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Activity assigning of fourth party logistics by particle swarm optimization-based preemptive fuzzy integer goal programming

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ABSTRACT

This paper proposes modified particle swarm optimization to solve the problem of activity assignment of fourth party logistics (4PL) with preemptive structure. In practice, decision makers must consider goals of different importance when they encounter 4PL decision problems. Previous studies have adopted weighted fuzzy goal programming to design optimization problems. However, it is difficult for decision makers to determine proper weights. This paper proposes a decision making method based on preemptive fuzzy goal programming and a modified PSO. The proposed method does not require weights, and prevents results without feasible solutions caused by improper resource setting. Furthermore, this paper proposes a modified PSO with mutation operator extension. Numerical analysis shows that proposed modified PSOs prevent algorithms from caving prematurely into local optimums.

1. Introduction

Cost reduction is one way for enterprises to increase their competitiveness when faced with the trends of the global manufacturing market. Some enterprises' logistics operations do not belong to their core competence. In recent years, enterprises have outsourced their logistics operations to logistics service providers to lower transportation costs. The service providers are known as third party logistics (3PL). 3PL service has grown rapidly since 1991. Lieb and Bentz (2004) showed that 83% of the top 500 manufacturers in the United States had already adopted 3PL service by 2003. However, most traditional 3PL providers only provide transportation and warehousing services. Foster (1999) pointed out that 3PL lacks the optimal integration capability for technology, warehousing capabilities and transportation service. Therefore, shippers and 3PL providers are not able to execute supply chain management themselves. They must execute supply chain integration and management with the aid of professional decision makers. Fourth party logistics (4PL) encourages strategic alliance among 3PLs, and manages the logistic process within the entire supply chain member. Bumstead and Cannons (2002), Lau and Goh (2002), and Mukhopadhyay and Setaputra (2006) provide the definitions and advantages of 4PL.

Previous studies on 3PL focused on distribution network planning. Ko, Ko, and Kim (2006) proposed a hybrid optimization and simulation approach in an uncertain environment, and created a dynamic 3PL distribution network problem. Ko and Evans (2007) adopted a mixed integer nonlinear programming model to plan a dynamic integrated 3PL distribution network that considers reverse logistics. Min and Ko (2008) proposed a reverse logistics problem with the location and allocation of repair facilities for 3PL management, which adopted a mixed integer programming model. However, past 3PL management approaches only considered single goal programming. 4PL operation executes logistics planning and considers supply chain resources allotment. Li, Ying, Liu, Chen, and Huang (2003) constructed a 4PL decision optimization problem for routing optimization that considers job decomposition and job assignment. Huang, Tong, Wang, Xu, and Wang (2006) adopted nonlinear integer programming and multi-graph to construct a 4PL routing optimization problem. Liu and Yao (2007) proposed a multi-objective optimization problem for the 4PL supply chain, which considers resource integration. They demonstrate goal importance by setting each goal's weight. However, practice enterprises may raise priorities for goals, according to customer requirements and the managers' viewpoints. Goal programming (GP) allows the expected target for each goal and allows tolerance. The primary objective of GP is to minimize deviation variables. The traditional GP model tends to be affected by targets with larger numbers. Fuzzy GP is capable of correcting this drawback, and the fuzzy membership function can demonstrate various functions of the achievement degree. Under goals of different importance, this paper constructs a 4PL activity assignment problem through a preemptive fuzzy goal programming model.

Weighted fuzzy GP and preemptive fuzzy GP are most widely adopted to construct decision problems for goals of different importance. The decision maker has difficulty determining weights in a weighted fuzzy GP model. In previous studies, each priority level's

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lower bound of preemptive fuzzy GP had to be set. This led to no feasible solution. This paper proposes a modified particle swarm optimization to solve the preemptive fuzzy zeros-one integer goal programming of 4PL operation assignment problem (PFZOIGP_4PLOAP). The determination of the goal weight and the priority level's lower bound is not required by the proposed method. The remainder of the paper is organized as follows: Section 2 introduces the assignment problem and previous studies related to GP; Section 3 constructs the proposed problem; Section 4 designs the modified PSO for PFZOIGP_4PLOAP. Section 5 analyzes the performance of the modified PSO, and the conclusions for this paper are in Section 6.

2. Relevant literature

Different from multi-objective programming, weighted fuzzy GP and preemptive fuzzy GP considers goals of different importance which are suitable for a decision environment with flexible resources.

2.1. Activity assignment problem

4PL operations integrate enterprises' and 3PL providers' resources. Leung, Cheung, and Hui (2000) proposed an e-commerce community network framework that took the effect of integration and consolidation effect into account. They introduced aviation logistics functions, and highlighted that activity integration and job consolidation lead to savings on transportation costs. Crainic (2000) also mentioned that effective operations consolidation improves enterprise resource utilization. Spellmann, Erickson, and Reynolds (2003) pointed out that server consolidation lowers the total cost of ownership and increases service levels. Berman (2006) illustrated that under global market trends, enterprises must satisfy multi-national customers, and the integration of multiple 3PL providers is a necessary operation management. According to the works above, it is clear that effective operations consolidation improves resource utilization and lowers transportation costs.

Most previous research adopted single objective mathematical programming to solve the activities/jobs assignment problem that considers operation integration and consolidation. Gui, Gong, and Cheng (2008) developed a cargo forwarders consolidation problem based on mixed integer programming. The purpose of their problem was to discover an optimal cargo item assignment to minimize the total expense paid. Bookbinder and Higginson (2002) proposed a probabilistic model based on the Poisson process and gamma distribution to search for optimal freight consolidation. Tyan, Wang, and Du (2003) adopted a mathematical programming model to construct the freight consolidation problem, and analyzed the performance of three freight consolidation policies. Wong, Leung, and Hui (2009) proposed a shipment planning problem that took into account integrations and consolidations; in their problem, the resource does not allow tolerance, and operations constraints include: the target deliver time, capacity limit, and target costs. The objective of their problem was to discover an optimal activities/jobs assignment to minimize setup and processing costs. Previous research considered a single objective, and did not allow resource tolerance. In practice, a decisions problem may need to consider multi-objective, and goals importance as different. Generally, managers also use a flexible resource to plan the decision problems. Preemptive GP is able to satisfy these decision conditions.

2.2. Preemptive fuzzy goal programming

In preemptive GP, decision makers divide goals into H priority levels. Goals of the same importance are categorized into the same priority level. First, the best solution is determined by the objective value of the upper priority level. When objective values of the upper priority level for two solutions are identical, the lower priority level's objective value will determine the better solution. In traditional preemptive GP, it is difficult for decision makers to determine a crisp target. In the same priority level, it tends to be affected by a goal of a larger number. Preemptive fuzzy GP prevents these drawbacks. Tsai, You, Lin, and Tsai (2008) adopted preemptive fuzzy GP to solve a channel allocation problem. The objectives of their problem include maximizing net profits, minimizing the customer claims rate, and minimizing the late lading rate. Chen and Weng (2006) adopted a preemptive fuzzy GP to design quality function deployment. Chen and Tsai (2001) designed constraints to render variables of the achievement degree of an upper priority level larger than those of a lower priority level. In the methodologies mentioned above, if decision makers make improper lower bounds for priority level, no feasible solution will be found.

In some studies such as: Iskander (2004), Tiwari, Dharmar, and Rao (1987), Hannan (1981) and Kim and Whang (1998), weighted fuzzy GP highlights goals with more importance by setting weights. It is difficult for decision maker to determine a goal weight. Badri (2001) adopted an analytic hierarchy process to determine object weight. To consider objectives of different importance, the approach taken by some studies is to increase problem constraints and sub-problems. Such studies include: Wang and Fu (1997), Akőz and Petrovic (2007) and Tiwari, Dharmar, and Rao (1986). This paper proposes a method based on a modified PSO and preemptive fuzzy GP. The proposed method does not require setting of weight and lower bound of the priority level, and only the fuzzy membership function was added.

3. Mathematical formulation for PFZOIGP_4PLOAP

Primary 4PL operation management assigns jobs to suitable 3PL provider to conduct transportation operations. In the proposed, resource constraints are flexible. In other words, resource constraints allow tolerance. This paper demonstrates a flexible resource scenario with the fuzzy theory. Furthermore, this paper transforms the fuzzy model into a crisp problem.

3.1. Fuzzy mathematical model

One of the characteristics of the proposed problem is that it considers the effect of integration and consolidation. The integration effect means that when a job is done by the same provider, and when two or more consecutive activities are executed, the setup cost is reduced. Π_l represents l-th consecutive integrated elements set. The consolidation effect is the consolidation of jobs that lowers setup costs. In other words, when a 3PL provider executes different jobs in the same activity, these jobs can be consolidated and executed collectively. Therefore the setup costs can be shared by these various jobs. Ψ_m represents m-th elements set so that different jobs are consolidated. Other notations in this paper are defined as follows:

Decision variables

x_{ijk} 1 if provider i is selected for performing activity j of job k, 0 otherwise

Y 1 if all elements in integration set Π_l are selected, 0 otherwise

z_m 1 if all elements in consolidation set Ψ_m are selected, 0 otherwise

Parameters

s_{ijk} costs for provider i that is designated to execute activity j of job k (i.e., setup cost and processing cost)

p_l reduced setup cost when all elements in integration set Π_l are integrated
q_m reduced setup cost when all elements in consolidation set Ψ_m are consolidated
C available budget resource
a_{jk} the capacity requirement for activity j in job k
A_{ij} the load capacity of provider i for activity j
Q_k maximum acceptable defect rate for job k
b_k product quantity of job k
d_{ijk} defect percent when provider i is designated to execute activity j of job k
C^U tolerance upper limit for resource C
A_{ij}^U tolerance upper limit for resource A_{ij}
Q_k^U tolerance upper limit for acceptable defect rate Q_k
L very large number
w_l^I number of elements in integration set Π_l
w_m^C number of elements in consolidation set Ψ_m

PFZOIGP_4PLOAP assign the activities of each operation to suitable 3PL providers to execute transportation operations. Objectives of the proposed problem include: minimizing budget resources, load capacity, and defect quantity. This paper prevents solutions from being affected by larger goals with the fuzzy theory. This approach normalizes each goal and limits the target achievement degree between 0 and 1. Goals and constraints of PFZOIGP_4PLOAP are formulated as follows:

(1) *Fuzzy goal 1:* Budget constraints

The first objective for PFZOIGP_4PLOAP is budget constraints. Overall cost should be less than or equal to the decision makers budget. The more total cost exceeds the budget the lower the degree of satisfaction. Because of the integration effect and consolidation effect, as seen in Eq. (1) the total cost calculation is: operation cost minus the saved setup cost.

$$Z_1 = \sum_i \sum_j \sum_k s_{ijk} x_{ijk} - \sum_l p_l y_l - \sum_m q_m z_m \underset{\sim}{\leq} C \tag{1}$$

where symbol "$\underset{\sim}{\leq}$" denotes fuzziness of $\leqslant$, i.e., approximately less than or equal to.

(2) *Fuzzy goal 2:* Load capacity limit

The number of activities for the 3PL provider to execute jobs should be less than or equal to the load capacity constraint it can handle. The more the capacity requirement of the 3PL provider exceeds load capacity constraints, the lower the degree of satisfaction, as seen in Eq. (2).

$$Z_{2ij} = \sum_k a_{jk} x_{ijk} \underset{\sim}{\leq} A_{ij} \quad \forall ij \tag{2}$$

(3) *Fuzzy goal 3:* Quality constraints

The quantity of defect products should be smaller than or equal to maximum acceptable defect quantity. The larger product defect quantity exceeds maximum acceptable defect quantity, the lower the degree of satisfaction, as seen in Eq. (3).

$$Z_{3k} = \sum_i \sum_j d_{ijk} b_k x_{ijk} \underset{\sim}{\leq} Q_k b_k \quad \forall k \tag{3}$$

(4) Hard constraints

$$\sum_i x_{ijk} = 1 \quad \forall j,k \tag{4}$$

$$y_l \leq x_{ijk} \quad \forall x_{ijk} \in \Pi_l \tag{5}$$

$$z_m \leq x_{ijk} \quad \forall x_{ijk} \in \Psi_m \tag{6}$$

$$\sum_{x_{ijk} \in \Pi_l} x_{ijk} - w_l^I + 1 \leqslant y_l + \sum_{\Pi_{l'} \in \Pi_l} y_{l'} \quad \forall l \tag{7}$$

$$\sum_{\Pi_{l'} \in \Pi_l} y_{l'} \leqslant (1 - y_l)L \quad \forall l \tag{8}$$

$$\sum_{x_{ijk} \in \Psi_m} x_{ijk} - w_m^C + 1 \leqslant z_m + \sum_{\Psi_{m'} \in \Psi_m} z_{m'} \quad \forall m \tag{9}$$

$$\sum_{\Psi_{m'} \in \Psi_m} z_{m'} \leqslant (1 - z_m)L \quad \forall m \tag{10}$$

$$x_{ijk}, y_l, z_m \in \{0,1\} \quad \forall i,j,k,l,m \tag{11}$$

Note that $\Pi_{l'}$ is a sub-integration of the integration set Π_l. $\Psi_{m'}$ is a sub-consolidation of consolidation set Ψ_m.

Eq. (4) shows that activity j of job k can only be dispatched to one 3PL provider. Eq. (5) indicates the integration of consecutive activities, Eq. (6) indicates the consolidation of jobs. When integration set Π_l is equal to 1, Eqs. (7) and (8) ensure that sub-integrations $\Pi_{l'}$ are not equal to 1. When consolidation set Ψ_m is equal to 1, Eqs. (9) and (10) ensure that sub-consolidations $\Psi_{m'}$ are not equal to 1. Eq. (11) is a zero-one integer constraint.

3.2. Crisp mathematical model

In PFZOIGP_4PLOAP, goals of different priority level vary. However, goals of each priority level possess additivity. This paper transforms a fuzzy mathematic model into an equivalent crisp formulation by a non-increasing function (Zimmermann, 1978). In this crisp formulation, the overall objective function is comprised of three variables of the achievement degree. The overall objective function is constructed as follows:

(1) Overall objective function

$$\text{Lexmax}\left\{\mu_{Z_1}, \sum_i \sum_j \mu_{Z_{2ij}}, \sum_k \mu_{Z_{3k}}\right\} \tag{12}$$

where lexmax defines lexicographical maximization of variables of the achievement degree.

(2) Goal constraints

$$\mu_{Z_1} = \begin{cases} 1 & \text{if} Z_1 \leqslant C \\ \frac{C^U - Z_1}{C^U - C} & \text{if } C < Z_1 \leq C^U \\ 0 & \text{if } C^U < Z_1 \end{cases} \tag{13}$$

$$\mu_{Z_{2ij}} = \begin{cases} 1 & \text{if } Z_{2ij} \leq A_{ij} \\ \frac{A_{ij}^U - Z_{2ij}}{A_{ij}^U - A_{ij}} & \text{if } A_{ij} < Z_{2ij} \leq A_{ij}^U \\ 0 & \text{if } A_{ij}^U < Z_{2ij} \end{cases} \tag{14}$$

$$\mu_{Z_{3k}} = \begin{cases} 1 & \text{if } Z_{3k} \leq Q_k b_k \\ \frac{Q_k^U b_k - Z_{3k}}{Q_k^U b_k - Q_k b_k} & \text{if } Q_k b_k < Z_{3k} \leq Q_k^U b_k \\ 0 & \text{if } Q_k^U b_k < Z_{3k} \end{cases} \tag{15}$$

This paper adopts a non-increasing function (Zimmermann, 1978) to demonstrate the three variables of the achievement degree: μ_{Z_1}, $\mu_{Z_{2ij}}$, and $\mu_{Z_{3k}}$, as seen in Eqs. (13)–(15). Other constraints of the crisp model are shown in Eqs. (4)–(11).

4. Preemptive goal evolutionary algorithm

PSO is an evolutionary computation that simulates the behavior of flocks of birds and schools of fish. The algorithm was first developed by Kennedy and Eberhart (1995) and swarm intelligence was further developed into an optimization technique. PSO is an algorithm that possesses memory. The global best solution during PSO's execution is memorized and each individual particle memories individual best solution is determined. Individual particles determine the distance and direction for moving, according to two memories. PSO is often adopted to solve multi-objective programming problems, as seen in: Omkar, Mudigere, Naik, and Gopalakrishnan (2008), Janson, Merkle, and Middendorf (2008), Wang and Singh (2008), Coello et al. (2004), and Hu and Eberhart (2002). However, multi-objective programming determines the Pareto optimal solution. In contrast to multi-objective programming, preemptive GP divides goals into several preemptive levels. Shi and Eberhart (1998) further added inertia weight in PSO. Inertia weight adjusts the importance of the global best solution and personal best solution. This paper proposes an algorithm that is applicable in preemptive GP, MPSO. The MPSO includes the mutation operator.

4.1. Solution representation

During programming, the main decision of the proposed modified PSO is to select a suitable 3PL provider i to execute activity j of job k. This paper applies matrix $\boldsymbol{S} = \{S_{jk} \mid k = 1, 2, \ldots, M; j = 1, 2, \ldots, N\}$ as a solution representation. S_{jk} defines a 3PL provider that executes activity j of job k. For instance, $S_{25} = 3$ means decision variable $x_{325} = 1$. Fig. 1 is an illustrative example for encoding. In the example, four jobs and five activities need to be assigned for each job. In the solution of the example, activity 5 of job 2 is executed by provider 3. To determine decision variables y_l and z_m, this paper select optimal integrations and consolidations among feasible solutions to maximize saving.

4.2. Update the new solution

In the PSO algorithm, the individual particle determines the distance and direction of movement by updating the velocity. Updating velocity is mainly affected by two memories. One is the individual best solution S^P_{jke}, and another is the global best solution S^G_{jk}. The velocity of updated particle e for activity j of job k is shown as follows:

$$v_{jke} = w v_{jke} + \phi_1 r_1 (S^P_{jke} - S_{jke}) + \phi_2 r_2 \left(S^G_{jk} - S_{jke}\right), \tag{16}$$

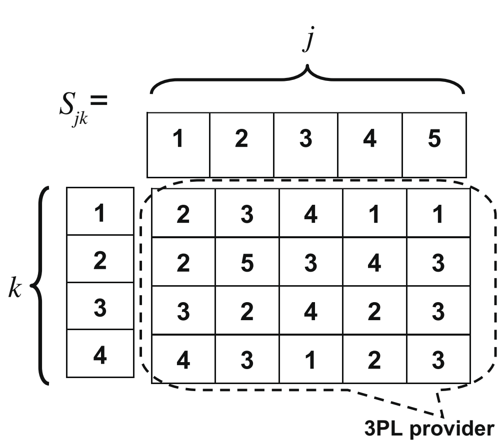


Fig. 1. An example of solution.

where S^P_{jke} presents current individual best solution for particle e in activity j of job k, S^G_{jk} presents current global best solution in activity j of job k. S_{jke} presents current solution for particle e in activity j of job k. w, ϕ_1 and ϕ_2 present adjustable parameters. r_1 and r_2 are uniformly random real value between [0, 1]. Updating solution for particle e in activity j of job k is shown as follows:

$$S_{jke} = I[S_{jke} + v_{jke}], \tag{17}$$

where $I[\ ]$ is the integer closest to the variable.

Note that $S_{jke} \in [S_{\min}, S_{\max}]$. $S_{\max}$ and $S_{\min}$ are the upper and lower feasible domain bounds of the variable S_{jke}, respectively.

4.3. Algorithm procedure

Most previous works solved preemptive GP problems by setting the bound of variables of the achievement degree. However, an improper bound setting may lead to a scenario without a feasible solution. This proposed algorithm does not set the bound of the priority level for preemptive GP problems. This paper proposes a MPSO approach which considers a mutation operator to determine the best matrix $\boldsymbol{S}$. In PFZOIGP_4PLOAP, each particle contains H goals of priority levels. The implementation procedure of this MPSO is shown as follows:

Step 1. Input parameters for the proposed algorithm (i.e., w, ϕ_1, ϕ_2, number of particles E, mutation rate b, δ, and maximum number of iterations G), and set initial iteration $g = 1$.
Step 2. Randomly generate E sets of initial solution and initial velocities.
Step 3. Calculate objective value p_d of priority level d for each particle. Then sort the particles by p_1 (i.e., μ_{Z_1}) value. If different particles possess same p_1 value, then sort particles by p_2 (i.e., $\sum_i \sum_j \mu_{Z_{2ij}}$), and so on. Best particle is ranked as rank 1.
Step 4. Memorize present individual best solution S^P_{jke} and present global best solution S^G_{jk}.
Step 5. Update velocity of the particle as Eq. (16).
Step 6. Update particle position (i.e., solution) through Eq. (17).
Step 7. If particle e satisfies mutation condition (i.e., $r_3 \leqslant b$) in activity j of job k, then the position of particle e is changed as follows:

$$S_{jke} = S_{jke} + \begin{cases} I\left[\frac{\delta(r_4 - 0.5)(S_{\max} - S_{jke})(G-g)}{G}\right], & \text{if } r_4 - 0.5 > 0 \\ I\left[\frac{\delta(r_4 - 0.5)(S_{jke} - S_{\max})(G-g)}{G}\right], & \text{otherwise} \end{cases} \tag{18}$$

where r_3 and r_4 are random numbers between [0, 1]. δ is an adjustable parameter.
Step 8. Calculate objective values p_d of each particle's priority level d, and update S^P_{jke} and S^G_{jk}.
Step 9. If $g \geqslant G$, then next step, else go to the Step 5 and $g = g + 1$.
Step 10. Return S^G_{jk}.

5. Implementation of PSO

In this paper, the 4PL operation assigns activities of each job to a suitable 3PL provider. In numerical analysis, this paper analyzes the effect of solution quality of MPSO. The effect of the resource and tolerance setting to the assignment result is also an important analytical point of this paper.

Table 1
Parameters of the test problem.

s_{ijk}	a_{jk}	A_{ij}
Discrete $U(1, 5)$	Discrete $U(1, 10)$	Discrete $U(1, 6)$
A_{ij}^U	b_k	d_{ijk}
Discrete $U(60, 90)$	Discrete $U(80, 210)$	$U(0.001, 0.009)$
Q_k	Q_k^U	
$U(0.001, 0.1)$	Discrete $U(20, 60)$	

5.1. Performance test

Wong, Chen, and Su (2008) propose a PSO approach which considers a perturbation strategy. The algorithm is called PPSO. The main feature of PPSO is that it prevents the algorithm from caving prematurely into local optimum due to perturbing particle velocity. In PFZOIGP_4PLOAP, this paper compares the performance of MPSO, traditional PSO (Shi & Eberhart, 1998) and PPSO. In the problem of this experiment, variable C is equal to 20 and C^U is equal to 400. Other variables are set, as seen in Table 1.

Variable settings of the algorithm are: $w = 0.8$, $\phi_1 = 1.2$, $\phi_2 = 1.2$, $E = 40$, and $G = 1000$. PPSO's perturbation rate is 0.01. Variable b of the proposed MPSO is equal to 0.4, and δ is equal to 3. These test problems include three 3PL providers and three jobs. The number of activities J is divided into four levels: 5, 10, 15 and 20. The numbers of job consolidations and activity integrations are 3 and 4, respectively. Each test is executed 50 times. In Table 2, it is clear that no satisfactory result can be achieved using traditional PSO to solve PFZOIGP_4PLOAP. In four levels, PSO's solution quality is unstable.

Table 3 shows PPSO's quality of solving PFZOIGP_4PLOAP at levels of 5 and 10 activities is stable. In four levels PPSO outperformed PSO. This result demonstrates that, PPSO's perturbation strategy indeed prevents prematurely caving into local optimum, but it is insufficient for the larger problem.

In Table 4 it is clear that the MPSO proposed in this paper obtains stable solution quality, and is better than two other PSO algorithms. The mutation operator designed in this paper makes MPSO perform better, which means the mutation operator prevents the solution from caving into local optimum.

Fig. 2 shows convergence processes of three different algorithms for the value of priority level 1. Traditional PSO caves prematurely into local optimum too early while calculating. It is difficult for particles to achieve better solution merely by changing position and updating velocity. PPSO includes perturbation strategy to increase the probability of particles to escape local optimum. MPSO makes some particles change their original direction and distance of movement, and prevents particles from converging prematurely. Among these methods, mutation operators most effectively improve the optimal solution S_{jk}^G, and prevent calculation from caving into local optimal, as seen in Fig. 3.

This paper also analyzes the algorithm to solve the problem with more 3PL providers. In the example, the number of 3PL increases from 3 to 10, and the other problem variable setting remains the same. Table 5 shows that in the example of more 3PL providers, MPSO outperformed two other algorithms, which means that the proposed algorithm's performance is less affected by the number of providers. PPSO discovers the same near-optimal solution with MPSO, but PPSO's solution quality for this example is unstable.

5.2. Effects of flexible resource

This proposed problem assumes that the decision maker allows flexible resources. This paper analyzes the effects of resource and tolerance settings on assignment results in four cases. Key variable settings in case 1 are: $C = 80$ and $C^U = 80$. In case 1, the budget is insufficient and there is no tolerance. Key variable settings in case 2 are: $C = 80$ and $C^U = 100$. Case 2 is an example that considers minor tolerance. Case 3 is an example that considers a larger tolerance. C and C^U are set at 80 and 200, respectively, in case 3. Case 4 is an

Table 2
Result of solving the example by PSO.

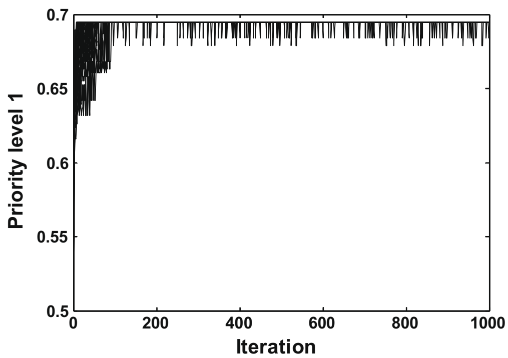
	$J = 5$			$J = 10$		
	Priority level 1	Priority level 2	Priority level 3	Priority level 1	Priority level 2	Priority level 3
Best	1.000	14.101	2.999	0.937	28.422	2.996
Mean	1.000	14.100	2.999	0.928	28.322	2.996
Worst	1.000	14.098	2.999	0.900	27.813	2.997
	$J = 15$			$J = 20$		
	Priority level 1	Priority level 2	Priority level 3	Priority level 1	Priority level 2	Priority level 3
Best	0.808	42.382	2.995	0.711	56.590	2.992
Mean	0.801	42.282	2.995	0.694	56.500	2.992
Worst	0.795	42.348	2.995	0.674	56.389	2.992

Table 3
Result of solving the example by PPSO.

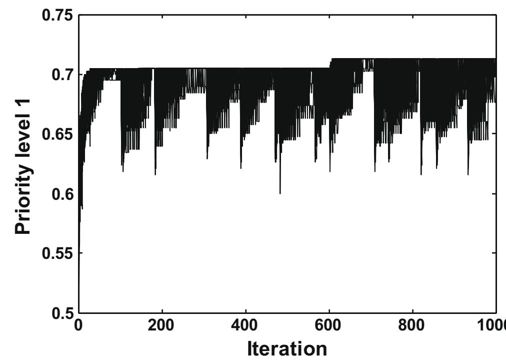
	$J = 5$			$J = 10$		
	Priority level 1	Priority level 2	Priority level 3	Priority level 1	Priority level 2	Priority level 3
Best	1.000	14.101	2.999	0.937	28.422	2.996
Mean	1.000	14.101	2.999	0.937	28.422	2.996
Worst	1.000	14.101	2.999	0.937	28.422	2.996
	$J = 15$			$J = 20$		
	Priority level 1	Priority level 2	Priority level 3	Priority level 1	Priority level 2	Priority level 3
Best	0.855	42.804	2.995	0.776	57.292	2.992
Mean	0.846	42.703	2.995	0.716	56.591	2.992
Worst	0.808	42.301	2.995	0.692	56.422	2.993

Table 4
Result of solving the example by MPSO.

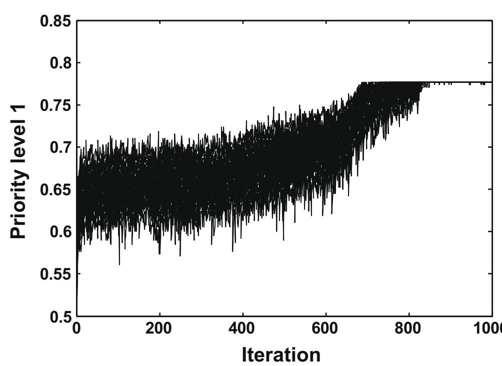
	$J = 5$			$J = 10$		
	Priority level 1	Priority level 2	Priority level 3	Priority level 1	Priority level 2	Priority level 3
Best	1.000	14.101	2.999	0.937	28.422	2.996
Mean	1.000	14.101	2.999	0.937	28.422	2.996
Worst	1.000	14.101	2.999	0.937	28.422	2.996
	$J = 15$			$J = 20$		
	Priority level 1	Priority level 2	Priority level 3	Priority level 1	Priority level 2	Priority level 3
Best	0.855	42.804	2.995	0.776	57.292	2.992
Mean	0.855	42.804	2.995	0.771	57.226	2.992
Worst	0.855	42.804	2.995	0.724	56.631	2.992



(a) OSP



(b) OSPP



(c) OSPM

Fig. 2. In an example with 20 activities, values vary for each particle's priority level 1: (a) the implementation of PSO; (b) the implementation of PPSO; and (c) the implementation of MPSO.

example without tolerance, but the budget is sufficient. Variables C and C^U of case 4 are 150. Other variables settings in these cases are identical to prior tests.

In these tests, PFZOIGP_4PLOAP includes three 3PL providers, three jobs and 20 activities. Table 6 shows the results of the four cases that apply MPSO. Due to insufficient budge and zero tolerance, variables of the achievement degree in case 1 of priority level 1 equal zero. Under such circumstances, a better solution can only be judged by priority level 2. Although there is tolerance in case 2, insufficient tolerance makes the solution identical to case 1. Most previous studies for preemptive fuzzy GP were done by setting a lower bound for the variables of the achievement degree. However, if cases 1 and 2 are solved by setting a lower bound, then a situation with no feasible solution may occur. Improper resource setting may yield a scenario where there is no solution that can achieve the lower bound set with decision makers. The MPSO

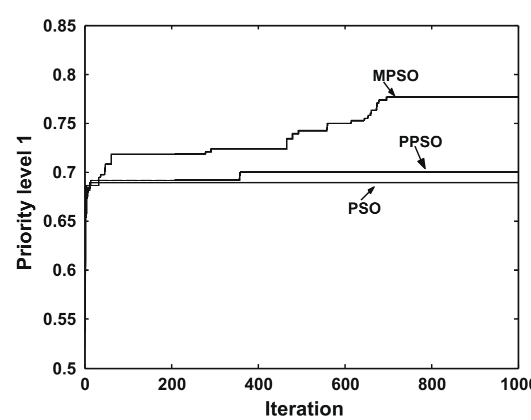


Fig. 3. In an example with 20 activities, the improvement of the best solution.

Table 5
Algorithms' performance with more 3PL providers.

	PSO			PPSO			MPSO		
	Priority level 1	Priority level 2	Priority level 3	Priority level 1	Priority level 2	Priority level 3	Priority level 1	Priority level 2	Priority level 3
Best	0.945	97.925	2.997	0.987	97.855	2.997	0.987	97.855	2.997
Mean	0.939	97.855	2.997	0.978	97.837	2.997	0.987	97.855	2.997
Worst	0.929	97.589	2.997	0.953	97.913	2.996	0.987	97.855	2.997

Table 6
Near-optimal solution for each case.

	Priority level 1	Priority level 2	Priority level 3
Case 1	0.000	57.780	2.994
Case 2	0.000	57.780	2.994
Case 3	0.792	57.254	2.992
Case 4	1.000	57.735	2.994

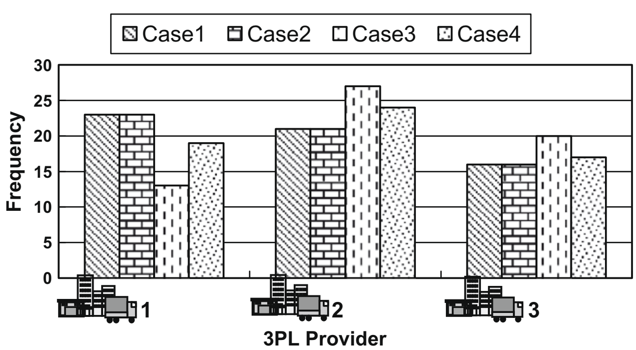


Fig. 4. Result of three assigned providers.

approach proposed in this paper will not lead to such a situation. The initial budget for case 3 is insufficient, but its tolerance is large. During case 3, better solution is mainly judged by the achievement degree of priority level 1. In case 3, the overall cost for a near-optimal solution is 105. When priority level 1 is equal to 1, better solution for case 4 is mainly judged by priority level 2.

A small budget insufficient, with no tolerance may cause 3PL providers' assigned frequency to be identical. For instance, in Fig. 4 the 3PL provider assigned frequency of cases 1, 3 and 4 is different, which means that the degree of tolerance is also a key for affecting the assignment results.

This paper surveys the value variation of priority level 2 in cases 1, 3 and 4, as Fig. 5. In the circumstances of case 1, the algorithm improves the value of priority level 2. The budget in case 1 is insufficient; therefore the priority level 1 value of all solutions is 0. As a result, the proposed algorithm in this paper selects better solution by judging value of priority level 2. Tolerance in case 3 is sufficient, therefore the primary criteria for algorithm solution quality is not the value of priority level 2. The budget in case 4 is sufficient and there is no tolerance, therefore the algorithm mainly judges better solution by evaluating the value of priority level 2 when the value of priority level 1 is 1 in case 4.

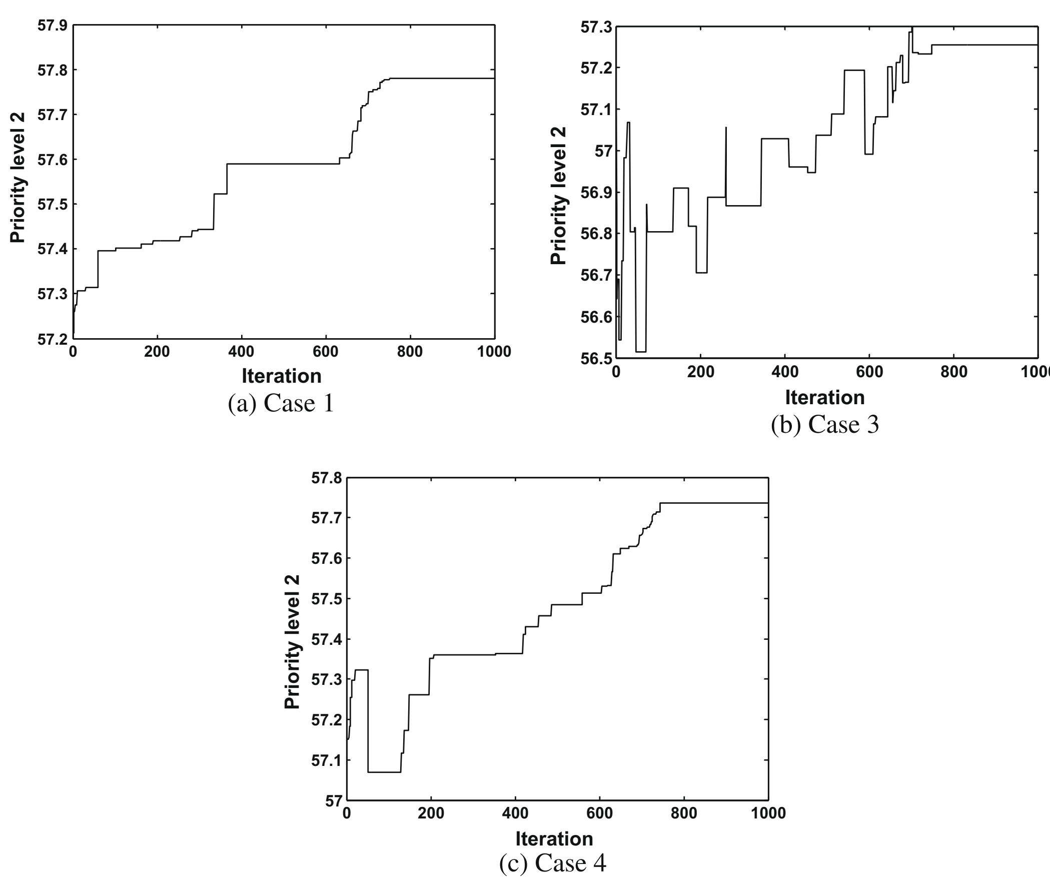


Fig. 5. Value variation of priority level 2 for the improvement of the best solution: (a) case 1 test; (b) case 3 test; and (c) case 4 test.

6. Conclusions

In the global market, enterprises face intensive challenges, and it is common for them to implement supply chain management to improve competitiveness. 4PL focuses on supply chain resource integration. In 4PL operations, an important decision problem allows decision makers to assign jobs/activities to suitable 3PL providers. In 4PL, proper activities integration and jobs consolidation saves transportation operation costs. Multi-objective programming seeks a non-dominated solution (i.e., Pareto optimal solution). In practice, the importance of different objectives may be different. For such problems, preemptive GP is a suitable tool. This paper proposes a preemptive fuzzy zeros-one integer goal programming problem for assigning activities of jobs (i.e., PFZOIGP_4PLOAP). In previous studies, the lower bound of priority level had to be set for traditional preemptive fuzzy GP. Improper lower bound setting easily led to results without feasible solutions. These studies also adopted weighted fuzzy GP to solve the optimization problem with goals of different importance. However, determining each goal's weight was a difficult task. This paper proposes the MPSO approach to solve PFZOIGP_4PLOAP. Performance of MPSO proposed in this paper outperforms methods in past studies, such as PSO and PPSO. In examples of more activities and 3PL providers, the solution quality of MPSO is relatively stable. For instance, in the test of Table 5, all of 50 solutions of MPSO are: priority level 1 = 0.987, priority level 2 = 97.855, and priority level 3 = 2.997. PSO and PPSO cannot detect this set of solution in each test. In the case of insufficient budget resources, better solution is judged by the value of priority level 2, such as in cases 1 and 2. If decision makers solve proposed problem by setting lower bound of priority level in cases 1 and 2, then the results without feasible solutions often occur. For the proposed PFZOIGP_4PLOAP, future research may include a routing problem to move the model closer to practical situations. Analysis of how 3PL providers' resource share affects operation performance based on PFZOIGP_4PLOAP is also a worthwhile research topic. Finally, applying the MPSO approach proposed in this paper in other fields and analyzing its qualities is also an important research direction.

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