$; else, $x_i = 0$.
y_{ik}: indicates whether retailer k is served by CDC i. If i is chosen, then $y_{ik} = 1$; else, $y_{ik} = 0$.

3.2. Objective functions

A multi-objective DCCLAP model using the above variables is proposed to minimize total costs and the environmental transportation effects.

Economic objective: In general, decision makers seek to minimize the total costs, which are made up of the transportation costs, fixed costs and operating costs. The minimization objective can be described as

$$\min Z_1 = \sum_{i=1}^{I}\sum_{j=1}^{J} C_{ij}^{p} P_{ji} + \sum_{i=1}^{I}\sum_{k=1}^{K} C_{ik}^{d} Q_{ik}(1+\widetilde{\widetilde{a}}_k) + \sum_{i=1}^{I}\sum_{n=1}^{N}\sum_{k=1}^{K} C_{in}^{w}\widetilde{\widetilde{b}}_i\widetilde{\widetilde{a}}_k Q_{ik} + \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{K}\sum_{n=1}^{N} C_{ij}^{p}\widetilde{\widetilde{a}}_k Q_{ik}(1-\widetilde{\widetilde{b}}_i)$$
$$+ \sum_{i=1}^{I} F_i^c X_i + \sum_{i=1}^{I}\sum_{j=1}^{J} V_i^c P_{ji} + \sum_{i=1}^{I}\sum_{k=1}^{K} RV_i^c \widetilde{\widetilde{a}}_k \tag{1}$$

Equation (1) calculates the total cost, in which $\sum_{i=1}^{I}\sum_{j=1}^{J} C_{ij}^{p} P_{ji}$ represents the cost of new product transported from factories to CDC, $\sum_{i=1}^{I}\sum_{k=1}^{K} C_{ik}^{d} Q_{ik}(1+\widetilde{\widetilde{a}}_k)$ calculated the transportation cost between CDCs and retailers, $\sum_{i=1}^{I}\sum_{n=1}^{N}\sum_{k=1}^{K} C_{in}^{w}\widetilde{\widetilde{b}}_i\widetilde{\widetilde{a}}_k Q_{ik}$ is the cost of returned product delivered from CDCs to disposal centers as well as the returned product transportation cost from CDCs to disposal centers is measured as $\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{K}\sum_{n=1}^{N} C_{ij}^{p}\widetilde{\widetilde{a}}_k Q_{ik}(1-\widetilde{\widetilde{b}}_i)$. The fixed cost of opening a new CDC is presented as $\sum_{i=1}^{I} F_i^c X_i$. $\sum_{i=1}^{I}\sum_{j=1}^{J} V_i^c P_{ji}$ shows the variable cost of new product. $\sum_{i=1}^{I}\sum_{k=1}^{K} RV_i^c\widetilde{\widetilde{a}}_k$ calculates the operation cost of returned product.

It is very difficult to handle the objective function with fuzzy random factors. Kruse and Meyer [35] point out that the fuzzy expected value may be represented by a single fuzzy number. Without a loss of generality, based on the theory proposed by Heilpern [36], the expected value operator is used to enable the conversion of the uncertain model into the deterministic. Now the fuzzy random objective function can be transformed into their crisp equivalences as shown in Eq. (2):

$$\min Z_1 = \sum_{i=1}^{I}\sum_{j=1}^{J} C_{ij}^{p} P_{ji} + \sum_{i=1}^{I}\sum_{k=1}^{K} C_{ik}^{d} Q_{ik}(1+EV[\widetilde{\widetilde{a}}_k]) + \sum_{i=1}^{I}\sum_{n=1}^{N}\sum_{k=1}^{K} C_{in}^{w} EV[\widetilde{\widetilde{b}}_i] EV[\widetilde{\widetilde{a}}_k] Q_{ik}$$
$$+ \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{K}\sum_{n=1}^{N} C_{ij}^{p} EV[\widetilde{\widetilde{a}}_k] Q_{ik}(1-EV[\widetilde{\widetilde{b}}_i]) + \sum_{i=1}^{I} F_i^c X_i + \sum_{i=1}^{I}\sum_{j=1}^{J} V_i^c P_{ji} + \sum_{i=1}^{I}\sum_{k=1}^{K} RV_i^c EV[\widetilde{\widetilde{a}}_k] \tag{2}$$

Note the $EV[\widetilde{\widetilde{a}}_k]$ or $EV[\widetilde{\widetilde{b}}_i]$ above represents two expected values: the first one being the fuzzy random variables converted into fuzzy numbers based on the theory proposed by Kruse and Meyer in 1987, and the second being used to transform the fuzzy numbers into deterministic numbers based on the theory proposed by Heilpern in 1992.

Environmental objective: The second objective is to minimize the environmental transportation effect in terms of the carbon emissions in the CLSC operation, an area which has attracted recent research attention [37]. The following expression represents the transportation carbon emissions between the CDCs and the factories, the CDCs and the retailers and the CDCs and the disposal centers.

$$\min Z_2 = \sum_{i=1}^{I}\sum_{j=1}^{J}\beta_{ij}P_{ji} + \sum_{i=1}^{I}\sum_{k=1}^{K}\beta_{ik}Q_{ik}(1+EV[\widetilde{\overline{a}}_k]) + \sum_{i=1}^{I}\sum_{n=1}^{N}\sum_{k=1}^{K}\beta_{in}EV[\widetilde{\overline{b}}_i]EV[\widetilde{\overline{a}}_k]Q_{ik}$$
$$+\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{K}\sum_{n=1}^{N}\beta_{ij}EV[\widetilde{\overline{a}}_k]Q_{ik}(1-EV[\widetilde{\overline{b}}_i]) \tag{3}$$

$\sum_{i=1}^{I}\sum_{j=1}^{J}\beta_{ij}P_{ji}$ refers to the environment pollution caused by transportation activities from factories to CDCs. $\sum_{i=1}^{I}\sum_{k=1}^{K}\beta_{ik}Q_{ik}(1+EV[\widetilde{\overline{a}}_k])$ is the summation of carbon footprints when transporting products between CDCs and retailers. $\sum_{i=1}^{I}\sum_{n=1}^{N}\sum_{k=1}^{K}\beta_{in}EV[\widetilde{\overline{b}}_i]$ $EV[\widetilde{\overline{a}}_{ki}]Q_{ik}$ is the total carbon footprint from CDCs to disposal centers. And $\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{K}\sum_{n=1}^{N}\beta_{ij}EV[\widetilde{\overline{a}}_k]Q_{ik}(1-EV[\widetilde{\overline{b}}_i])$ express the carbon footprints from CDCs to factories when delivering returned products.

3.3. Constraints

Note that the CDC has its own capacity limit and it cannot service any goods beyond its capacity. Thus we need capacity restriction. The constraint can be written as follows:

$$\sum_{k=1}^{K}EV[\widetilde{\overline{a}}_k]Q_{ik} + \sum_{j=1}^{J}P_{ji} \le \alpha_i \quad \forall i \in \Omega \tag{4}$$

$\widetilde{\overline{a}}_{ki}$ is a fuzzy random variable indicating the return rate of the used product to transport from retailer k to CDC i. Q_{ik} shows product quantity from CDC i to the retailer k. P_{ji} indicates the quantity of product to transport from factory j to CDC i. α_i refers to the capacity of the the capability of the CDC i.

As for capability constraint, the factory can manufacturing the new products that the retailers need and the returned products send back by CDCs.

$$\sum_{k=1}^{K}D_k + \sum_{i=1}^{I}\sum_{k=1}^{K}\sum_{n=1}^{N}C_{ij}^{p}EV[\widetilde{\overline{a}}_k]Q_{ik}(1-EV[\widetilde{\overline{b}}_i]) \le \sum_{j=1}^{J}\gamma_j \tag{5}$$

D_k refers to the demand of retailer k and γ_j is the capability of the factory j. $\sum_{i=1}^{I}\sum_{k=1}^{K}\sum_{n=1}^{N}C_{ij}^{p}EV[\widetilde{\overline{a}}_k]Q_{ik}(1-EV[\widetilde{\overline{b}}_i])$ calculates the returned product transported to factory j for remanufacture.

Considering the products in the retailers are all from the CDCs, the recycled products are less than the product transported from factory to the CDC And it can be described as follows:

$$\sum_{j=1}^{J}P_{ji} \ge \sum_{k=1}^{K}EV[\widetilde{\overline{a}}_k]Q_{ik} \tag{6}$$

P_{ji} is a variable indicating the quantity of new product transported from the factory j to CDC i. $\widetilde{\overline{a}}_kQ_{ik}$ refers to the quantity of returned product transported from retailer k to CDC i.

The product provided to the retailer should at least meet the retailer's demand.

$$\sum_{i=1}^{I}Q_{ik} \ge \sum_{k=1}^{K}D_k \tag{7}$$

Q_{ik} indicates the product quantity CDC i to the retailer k. the stochastic variable D_k is the demand of the retailer k according to the order.

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The returned products transported to the CDCs are more than the products transported to the disposal centers.

$$\sum_{k=1}^{K} EV[\widetilde{\overline{a}}_k]Q_{ik} \geq \sum_{n=1}^{N}\sum_{k=1}^{K} EV[\widetilde{\overline{b}}_i]EV[\widetilde{\overline{a}}_k]Q_{ik} \tag{8}$$

$EV[\widetilde{\overline{a}}_k]Q_{ik}$ is the expression of returned product quantity from the retailer k to CDC i, $EV[\widetilde{\overline{b}}_i]EV[\widetilde{\overline{a}}_k]Q_{ik}$ presents the product quantity transported from CDC i to retailer k.

The CDC should be at least one but no more than the upper limit.

$$1 \leq \sum_{i=1}^{I} x_i \tag{9}$$

$$\sum_{i=1}^{I} x_i \leq U \tag{10}$$

U is the upper limit of the CDCs, which is decided by the demand, the returned product quantity and the fixed capability.

It should make sure that each retailer is served by one CDC.

$$\sum_{i=1}^{I} y_{ik} = 1 \tag{11}$$

Since x_i and y_{ik} are binary variables, the following constraints are needed:

$$x_i = \{0, 1\}, \quad \forall i \in \Omega, \tag{12}$$

$$y_{ik} = \{0, 1\}, \quad \forall i \in \Omega, \quad \forall k \in \Phi \tag{13}$$

x_i is a binary variable indicating whether a CDC is opened at point i . If location i is chosen to open a CDC, then $x_i = 1$; otherwise, $x_i = 0$. y_{ik} is a binary variable indicating whether retailer k is served by CDC i. If $y_{ik} = 1$, then retailer k is served by CDC i; otherwise, $y_{ik} = 0$.

3.4. Global model

From the formulation above, a multi-objective model for the CDCLAP with capacity, flow and quantity constraints is developed with the aims of minimizing total costs and total transportation pollution. In the CLSC, both new and returned products are considered. The product can be reproduced to save raw materials and reduce waste and pollution. In our model, all costs involved in the CDCLAP are considered as well as the influence of the transportation activity pollution. Fuzzy random theory is used to deal with the real world complex uncertainties and ensure more scientific decisions. Therefore, this CDC situation is closer to the real situation as it can deal with complicated practical problems. Finally, the global model is given:

$$
\begin{aligned}
\min Z_1 = & \sum_{i=1}^{I}\sum_{j=1}^{J} C_{ij}^{p} P_{ji} + \sum_{i=1}^{I}\sum_{k=1}^{K} C_{ik}^{d} Q_{ik}(1 + EV[\widetilde{a}_k]) + \sum_{i=1}^{I}\sum_{n=1}^{N}\sum_{k=1}^{K} C_{in}^{w} EV[\widetilde{\widetilde{b}}_i] EV[\widetilde{a}_k] Q_{ik} \\
& + \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{K}\sum_{n=1}^{N} C_{ij}^{p} EV[\widetilde{a}_k] Q_{ik}(1 - EV[\widetilde{\widetilde{b}}_i]) + \sum_{i=1}^{I} F_i^c X_i + \sum_{i=1}^{I}\sum_{j=1}^{J} V_i^c P_{ji} + \sum_{i=1}^{I}\sum_{k=1}^{K} RV_i^c EV[\widetilde{a}_k] \\
\min Z_2 = & \sum_{i=1}^{I}\sum_{j=1}^{J} \beta_{ij} P_{ji} + \sum_{i=1}^{I}\sum_{k=1}^{K} \beta_{ik}(Q_{ik} + EV[\widetilde{a}_k]) + \sum_{i=1}^{I}\sum_{n=1}^{N} \beta_{in} EV[\widetilde{\widetilde{b}}_i] + \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{K}\sum_{n=1}^{N} \beta_{ij}(EV[\widetilde{a}_k] - EV[\widetilde{\widetilde{b}}_i])
\end{aligned}
$$

$$
s.t.\begin{cases}
\sum_{k=1}^{K} EV[\widetilde{a}_{ki}] Q_{ik} + \sum_{j=1}^{J} P_{ji} \le \alpha_i x_i \quad \forall i \in \Omega \quad \forall j \in \Psi \quad \forall k \in \Phi \\
\sum_{k=1}^{K} D_k + \sum_{i=1}^{I}\sum_{k=1}^{K}\sum_{n=1}^{N} C_{ij}^{p} EV[\widetilde{a}_k] Q_{ik}(1 - EV[\widetilde{\widetilde{b}}_i]) \le \sum_{j=1}^{J} \gamma_j \quad \forall j \in \Psi \quad \forall k \in \Phi \quad \forall n \in \Upsilon \\
\sum_{j=1}^{J} P_{ji} \ge \sum_{k=1}^{K} EV[\widetilde{a}_{ki}] \quad \forall i \in \Omega \quad \forall j \in \Psi \quad \forall k \in \Phi \\
\sum_{k=1}^{K} EV[\widetilde{a}_k] Q_{ik} \ge \sum_{n=1}^{N}\sum_{k=1}^{K} EV[\widetilde{\widetilde{b}}_i] EV[\widetilde{a}_k] Q_{ik} \quad \forall i \in \Omega \quad \forall k \in \Phi \quad \forall n \in \Upsilon \\
\sum_{i=1}^{I} Q_{ik} \ge \sum_{k=1}^{K} D_k \quad \forall i \in \Omega \quad \forall k \in \Phi \\
1 \le \sum_{i=1}^{I} x_i \quad \forall i \in \Omega \\
\sum_{i=1}^{I} x_i \le U \quad \forall i \in \Omega \\
y_{ik} \le x_i \quad \forall i \in \Omega, \quad \forall k \in \Phi \\
\sum_{i=1}^{I} y_{ik} = 1 \quad \forall i \in \Omega \quad \forall k \in \Phi \\
x_i = \{0, 1\} \quad \forall i \in \Omega, \\
y_{ik} = \{0, 1\} \quad \forall i \in \Omega, \quad \forall k \in \Phi
\end{cases} \tag{14}
$$

4. The heuristic algorithms based on Pgln-PSO

Particle swarm optimization (PSO) is a recent evolutionary algorithm which simulates social behavior such as birds flocking and fish schooling [38]. The PSO searches the feasible zone to seek solutions using a fixed population of individuals, which are updated to achieve the optimal solution. The particles [39] are characterized by their position and velocity, which are decided on by their flying experience or discoveries or those of their companions. They fly through the problem spaces following the current optimum particles to find the best solution between the populations and the best solution for each population. The PSO has been widely used to solve NP-hard problems [38]. However, in the basic PSO, it was found that the particles in the swarm were weak and clustered rapidly toward the global best particle [25]. Global-local-neighbor particle swarm optimization (glnPSO) proposed by Ai and Kachitvichyanukul [30] improves the weakness of the basic PSO. Xu and Yan [40] proposed a global-local-neighbor particle swarm optimization with exchangeable particles (GLNPSO-ep), which was even more advanced. In this section, a priority-based global-local-neighbor particle swarm optimization (pb-glnPSO) is proposed to solve the multi-objective CDCLAP in the CLSC.

4.1. Notations for the Pb-glnPSO

The basic elements of the PSO are particles, population, velocity, inertia weight, individual best and global best. The notations needed for the pb-glnPSO are as follows:

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τ: iteration index, and $\tau = 1, 2, ...T$.
d: dimension index, and $d = 1, 2, ...D$.
l: particle index, and $l = 1, 2, ...L$.
ω_τ: inertia weight in $\tau - th$ iteration.
$v_{ld}(\tau)$: velocity of the lth particle at the dth dimension in the τth iteration.
$p^l_d(\tau)$: position of the lth particle at the dth dimension in the τth iteration.
p^{best}_{ld}: personal best position.
p^{best}_{gd}: global best position.
p^{Lbest}_{ld}: local best position.
p^{Nbest}_{ld}: near neighbor best position.
c_p: personal best position acceleration constant.
c_g: global best position acceleration constant.
c_l: local best position acceleration constant.
c_n: near neighbor best position acceleration constant.
p^{max}: maximum position value.
p^{min}: minimum position value.
P_l: velocity vector of l-th particle.
V_l: position vector of l-th particle.
P^{best}_l: vector personal best position of l-th particle.
P^{best}_g: vector global personal best position.
P^{Lbest}_l: vector local best position of l-th particle.
r_1, r_2, r_3, r_4: uniform distributed random number within [0,1].
$Fitness(P_l)$: fitness value of P_l.

4.2. Encoding and decoding algorithm

The decoding process is based on the priority-based encoding developed by Gen and Cheng and the priority-based decoding and encoding proposed by Gen and Altiparmak [41]. The priorities of the CDCs and the retailers are equal to the total number of retailers and CDCs. At each step, the CDC(retailer) with the highest priority is selected and connected to a retailer (CDC) under a minimum transportation cost constraint. Table 1 shows the decoding algorithm for the priority-based encoding and its trace table, with the priority-based encoding considered random. The CDCLAP is solved in two stages [15]. In the first stage, the location for the CDCs is chosen and the transportation between the CDCs and the retailers calculated, while the second stage deals with the allocations between the factories and CDCs.

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Table 1. Decoding for the location and allocation problem

Procedure 1:	Decoding of the priority for the location and allocation problem
Input:	Ω: set of CDCs, $i \in \Omega = \{1,2,3,...,I\}$, Φ: set of retailers, and $k \in \Phi = \{1,2,3,...,K\}$,
	D_k: demand of retailer k, $k \in \Phi$,
	α_i: the capability of the CDCs i, $i \in \Omega$, $EV[\widetilde{a}_k]$: the return rate of retailer k, $k \in \Phi$,
	C^d_{ik}: unit transportation cost between the CDC i and retailer k, $i \in \Omega, k \in \Phi$,
	$p(i+k)$: the priority settled, $i \in= \{1,2,3,...,I\}, k \in \Phi$,
Output:	Q_{ik}: the product quantity transported from CDC i to the retailer k.
	Q_{ik}: the product quantity transported from retailer k to CDC i.
Step 1.	$Q_{ik} \longleftarrow 0, i \in \Omega, k \in \Phi, Q_{ki} \longleftarrow 0, i \in \Omega, k \in \Phi$,
Step 2.	$t \longleftarrow \arg\max p(l), l \in \|\Omega\| + \|\Phi\|$; select a node
Step 3.	If $t \in \Omega$, then $i^* \longleftarrow t$; select a CDC,
	$k^* \longleftarrow \arg\min C^d_{ik} \| p(k) \neq 0, k \in \Phi$; select a retailer with the lowest cost
	else, $k^* l$; select a retailer
	$i^* \longleftarrow \arg\min C^d_{ik} \| p(i) \neq 0, i \in \Phi$; select a CDC with the lowest cost
Step 4.	$Q_{ik} \longleftarrow min D_k(1+EV[\widetilde{a}_k]), \alpha_i$; assign the available amount of units
	Update the availabilities on CDC (i^*) and retailer (k^*)
	$D_{k^*} = D_{k^*} - Q_{i^*k^*}$ $\alpha_i = \alpha_i - Q_{i^*k^*}$
Step 3.	If D_{k^*}=0 then $p_{k^*} = 0$
	If $\alpha_{i^*} = 0$ then $p_{i^*} = 0$
Step 5.	If $p(\|i\|+k)$=0, $k \in \Phi$, then calculate transportation cost, find the chosen CDC and return,
	else goto Step 1.

4.3. Update

Based on the above notations and the glnPSO proposed by Ai and Kachitvichyanukul [30], the inertia weight, velocity and position are updated using the following Equation.

$$\omega(\tau) = \omega(T) + \frac{\tau - T}{1 - T}[\omega(1) - \omega(T)] \tag{15}$$

$$v^l_d(\tau+1) = \omega(\tau)v^l_d(\tau) + c_p r_1[p^{best}_{ld}(\tau) - p^l_d(\tau)] + c_g r_2[p^{best}_{gd}(\tau) - p^l_d(\tau)] + c_l r_3[p^{best}_{gd}(\tau) - p^l_d(\tau)] + c_n r_4[p^{best}_{gd}(\tau) - p^l_d(\tau)] \tag{16}$$

$$p^l_d(\tau+1) = p^l_d(\tau) + v^l_d(\tau+1) \tag{17}$$

The glnPSO has been widely used in solving NP-hard facilities location and allocation problems.

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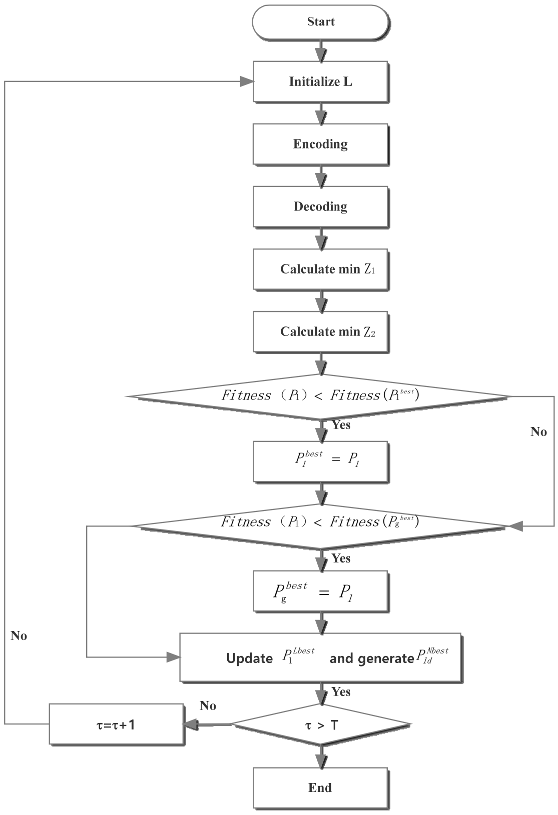

Figure 2. The heuristic algorithms based on pb-glnPSO

4.4. Overall process of the pb-glnPSO

In this paper, the glnPSO presented above is used to solve the location and allocation problem. Due to uncertainties and environmental changes, a priority-based global-local-neighbor particle swarm optimization (pb-glnPSO) is proposed to solve this model. As the company pays close attention to the economic costs, the environmental factor is dealt with as a constraint which has upper limits. The algorithmic details are as follows.

Step 1: Initialize P particles as a swarm: $l = 1, ...L$, (the particle is the priority).

Step 2: Constraints check. If in the feasible region, goto step 3; otherwise, return to step 1.

Step 3: Calculate the fitness according to the decoding algorithm in Table 1.

Step 4: Update the particle positions and velocities.

Step 4.1: Acquire the expected value for Z from the above algorithm.

Step 4.2: For $l = 1, 2, ...L$, decode each particle to an installment group. Calculate the fitness value of each particle and set as the position of the l-th particle as its personal best. The global best position is chosen from these personal best positions.

Step 4.3: Update pbest: For $l = 1, 2, ...L$, if $Fitness(P_l) < Fitness(P_l^{best})$, $P_l^{best} = P_l$.

Step 4.4: Update gbest: For $l = 1, 2, ...L$, if $Fitness(P_l) < Fitness(P_g^{best})$, $P_g^{best} = P_l$.

Step 4.5: Update lbest: For $l = 1, 2, ...L$, among all pbest of M neighbors around the l-th particle, set the personal best which has the best fitness value as P_l^{Lbest}.

Step 4.6: Generate nbest: For $l = 1, 2, ...L$, and $d = 1, 2, ...D$, find the p_{od} ensuring that the FDR takes a maximum value, and set p_{od} as P_{ld}^{Nbest}.

Step 4.7: Update the position and the velocity of each l-th particle using Equation (18).

Step 4.8: Check whether the particles are beyond the mark. If $p_{ld} > P^{max}$, the $p_{ld} = P^{max}$; otherwise, if $p_{ld} < P^{min}$, thenn $p_{ld} = P^{min}$.

Step 5: Based on the above calculation, replace the ranking vector using the new numbers.

Step 6: If the stopping criterion is met, stop; otherwise, $\tau = \tau + 1$ and return to step 2. The overall process can be clearly seen in Fig 2.

5. Case Study

5.1. Case presentation

This model is motivated by a beer company in a developing country that bottles beer in plastic or glass bottles. The supply chain intends to allow customers to return the bottles to the retailers after the beer has been consumed, after which the returned bottles are sent to the CDCs where they are inspected, consolidated and sorted. After processing and disinfecting, the bottles are filled with beer and sold again. Now the company is considering the construction of several CDCs to allow for bottle recycling as producing a new bottle is far more expensive than recycling a used bottle.

Table 2. CDCs information (unit:1×10^2RMB)

Node	location	capability	fixed cost	NPV cost	RPV cost	$\tilde{\bar{b}}_i$	Parameters $\bar{\rho}$
1	(23,23)	900	12300	0.01	0.05	(0.18,$\bar{\rho}_1$,0.25)	$\bar{\rho}_1 \sim N(0.21,0.02)$
2	(25,35)	550	12100	0.02	0.06	(0.23,$\bar{\rho}_2$,0.28)	$\bar{\rho}_2 \sim N(0.25,0.02)$
3	(34,29)	1050	15600	0.01	0.05	(0.14,$\bar{\rho}_3$,0.24)	$\bar{\rho}_3 \sim N(0.18,0.04)$
4	(32,25)	650	11300	0.01	0.07	(0.16,$\bar{\rho}_4$,0.22)	$\bar{\rho}_4 \sim N(0.18,0.03)$
5	(35,37)	1050	17800	0.01	0.05	(0.25,$\bar{\rho}_5$,0.30)	$\bar{\rho}_5 \sim N(0.28,0.02)$
6	(36,31)	1050	22400	0.01	0.06	(0.17,$\bar{\rho}_6$,0.26)	$\bar{\rho}_6 \sim N(0.22,0.03)$
7	(29,28)	1050	16300	0.02	0.07	(0.15,$\bar{\rho}_7$,0.23)	$\bar{\rho}_7 \sim N(0.20,0.02)$
8	(18,21)	800	14900	0.01	0.06	(0.19,$\bar{\rho}_8$,0.28)	$\bar{\rho}_8 \sim N(0.24,0.03)$
9	(29,23)	1100	26500	0.01	0.06	(0.12,$\bar{\rho}_9$,0.22)	$\bar{\rho}_9 \sim N(0.17,0.04)$
10	(35,26)	1050	22000	0.02	0.05	(0.17,$\bar{\rho}_{10}$,0.23)	$\bar{\rho}_{10} \sim N(0.20,0.02)$

To illustrate the validity of the model and the usefulness of the solution method, the data needed to examine the CLSC performance for the four objectives is presented here. Based on the market analysis, ten coordinates for the CDC alternatives are given: location, capability, fixed costs and new product variable costs (NPV cost) and recycled product variable costs (RPV cost). These are shown in Table 2. Supermarkets and restaurants are considered to beer tailers with flexible demand. Table 3 presents the information regarding the retailers, factories and disposal centers. It can be seen from that Table 3, k_1 to k_{30} represents 30 different retailers, while j_1 to j_4 are the 4 different factories at different locations with variable capabilities and n_1 indicates the location and capability of the disposal center. Therefore, 30 retailers, 4 factories and 1 waste disposal center are considered in this study. The unit transportation costs and pollution are related to the distances between the facilities. The retailers' return rates are shown in Table 4, which are considered to be fuzzy random variables.

Table 3. Rtailers, factories and disposal center

Node	location	demand	Node	location	demand	Node	location	demand
k_1	(27,28)	50	k_{11}	(26,39)	60	k_{21}	(25,31)	70
k_2	(30,19)	60	k_{12}	(38,26)	40	k_{22}	(29,35)	90
k_3	(32,22)	40	k_{13}	(38,34)	50	k_{23}	(18,29)	50
k_4	(37,16)	80	k_{14}	(36,25)	70	k_{24}	(18,14)	60
k_5	(23,29)	30	k_{15}	(41,19)	40	k_{25}	(35,11)	80
k_6	(27,17)	40	k_{16}	(27,33)	30	k_{26}	(23,33)	50
k_7	(33,26)	80	k_{17}	(25,39)	20	k_{27}	(36,37)	60
k_8	(34,32)	40	k_{18}	(38,37)	40	k_{28}	(28,26)	40
k_9	(37,22)	100	k_{19}	(36,27)	50	k_{29}	(25,24)	30
k_{10}	(17,22)	90	k_{20}	(39,28)	60	k_{30}	(32,19)	80
j_1	(13,22)	920	j_2	(31,44)	530	j_3	(32,15)	850
j_4	(42,31)	940	n_1	(18,47)	800			

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Table 4. Retailers' return rates and CDCs' disposal rate

Node	$\widetilde{a}_k$	Parameters $\bar{\varsigma}$	Node	$\widetilde{a}_k$	Parameters $\bar{\varsigma}$
1	(0.28,$\bar{\varsigma}_1$,0.33)	$\bar{\varsigma}_1 \sim N$(0.31,0.02)	16	(0.74,$\bar{\varsigma}_{16}$,0.79)	$\bar{\varsigma}_{16} \sim N$(0.77,0.04)
2	(0.52,$\bar{\varsigma}_2$,0.62)	$\bar{\varsigma}_2 \sim N$(0.56,0.02)	17	(0.70,$\bar{\varsigma}_{17}$,0.75)	$\bar{\varsigma}_{17} \sim N$(0.73,0.04)
3	(0.32,$\bar{\varsigma}_3$,0.38)	$\bar{\varsigma}_3 \sim N$(0.36,0.03)	18	(0.75,$\bar{\varsigma}_{18}$,0.80)	$\bar{\varsigma}_{18} \sim N$(0.78,0.02)
4	(0.62,$\bar{\varsigma}_4$,0.73)	$\bar{\varsigma}_4 \sim N$(0.67,0.04)	19	(0.68,$\bar{\varsigma}_{19}$,0.75)	$\bar{\varsigma}_{19} \sim N$(0.72,0.03)
5	(0.55,$\bar{\varsigma}_5$,0.62)	$\bar{\varsigma}_5 \sim N$(0.58,0.02)	20	(0.55,$\bar{\varsigma}_{20}$,0.65)	$\bar{\varsigma}_{20} \sim N$(0.61,0.02)
6	(0.65,$\bar{\varsigma}_6$,0.72)	$\bar{\varsigma}_6 \sim N$(0.69,0.02)	21	(0.35,$\bar{\varsigma}_{21}$,0.45)	$\bar{\varsigma}_{21} \sim N$(0.39,0.04)
7	(0.73,$\bar{\varsigma}_7$,0.81)	$\bar{\varsigma}_7 \sim N$(0.78,0.03)	22	(0.35,$\bar{\varsigma}_{22}$,0.42)	$\bar{\varsigma}_{22} \sim N$(0.38,0.03)
8	(0.72,$\bar{\varsigma}_8$,0.78)	$\bar{\varsigma}_8 \sim N$(0.75,0.03)	23	(0.55,$\bar{\varsigma}_{23}$,0.60)	$\bar{\varsigma}_{23} \sim N$(0.58,0.03)
9	(0.75,$\bar{\varsigma}_9$,0.82)	$\bar{\varsigma}_9 \sim N$(0.8,0.04)	24	(0.52,$\bar{\varsigma}_{24}$,0.62)	$\bar{\varsigma}_{24} \sim N$(0.56,0.04)
10	(0.34,$\bar{\varsigma}_{10}$,0.38)	$\bar{\varsigma}_{10} \sim N$(0.36,0.02)	25	(0.62,$\bar{\varsigma}_{25}$,0.72)	$\bar{\varsigma}_{25} \sim N$(0.66,0.04)
11	(0.42,$\bar{\varsigma}_{11}$,0.48)	$\bar{\varsigma}_{11} \sim N$(0.46,0.02)	26	(0.69,$\bar{\varsigma}_{26}$,0.75)	$\bar{\varsigma}_{26} \sim N$(0.72,0.03)
12	(0.46,$\bar{\varsigma}_{12}$,0.50)	$\bar{\varsigma}_{12} \sim N$(0.48,0.04)	27	(0.29,$\bar{\varsigma}_{27}$,0.35)	$\bar{\varsigma}_{27} \sim N$(0.32,0.03)
13	(0.65,$\bar{\varsigma}_{13}$,0.70)	$\bar{\varsigma}_{13} \sim N$(0.67,0.04)	28	(0.40,$\bar{\varsigma}_{28}$,0.46)	$\bar{\varsigma}_{28} \sim N$(0.43,0.02)
14	(0.62,$\bar{\varsigma}_{14}$,0.68)	$\bar{\varsigma}_{14} \sim N$(0.64,0.03)	29	(0.42,$\bar{\varsigma}_{29}$,0.48)	$\bar{\varsigma}_{29} \sim N$(0.45,0.03)
15	(0.72,$\bar{\varsigma}_{15}$,0.78)	$\bar{\varsigma}_{15} \sim N$(0.75,0.04)	30	(0.50,$\bar{\varsigma}_{30}$,0.58)	$\bar{\varsigma}_{30} \sim N$(0.54,0.04)

5.2. Sensitivity analysis on the parameters

To find the best solution to the proposed model, a series of experiments were conducted, all of which were performed using a MATLAB 7.0 on a workstation with an Intel(R) Corei5, a Pentium 4, 1.83GHz clock pulse with 4GB memory and Windows 10 operating system. A sensitivity analysis was performed to exhibit the effectiveness and behavior of the proposed algorithm, as shown in Table 5. Several parameters were changed, including the population size N, maximum generation T and acceleration constant c_p, c_g, c_l and c_n. After trying various values for the population size and maximum generations, the results were found to be better when T was from 200 to 400 and N was from 30 to 50. The different fitness values obtained using the pb-glnPSO with the different parameters N T c_1 and c_2 are shown in Table 5.

Table 5. Sensitivity analysis (unit:1×10^2RMB)

	T=200	T=300	T=400	T=200	T=300	T=400	T=200	T=300	T=400
0.5	88049.270	85447.261	86943.479	89889.371	88266.237	84859.596	86479.923	84830.640	88233.839
1	87056.401	84125.454	84428.258	88679.314	87459.033	84199.470	85596.767	83448.794	85614.352
1.5	86601.808	84465.348	84315.569	85486.560	86564.333	84041.957	84698.625	83257.776	82930.618
2	85614.087	82308.935	83058.532	82914.087	82434.420	83681.801	82884.954	81920.133	82585.367
2.5	85844.692	83102.944	87782.377	85170.526	83198.452	86792.664	83448.789	84469.925	83177.298

As can be seen from Table 5, when the parameters c_p, c_g, c_l and c_n increase, the fitness value improves except for c_p=c_g=c_l=c_n=2.5 with the same generation and popsize, with the fitness value increasing from c_p=c_g=c_l=c_n=2 toc_p=c_g=c_l=c_n=2.5. Therefore, when c_p=c_g=c_l=c_n=2, the result is optimal. For T, given the same c_p, c_g, c_l and c_n and population size, the results shows that when T is 300, the fitness value is better than for any other generation. Finally, for N, the results improve as the population size increases and is optimal when N is 50. The most effective and efficient results are gained with T at 300, N at 50 and c_p=c_g=c_l=c_n=2.

5.3. Result analysis

In this section, the pb-glnPSO is performed to solve the model using the above data. The parameters for the problem were set as follows: Population size: *popsize*=50; Maximum generation: *maxGen*=300; Inertia weight: $\omega(1)$=1 and $\omega(T)$=0.1; Acceleration constant: c_p=c_g=c_l=c_n=2. After running the program 20 times, the best satisfactory solution was found. Figure 4 shows the specific objective values found by the Pb-glnPSO in different iterations and shows the reductions in the total

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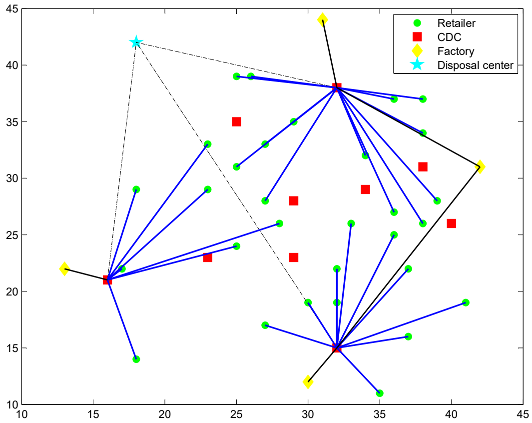

Figure 3. The distribution strategy

costs. The results are presented in Table 6 and Figure 3. From the calculation, at least 3 CDCs could satisfy all markets. The result show that alternative CDC positions4, 5 and 8 should be chosen as CDC 4 can send products to markets 2, 3, 4, 6, 7, 9, 14, 15, 25, 30, CDC 5 can transport products for 1, 8, 11, 12, 13, 16, 17, 18, 19, 20, 21, 22, 27 and retailers 5, 10, 23, 24, 26, 28, 29 can be serviced by CDC 8. The total cost is 81.936million RMB, in which the fixed costs are 44 million RMB, the transportation costs are 37.759 million RMB and the operating costs are 17.7 million RMB.

Table 6. Results

Factories		DR-centers		Markets		Factories		DR-centers		Markets	
Node	location	Node	location	Node	location	Node	location	Node	location	Node	location
				5	(23,29)					1	(27,28)
				10	(17,22)					8	(34,32)
				23	(18,29)					11	(26,39)
1	(13,22)	8	(18,21)	24	(18,14)	2	(31,44)	5	(35,37)	12	(38,26)
				26	(23,33)					13	(38,34)
				28	(28,26)					16	(27,33)
				29	(25,24)					17	(25,39)
				2	(30,19)					25	(35,11)
				3	(32,22)			4	(32,25)	30	(32,19)
				4	(37,16)					18	(38,37)
3	(32,15)	4	(32,25)	6	(27,17)	4	(42,31)			19	(36,27)
				7	(33,26)					20	(39,28)
				9	(37,22)					21	(25,31)
				14	(36,25)			5	(35,37)	22	(29,35)
				15	(41,19)					27	(36,37)

5.4. *Algorithm comparison*

To better illustrate the effectiveness of the proposed algorithm, a brief comparison between the pb-glnPSO, glnPSO and an immune algorithm(IM) is given in this section. The glnPSO is a well-respected evolutionary algorithm and has been successfully implemented in a variety of engineering and combinatorial problems.The IM has also being widely used to solve facilities location problems.

To establish the solution quality for the pb-glnPSO, it is compared with the glnPSO and the IM. Each run time for the pb-glnPSO, glnPSO and the IM was around 80s. The pb-glnPSO, glnPSO and IM were run 20 times using the same data. For a fair comparison between the groups, each population with the same number was initialized with the population size set at50 and the maximum generation at 300. In the glnPSO, an acceleration constant was designed as c_p=c_g=c_l=c_n=2 and the inertia weight

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was$\omega(1)$=1 and $\omega(T)$=0.1. For the IM algorithm, the crossover probability was1 and the mutation probability was 0.1.

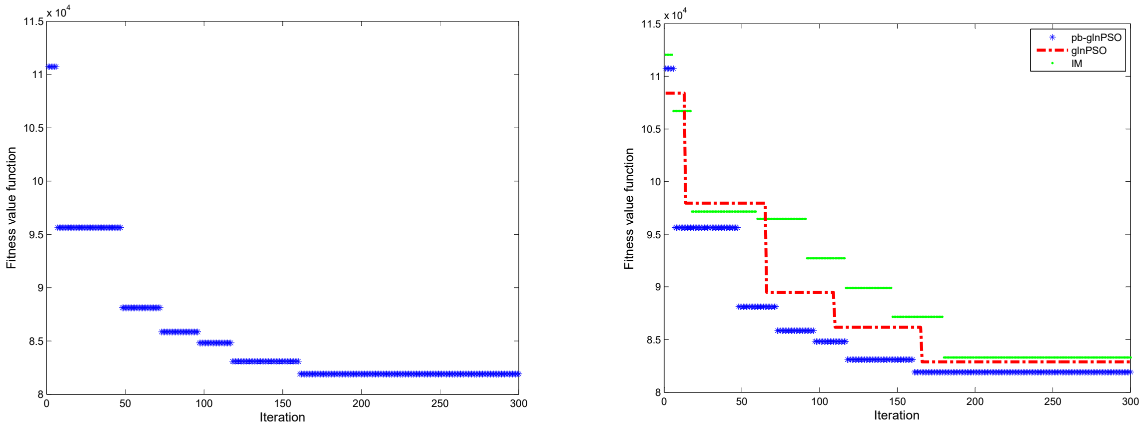

Figure 4. The iterative process of pb-glnPSO,glnPSO and IM

From Figure 4, it can be seen that the pb-glnPSO outperformed both the glnPSO and the IM, and as the glnPSO converged faster, it had a better result than the IM. This demonstrates that a better solution can be obtained using the glnPSO, and especially using the pb-glnPSO. The blue profile shows the convergence for the best in history for the pb-glnPSO. It can be seen from Figure 4 that as the programs ran, the results become stable for the pb-glnPSO and glnPSO after about the 160th generation, while the IM became stable after the 180th generation. As is shown in Figure 4, the best solution for the pb-glnPSO was superior to, more stable than and had the smallest CPU run time than the other algorithms(Table 7), with the IM having the highest run time.

Table 7. Results of the pb-glnPSO, glnPSO, and IM

Item	Pb-glnPSO	glnPSO	IM
Best result	81920.133	82884.954	83315.569
Worst result	83102.944	84826.640	85585.473
Average result	82431.119	83877.688	84179.884
Difference between the best and the worst	1182.811	1941.686	2269.904
Difference between the average and the best	510.986	992.734	864.315
Standard deviation	317.467	553.194	680.326
CPU time	88.7969	124.9844	161.5000

6. Conclusion

Economic development has caused many environmental pollution problems,the seriousness of which has encouraged people to recycle and reuse products. To examine this problem and seek appropriate solutions, a multi-objective collection-distribution center location and allocation problem in a closed loop supply chain under a fuzzy random environment was presented in this paper for the beer industry in China. For this problem, a new model was formulated, in which the decision makers sought to minimize costs and pollution underflow, capability and quantity limit constraints. To more accurately represent actual production situations, the return rate and disposal rate were considered fuzzy random variables. A heuristic algorithm, the pb-glnPSO, was then applied to solve the problem. Based on the proposed priority, the distribution and collection activity was shown to satisfy retailer demand, and reduce costs and pollution after the CDCs started operations. After calculation, the best solution was determined and the advantages of the algorithm illustrated. The proposed model and method can be applied for the location and allocation of CDCs in the beer industry, assisting in improving effective supply chain management. The model was shown to assist in generating retailer demand and dealing with the returned products first, which could benefit company recycling and reuse policies. At the same time, the transportation costs and pollution were reduced because of the reduction in losses from empty loads.

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Sample Availability: Samples of the compounds ...... are available from the authors.