Research Article

A Grasshopper Optimization-Based Approach for Task Assignment in Cloud Logistics

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Received 21 January 2020; Revised 21 February 2020; Accepted 6 March 2020; Published 4 April 2020

Academic Editor: Mauro Gaggero

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A framework for the algorithm-based CL platform is established, based on which, the operational mode of it is described in detail. An integrated logistics task assignment model is built to optimally match logistics service resources and task of large scale in the algorithm-based CL. Particularly, an improved grasshopper optimization-based bitarget optimization algorithm (GROBO) is proposed to solve the biobjective programming model for service matching in CL. The case of Linyi small commodity logistics is taken as an application. Simulation results show that the proposed GROBO provides better solutions regarding to searching efficiency and stability in solving the model.

1. Introduction

With the rapid development of modern manufacturing and e-commerce, logistics industry gets a great potential of growth. However, due to the low level of information sharing, the utilization of transportation capacity is very low in logistics industry [1]. This low transportation utilization results in a high cost and low customer satisfaction in logistics industry.

One of the solutions to solve the aforementioned problem is to improve the information sharing among the current logistics companies using information technology, such as “internet plus logistics” and logistics alliance. With the development of information technologies such as cloud computing and virtualization, a new service-oriented mode of logistics based on cloud computing, named Cloud Logistics (CL), has been put forward. According to Holtkamp et al. [2], Qi [3], Wang et al. [4], and Kong [5], CL has the following characteristics.

Firstly, CL is a viable solution for logistics companies, logistics hub, and various kinds of comprehensive enterprises’ logistics departments. It relies on large-scale cloud computing capabilities, standard operating procedures, flexible business coverage, precise process control, intelligent decision support, and in-depth information sharing.

Secondly, CL is an IT support for logistics companies. The CL platform is seen as a web-based service platform that provides decision support for logistics companies.

In terms of these characteristics, CL will play an irreplaceable role in information sharing, resource allocation optimization, and cost reduction in logistics industry. However, for the current proposed CL platforms, it requires the information sharing between the logistics companies by a CL platform which often belongs to a specific logistics company. This logistics company-owned CL platform often discourages information sharing from other logistics companies due to the sensitive commercial information. Therefore, in our paper, we would like to propose an algorithm-based independent CL platform which can be utilized by all the logistics companies, but it is independent from any of these companies. We simply call this type of CL platform as algorithm-based CL platform. An ideal algorithm-based CL platform should carry out its business by the built-in algorithms or heuristics without human beings involved. It functions as an independent platform to support logistics companies to make their decisions on scheduling its task and resource capacity by taking anonymous outsourcing partners into consideration. In this way, the logistics companies can feel comfortable to issue their extraservice resources to the resource pool of the algorithm-based CL platform and service requests to the task pool of the platform. The algorithm-based CL platform allocates various logistics tasks to different service resources.

Contributions of this paper include the following: (1) the framework of the algorithm-based CL platform is proposed and (2) the algorithm for optimally assigning tasks from the task pool to the available resources in the resource pool is developed.

Rest of this paper is organized as follows. Section 2 is a literature review which provides as the basis of our research. Section 3 provides a description of the algorithm-based CL platform framework, as well as an illustration of its operational mode. The mathematical model of task assignment in the algorithm-based CL platform is provided in Section 4, and Section 5 is a grasshopper optimization-based bitarget optimization algorithm to solve the established biobjective model for service matching in the lgorithm-based CL platform. Section 6 provides an application to validate the framework and the model of algorithm-based CL platform. Conclusions and limitations of this study are given in Section 7.

2. Related Work

As to our best knowledge, there has not been found any paper which clearly describes the work as presented in this paper. However, there are some papers which can be used as references in our research and are briefly reviewed and discussed.

2.1. Research on Cloud Logistics. Many scholars have noticed the integration of cloud computing with logistics. Subramanian et al. [6] examine the green and cost benefits of integration of logistics and cloud computing. Their results show that small- and medium-sized logistics service providers are attracted by cloud computing to reduce cost and to gain sustainability through increased benefits. Subramanian and Abdulrahman [7] further examine the cooperation of logistics and cloud computing service providers from a resilience perspective. The relationship between the vulnerability factor, capability factor, and collaboration benefits offered by cloud computing service providers based on 236 logistics service firms' perceptions is investigated in their study. They suggest that the security impediment is a major factor affecting cooperative resilience between logistics service and cloud-computing service providers. Wang et al. [4] propose a new intelligently networked logistics service mode called "cloud logistics (CL)" under the environment of Internet of Things (IoT). They also put forward the CL-based one-stop service platform for logistics center, which is able to provide the supply chain users with comprehensive, fast, and efficient logistics services. To build an intelligent CL system, Liu et al. [8] analyze the incentive model of information sharing and proposes the incentive distribution mechanism and regulatory mechanism in CL. Banyai [9] introduces an approach using Internet-based technologies to support virtual logistic networks. Niharika and Ritu [10] design a cloud-computing supported logistics tracking information management system to support whole-ranged and real-time logistics tracking services, which allows customers to tap into anywhere and anytime the ability needed to run business more efficiently and to achieve high customer satisfaction. Li et al. [11] design a cold chain logistics system based on cloud computing, which helps bring better cooperation between cold chain logistics and their customers, realize co-control of product sales information, and maximize interest of all parties. Yang et al. [12] establish the intelligent logistics service platform based on cloud computing, through which the open-access cloud services including distribution, positioning, navigation, and scheduling can be offered. Li et al. [13] study the problem of resource virtualization and service encapsulation in Cloud Logistics (CL). They consider service selection in CL as an optimization problem, and particle swam optimization algorithm is applied to get the solution. Qi [3] notices the platform "island" phenomenon in cloud logistics platforms and proposes a logistics-sharing mechanism based on cloud federal services, which achieves multiple cloud logistics collaboration and interaction with each other. Chen et al. [14] propose a Logistics Cloud based on SaaS and IoT. Furthermore, they (2014) propose a new approach for developing cloud-based manufacturing systems, in which enterprises can develop their own cloud-based logistics management information systems. Considering the classification and the features of the cloud logistics resources, Zhong et al. [15] establish a uniform resource expression model, achieving the mapping from cloud logistics physical resources to virtual resources. Zhang et al. [16] construct a smart box-enabled product-service system for cloud logistics. They also propose a real-time information-driven logistics task optimisation method by designing the cloud logistics platform based on cloud computing.

In short, although many researchers have noticed the potential of the new paradigm of cloud logistics and have carried out some related work, most of these studies are dealing with the concept and framework. Studies on CL are not yet well established. There is neither clear definition nor systematic description of an algorithm-based CL platform in the available literature. Research on task-service matching in CL is even more scarce.

2.2. Service Matching under Environment of Cloud Computing. Intelligent management and allocation of logistics service resources according to customer requirements are of vital importance for sustainable implementation and development of CL. Therefore, with the rapid development of logistics industry, the supply-demand matching problem of logistics tasks and services in CL need to be modelled specifically. However, as the concept of CL is not mature enough, research on service matching or service resource scheduling in CL is scarce. There are plenty of papers dealing with problems of service selection and resource allocation under the topic of cloud manufacturing. In view of service selection optimization and scheduling in cloud manufacturing, Akbaripour et al. [17] propose a mixed-integer programming model with basic composition structures. Availability of resources and transportation is taken into account in their proposed model. Zhou et al. [18] put forward a 3D printing service matching and selection method to reduce delivery time of tasks from service suppliers to service demanders. A 3D printing service scheduling (3DPSS) method is also proposed to generate optimal scheduling solutions. Bouzary et al. [19] formulate the Qos-aware service composition and optimal service selection (SCOS) problem to meet user's requirements while keeping up the optimal service performances in cloud manufacturing (CMfg) context. A modified discrete invasive weed algorithm is then proposed and applied for solving the NP-hard SCOS problem. Rehman et al. [20] present a cloud service selection method utilizing history of service quality over different time periods and conduct parallel multicriteria decision analysis to rank all cloud services. The problem of resource service matching for aggregated resources with capacity restraint in cloud manufacturing is discussed by Zhang et al. [21]; an improved genetic algorithm is proposed to avoid premature evolution of populations and thus getting the optimal solution. Somu et al. [22] present a hypergraph-based computational model to help users in the selection of a suitable cloud service provider, and the Minimum Distance-Helly Property algorithm is proposed to rank the cloud service providers. To realize effective and intelligent supply-demand matching of manufacturing resources and capabilities, the concept of manufacturing service supply-demand matching simulator is proposed by Tao et al. [23]. They design a hypernetwork-based architecture for the simulator as well as its key functions and subsystems. As task workload is the basis for task scheduling in cloud manufacturing, Liu et al. [24] put forward a work-load-based multitask scheduling model. Their method incorporates task workload modelling and a number of other essential service attributes such as service efficiency and service quality. Focusing on diverse manufacturing tasks and aiming to address the scheduling issue in CMfg, Zhou et al. [25] build a mathematical model of task scheduling based on analysis of the scheduling process in CMfg. A scheduling method aiming for diverse tasks is also proposed to solve this scheduling problem. Zhou et al. [26] analyze the characteristics of logistics selection (LSS) problems in CMfg and build a mathematical model for optimal selection of logistics services to guarantee just-in-time delivery of products to service demanders. For service-oriented manufacturing modes, Zhou et al. [27] construct a mathematical model of the dynamic cloud scheduling problem and propose a scheduling method based on dynamic data-driven simulation to improve the scheduling performance. In view of on-demand supply of cloud manufacturing service, Huang et al. [28] propose a two-dimensional optimization mechanism and method, which aims at decoupling contradiction existing among individuation, cos, and response time. Considering the autonomous decision rights of different service suppliers, Zhang et al. [21] introduce a decentralized decision mechanism named analytical target cascading to solve the manufacturing service configuration problem, which is based on the hierarchical structure of the cloud service system.

Current research on service scheduling under the environment of cloud computing has mostly focused on cloud manufacturing. The work on cloud manufacturing can be taken for valuable references for the research on CL due to some similarities between cloud manufacturing and cloud logistics. However, these research results cannot be directly applied to CL service-matching problems since CL has its own characteristics. One of the challenges is that tasks in the task pool and resources in the resource pool of the algorithm-based CL platform are uncertain. They may be submitted or withdrawn by logistics companies at any time. Therefore, service-demand matching problem in CL is different from that of other cloud services. To meet this challenge, an improved Grasshopper optimization algorithm is proposed in this paper to solve the bitarget optimization model, which suits well to computation of nondeterministic and large-scale problem.

3. Framework of the Algorithm-Based CL

3.1. Participators of the Algorithm-Based CL and Their Activities. As shown in Figure 1, there are mainly three types of participators involved in the algorithm-based CL, which are operators of the platform, service demanders, and resource providers:

(1) *Operators of the Platform*. Primary duties of operators of the platform are to maintain the interests of different participators and ensure the smooth running of all logistics activities. All the allocation and scheduling of logistics tasks and resources are carried out on the algorithm-based CL platform through its built-in algorithms, which are intelligent and automated without human intervention. Both resource providers and service demanders are anonymous to each other and will be satisfied with the scheduling and allocation of the algorithm-based CL platform.

(2) *Resource Providers of Logistics Services*. Resource providers of logistics services include not only third-party logistics enterprises and fourth-party logistics enterprises but also idle logistics resources from other large-sized logistics enterprises. They can send their extrasporadic resources to the algorithm-based CL platform to seek for services from other companies. They issue and offer the detailed information of these extraresources, and the CL platform will then store the information in its resource pool.

(3) *Service Demanders*. Service demanders here refer to any individuals, enterprises, and logistics companies that request for logistics services. Logistics companies may send their extraservices, which is beyond their current capacity, to the algorithm-based CL platform to seek for an economical and time effective outsourcing service provider. They send their service tasks to the CL platform through computers or smart mobile phones. The platform will store the demand information in the task pool.

3.2. Characteristics of the Algorithm-Based CL Platform. Operation of the algorithm-based CL platform is totally automatic, without human intervention. Preset algorithms are invoked to implement all service matching. Procedures

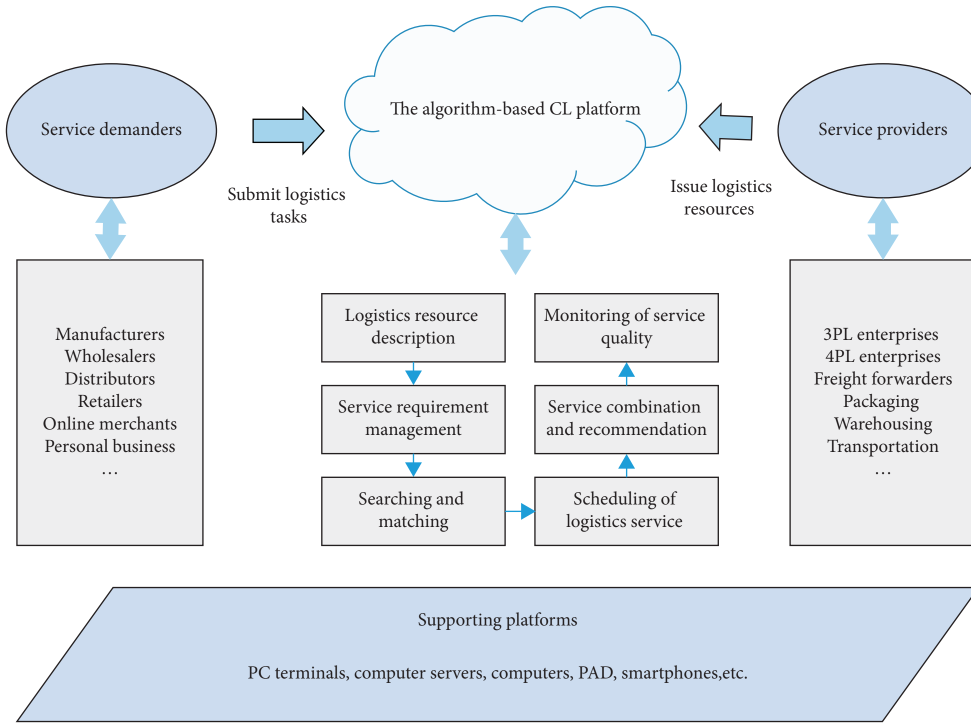

Figure 1: Framework of the algorithm-based CL.

on the platform are automated through its built-in algorithms or heuristics. Meanwhile, contract design is necessary to ensure sustainable operation of the algorithm-based CL platform. Users (service demanders and providers) cannot withdraw their submission without constraints. A time fencing must be specified, as well as mechanisms for penalty must be considered and included in the contract. Once users, both service demanders and providers, submit their tasks or resources, they can withdraw or modify before scheduling time fence, and no withdraws or modifications are allowed within time fencing. Otherwise, penalty is applied. All users must register on the platform and sign contract with the CL platform to accept relative clauses.

As described above, the algorithm-based CL platform is like the idea of blockchain applied in logistics. Characteristics of the algorithm-based CL platform can be concluded as follows.

Firstly, the algorithm-based CL platform is a pattern of nonasset operation. The platform does not have the ownership of logistics resources, nor the right to use them. It only gathers all information which is relative to logistics activities, including a great amount of information of logistics tasks and resources. The algorithm-based CL platform then allocates resources to different tasks according to provided algorithms.

Secondly, the proposed CL should be artificial intelligent and automated. Operator of the platform regulates and monitors the operation of the platform. However, it does not intervene the allocation and scheduling of resources, which are all realized intelligently based on built-in algorithms and procedures.

Lastly, the algorithm-based CL platform is a multifunction service platform of logistics. Due to its information superiority, CL is able to unite participators of logistics in greatest scope and optimize allocation of logistics resources to the largest extent. It provides intelligent and comprehensive services to users. Compared with traditional logistics services, the algorithm-based CL platform is able to provide integrated logistics with high efficiency through coordinating various logistics service resources on the platform.

4. Task Assignment Model for Service Matching in CL

Assignment of tasks in the algorithm-based CL platform can be divided into two steps:

Step 1: to obtain information of service requests from service demanders in the task pool and service resources from service providers in the resource pool

Step 2: to match tasks and resources

The main goal of matching tasks and resources is to minimize the cost and delivery time. Therefore, a biobjective programming model for task assignment in the algorithm-based CL platform is established.

4.1. Assumptions

4.1.1. Parameters. Parameters and notations used in the model are listed in Table 1.

4.1.2. Assumptions

(1) Tasks to be assigned are integrated logistics tasks which have been packaged by the CL platform, and logistics service resources have also been assorted by the platform.

Table 1: Parameters for the model.

No.	Parameters	Clarification
1	i	Logistics tasks to be assigned on the CL platform, $i = 1, 2, \ldots, n$
2	j	Logistics service resources, $j = 1, 2, \ldots, m$
3	x_{ij}	Decision variables, $x_{ij} = 1$ means task i is conducted by resource j; or else, $x_{ij} = 0$
4	c_{ij}	Unit cost of resource j to conduct task i
5	t_{ij}	Time needed of resource j to conduct task i
6	t_i	Expected time of task i to be finished
7	q_i	Quantity of task i
8	ζ_i	Unit value of service objects relative to task i, meaning the market price for the relative goods
9	ρ_{ij}	Rate of damages or mistakes of resource j to finish task i
10	v_i	Unit price of the logistics service to finish task i
11	w_i	Extent of impact that an information error will have on task i
12	p	The probability that an information error happens

(2) For the same i and when $j = 1, 2, \ldots, m$, c_{ij} and t_{ij} can be different from each other, and at least one of the following inequalities holds:

$$\theta_{ij}^{-} \leq q_i \leq \theta_{ij}^{+}. \tag{1}$$

The above mentioned assumption means that, in the task assignment model, an integrated task package can be done by at least one resource. Time and cost needed for different service resources to finish the task package can be different.

(3) We have

$$\sum_{j=1}^{m} x_{ij} = 1, \quad i = 1, 2, 3, \ldots, n. \tag{2}$$

This means that each integrated task package must be assigned to only one logistics service resource. Of course, capable logistics service providers can issue information of multiple resources, so as to carry on multiple task packages under the prerequisite of guaranteeing service quality.

(4) Logistics service resources are independent of each other, with no constraints between them.

4.2. Establishment of the Task Assignment Model. As mentioned before, goal of task assignment for service matching in the algorithm-based CL platform is to minimize both total cost and delivery time. Firstly, composition of cost is analyzed as follows:

(1) Activity-based cost c_1: activity-based cost is the cost to finish the basic logistics tasks such as transportation, warehouse, package, and handling. It should be the product of unit price and quantity of the task:

$$c_1 = \sum_{i=1}^{n} \sum_{j=1}^{m} c_{ij} \times q_i \times x_{ij}. \tag{3}$$

(2) Damage-caused cost c_2: rate of damages or mistakes is the indicator to measure the quality of logistics service:

$$c_2 = \sum_{i=1}^{n} \sum_{j=1}^{m} x_{ij} \times q_i \times \rho_{ij} \times \zeta_i. \tag{4}$$

(3) Cost of information delivery c_3: as there is huge amount of information on the CL platform, cost of information delivery is the loss due to information delay, distortion, or error:

$$c_3 = \sum_{i=1}^{n} \sum_{j=1}^{m} v_i \times q_i \times p \times w_i \times x_{ij}. \tag{5}$$

Finally, function of total cost is expressed as follows:

$$\begin{aligned} C(x) = {} & \sum_{i=1}^{n} \sum_{j=1}^{m} c_{ij} \times q_i \times x_{ij} + \sum_{i=1}^{n} \sum_{j=1}^{m} x_{ij} \times q_i \times \rho_{ij} \times \zeta_i \\ & + \sum_{i=1}^{n} \sum_{j=1}^{m} v_i \times q_i \times p \times w_i \times x_{ij}. \end{aligned} \tag{6}$$

Meanwhile, function of time is

$$T(x) = \sum_{i=1}^{n} \sum_{j=1}^{m} t_{ij} x_{ij}. \tag{7}$$

Therefore, we finally get the biobjective programming model for task assignment in the algorithm-based CL:

$$\begin{aligned} \min C(x) = {} & \sum_{i=1}^{n} \sum_{j=1}^{m} c_{ij} \times q_i \times x_{ij} + \sum_{i=1}^{n} \sum_{j=1}^{m} x_{ij} \times q_i \times \rho_{ij} \\ & \times \zeta_i + \sum_{i=1}^{n} \sum_{j=1}^{m} v_i \times q_i \times p \times w_i \times x_{ij}, \\ \min T(x) = {} & \sum_{i=1}^{n} \sum_{j=1}^{m} t_{ij} x_{ij}, \\ \text{s.t.} & \sum_{j=1}^{m} x_{ij} = 1, \quad i = 1, 2, 3, \ldots, n, \end{aligned} \tag{8}$$

$$\sum_{i=1}^{n} \sum_{j=1}^{m} x_{ij} \leq m, \tag{9}$$

$$\theta_{ij}^{-} \leq q_i \leq \theta_{ij}^{+}, \tag{10}$$

$$t_{ij} x_{ij} - f t_i \leq 0. \tag{11}$$

Constraint (8) means that one task package must be finished by only one logistics resource. Constraint (9) means that the number of resources allocated to conduct different tasks should be no more than the total number of resources on the CL platform. Constraint (10) is to ensure that when task i is conducted by resource j, quantity of task i must be in the range of resource j's capacity, which means that the allocated resource must have the ability to finish the task package. Finally, constraint (11) is a time constraint, ensuring that time needed for resource j to finish task package i must be less than expected time, which means that, in order to satisfy customers' requirement, the logistics task should be finished on time.

5. Grasshopper Optimization-Based Biobjective Algorithm (GROBO) for Solution

5.1. Grasshopper Optimization Algorithm. There are many algorithms in the literature for solving multiobjective algorithm, such as Nondominated Sorting Genetic Algorithm (NSGA) [29], Multiobjective Particle Swarm Optimization (MOPSO) [30], Multiobjective Ant Colony Optimization [31], and Multiobjective Differential Evolution [32]. All these algorithms are proved to be effective in finding nondominated solutions for multiobjective problems. However, there is no algorithm capable of solving optimization algorithms of all kinds. Grasshopper optimization (GRO) algorithm is proposed by Saremi et al. [33]. GRO is able to solve real problems with unknown search spaces. The main characteristics of the swarm in the larval phase are slow movement and small steps of grasshoppers. In contrast, long range and abrupt movement is the essential feature of the swarm in adulthood. As the target is improved over the course of iterations, approximation of global optimum becomes more accurate proportional to the number of iterations. The mathematical model employed to simulate swarming behaviour of grasshoppers is presented as follows:

$$X_i = S_i + G_i + A_i, \tag{12}$$

where X_i defines the position of the ith grasshopper, S_i is the social interaction, G_i is the gravity force on the ith grasshopper, and A_i shows the wind advection. To provide random behaviour, the equation can be written as follows:

$$X_i = r_1 S_i + r_2 G_i + r_3 A_i, \tag{13}$$

where r_1, r_2, and r_3 are random numbers in [0, 1].

$$S_i = \sum_{\substack{j=1\\ j\neq i}}^{N} s\left(d_{ij}\right) d'_{ij}, \tag{14}$$

where d_{ij} is the distance between the ith and the jth grasshopper, calculated as $d_{ij} = |x_j - x_i|$. $d'_{ij} = ((x_j - x_i)/d_{ij})$ is a unit vector from the ith grasshopper to the jth grasshopper. N is the number of grasshoppers. s is a function to define the strength of social forces, $s(r) = fe^{(-r/l)} - e^{-r}$, where f indicates the intensity of attraction and l is the attractive length scale.

Gravity force G_i can be written as follows:

$$G_i = -ge'_g, \tag{15}$$

where g is the gravitational constant and e'_g shows a unity vector.

Wind advection A_i can be written as follows:

$$A_i = -ue'_w, \tag{16}$$

where u is a constant drift and e'_w is a unity vector in the direction of wind.

Nymph grasshoppers have no wings, so their movements are highly correlated with wind direction.

However, this mathematical model (equation (12)) cannot be used directly to solve optimization problems, mainly because the grasshoppers quickly reach the comfort zone and the swarm does not converge to a specified point. A modified version of this equation is proposed as follows (equation(17)) to solve optimization problems:

$$X_i^d = c\left(\sum_{\substack{j=1\\ j\neq i}}^{N} c\frac{\mathrm{ub}_d - \mathrm{lb}_d}{2} s\left(d_{ij}\right) d'_{ij}\right) + \widehat{T_d}, \tag{17}$$

where ub_d is upper bound in the Dth dimension and lb_d is lower bound in the Dth dimension.

$\widehat{T_d}$ is the value of the Dth dimension in the target (best solution found so far), and c is a decreasing coefficient to shrink the comfort zone, repulsion zone, and attraction zone. It shows that the next position of a grasshopper is defined based on its current position, position of the target, and position of all other grasshoppers. Note that the first component of this equation considers the location of the current grasshopper with respect to other grasshoppers.

It should be noted that the inner c contributes to the reduction of repulsion/attraction forces between grasshoppers proportional to the number of iterations, while the outer c reduces the search coverage around the target as the iteration count increases. For balancing exploration and exploitation, the parameter c is required to be decreased proportional to the number of iteration. This mechanism promotes exploitation as the iteration count increases. The coefficient c reduces the comfort zone proportional to the number of iterations and is calculated as follows:

$$c = c\max - l\frac{c\max - c\min}{L}, \tag{18}$$

where $c$max is the maximum value, $c$min is the minimum value, l indicates the current iteration, and L is the maximum number of iterations.

5.2. Bitarget Optimization Process. The original GRO is used to solve single target optimization, and a biobjective optimization method is proposed based on GRO in this paper. Grey relational grade is introduced to be used as optimization criteria. It is applied to measure the similarity between two solutions of two objective functions, based on which optimal solution of the biobjective programming is selected and obtained.

The flowchart of the bitarget optimization process is shown in Figure 2.

Two objectives f_1 and f_2 are considered during the selection of grasshoppers' position in the study. The optimization criterion is formulated as follows:

$$\mathrm{GR}\left(\mathrm{Grasshoppers}_i^d\left(f_1\right), \mathrm{Grasshoppers}_i^d\left(f_2\right)\right) > \Delta G. \tag{19}$$

GR( ) is the Grey relational grade which is used to calculate the similarity between two solutions from the two objective functions. ΔG is the designed threshold. In every iteration, the grasshoppers' position will be updated if the optimization criterion is met.

The pseudocode of the proposed GROBO algorithm is shown as follows (Algorithm 1):

6. A Practical Application

6.1. Background. The case of small commodity logistics in Linyi of Shandong Province in China is considered here. There are 9 logistics enterprises and 8 logistics task packages which are collected for the case study [5]. Task packages to be assigned are noted as i. Logistics service resources are provided by 4 large logistics companies, i.e., Huayu Logistics, Tianyuan International Logistics, Zhonglian Logistics, and Jinlan Logistics, and 5 small and medium-sized logistics enterprises, i.e., Linfeng Logistics, Lujiang Logistics, Huaqiang Logistics, Shunanda Logistics, and Bangtaicang Logistics. Resources provided are noted as j. Details of tasks and resources can be found in Kong [5]. According to the data and information in Kong [5], we can get relative values for parameters as follows:

$$\begin{aligned}
W &= \left(w_1, w_2, \ldots, w_8\right) = (0.25, 0.1, 0.25, 0.25, 0.2, 0.22, 0.2, 0.1),\\
\left(q_1, q_2, \ldots q_8\right) &= (2, 150, 150, 150, 2, 1, 1, 8, 5),\\
\left(v_1 q_1, \ldots, v_8 q_8\right) &= (6000, 8250, 33000, 1600, 372, 450, 72800, 25000),\\
\left(\delta_1 q_1, \ldots, \delta_8 q_8\right) &= (180000, 60000, 60000, 400000, 400000, 400000, 19200000, 20000000),\\
\mathrm{Ft} &= \left(\mathrm{ft}_1, \ldots, \mathrm{ft}_8\right)\left(3, \frac{5}{12}, 2, 2, 4, 1, 2, 2\right),\\
C = \left(c_{ij}\right) &= \begin{pmatrix}
- & 7000 & 7240 & - & - & 7100 & - & - & 6950\\
55 & 62 & - & 71 & 75 & 61 & 74 & 76 & 79\\
230 & 241 & 245 & 221 & 198 & 225 & 237 & 220 & -\\
760 & 800 & 760 & 800 & 770 & 820 & 815 & 790 & 785\\
- & 365 & 370 & - & - & 386 & - & - & 370\\
470 & 435 & 435 & 430 & 450 & 470 & 460 & 445 & -\\
9280 & 8940 & 9050 & 8900 & 9300 & 8970 & 8900 & 9105 & -\\
5160 & 4700 & 5020 & 5150 & 4960 & 4940 & 5200 & 4750 & -
\end{pmatrix},\\
P = \left(\rho_{ij}\right) &= \begin{pmatrix}
- & 1.8 & 2.5 & - & - & 1.9 & - & - & 1\\
1 & 1.9 & - & 2.1 & 2.3 & 2.5 & 3 & 2.2 & 1.6\\
1.6 & 1.7 & 2 & 2 & 1 & 2 & 3 & 1.6 & -\\
1.2 & 1.3 & 0.7 & 0.9 & 1 & 0.8 & 1 & 1.3 & 0.7\\
- & 0.5 & 0.7 & - & - & 0.9 & - & - & 0.5\\
2.5 & 2.3 & 1.5 & 2 & 2.9 & 2.6 & 1.9 & 2 & -\\
0.7 & 0.55 & 0.6 & 0.5 & 0.3 & 0.5 & 0.4 & 0.7 & -\\
0.2 & 0.3 & 0.1 & 0.2 & 0.2 & 0.3 & 0.2 & 0.1 & -
\end{pmatrix},\\
T = \left(t_{ij}\right) &= \begin{pmatrix}
- & 2.9 & 3.3 & - & - & 3.1 & - & - & 2.7\\
0.3458 & 0.4 & - & 0.4042 & 0.4333 & 0.4083 & 0.4 & 0.4125 & 0.4083\\
2 & 1.9 & 1.8 & 1.6 & 1.6 & 1.6 & 1.7 & 1.7 & -\\
2 & 1.86 & 1.65 & 1.8 & 1.8 & 1.7 & 1.78 & 1.86 & 1.79\\
- & 3.5 & 3.3 & - & - & 3.5 & - & - & 3.9\\
1.2 & 1 & 0.8 & 0.7 & 0.9 & 0.9 & 0.7 & 0.8 & -\\
2 & 1.72 & 1.85 & 1.8 & 1.9 & 1.7 & 1.7 & 1.88 & -\\
1.9 & 1.82 & 1.8 & 1.95 & 1.8 & 1.7 & 1.78 & 1.66 & -
\end{pmatrix}.
\end{aligned} \tag{20}$$

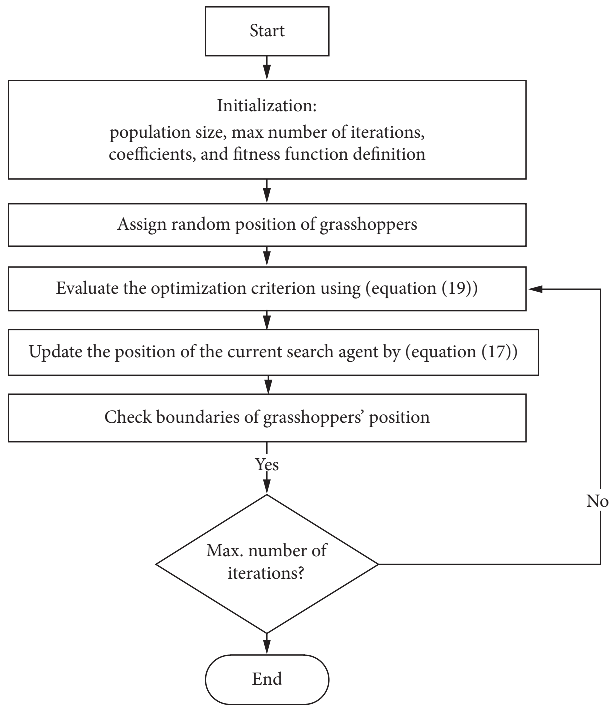

Figure 2: Flowchart for the biobjective optimization.

Initialize the swarm $X_i (i = 1, 2, \ldots, n)$
Initialize $c$max, $c$min, and maximum numbers of iterations
Calculate the fitness $f_1()$ and $f_2()$ of each search agent
T = the best search agent
While (l < Max number of iterations)
Update c using (equation (18))
for each search agent
Normalize the distance between grasshoppers
Update the position of the current search agent by equation (17)
Bring the current agent back if it goes outside the boundaries
end for
Update T if there is a better solution
$T = X_{i1}^d$ or X_{i2}^d
if $(f_1(T) > f_1(X_{i1}^d)) \& (f_2(T) > f_2(X_{i2}^d)) \& (\mathrm{GR}(X_{i1}^d, X_{i2}^d) > \Delta G)$
$l = l + 1$
end while
Return T

Algorithm 1

Current service-task matching plan is shown in Table 2, which means that the 8 tasks are conducted by resource 9, 1, 4, 5, 2, 3, 6, and 8, respectively. In such assignment, total cost is 9663600 CNY, and time needed is 14.1058 hours.

Table 2: Current service-task matching plan.

Task (i)	1	2	3	4	5	6	7	8
Resource (j)	9	1	4	5	2	3	6	8

6.2. Results and Discussion. The proposed task assignment model for service matching in the algorithm-based CL platform is then applied, as well as the proposed improved GROBO algorithm is introduced to solve the biobjective programming model. Meanwhile, comparisons are made with GROMO1, PSOMO (Particle Swarm Optimization-based Multiobjective Optimization), and NSGA-II (Improved Nondominated Sorting Genetic Algorithm). GROMO1 is also the grasshopper-based multiobjective algorithm which simply transfers multiobjective problem into single objective problem through a sum over the

Table 3: Solutions of optimization results.

Method	Objective $l\ C(x)$ (CNY)	Objective 2 $T(x)$ (h)	Runtime (s)
GROBO	$0.9315 * 1.0\hat{0}7$	14.1558	0.9510
GROMO1	$1.1748 * 1.0\hat{0}7$	14.7125	0.9333
PSOMO	$1.1854 * 1.0\hat{0}7$	14.4683	0.9621
NSGA-II	$0.9494 * 1.0\hat{0}7$	14.3683	2.4631

multiobjectives after standardization. The swarm population and max number of iterations are 100 and 100, respectively. Initial positions are random assigned. Results of simulations are shown in Table 3. From columns 1 and 2, it can be seen that the proposed algorithm performs better than others considering both of the two objective functions $C(x)$ and $T(x)$. Column 3 shows comparison of runtime. Therefore, comprehensively speaking, the proposed algorithm GROBO performs better than the others on optimization results without sacrifice in runtime. It is effective and efficient on the whole.

Solution from proposed algorithm is $(x)_{ij}$:

$$(x)_{ij} = \begin{pmatrix} 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \end{pmatrix}. \tag{21}$$

In such arrangement of task assignment, total cost is 9315000 CNY and time needed is 14.1558 hours. Compared with current arrangement, 348600 CNY can be saved, while almost the same time needed.

7. Conclusions and Limitations

A framework for the algorithm-based CL platform is established in this paper and its operational mode is described. Issue of nondeterministic task assignment for service matching is dealt with in this research, which is one of the most essential problems in the algorithm-based CL. An integrated logistics task assignment model is built to optimally match logistics service resources and tasks of large scale in the algorithm-based CL. Particularly, considering the large-scale services in CL environment, an improved grasshopper optimization-based bitarget optimization algorithm (GROBO) is proposed to solve the biobjective programming model for service matching in CL. The case of Linyi small commodity logistics is taken as a practical application. Comparisons with GROMO1, PSOMO, and NSGA-II are also provided to show the efficiency and effectiveness of the proposed model. Simulation results show that the proposed GROBO is of satisfactory performance regarding to searching efficiency and stability in solving the model.

Although our results show that cost can be reduced significantly with introduction of the algorithm-based CL platform, several loopholes may still remain for someone who takes advantages out of the algorithm-based platform. Behaviours of participators should be monitored and penalty mechanisms should be introduced to leave no loopholes. Scope of the work has been achieved, and the above-mentioned limitation of the algorithm-based CL platform is concerned with different areas from this work. We address the issue of nondeterministic task assignment for service matching in CL, while the mentioned problem is related to profit distribution mechanism and contract design, which will be the future work for the implementation and development of algorithm-based CL platform.

Data Availability

The simulation data used to support the findings of this study are from the reference Kong [5].

Conflicts of Interest

No potential conflicts of interest were reported by the authors.

Acknowledgments

The authors express sincere appreciation to Dr. Xianlei Lu for the helpful comments and suggestions to improve the quality of the paper. This work was supported by the Humanities and Social Science Foundation of Ministry of Education under Grant no. 19YJA880068.

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