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A Novel Bi-level Programming Model for Cloud Logistics Resources Allocation

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Abstract. The logistics resources allocation study involves many interests under the cloud logistics environment, but most previous publications focused the traditional decision making model in terms of quality of service (QoS) attributes including cost, quality and time, with ignoring the flexible factors and reliability of the cloud logistics service portfolio. To fill the gap, the uncertain factors of logistics service process and the interests of multi stakeholders including logistics service demanders and operators of cloud logistics service platform are considered in logistics resources allocation problem. The novel bi-level programming model is formulated based on QoS criteria and flexible factors of cloud logistics service composition. In addition, the non-dominated Sorting Genetic Algorithm II (NSGA-II) is designed and employed to deal with the NP-hard problem. A numerical case is conducted to verify the effectiveness of the established mathematical model and the validity of the algorithm.

Keywords: bi-level programming, cloud logistics, flexible factors, logistics resources allocation, non-dominated Sorting Genetic Algorithm II (NSGA-II)

1 Introduction

The soaring online consumption and the development of e-commerce have motived the theoretical and practical innovation of modern logistics by integrating with information technology and intelligent systems [1]. The information technologies contribute to the connection and integration of physical and virtual scenarios, which allows scaling autonomous logistics service in a more flexible way [2-3]. With an increasing focus on individualization, specialization and flexibility of the logistics service, the successful employment of cloud computing and IoT has promoted the innovation of the logistics by

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developing a new IT-based logistics service mode, calling cloud logistics [4]. The cloud logistics mode realizes the logistics resource matching optimization and agile service by combining advanced techniques (cloud computing, Internet of Things, SOA, communication protocol, and service-oriented technology). By managing a huge amount of distributed and idle logistics resources, cloud logistics provides a more efficient way to meet various logistics requirements [5].

In order to improve the service efficiency and achieve quick responses, the cloud logistics servicing mode through the e-commerce platform has adopted by Chinese logistics industry [6]. The information sharing philosophy and systematic optimization of logistics resources is regarded as a triumph for industrial applications. An increasing logistics enterprises are committing to participate the new logistics service mode, which not only improves the service efficiency and quick responses, but also assists organizations to achieve the cost reduction and resource deployment [7]. All participated physical logistics firms can be selected and regarded as optional service providers to meet the complex logistics tasks required.

To achieve the high efficiency and sustainability, the concept, mechanism, information technology and operations management of the loud logistics have been studied and addressed by many scholars and practitioners. Cloud logistics service (CLS) contributes to quicker resources searching and responses for both of the service provider and demander by virtualization of physical logistic resources in the whole procedures [8]. All the trades and negotiations can be implemented on the cloud logistics platform, and also the available logistics resources can be deployed and allocated concerning customer requirements. Both of the service provider and demander can acquire necessary information based on the network technique and internet-based systems. Driven by the physical logistics resources virtualization and cloud computing technologies, the real-time information-driven logistics resources allocation model has been studied and implemented. The sharing requirements and cloud logistics resources improves the efficiency of logistics service and makes it more flexible and personalized [9].

The resources of a logistics center are encapsulated in web, and logistics service demander can seek appropriate resources to fulfil the required tasks [8]. There are two kinds of logistics resources including online and offline resources, and customers can seek for the required logistics service configuration through the cloud logistics platform [10]. The coded logistics resources are storaged and can been searched at the cloud logistics platform, which can provide a dynamic information updates for logistics service demanders [11]. The effective operation and design of cloud platform are the prerequisite of the success of logistics resources deployment and efficiency improvement. Similar to cloud manufacturing resources allocation, the significant objective of the cloud logistics platform is to derive optimal service configuration results for logistics service demander [12]. Due to the complicated logistics tasks, and the discrepancy attributes in terms of cost, execution and service quality of different logistics service candidates, as well as lacking of enough contact, the logistics resources deployment and allocation is a difficult task and plays a significant role on the performance of cloud logistics service platform [13]. In addition, the performance of logistics resources allocation model and mechanism will directly influence the quality and efficiency of the logistics service, as well as the physical operations. Therefore, it is of great significance to study logistics resources allocation in the cloud logistics environment.

Even though there are some theoretical researches, the practical application of cloud logistics is still at its infancy. Due to the innovation of the cloud logistics, organizations can achieve more profit by joint distribution or resources sharing. Therefore, the scientific cooperation and profit allocation mechanism is of great significance in cloud logistics serve mode. Wang [14] constructed a linear optimization model to help the total cost minimization of logistics joint distribution network, and the modified Shapley value model is employed to deal with profit allocation through the strategic cooperative mechanism based on Game theory. The cloud logistics is a service mode for logistics service provisioning and management based on cloud computing and IOT technologies. One crucial issue of the cloud logistics mode is resources virtualization, and the other is solution generation including individual and complex services [8].

To improve the operation efficiency in cloud logistics service mode, a vast majority of decision making models and optimization techniques are developed and researched. Ficco [15] presented a simulation–based system in private cloud platform, and the multi-objective optimization method is developed to deal with task allocation. Ma [16] proposed an improved ELECTRE method to solve the time-aware trustworthiness ranking prediction of cloud service in risk-sensitive and performance-cost-sensitive industry scenarios. Liu [17] formulated a multi-objective scheduling model to optimize the total operation cost, finishing time and tardiness of logistics tasks considering time windows of resources and due date of tasks. Bi [18] formulated a multi-objective nonlinear programming model, targeting overall logistics cost minimization and distribution center optimization. Xu [19] developed a multi-objective optimization model to deal with the logistics resources assignment (TRA) problem concerning demand uncertainty, and a hybrid heuristic algorithm integrating genetic operations and Tabu search is designed to resolve the N-N model. The dynamic characteristic is one of the crucial factors in cloud logistics resource allocation, Nalan [20] proposed an extended evolutionary algorithm to solve the stochastic multi-period task-resources allocation problem. Based on the diversity and complexity of cloud logistics tasks and large-scale characteristics of data information, Wu [21] proposed a new cloud logistics mode to deploy the complex logistics sub-tasks, and a multi-objective programming model is formulated whose targets focus on operation cost, running time and delivery quality optimization. Another important optimization objective is the quality of service (QoS) in cloud scenarios [22-23]. Li [8] addressed the QoS attributes (time, cost, reliability and availability) by developing a multi-objective programming model to optimize the logistics resources.

The logistics resource allocation model can be applied to deal with the cloud logistics service portfolio selection for the complex logistics demander. Based on status of the logistics resources, the cloud logistics resources are divided into online service resources and off-line service resources. After being virtualized, the online service resources are directly encapsulated and run on the cloud logistics service platform, which can be queried and invoked by users, and returns the service result for the users. Because of the problems of goods, equipment, personnel, and information and so on, many logistics services more perform for the offline service resources. For off-line service resources, it is not sensitive to the make responses compared with online logistics resources, which may lead to failure of logistics service or low-efficiency.

The above-mentioned publications focus on cloud logistics techniques and logistics resource allocation study under certain scenario. In practical, due to the risks and uncertainties of the cloud logistics resources, as well as the dynamic logistics tasks, the occurrence of unpredictable risks may bring obstacles and delays on providing logistics services on the cloud platform, which will harm the stakeholders of the cloud logistics platform and participants. However, there exist a large number of uncertain or ambiguous factors due to the virtual characteristics that the heterogeneity, discrete distribution and autonomy of logistics resources, as well as the trans-temporal, spatial, autonomy of authority etc. [21]. The previous studies mainly focus on traditional performance indexes in terms of time, cost and quality, ignoring the uncertain factors especially under cloud logistics scenario. To provide a reliable cloud logistics service, not only QoS goals should be targeted as optimization objectives, but also the reliability and robustness of the logistics service provided should be taken into consideration. To fill this gap, the paper considers the uncertain factors in the optimization model, and develops a novel bi-level programming model for cloud logistics resource optimization, where the logistics service requester is the decision maker in the upper model, and the operator of cloud logistics service platform is the determiner in the lower model [24-25]. To solve the NP-hard problem, the non-dominated sorting genetic algorithm II (NSGA-II) is designed and employed in this study.

The contributions of this paper are threefold as follows:

(1) To improve the efficiency and robustness of cloud logistics platform, a novel bi-level programming model is formulated and developed to deal with the logistics resources allocation problem under cloud logistics scenario.

(2) The flexible factors are concerned in the bi-level programming model, including the capability of changing response on logistics resources and logistics tasks, as well as the process services performance of cloud logistics service portfolio.

(3) To solve the novel bi-level programming model, the non-dominated sorting genetic algorithm II (NSGA-II) is employed and applied in a practical logistics scenario.

The reminder of the paper is constructed as follows. The research problem is described in Section 2. Then we formulated the bi-level programming model in the subsequent section. In section 4, the non-dominated Sorting Genetic Algorithm II (NSGA-II) is designed to resolve the cloud logistics resources allocation problem. The numerical case is presented in Section 5. At last, we close the paper with conclusions.

2 Problem Description

Different from traditional logistics service modes, the cloud logistics includes the logistics service demanders, the logistics service providers and the cloud logistics service platform operators. The cloud logistics platform provides an opportunity for logistics service demanders to discover the corresponding logistics service provider in an efficient way. Also, the platform assists to build a link between demanders and suppliers. To improve the service efficiency under cloud logistics environment, how to allocate and deploy the logistics service resources to service demander is of great significance in cloud logistics. The logistics service resources (*LSR*) allocation process is presented in Fig. 1, and logistics resources owned by multi kinds of service providers are deployed to satisfy the complex logistics business.

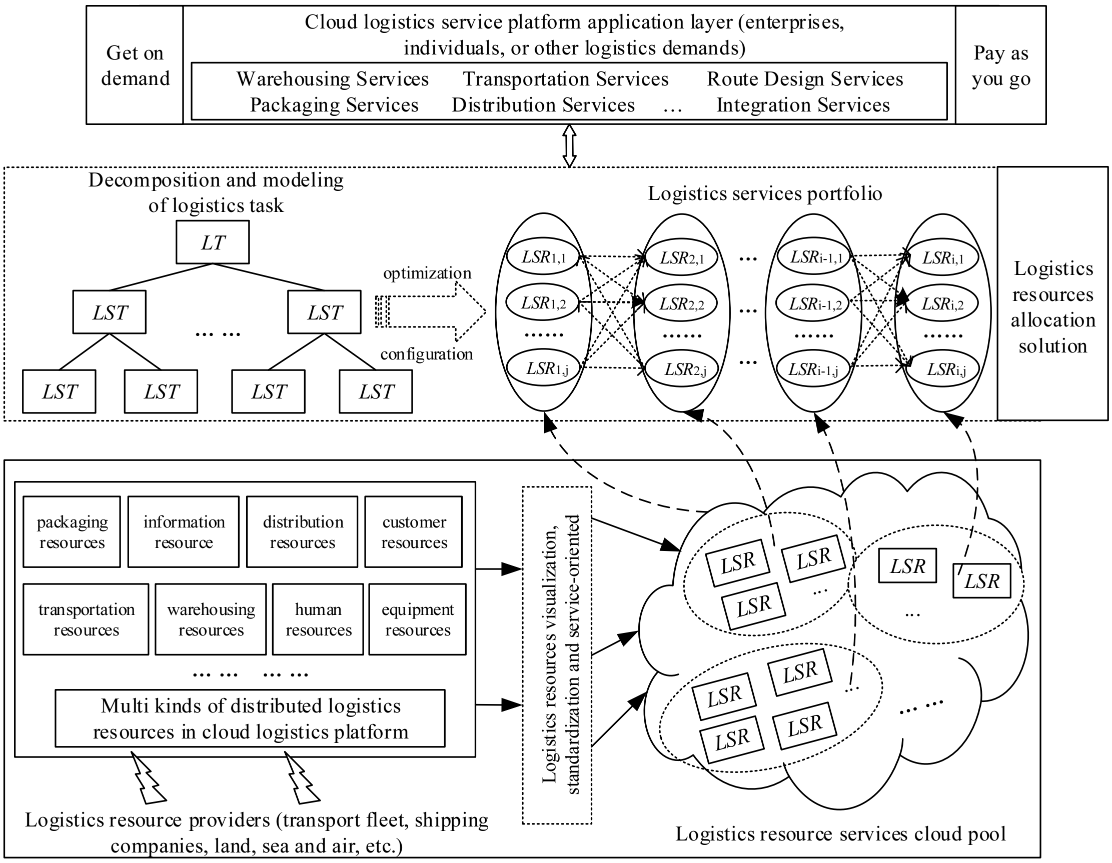

Fig. 1. The multi-stakeholders of logistics resources allocation model in cloud logistics platform

The cloud logistics service platform can provide full life cycle logistics services, including warehousing services, transportation services, packaging services, distribution services, information services, etc.

Due to the relatively coarse granularity of logistics tasks (*LT*), the cloud logistics service platform decomposes the complex *LT* into the implemented standard logistics sub-task (*LST*) sequence $LST_i\left(i \in \{1,2,...,n\}\right)$, and form the virtual logistics service resource cloud pool by means of virtualization and service. Each sub-task LST_i has k_i candidate resources, and $LSR_{i,j}\left(j \in \{1,2,...,k_i\}\right)$ denoted the j candidate resource of the i subtask.

3 Model Formulation

Logistics service composition is the main form of realizing complex logistics tasks in cloud logistics. The logistics service providing process is task-resource matching process, which can be regarded as an optimization model. In the choice of logistics services, customers often consider the QoS properties in terms of cost (*C*), time (*T*)and delivery quality (*Q*). The generated cloud logistics solutions are easily affected by the changes of logistics tasks and logistics resources, leading to the low quality and unsatisfied efficiency. Therefore, the flexible factors of the logistics service combination should be addressed during the logistics resources allocation in the cloud logistics platform, including the following three aspects: the capability to respond to the logistics tasks changes (F_T), the capability to respond to logistics resources changes (F_R) and process service evaluation (F_P).

The multi-objective problem is transformed to a single objective model by using linear weighting method and hierarchical optimization method. However, due to the multi-stakeholders' involvement, such as the logistics service demanders and the cloud logistics service platform operators. In addition, the interactive variable and constraints limits the application of traditional multi-objective optimization method. The Bi-level programming model is a hierarchical model, whose upper and lower layer optimization problems are their respective objective functions and constraints [5]. The lower-level optimization problem optimizes its objective function under the parameters of the upper-level optimization problem. The upper-level optimization problem depends on the optimal feedback of the lower-level optimization problem to optimize its objective function. The mathematical description of the bi-level programming model is:

$$(U) \min F\left(x, y\right) \tag{1}$$

$$\text{s.t. } G\left(x, y\right) \le 0 \tag{2}$$

$$(L) \min f\left(x, y\right) \tag{3}$$

$$\text{s.t. } g\left(x, y\right) \le 0 \tag{4}$$

which (*U*) is the upper level planning and (*L*) is the lower level planning; The Eq. (1) is the objective function of the upper layer planning and x is the decision variables for the upper level planning. Eq. (2) is the constraint for decision variable x. Similarly, Eq. (3) is the objective function of the lower layer planning and y is the decision variables for the lower level planning. Eq. (4) is the constraint for decision variable y.

Upper and lower optimization problems are relatively independent, and their optimization processes are interdependent. To consider the requirements of logistics service demanders and the risk of cloud logistics service platform operators simultaneously, the bi-level programming method is appropriate to solve the above-mentioned problem, which is illustrated in Fig. 2.

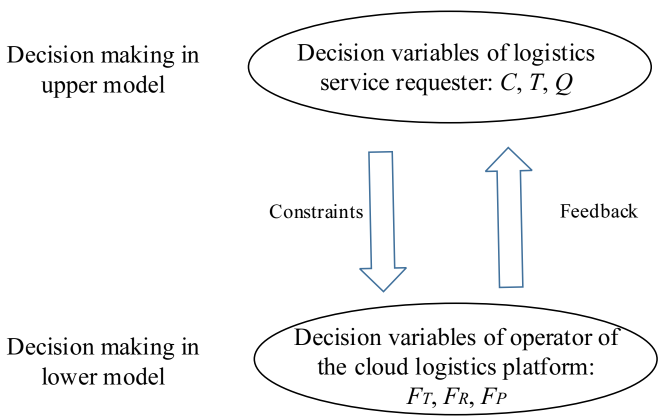

Fig. 2. Bi-level programming philosophy for cloud logistics resource allocation study

3.1 QoS's Attributes of Cloud Logistics Service Composition

In the cloud logistics resources allocation problem, the logistics service demanders are regarded as the upper decision maker in the bi-level programming model, and the QoS attributes of the cloud logistics service composition are measured. The objective functions of the cloud logistics service portfolio with respect to cost (C), time (T) and delivery quality (Q) are as follows:

Cost objective. The cost of cloud logistics service portfolio C includes the execution cost of each sub-task service C_z and the costs associated with warehousing, maintenance that occurred between tasks convergence C_b, where n is the number of logistics sub-tasks. The objective function of cloud logistics service portfolio cost C can be denoted as:

$$\min C = C_z + C_b = \sum_{i=1}^{n} C_z(i)u_i + \sum_{i=1}^{n} C_b(i,i+1)u_{i,i+1} \tag{5}$$

Time objective. The cloud logistics service portfolio time includes the execution time of each sub-task T_z and the waiting time between the task connection T_b. The objective function of cloud logistics service portfolio time T can be denoted as:

$$\min T = T_z + T_b = \sum_{i=1}^{n} T_z(i)u_i + \sum_{i=1}^{n} T_b(i,i+1)u_{i,i+1} \tag{6}$$

Delivery quality objective. The quality of delivery is measured by the delivery perfectness ratio of the goods at the time of the completion of the logistics sub-task Q_{qd}. The objective function of the delivery quality of cloud logistics service portfolio Q can be denoted as:

$$\min Q = 1 - Q_{qd} = 1 - \sum_{i=1}^{n} Q_{qd}(i)u_i \Big/ n \tag{7}$$

The constraints of the QoS attributes of the cloud logistics service portfolio are as follows:

$$C \le C_p \tag{8}$$

$$T \le T_p \tag{9}$$

$$Q_{qd} \ge Q_p \tag{10}$$

While, Eq. (8) means the total cost of completion of logistics tasks by cloud logistics service portfolio C cannot exceed the plan cost of the customer C_p; Eq. (9) means the total time of completion of logistics tasks by cloud logistics service portfolio T cannot exceed the expected total time T_p required by logistics customer; Eq. (10) means the delivery perfectness ratio of each logistics resource at the time of the completion of the logistics task cannot be less than the minimum delivery perfectness ratio of customer requirements.

According to the formulated objective functions and constraints, the QoS multi-objective optimization problem is transformed into a single objective problem by linear weighting method, which is as shown:

$$\min S = W_C\left(C/C_p\right) + W_T\left(T/T_p\right) + W_Q\left(Q/Q_p\right) \tag{11}$$

Where, W_C, W_T, and W_Q are relative importance of cost, time, and delivery quality objective attribute, respectively, and $W_C + W_T + W_Q = 1$.

3.2 Flexible Factors of Cloud Logistics Service Portfolio

In the problem of optimal allocation of logistics resources in the cloud logistics, the cloud logistics service platform operators are taken as the lower decision maker in the bi-level planning model. The flexible factors of the cloud logistics service portfolio are related to the reliability of the logistics service and the completion of the logistics task, which represented the interests of the lower decision-makers.

The objective function of flexible factors reflects the ability to cope with changes in logistics resources, the capability of change response of logistics tasks and process services performance of cloud logistics service portfolio are as shown:

The capability to cope with the changes of logistics resources. The reliability of logistics resource service F_{RR} , the number of logistics resources provided by the same supplier F_{RS} and the number of business cooperation F_{RC} would affect the capability of the cloud logistics service platform to cope with the changes of logistics resources F_R. The objective function can be denoted as:

$$\max F_R = W_{RR}F_{RR} + W_{RS}F_{RS} + W_{RC}F_{RC} = W_{RR}\frac{\sum_{i=1}^{n} F_{RR}(i)u_i}{n} + W_{RS}\frac{\sum_{i=1}^{n} F_{RS}(i)u_i}{n} + W_{RC}\frac{\sum_{i=1}^{n} F_{RC}(i)u_i}{n} \quad \textbf{(12)}$$

Where, $W_{RR} + W_{RS} + W_{RC} = 1$.

The capability to deal with the changes of logistics tasks. The number of enterprise cooperation of logistics resource providers F_{RC}, logistics resource functional diversity F_{TD} and its species F_{TV} would affect the capability of the cloud logistics service platform to cope with the logistics resources changes F_T. The objective function can be denoted as:

$$\max F_T = W_{TC}F_{RC} + W_{TD}F_{TD} + W_{TV}F_{TV} = W_{TC}\frac{\sum_{i=1}^{n} F_{RC}(i)u_i}{n} + W_{TD}\frac{\sum_{i=1}^{n} F_{TD}(i)u_i}{n} + W_{TV}\frac{\sum_{i=1}^{n} F_{TV}(i)u_i}{n} \quad \textbf{(13)}$$

Where, $W_{TC} + W_{TD} + W_{TV} = 1$.

Process service evaluation. The cloud logistics platform has made logistics service demanders more options, and consumers pay close attention to other personnel requirements. The logistics service demanders not only focus on the task accomplishment, but also the process techniques such as standard operation and information technology etc. Therefore, the process service performance is another considered index, and is denoted by the evaluation of diachronic service. The objective function can be denoted as:

$$\max F_P = \sum_{i=1}^{n} F_P(i)u_i \Big/ n \quad \textbf{(14)}$$

The constraints of the flexible factors of cloud logistics service portfolio are as follows:

$$F_{RR} \geq F_{RR\min} \quad \textbf{(15)}$$

$$F_{RS} \geq F_{RS\min} \quad \textbf{(16)}$$

$$F_{RC} \geq F_{RC\min} \quad \textbf{(17)}$$

$$F_{TD} \geq F_{TD\min} \quad \textbf{(18)}$$

$$F_{TV} \geq F_{TV\min} \quad \textbf{(19)}$$

$$F_P \geq F_{P\min} \quad \textbf{(20)}$$

Where, $F_{RR\min}$, $F_{RS\min}$, $F_{RC\min}$, $F_{TD\min}$, $F_{TV\min}$ and $F_{P\min}$ are the minimum reliability, the minimum number of logistics resources, the minimum number of cooperative enterprises, the minimum diversity of logistics resources, the minimum species of logistics resources and the minimum service evaluation that cloud logistics service platform required.

Therefore, the objective function of the flexible factors of cloud logistics service portfolio can be denoted as:

$$\max F = \left(F_R, F_T, F_P\right)^T \quad \textbf{(21)}$$

3.3 The Bi-level Programming Model

Based on the above analysis, the paper formulates the bi-level programming model to optimize logistics resources in the cloud logistics, which is as followed:

$$\text{(U)}\min S = W_C\left(C/C_p\right) + W_T\left(T/T_p\right) + W_Q\left(Q/Q_p\right),\ W_C + W_T + W_Q = 1 \quad \textbf{(22)}$$

$$\text{s.t. } C \le C_p \quad \textbf{(23)}$$

$$T \le T_p \quad \textbf{(24)}$$

$$Q_{qd} \ge Q_p \quad \textbf{(25)}$$

$$\sum_{i=1}^{n} u_i \ge 1 \quad \textbf{(26)}$$

$$u_i\left(u_i - 1\right) = 0 \quad \textbf{(27)}$$

$$\sum_{i=1}^{n} u_{i,i+1} \ge 1 \quad \textbf{(28)}$$

$$u_{i,i+1}\left(u_{i,i+1} - 1\right) = 0 \quad \textbf{(29)}$$

$$\text{(L)}\max F = \left(F_R, F_T, F_P\right)^T \quad \textbf{(30)}$$

$$\text{s.t. } F_{RR} \ge F_{RR\min} \quad \textbf{(31)}$$

$$F_{RS} \ge F_{RS\min} \quad \textbf{(32)}$$

$$F_{RC} \ge F_{RC\min} \quad \textbf{(33)}$$

$$F_{TD} \ge F_{TD\min} \quad \textbf{(34)}$$

$$F_{TV} \ge F_{TV\min} \quad \textbf{(35)}$$

$$F_P \ge F_{P\min} \quad \textbf{(36)}$$

$$\sum_{i=1}^{n} u_i \ge 1 \quad \textbf{(37)}$$

$$u_i\left(u_i - 1\right) = 0,\ i = 1, 2, \ldots, n \quad \textbf{(38)}$$

The model regards the logistics service demanders and cloud logistics service platform operators as the upper and lower optimization target, which guarantee the benefit of logistics service demanders. Besides, the risk and flexibility factors of cloud logistics service platform operators are also taken into account.

4 Algorithm Design

The problem of cloud logistics resources allocation problem has proven to be a NP-Hard problem [12, 26], and the bi-level programming model is formulated to deal with this industrial issue. The upper-level programming (U) is a single-objective optimization and the lower-level programming (L) is a multi-objective optimization. To solve the optimization problem, the NSGA-II algorithm is employed and applied in this paper, and the procedures of the algorithm are as follows.

Step 1. The search space of NSGA-II algorithm is limited in the constraints of the model, and encoded the cloud logistics service composition. Chromosome encoding expression is chosen generally applicable real number encoding, which solve the continuous parameter optimization problem, to form an individual gene corresponding to cloud logistics service combination [27].

Step 2. Let $t=0$; initialize the population p_0; the population size is N. The non-dominated rank and the distance of the population p_0 were calculated.

Step 3. The selection operation is performed from the non-dominant ranking value and the crowding degree in p_0 individuals to generate the sub-population Q_0 of scale N through crossing and mutating.

Step 4. The populations p_t and Q_t are merged to form a population R_t of scale $2N$.

Step 5. k non-dominated set of solutions $F_1, F_2, ..., F_k$ can be obtained by fast non-dominated sorting for R_t, in which F_1 is the optimal non-dominated set, and F_2 is the suboptimal non-dominated set. so on and so forth.

Step 6. When the total number more than N, which started from F_1 to take the genetic individual, assuming that the non-dominated solution set at this time F_i.

Step 7. Since the sum of the number of individuals in the monodominant solution set $F_1, F_2, ..., F_i$ is greater than N, congestion degree calculated the individuals in F_i. Choosing the better individuals in F_i and all the individuals from F_1 to F_{i+1} to make up a new population p_{t+1} of scope N according to the elite retention strategy,

Step 8. let $t=t+1$, and select, cross and variate p_{t+1} to form Q_{t+1}. Repeating the iterations from step 4 to step 8 until $t=\max gen$, and $\max gen$ is the maximum number of iterations to obtain the Pareto solution set of the lower layer objective function of the bi-level programming model of optimal allocation of logistics resources.

Step 9. The Pareto solution set obtained in step 8 is taken as the feasible solution set of the upper layer objective function of the bi-level programming model to calculate and sort the objective function values of each solution to obtain the final solution of the bi-level programming model.

5 Numerical Case

5.1 Background and Data Collection

Logistics tasks and the corresponding requirements are usually submitted to the cloud logistics service platform by users. Logistics tasks would be decomposed in to 6 (n=6) sub-logistics tasks LST_i by cloud logistics service platform according to certain rules. Each sub-logistics task LST_i will be served by a candidate logistics service $LSR_{i,j}$ and the finally there is a logistics resources portfolio, shown in Table 1. The parameters of the candidate logistics service in the bi-level programming model of logistics resources are shown as Table 2.

Table 1. Sub-logistics tasks and candidate logistics services

Logistics sub-tasks (LST)	LST_1	LST_2	LST_3	LST_4	LST_5	LST_6
Logistics service candidates	$LSR_{1,1}$	$LSR_{2,1}$	$LSR_{3,1}$	$LSR_{4,1}$	$LSR_{5,1}$	$LSR_{6,1}$
	$LSR_{1,2}$	$LSR_{2,2}$	$LSR_{3,2}$	$LSR_{4,2}$	$LSR_{5,2}$	$LSR_{6,2}$
	$LSR_{1,3}$	$LSR_{2,3}$	$LSR_{3,3}$	$LSR_{4,3}$	$LSR_{5,3}$	
		$LSR_{2,4}$		$LSR_{4,4}$		

Table 2. Relevant parameters of candidate logistics service

Logistics service candidates	C_z	C_b		Tz	Tb		Q_{qd}/%	F_{RR}/%	F_{RS}	F_{RC}	F_{TD}	F_{TV}	F_P/%
$LSR_{1,1}$	0.9	$LSR_{2,1}$	0.2	1	$LSR_{2,1}$	0.9	99.4	99.5	3	10	2	3	95
		$LSR_{2,2}$	0.3		$LSR_{2,2}$	1.1							
		$LSR_{2,3}$	0.4		$LSR_{2,3}$	1.3							
		$LSR_{2,4}$	0.3		$LSR_{2,4}$	0.9							
$LSR_{1,2}$	1.1	$LSR_{2,1}$	0.3	0.8	$LSR_{2,1}$	1.1	99.8	99.8	2	12	3	2	92
		$LSR_{2,2}$	0.4		$LSR_{2,2}$	1.2							
		$LSR_{2,3}$	0.2		$LSR_{2,3}$	0.9							
		$LSR_{2,4}$	0.4		$LSR_{2,4}$	1.3							
……							…….						
$LSR_{6,1}$	1	User	0.4	2	User	0.9	99.7	99.6	5	3	1	4	91
$LSR_{6,2}$	1.2	User	0.3	1.5	User	0.5	99.9	99.8	7	3	3	2	87

Assuming the parameters in the bi-level programming model example parameters were as follows: W_C=0.4 , W_T=0.3 , W_Q=0.3 ; W_{RR}=0.5 , W_{RS}=0.3 , W_{RC}=0.2 ; W_{TC}=0.3 , W_{TD}=0.4 , W_{TV}=0.3 ; C_p=200 , T_p=60 , Q_p=99.2% ; $F_{RR\min}$=89% , $F_{RS\min}$=1 , $F_{RC\min}$=3 , $F_{TD\min}$=1 , $F_{TV\min}$=2 , $F_{P\min}$=85% . The bi-level programming model of logistics resources allocation in Eq. (22)-(38) will becomes the following detail case:

$$\text{(U)}\min S=\min\left(C/175000+3T/100+Q/331\right) \quad \textbf{(39)}$$

$$s.t.\quad C\le 700000 \quad \textbf{(40)}$$

$$T\le 10 \quad \textbf{(41)}$$

$$Q_{qd}\ge 0.992 \quad \textbf{(42)}$$

$$\sum_{i=1}^{n}u_i\ge 1 \quad \textbf{(43)}$$

$$u_i\left(u_i-1\right)=0 \quad \textbf{(44)}$$

$$\sum_{i=1}^{n}u_{i,i+1}\ge 1 \quad \textbf{(45)}$$

$$u_{i,i+1}\left(u_{i,i+1}-1\right)=0 \quad \textbf{(46)}$$

$$\text{(L)}\max F=\left(F_R,F_T,F_P\right)^T \quad \textbf{(47)}$$

$$s.t.\quad F_{RR}\ge 0.89 \quad \textbf{(48)}$$

$$F_{RS}\ge 1 \quad \textbf{(49)}$$

$$F_{RC}\ge 3 \quad \textbf{(50)}$$

$$F_{TD}\ge 1 \quad \textbf{(51)}$$

$$F_{TV}\ge 2 \quad \textbf{(52)}$$

$$F_P \geq 0.85 \tag{53}$$

$$\sum_{i=1}^{n} u_i \geq 1 \tag{54}$$

$$u_i\left(u_i - 1\right) = 0\,,\ i = 1,2,\ldots,6 \tag{55}$$

5.2 Results

The NSGA-II genetic algorithm is used to solve the model example Eq. (39) – (55). Let initial population size of the algorithm P_0=100, maximum generation *Maxgen* is 150, crossover probability factor p_c=0.6, and mutation probability operator p_m=0.04. The designed algorithm is implemented in MATLAB R2016a (3.30GHz, 8.00G, and Windows 10).

After 30 generations of iterative evolution, the optimal Pareto optimal solution of the lower layer optimization model is obtained, and the Pareto front edge of the Pareto optimal solution set is calculated and can be found in Fig 3.

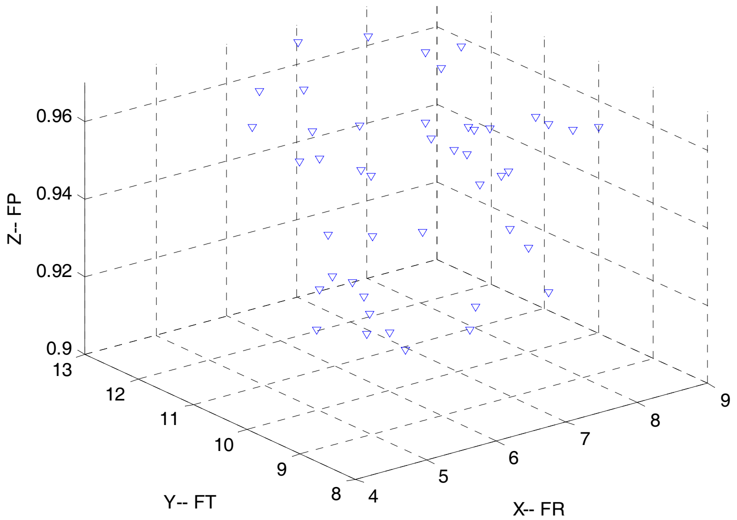

Fig. 3. The Pareto front of the lower optimization

The Pareto optimal solution of the lower layer optimization target of the logistics resource optimization model is taken as the feasible solution of the upper layer optimization goal. And then the optimal value of the corresponding upper layer optimization model can be derived and obtained. The first 5 groups are listed in Table 3 below. The results recommended the feasible solutions to cloud logistics service demanders in the cloud platform, and they can make decisions according to their specific circumstances.

Table 3. Optimal order of logistics resource allocation in cloud logistics

item	cloud logistics services portfolio						C	T	Q_{qd}/%	S
1	$LSR_{1,3}$	$LSR_{2,1}$	$LSR_{3,2}$	$LSR_{4,1}$	$LSR_{5,1}$	$LSR_{6,1}$	81.1	18.1	99.57	0.5537
2	$LSR_{1,1}$	$LSR_{2,1}$	$LSR_{3,2}$	$LSR_{4,1}$	$LSR_{5,3}$	$LSR_{6,2}$	82.9	17.9	99.62	0.5566
3	$LSR_{1,2}$	$LSR_{2,1}$	$LSR_{3,1}$	$LSR_{4,3}$	$LSR_{5,2}$	$LSR_{6,1}$	78.9	22.2	99.60	0.5700
4	$LSR_{1,2}$	$LSR_{2,3}$	$LSR_{3,3}$	$LSR_{4,2}$	$LSR_{5,2}$	$LSR_{6,2}$	81.6	22.2	99.82	0.5761
5	$LSR_{1,2}$	$LSR_{2,3}$	$LSR_{3,2}$	$LSR_{4,1}$	$LSR_{5,2}$	$LSR_{6,1}$	84.9	21.2	99.77	0.5775

Compared with previous publications, the benefits of cloud logistics platform operators and constraints are taken into consideration, and the bi-level programming model is constructed to deal with the cloud logistics resources allocation. The first 20 solutions of logistics resource portfolio thorough the upper layer model are generated and obtained as Table 4 listed. Meanwhile, the 20 solutions are ranked by non-dominance rank concerning flexible factors, and we can obtain the optimal solution of the bi-level programming model. The case verifies the validity of the proposed bi-level programming model and the employed algorithm.

Table 4. Optimal ranked of upper - level programming

Item	Cloud logistics services portfolio						C	T	Q_{qd}/%	S
1	$LSR_{1,1}$	$LSR_{2,4}$	$LSR_{3,1}$	$LSR_{4,1}$	$LSR_{5,1}$	$LSR_{6,1}$	75.3	19.3	99.5	0.5479
2	$LSR_{1,2}$	$LSR_{2,2}$	$LSR_{3,1}$	$LSR_{4,4}$	$LSR_{5,1}$	$LSR_{6,1}$	78.3	18.8	99.7	0.5520
3	$LSR_{1,1}$	$LSR_{2,1}$	$LSR_{3,1}$	$LSR_{4,1}$	$LSR_{5,3}$	$LSR_{6,2}$	77.3	19.3	99.6	0.5523
4	$LSR_{1,3}$	$LSR_{2,1}$	$LSR_{3,2}$	$LSR_{4,1}$	$LSR_{5,1}$	$LSR_{6,1}$	81.1	18.1	99.6	0.5537
5	$LSR_{1,1}$	$LSR_{2,1}$	$LSR_{3,2}$	$LSR_{4,4}$	$LSR_{5,1}$	$LSR_{6,2}$	81.6	18.3	99.7	0.5561
6	$LSR_{1,1}$	$LSR_{2,1}$	$LSR_{3,2}$	$LSR_{4,1}$	$LSR_{5,3}$	$LSR_{6,2}$	82.9	17.9	99.6	0.5566
7	$LSR_{1,1}$	$LSR_{2,1}$	$LSR_{3,3}$	$LSR_{4,2}$	$LSR_{5,1}$	$LSR_{6,1}$	78.3	20.7	99.6	0.5612
8	$LSR_{1,3}$	$LSR_{2,1}$	$LSR_{3,1}$	$LSR_{4,1}$	$LSR_{5,3}$	$LSR_{6,1}$	77.6	21.5	99.6	0.5636
9	$LSR_{1,2}$	$LSR_{2,1}$	$LSR_{3,2}$	$LSR_{4,3}$	$LSR_{5,3}$	$LSR_{6,1}$	84.0	19.6	99.7	0.5673
10	$LSR_{1,2}$	$LSR_{2,2}$	$LSR_{3,2}$	$LSR_{4,2}$	$LSR_{5,2}$	$LSR_{6,2}$	85.5	19.0	99.8	0.5678
11	$LSR_{1,2}$	$LSR_{2,1}$	$LSR_{3,1}$	$LSR_{4,3}$	$LSR_{5,2}$	$LSR_{6,1}$	78.9	22.2	99.6	0.5700
12	$LSR_{1,2}$	$LSR_{2,3}$	$LSR_{3,2}$	$LSR_{4,2}$	$LSR_{5,3}$	$LSR_{6,2}$	84.4	20.1	99.7	0.5707
13	$LSR_{1,2}$	$LSR_{2,3}$	$LSR_{3,3}$	$LSR_{4,2}$	$LSR_{5,2}$	$LSR_{6,2}$	81.6	22.2	99.8	0.5761
14	$LSR_{1,2}$	$LSR_{2,3}$	$LSR_{3,2}$	$LSR_{4,4}$	$LSR_{5,2}$	$LSR_{6,2}$	85.4	20.7	99.9	0.5763
15	$LSR_{1,2}$	$LSR_{2,3}$	$LSR_{3,2}$	$LSR_{4,2}$	$LSR_{5,2}$	$LSR_{6,1}$	85.5	20.9	99.8	0.5774
16	$LSR_{1,2}$	$LSR_{2,3}$	$LSR_{3,2}$	$LSR_{4,1}$	$LSR_{5,2}$	$LSR_{6,1}$	84.9	21.2	99.8	0.5775
17	$LSR_{1,1}$	$LSR_{2,1}$	$LSR_{3,3}$	$LSR_{4,1}$	$LSR_{5,2}$	$LSR_{6,1}$	81.8	23.0	99.6	0.5797
18	$LSR_{1,1}$	$LSR_{2,1}$	$LSR_{3,3}$	$LSR_{4,2}$	$LSR_{5,2}$	$LSR_{6,2}$	81.0	23.4	99.7	0.5804
19	$LSR_{1,2}$	$LSR_{2,3}$	$LSR_{3,2}$	$LSR_{4,4}$	$LSR_{5,2}$	$LSR_{6,1}$	86.0	21.6	99.8	0.5818
20	$LSR_{1,3}$	$LSR_{2,4}$	$LSR_{3,2}$	$LSR_{4,3}$	$LSR_{5,2}$	$LSR_{6,1}$	85.1	23.5	99.7	0.5891

5.3 Algorithm Efficiency Experiment

To verify the effectiveness of the employed algorithm, the algorithm efficiency is validated by experiment tests.

The population size (P0) and maximum generation (*Maxgen*) are of great significance to algorithm's performance [28-29]. To validate the algorithm efficiency, we perform the experiment analysis on P0 and *Maxgen* parameter. The operation time of the designed algorithm is found in Fig. 4 when population size covering from 50 to 500, and in Fig. 5 when maximum generation (*Maxgen*) increasing from 100 to 1000.

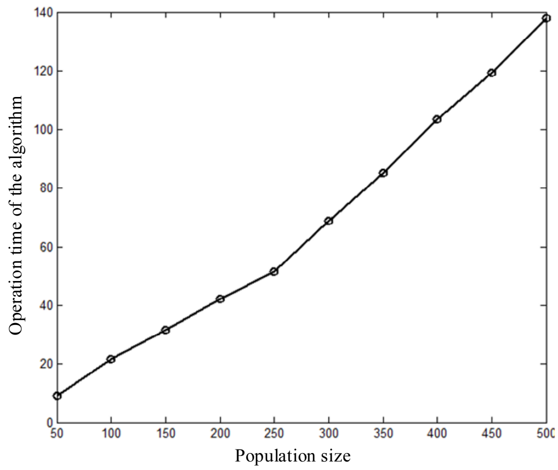

Fig. 4. Operation time regarding P0

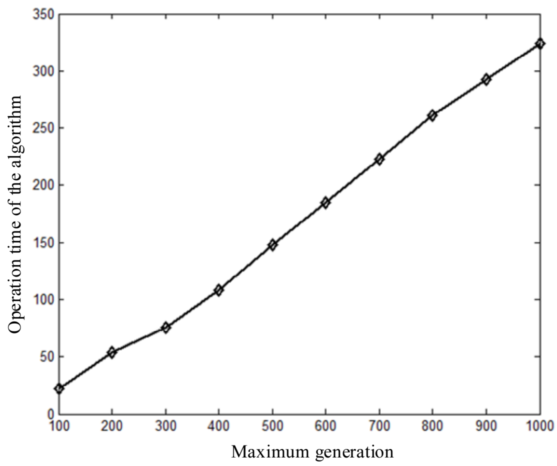

Fig. 5. Operation time regarding *Maxgen*

As can be seen from the abovementioned two figures, the operation time of the algorithm increases with the growth of population size P0 and *Maxgen* parameters. However, it takes 23.8 seconds to derive the best solution, and the operation time is acceptable for cloud logistics platform.

5.4 Managerial Insight

Considering the unexpected situations in the process of logistics task service, as well as the profits of logistics service demanders and cloud logistics service platform operators, the novel bi-level programming model is constructed to deal with logistics allocation problem. This study contributes to the deployment of logistics resources for the cloud logistics platform.

The logistics resources allocation and deployment is the main realization form of the accomplishment of logistics tasks in cloud platform [30]. The cloud logistics tasks contain a many kinds of tasks with multi procedures in cloud platform, which can be served by many resource combinations. There is a vast majority of logistics resources in the cloud platform with different attributes (cost, delivery time and service quality etc.), and how to deploy the discrete logistics resources to the dynamic logistics task is a very complex job and is significant to the operation of the cloud logistics platform. The bi-level model in this paper contributes to the efficiency improvement of cloud logistics service.

However, the uncertain and risk factors are also influence the reliability of logistics service in industrial application. Therefore, the flexible attributes are taken into account for cloud logistics resource allocation in this paper, besides the requirement of the logistics demanders is addressed. All the constraints considered in the model are conducive to the smooth operation and high robustness of cloud logistics service. The twofold contributions of the cloud logistics service allocation model provide a guarantee for the guarantee for the operation of cloud logistics platform.

6 Conclusion

In this paper, we address the logistics resources deployment model considering flexible factors, and a novel bi-level programming model is formulated to cope with cloud logistics resources allocation problem. The proposed model not only guarantees the benefits of the logistics service demanders and the cloud logistics service platform operators, but also ensures that the logistics tasks of consumers are served and carried out smoothly. Besides, the non-dominated sorting genetic algorithm (NSGA-II) of elite strategy is employed to solve the programming model.

This paper by researching the cloud logistics resources allocation problem with a bi-level programming model enriches and contributes to the development of cloud logistics, while there exist some limitations. Due to the complexity and diversity of logistics tasks and logistics resources, as well as the increasingly dynamic characteristics under cloud logistics environment, this study is assumed that each logistics sub-task is served by only one candidate. However, in practice, the cloud logistics platform serves for a vast majority of logistics enterprises with multiple kinds of logistics tasks. Therefore, the deeper study of more complex logistics resources deployment that one logistics task can be served by the logistics resource combination will be preferred. Besides, other heuristic algorithms with different optimization strategies also need to be developed to improve the efficiency of the problem-solving in the future.

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