Int J Adv Manuf Technol (2014) 71:1549–1563
DOI 10.1007/s00170-013-5578-5

ORIGINAL ARTICLE

Research on selection strategy of machining equipment in cloud manufacturing

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Received: 16 June 2013 / Accepted: 18 December 2013 / Published online: 12 January 2014

Abstract Cloud manufacturing (CM) is a new type of networked manufacturing model, which is proposed in 2010. Optimization technology is one of the key techniques for CM operation, which are used for the efficient integration of manufacturing resources. In all kinds of manufacturing resources, the machining equipment is one of the most important resources. Using optimization techniques to achieve optimal selection of machining equipment is rarely studied in the CM. In order to handle the optimization selection of machining equipment in CM, comparing with the existing resources optimal configuration, an optimal selection strategy is introduced for the machining equipment in CM. In the selection strategy, first, a multiple objective and binary integer programming model is proposed to describe the optimal selection of machining equipment in CM. Second, after analyzing the mathematical model and the real-world problem of the machining equipment selection in CM, the priority method is adopted to convert the multiple-objective problem into a single-objective problem. Third, an improved particle swarm optimization (IPSO) algorithm based on a novel encoding scheme and fitness function is presented to solve the single-objective mathematical model. Finally, the simulation experiments verify the effectiveness of the IPSO algorithm and show that the selection strategy is more objective and effective to help the client select the machining equipment in the CM than current resources optimization model. This research provides a theoretical support for the development of CM.

Keywords Cloud manufacturing · Machining equipment selection · Particle swarm optimization · Multiple objective programming · Binary integer programming

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1 Introduction

In recent years, the next generation of information technology obtains fast development and widespread application, for example, cloud computing and Internet of Things technology. At the same time, servitization is one of the development movements in modern manufacturing [1]. The concept of integration between manufacturing and service gets comprehensive and rapid upgrade based on IT technology. Many manufacturing enterprises are changing from manufacturing product providers to manufacturing service providers for adapting to dynamic market demand. Under this background, a new service-oriented networked manufacturing model called cloud manufacturing (CM) was proposed in 2010 [2]. The basic idea of the CM is that all manufacturing resources are collected in a virtual resource pool, and on-demand use of manufacturing services is provided for all types of users. Nowadays, the research of CM has gradually entered into the needs of different industries [3–7], such as mold, aerospace, electronics, and automobile. On the other hand, many researchers focus on the CM model and system in the different stages of product life cycle [8–11]. We had proposed a cloud manufacturing system (CMS) for machining equipment from the perspective of product life cycle [12]. The system's goal include constructing a third-party CM service platform, establishing relevant CM service for the machining equipment resources demanders (client) and their provider (service supplier).

In order to realize the system goal, one of the important keys is to achieve the optimal allocation of machining equipment. In other words, how the system selects the optimal machining equipment in the resource pool is the key issue when the client submits process (or processes) to the CMS. (detailed description in Section 3).

Currently, there are two kinds of resources optimization from the perspective of networked manufacturing concept.

One is collaborative networked manufacturing based on Internet, which uses corporations as nodes; the other is workshop (factory) networked manufacturing system, which uses computer and equipment (including machine tools, cutting tools, logistics vehicle) in workshop (factory) as nodes. From the perspective of resources optimizing selection, it mainly includes supplier selection, outsourcing manufacturer selection and shop scheduling.

In the networked manufacturing supplier's selection, the decision theory is mainly used to select raw materials and components suppliers for strategic cooperation [13–15], which reduces producing cost and improves product quality for the core enterprise. In the networked supply chain management, the core enterprise selects all the supply chain nodes ranging from the raw materials suppliers, parts, and component suppliers to partly outsourcing manufacturers. In the selection of outsourcing manufacturers under the networked manufacturing environment, machine parts are used as the smallest task granularity to build optimization model [16, 17]. The typical resources optimization configuration in workshop (factory) is shop scheduling, including job shop and flow shop, which researches on the optimization of n workpieces machining process on m machines [18].

Comparing with the existing resources optimal configuration, it is found that the existing models lack of resources optimization abstraction and the mathematical models lack practicality. The objective function is described differently in different resources optimal configuration. For example, some literatures [14, 17, 19] only consider time or cost, or time and cost, and some [20–22] do not consider the logistics time and cost between resource provider nodes. In addition, the optimization parameters are not clear. For example, the quality parameter has different definition at different level of manufacturing activities. Compared with the above two types of networked manufacturing resources selection, the optimization goal and optimization parameters are different with before in this research. Therefore, it is necessary to set up the mathematical model for optimal selection of machining equipment in CM. In this paper, a selection strategy of machining equipment in CM is presented and the solution is also given in detail.

The rest of this paper is organized as follows. Relative research is presented in Section 2. The problem description and mathematical model are detailed in Section 3. The algorithm design is explained in Section 4. In Section 5, the simulation experiment and discussion is presented. Especially, the comparison results are provided to demonstrate how our model can be applied for real-world optimal selection of machining equipment in CM. Section 6 provides a conclusion of this paper and concise further research direction.

2 Relative research

Our work is related to resources optimizing configuration in networked manufacturing and resource optimization selection in shop scheduling. In this section, relative research domain will be brief mentioned.

There are a lot of research supplier selection problems in the networked manufacturing. For example, Sarfaraz and Balu [23] presented a multi-objective criteria pertaining to supplier selection process by combination of quality function deployment, analytical hierarchy process(AHP) and preemptive goal programming techniques. Wang and Huang [24] used AHP and preemptive goal programming based multicriteria decision-making methodology to take into account both qualitative and quantitative factors in supplier selection. Wang [25] searched supplier selection in a quantity discount environment using multi-objective linear programming, AHP, and fuzzy compromise programming. Single supplier selection is a multicriteria problem, and the decision theory method is widely used to solve this problem. Another stream of supplier selection research is supply chain management. For example, Kawtummachai and Hop [26] proposed an algorithm for allocation of products and order quantities among multiple suppliers with the objective of minimizing the total purchase cost for various service levels under uncertain demand. Li et al. [19] developed a model for optimizing the supply chain configuration, which included sourcing and planning decision. Yohanes Kristianto [27] presented a decision support system for integrating manufacturing and product design into the reconfiguration of the supply chain network. In the shop scheduling, more about the optimal selection for machining equipment can be found. For example, Lim et al. [22] introduced a multiagent system using iterative bidding mechanism to select machining equipment for enhancing manufacturing agility. Tasgetiren et al. [28] presented a variable iterated greedy algorithm with differential evolution, designed to solve the no-idle permutation flow shop scheduling problem. Moslehi et al. [29] presented two mixed binary integer programming models for the shop scheduling problem. Naderi et al. [30] presented a multi-objective open shop scheduling using a hybrid immune algorithm to solve open shop problems.

Overall, the choice of suppliers is a form of resource selection for the core enterprise. But the selection objective and parameters are very different with selection of machining equipment in CM. The optimal allocation of resources in networked supply chain management is broader range, including all kind of resources in sourcing, planning, designing, fabricating, and distribution. Moreover, the relationship between the core enterprise in the supply chain and other partners is strategic cooperation or long term cooperation, which is not temporary working relationship. Therefore, the above mentioned field resource optimization models cannot be applied to optimal allocation of resources under the CM environment. In the shop scheduling, the logistics time and cost of workpiece from one device to another device have not been considered in numerous models. However, our work in this paper is an interregional optimal selection of machining equipment in CM environment. The logistics time and cost of the workpiece need to be considered, which have great impact on the result of optimal selection (Section 5 will discuss its impact).

3 Problem description and mathematical model

3.1 Problem description

Based on the current network manufacturing resource optimal selection and shop scheduling problem, a process-level machining equipment selection problem is described in Fig. 1.

Assuming that the manufacturing resources demander (client) submits some parts machining processes to the cloud manufacturing platform (CMP), it is called m tasks. Based on resources discovery, the CMP has returned candidate resources for each task. Meanwhile, the candidate resource providers are named as candidate service suppliers, marking R_{ij}. Corresponding candidate resources of the task i are marked as $\{R_{i1}, R_{i2}, ,R_{ini}\}$, where $i= 1, 2, \ldots, m,$ and the n_i is the number of candidate resources of the ith task. The concept of logistics time is the logistics days of parts are transported from client or one service supplier to next service supplier or client. The logistics cost is the charge fee of logistics company when parts are transported from client or one service supplier to next service supplier or client. The service time is the days from the service supplier receive the parts to submit to the logistics company. The service cost is the outsourcing cost of the service supplier completes the parts, including process charge and so on. And the quality in the machining refers to the passing rate.

Where

$t(oj)$	is the logistics time from the client to the first service supplier
$c(oj)$	is the logistics cost from the client to the first service supplier
$t(ij)$	is the service time of the service supplier R_{ij} completes the ith task
$c(ij)$	is the service cost of the service supplier R_{ij} completes the ith task
$q(ij)$	is the pass rate of service supplier R_{ij} completes the ith task, j=1, 2, …, n_i
$t(ij,(i+1)k)$	is the logistics time from the service supplier R_{ij} to the service supplier $R_{(i+1)k}$, $c(ij,(i+1)k)$ is the logistics cost from the service supplier R_{ij} to the service supplier $R_{(i+1)k}$
$t(mj)$	is the logistics time from the jth service supplier in the mth task to the client
$c(mj)$	is the logistics cost from the jth service supplier in the mth task to the client.

The optimization problem is how to choose the service suppliers when the client total cost and time is the shortest, and the pass rate is the highest. From the goal programming perspective, the problem is a multiple objective programming problem; from the integer programming perspective, it belongs to binary integer programming (BIP) problem; from

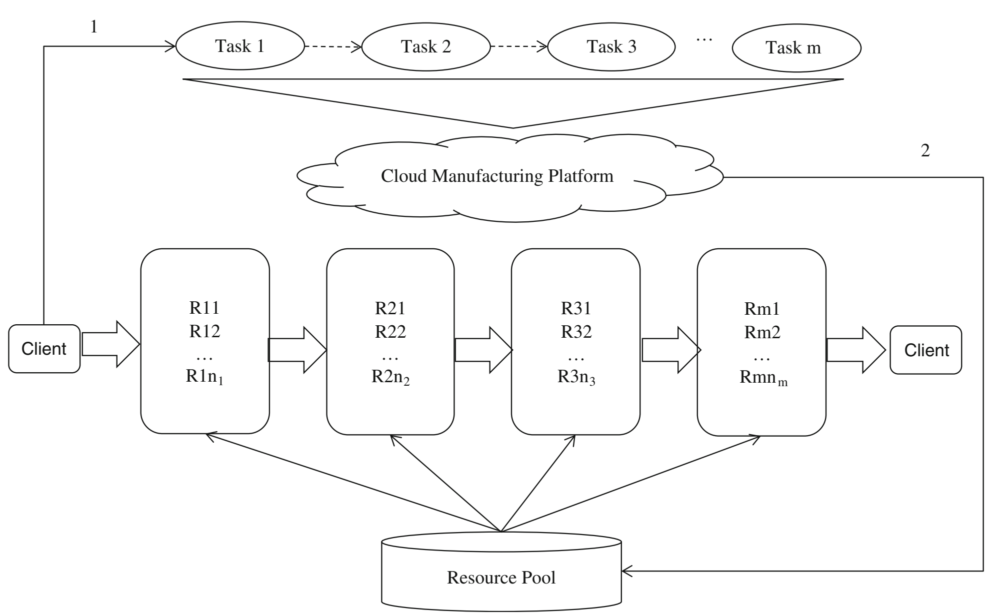

Fig. 1 Schematic diagram of machining equipment selection

the perspective of combination optimization problem, the problem is a typical similar TSP or 0–1 knapsack combinatorial problems. Therefore, this paper will consider the problem of selecting the machining equipment (service suppliers) to be a BIP model, and then it is transformed into a single objective programming model by using the priority method. Finally, the intelligent computation is used to solve the model.

3.2 Mathematical model

Set the decision variables α, $\beta_{mn_m}, x_{ij}, x_{ij,(i+1)k}$, where α=0 or 1; $\beta_{mn_m}=0$ or 1; x_{ij}=0 or 1; $x_{ij,(i+1)k}$=0 or 1.

$$\alpha=\begin{cases}1\text{, the client to service supplier } R_{1j} \text{ exist logistics}\\ 0\text{, the client to service supplier } R_{1j} \text{ do not exist logistics}\end{cases}\tag{1}$$

When α=0, it denotes task 1 is the first process of part manufacturing, and the service supplier offer rough material. When α=1, it denotes task 1 is the first process of part manufacturing, but the client offer rough material or task 1 is not the first process of part manufacturing.

$$\beta_{mn_m}=\begin{cases}1\text{, the } n_m \text{ service supplier in the } m\text{th task is selected}\\ 0\text{, the } n_m \text{ service supplier in the } m\text{th task is not selected}\end{cases}\tag{2}$$

$$x_{ij}=\begin{cases}1\text{, the } j\text{th service supplier in the } i\text{th task is selected}\\ 0\text{, the } j\text{th service supplier in the } i\text{th task is not selected}\end{cases}\tag{3}$$

$$x_{ij(i+1)k}=\begin{cases}1\text{, the } i,j\text{th service supplier to the } i+1,k\text{th service supplier is selected}\\ 0\text{, the } i,j\text{th service supplier to the } i+1,k\text{th service supplier is not selected}\end{cases}\tag{4}$$

So, the time mathematical model is:

$$f(t)=f(t_t)+f(t_s)\tag{5}$$

$$f(t_s)=\sum_{i=1}^{m}\sum_{j=1}^{n_i}x_{ij}t(ij)\tag{6}$$

$$f(t_t)=\alpha\sum_{j=1}^{n_1}x_{1j}t(0j)+\sum_{i=1}^{m-1}\sum_{j=1}^{n_i}\sum_{k=1}^{n_{i+1}}x_{ij(i+1)k}t(ij,(i+1)k)+\sum_{j=1}^{m_i}\beta_{mn_m}t(mj)\tag{7}$$

Where, Formula (5) is the total time objective function, including logistics time $f(t_t)$ and service time $f(t_s)$. Formula (6) is total service time objective function. Formula (7) is logistics time objective function, which is consists of three parts: $\alpha\sum_{j=1}^{n_1}x_{1j}t(0j)$ denotes the logistics time from the client to the jth service supplier in the first task; $\sum_{i=1}^{m-1}\sum_{j=1}^{n_i}\sum_{k=1}^{n_{i+1}}x_{ij(i+1)k}t(ij,(i+1)k)$ denotes the logistics time of adjacent two service suppliers; $\sum_{j=1}^{m_i}\beta_{mn_m}t(mj)$ denotes the logistics time from the jth service supplier in the last task to the client. Similarly, the cost mathematical model is:

$$f(c)=f(c_t)+f(c_s)\tag{8}$$

$$f(c_s)=\sum_{i=1}^{m}\sum_{j=1}^{n_i}x_{ij}c(ij)\tag{9}$$

$$f(c_t)=\alpha\sum_{j=1}^{n_1}x_{1j}c(0j)+\sum_{i=1}^{m-1}\sum_{j=1}^{n_i}\sum_{k=1}^{n_{i+1}}x_{ij(i+1)k}c(ij,(i+1)k)+\sum_{j=1}^{m_i}\beta_{mn_m}c(mj)\tag{10}$$

The meaning of Formula (8)–(10) is similar as Formula (5)–(7). Similarly, the pass rate is as follows:

$$f(q)=\sum_{i=1}^{m}\sum_{j=1}^{n_i}x_{ij}q(ij)\tag{11}$$

Where, $q(ij)$ denotes the qualification rate that the candidate service supplier R_{ij} promised. Therefore, the BIP model of the problem is:

$$\begin{cases} \min f(t) = f(t_t) + f(t_s) \\ \min f(c) = f(c_t) + f(c_s) \\ \min(1-f(q)) \end{cases}$$
$$s.t.\begin{cases} f(t) \le T\max \\ \sum_{j=1}^{n_i} x_{ij} = 1 \\ \sum_{j=1}^{n_i}\sum_{k=1}^{n_{i+1}} x_{ij(i+1)k} = 1 \\ \sum_{j=1}^{n_m} \beta_{mn_m} = 1 \\ x_{ij} = 0 \text{ or } 1, i = 1,2,\cdots,m; j = 1,2,\cdots,n_i \\ x_{ij(i+1)k} = 0 \text{ or } 1, k = 1,2,\cdots n_{i+1} \\ \beta_{mn_m} = 0 \text{ or } 1 \end{cases} \tag{12}$$

When the m is equal to 1 the problem becomes a single-process problem. Its mathematical model is:

$$f(t) = f(t_s) + f(t_t) \tag{13}$$

$$f(t_s) = \sum_{j=1}^{n} x_j t(j) \tag{14}$$

$$f(t_t) = \alpha\sum_{j=1}^{n} x_j t(0j) + \sum_{j=1}^{n} x_j t(0j) \tag{15}$$

Where, $t(j)$ denotes the service time of the jth service supplier; j=1,2, …, n; n is the maximum number of candidate services supplier; and x_j denotes the jth service supplier is selected.

Similarly, the cost function is denoted as follows:

$$f(c) = f(c_s) + f(c_t) \tag{16}$$

$$f(c_s) = \sum_{j=1}^{n} x_j c(j) \tag{17}$$

$$f(c_t) = \alpha\sum_{j=1}^{n} x_j c(0j) + \sum_{j=1}^{n} x_j c(0j) \tag{18}$$

Namely:

$$\begin{cases} \min f(c) == f(c_s) + f(c_t) \\ \min f(t) = f(t_s) + f(t_t) \\ \min\ (1-f(q)) \end{cases}$$
$$s.t.\begin{cases} f(t) \le T_{\max} \\ \sum_{j=1}^{n} x_j = 1 \\ x_j = 0 \text{ or } 1, j = 1,2,\cdots n \end{cases} \tag{19}$$

When m is greater than 1, task i and task $i+1$ are isolated from each other. Then, the multiprocess problem is converted into single-process problem, which mathematical model is as Formula (19). When m is greater than 1, task i and task $i+1$ insulated from each other, but task k and task l have dependence, then the multiprocess problem is converted into multiple and single hybrid problem. But from the perspective of task submitter (client), this process respectively belong to multiple and single process manufacturing activity. From the perspective of system optimization, it belongs to single and multiple process problems in different times. So only the single process solution and the multiple process solution need to design in the CMS. For the solving algorithm of single process problem is simple, this paper will focus on the solving algorithm of multiple process problem.

4 Algorithm design

The above problem has multiple characteristics of multi-objective, nonlinear, and 0–1 integer programming. The common method is that firstly converting the multi-objective into single objective for this kind of mathematical model. Conversion methods mainly include linear weighted method, priority method, etc. At present, the linear weighted method is frequently used as a conversion method in a lot of published literature, which has similar resources optimal selection with our paper [16, 19, 31]. However, many multi-objective programming problems are reflection of the actual problem, and all the parameters have physical units. Therefore, it is difficult for the clients to issue all targets in the unified unit to measure or determine a reasonable weighting factor as the coefficient of coordination objective. The client needs to modify the weighting factor many times in order to achieve the optimum results, which will reduce the automation of CMS operation. In addition, the above variables (*t*/*c*/*q*) only have single border restrictions, which can take the extremum method of unipolar value. Thus, the client is difficult to estimate the boundary value time, cost, and pass rate. However, the above boundary values are hard to determinate. Nevertheless, these parameters are very important for the particle problem, which cannot be reflected based on linear weighted method.

We adopt the priority method as conversion method in order to reflect the actual need more objectively. The outsourcing process (processes) will eventually be returned to the client after the completion of machining part. The time index is the most concerned for the client, and the boundary value of maximum time is presented by the client. What's more, the total cost is also a particularly concerned index for the client, which is deterministic indicator. Under meeting the schedule requirement, this indicator should be given priority. the last parameter is pass rate. Therefore, the above multi-objective can be expressed as:

$$\text{Min } 1\text{-}f(q)$$
$$s.t.\begin{cases} f(t)\le T_{\max} \\ f(t)\le f_t^* \\ f(c)\le f_c^* \\ \sum_{j=1}^{n_i} x_{ij}=1 \\ \sum_{j=1}^{n_i}\sum_{k=1}^{n_{i+1}} x_{ij(i+1)k}=1 \\ \sum_{j=1}^{n_m}\beta_{mn_m}=1 \\ x_{ij}=0 \text{ or } 1, i=1,2,\cdots,m; j=1,2,\cdots,n_i \\ x_{ij(i+1)k}=0 \text{ or } 1, k=1,2,\cdots n_{i+1} \\ \alpha,\beta_{mn_m}=0 \text{ or } 1 \end{cases} \tag{20}$$

Where, f_t^* denotes the optimal value of $f(t)$, f_c^* denotes the optimal value of $f(c)$.

The multiple objective programming is converted into single objective problem by the above method. It is a nonlinear programming problem from the perspective of model variables. Overall, the nonlinear programming has not a general solving method like linear programming which has commonly simplex method. Nonlinear programming algorithm's applicability is limited in scope. It mainly uses analytical method and numerical method from the perspective of solving method. Most practical nonlinear programming problems are solved using numerical methods, because the analytic method is only applicable to a significant analytic objective function. Nevertheless, even if the partial derivative of the objective function can be found, the solving of nonlinear equations is very complicated and even no solution. Currently, the most used in nonlinear programming algorithm is intelligent algorithm, including genetic algorithm, simulated annealing algorithm, ant colony algorithm, particle swarm optimization, etc., and the combination of the above algorithm and improved algorithm.

The genetic algorithm (GA) [32] is an evolutionary computation algorithm inspired by biological evolution, which is proposed by holland in 1975. The ant colony algorithm [33] is a stochastic optimization algorithm

Table 1 Candidate service suppliers' data

Process	Services suppliers name	Service time (unit time)	Service cost (unit cost)	Pass rate (%)
Process 1—machine type: lathe	R11	31	34	95
	R12	36	75	94
	R13	42	73	93
	R14	6	1	98
	R15	16	82	90
Process 2—machine type: mill	R21	28	14	92
	R22	3	24	90
	R23	39	39	90
	R24	1	33	82
	R25	23	42	90
Process 3—machine type: drill	R31	2	58	95
	R32	43	44	90
	R33	25	68	95
	R34	46	42	90
	R35	32	88	93
Process 4—machine type: planer	R41	46	26	93
	R42	46	68	90
	R43	8	70	96
	R44	15	27	90
	R45	1	39	90
Process 5—machine type: grinder	R51	36	4	95
	R52	49	35	90
	R53	19	44	98
	R54	14	19	96
	R55	42	76	90

(technology) by simulating the behavior of ants, which is proposed by an Italian scholar Dorigo in 1991. The particle swarm optimization (PSO) [34] is proposed by Kennedy et al. in 1995, which is a group of stochastic optimization techniques based on the social behavior of birds simulation. Among them, the genetic algorithm, ant colony algorithm and PSO belong to intelligent computing. The PSO combines the evolutionary computation and the swarm intelligence computing, which has dual characteristics of evolutionary computations such as genetic algorithm and swarm intelligence algorithm such as ant colony algorithm. It shows more intelligent in the global search and local search. In recent years, there are more and more optimization studies based on PSO, which indicates that research on the PSO is still a hot field in intelligent algorithm and shows that the PSO has strong advantage to solve the same problem compared with the past intelligent algorithm. On the other hand, the above single problem is also typical 0–1 integer programming problem, which is the NP problem as we all know. Currently, there are exact methods for solving approach (such as recursion, backtracking, branch and bound method, etc.), approximation algorithms (such as greedy method, Lagrange method, etc.) as well as intelligent optimization algorithms (such as simulated annealing, genetic algorithms, genetic annealing evolutionary algorithm, and ant colony algorithm). Through analyzing the nonlinear integer programming problem and 0–1 integer programming solving method, an improved PSO algorithm is proposed.

PSO is a population-based stochastic optimization method introduced firstly by Eberhart and Kennedy [34] for continuous optimization problems. It is inspired by the social behavior of organisms such as bird flocking and fish schooling. Shi et al. [35] proposed a modified particle swarm optimizer in 1999, which is called standard PSO (SPSO). The SPSO refers to add inertia weight factor in the original PSO velocity update formula. The new velocity update formula is as follows:

$$v_{id}^{t+1} = w \times v_{id}^{t} + c_1 r_1 \left(p_{id}^{t} - x_{id}^{t}\right) + c_2 r_2 \left(p_{gd}^{t} - x_{id}^{t}\right) \tag{21}$$

Table 2 Client A, candidate service suppliers' logistics cost data

Name	Logistics cost (unit cost) i				
	1	2	3	4	5
Client A—service supplier R1i	39	82	86	58	63
Service supplier R11–R2i	80	78	61	92	28
Service supplier R12–R2i	75	31	98	58	53
Service supplier R13–R2i	37	53	52	1	69
Service supplier R14–R2i	21	8	47	12	49
Service supplier R15–R2i	79	11	80	86	53
Service supplier R21–R3i	94	13	22	48	44
Service supplier R22–R3i	32	67	49	84	12
Service supplier R23–R3i	67	49	90	20	49
Service supplier R24–R3i	43	18	57	55	85
Service supplier R25–R3i	83	49	84	62	87
Service supplier R31–R4i	76	14	73	3	27
Service supplier R32–R4i	16	5	58	61	20
Service supplier R33–R4i	86	85	24	36	56
Service supplier R34–R4i	98	56	66	4	64
Service supplier R35–R4i	51	92	8	48	41
Service supplier R41–R5i	88	69	62	19	20
Service supplier R42–R5i	58	58	66	12	94
Service supplier R43–R5i	15	81	72	20	8
Service supplier R44–R5i	19	87	89	14	10
Service supplier R45–R5i	40	98	98	18	14
Service supplier R5i—client A	74	0	76	4	16

Table 3 Client A, candidate service suppliers' logistics time data

Name	Logistics time (unit time) i				
	1	2	3	4	5
Client A—service supplier R1i	5	0	4	1	1
Service supplier R11–R2i	8	5	0	8	1
Service supplier R12–R2i	3	3	8	3	5
Service supplier R13–R2i	4	1	1	2	4
Service supplier R14–R2i	0	2	0	7	8
Service supplier R15–R2i	1	9	3	0	7
Service supplier R21–R3i	6	6	4	0	7
Service supplier R22–R3i	3	4	1	6	0
Service supplier R23–R3i	8	9	9	6	0
Service supplier R24–R3i	1	1	3	5	0
Service supplier R25–R3i	9	7	2	7	7
Service supplier R31–R4i	5	7	0	7	9
Service supplier R32–R4i	7	5	2	7	6
Service supplier R33–R4i	9	1	0	2	1
Service supplier R34–R4i	2	5	5	6	7
Service supplier R35–R4i	4	2	7	5	1
Service supplier R41–R5i	4	1	6	3	1
Service supplier R42–R5i	7	2	0	0	6
Service supplier R43–R5i	8	8	0	7	3
Service supplier R44–R5i	1	0	7	3	6
Service supplier R45–R5i	1	2	9	6	7
Service supplier R5i—client A	3	0	5	7	5

$$x_{id}^{t+1} = x_{id}^{t} + v_{id}^{t+1} \tag{22}$$

$$w = w_{\text{start}} - \frac{w_{\text{start}} - w_{\text{end}}}{t_{\max}} \times t \tag{23}$$

Where, w is the inertia weight, c_1 and c_2 are learning factor respectively, general admission $c_1=c_2=2$, and r_1 and r_2 are distributed in the (0, 1) random number.

Shi et al. recommend the w_{start} is 0.9 and the w_{end} is 0.4, so that the algorithm will have good performance. A lot of

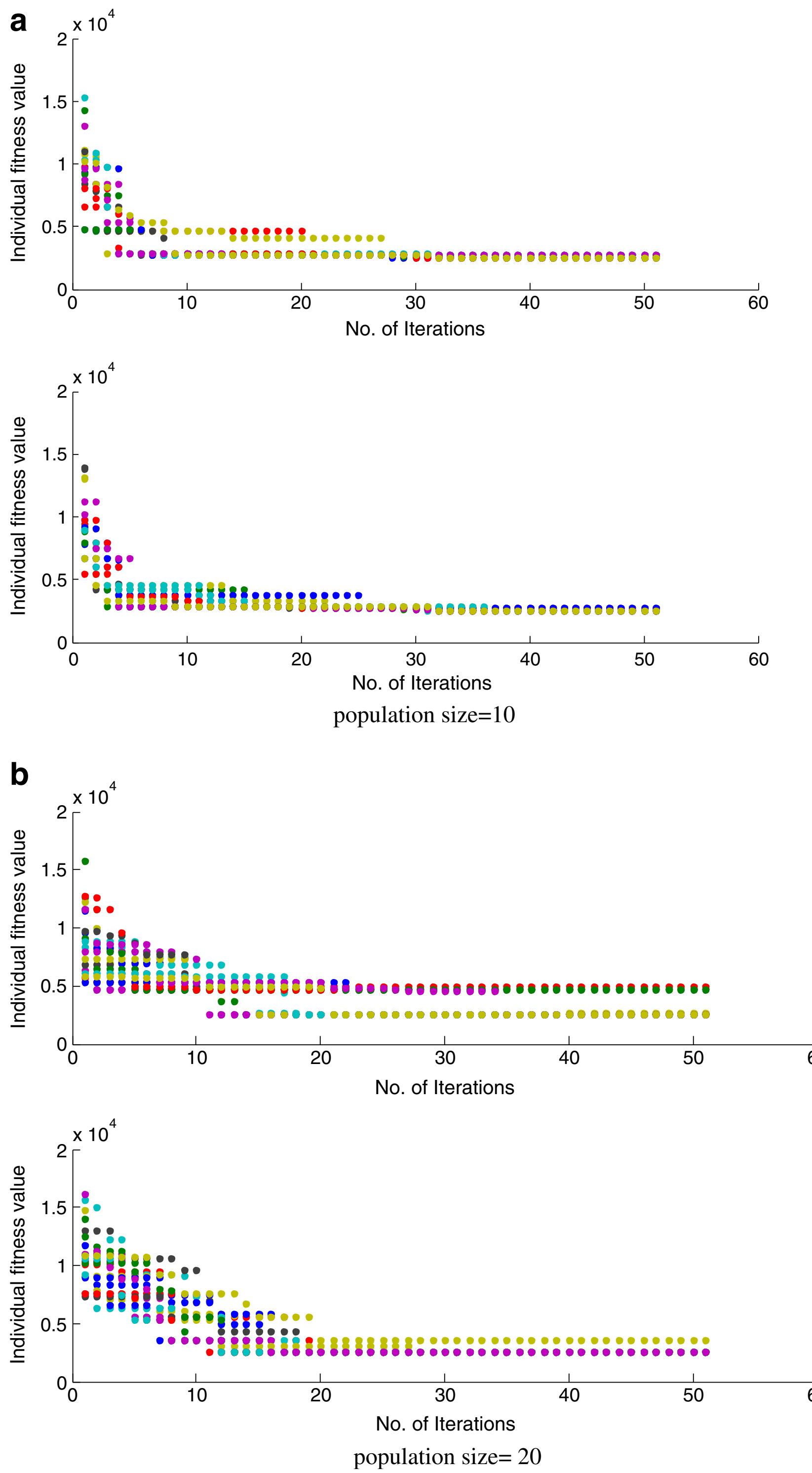

Fig. 2 Change in individual fitness

Table 4 Test results of IPSO algorithm

Test no.	Task no.	V_{max}	$c_1=c_2$	Popsize	MaxIter	r_c	r_t	Fitness value	When convergence?
1	5	2	2	10	50	500	100	2,516	12
2	5	2	2	10	50	500	100	2,516	19
3	5	2	2	10	50	400	100	2,516	13
4	5	2	2	10	50	400	100	2,516	15
5	5	2	2	10	50	500	80	2,516	45
6	5	3	2	10	50	500	80	2,516	13
7	5	3	2	10	50	400	80	2,516	24
8	5	3	2	10	50	400	80	2,516	43
9	5	3	2	10	50	500	80	2,516	18
10	5	3	2	10	50	500	100	2,516	27
11	5	2	2	20	50	500	100	2,516	28
12	5	2	2	20	50	500	100	2,516	16
13	5	2	2	20	50	400	100	2,516	26
14	5	2	2	20	50	400	100	2,516	32
15	5	3	2	20	50	500	80	2,516	25
16	5	3	2	20	50	500	80	2,516	20
17	5	3	2	20	50	400	80	2,516	34
18	5	3	2	20	50	400	80	2,516	41
19	5	3	2	20	50	500	80	2,516	46
20	5	3	2	20	50	500	100	2,516	25

literature [36–39] show the basic structure of SPSO algorithm, which is summarized as follows:

```
Procedure PSO Algorithm
Begin
  t←0;
  initialize X^t and V^t; evaluate fiteness(t);
  while (not termination condition ) do
  update V^(t+1) and X^(t+1);
  evaluate fiteness(t+1);
  t←t+1;
  end while
  return best solution;
End
```

Table 5 Changed logistics cost data

Name	Logistics cost (unit time) i				
	1	2	3	4	5
Client A—service supplier R1i	100	164	172	150	126
Service supplier R5i—client A	120	105	152	110	90

However, typical particle swarm algorithm is designed for continuous function. In this research the variables are logical variables 0 and 1. Therefore, the use of particle swarm needs firstly to convert variable, which is a difficult point for PSO applied to practical problem, especially combinatorial optimization problem. Real random coding mode is a coding method used in the GA, which is proposed by Bean [40]. Its basic principle is randomly generate n-dimensional vector $x=[x_1,x_2,\cdots x_n]$, $x_i\in[0,1]$, $i\in[1,n]$. According to the value of x_i in x, and backing subscript i permutations, a segmented random vector encoding mode is proposed. Set the particle swarm location as n-dimensional vector:

$$X = [x_{11}, x_{12}, \cdots x_{1n1}, x_{21}, x_{22}, \cdots x_{2n2}, \cdots x_{m1}, x_{m2}, \cdots x_{mnm}] \tag{24}$$

Then, Formula (24) is converted into the vector block:

$$X = [X_1, X_2, \cdots X_m] \tag{25}$$

Where,

$$\left\{ \begin{array}{c} X_1 = [x_{11}, x_{12}, \cdots x_{1n1}] \\ X_2 = [x_{21}, x_{22}, \cdots x_{2n2}] \\ \cdots \\ X_m = [x_{m1}, x_{m2}, \cdots x_{mnm}] \end{array} \right\} \tag{26}$$

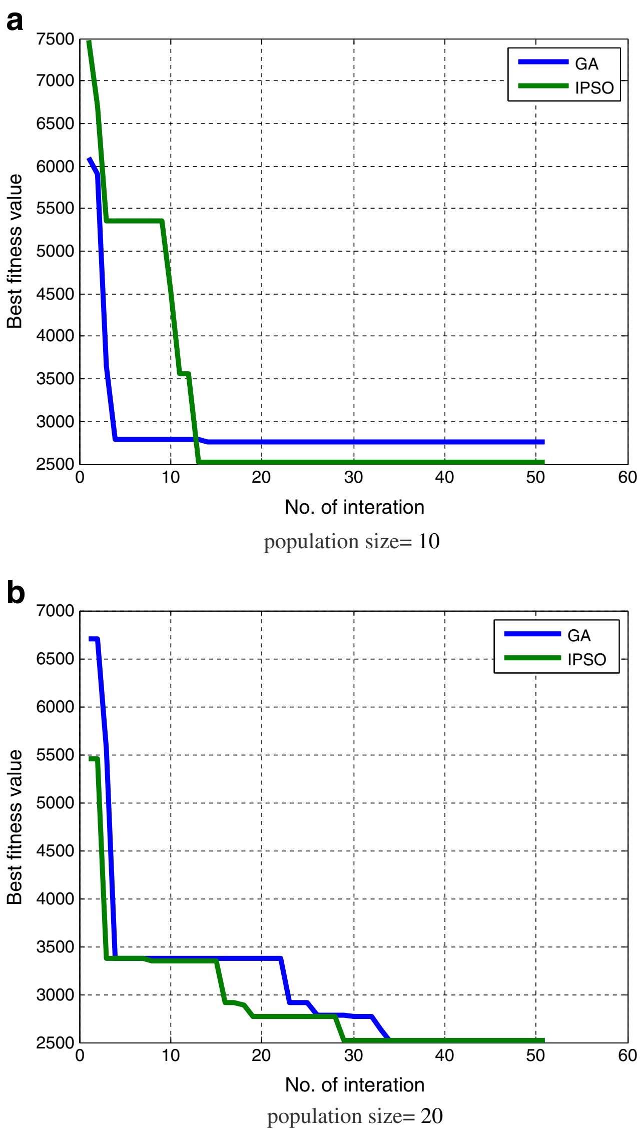

Fig. 3 IPSO and GA convergence graph

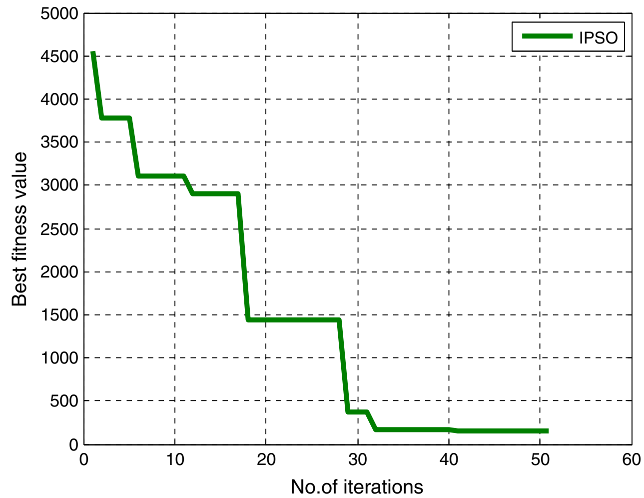

Fig. 5 Convergence graph without considering logistic effect

Select from $X_1, X_2 \cdots X_m$ where the subscript of their largest element value as the target combination vector which is the service supplier's number (the optimal combination of machining equipment).

In addition, the fitness function is used to evaluate particle in the PSO algorithm, which is the function of the particle position. A particle's fitness value is determined by its location, usually taking the fitness function as objective function. The constraints of objective function will make the solution leave the solution space with the particle change in position and velocity, causing the solution is not feasible. This is a common problem in constrained optimization. If the constraint problem can't be handled, the solution is not a reasonable solution. Currently, the most widely used treatment for constrained optimization method is to learn the traditional method of introducing penalty function. The penalty function method is used to construct the first stage particle fitness

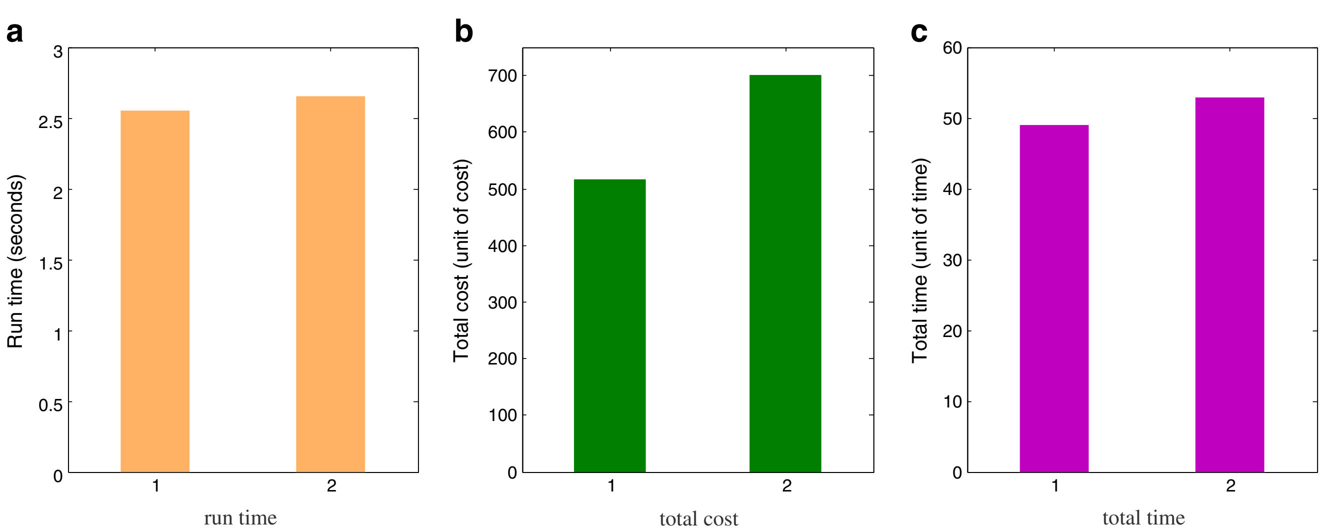

Fig. 4 Comparison of algorithm performance (1=IPSO; 2=GA)

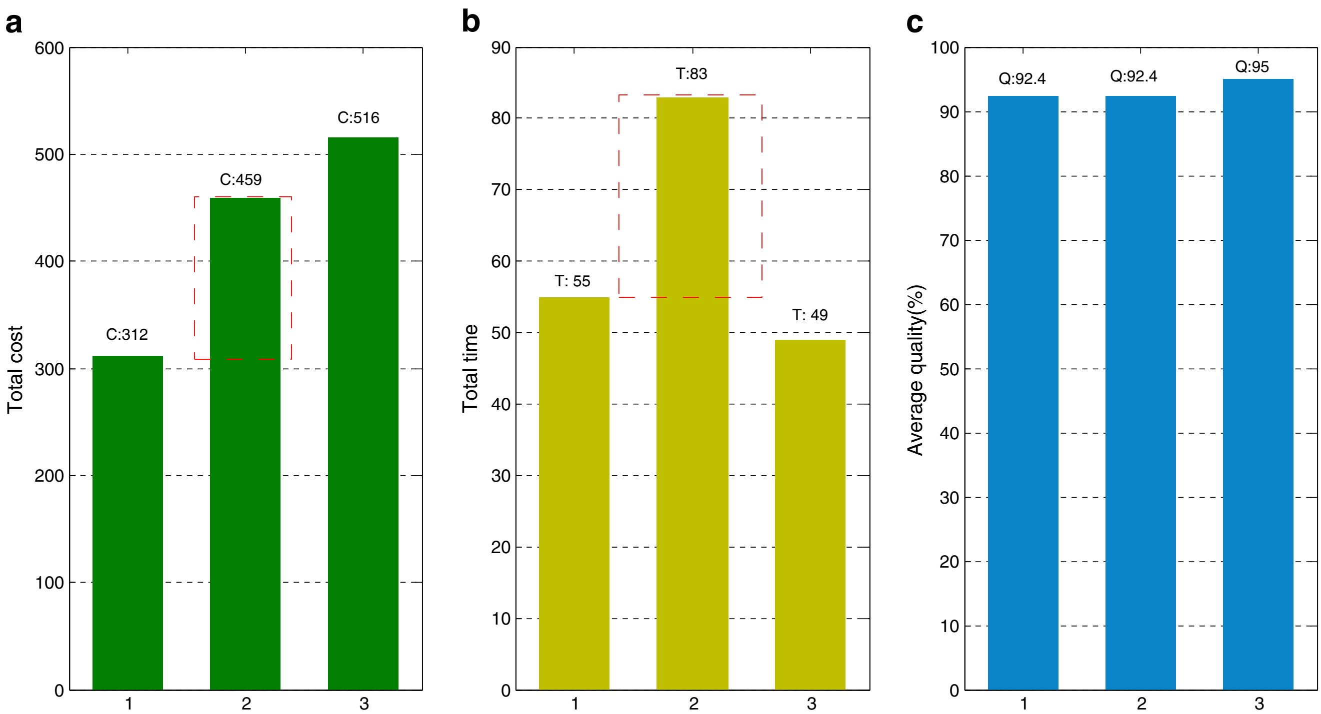

Fig. 6 Comparison results with considering the logistics

function based on the objective function and constraints in formula (20):

$$\text{Min} \quad \phi(c, r_t) = f(c) + r_t[\max(f(T), 0)] \tag{27}$$

Where $f(T)=f(t)-T_{\max}$, r_t is the total time penalty coefficient, which is a sufficiently large positive number.

Set [Min $\phi(c,r_t)$]$=f_t^*$,$f(C)=f(c)-f_t^*$, then the second-level particle fitness function is constructed:

$$\text{Min} \quad \phi(c, q, r_t, r_c) = 1 - f(q) + r_c[\max(f(C), 0)] \tag{28}$$

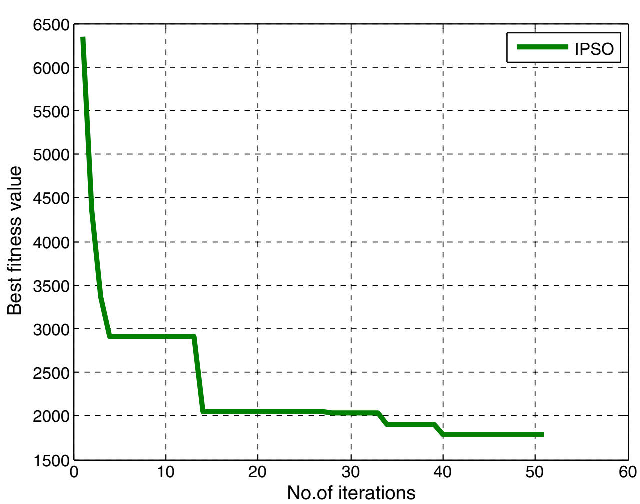

Fig. 7 Convergence graph without considering logistic effect between suppliers and client A

Where r_c is the total cost penalty coefficient, which is a sufficiently large positive number. Combining Formulas (24) and (25), the particle fitness function is:

$$\text{Min} \quad \phi(c, q, r_t, r_c) = 1 - f(q) + r_c[\max(f(c) - (f(c) + r_t[\max((f(t) - T_{\max}), 0)]), 0)]$$

According to the above improvement point, the improved PSO algorithm step is as follows:

Step 1: Initialize the particle swarm

1.1 According to the above variables into principles, Formula (24)–(26), convert the problem state space into particle swarm position space

1.2 Define the range of particle position components

1.3 Define population size

1.4 Define cognitive and social coefficients c_1, c_2, weight coefficients start and end values

1.5 Define the maximum number of iterations

Step 2: Initialize particle position and velocity

Step 3: Evaluate the particle swarm according the particle fitness function, Formula (29)

Step 4: Update the particle position and velocity according the SPSO velocity Formulas (21)–(23)

Step 5: Evaluate the particle swarm according the Formula (29)

Step 6: Judgment iteration termination condition, if it reaches the maximum number of iterations then end iteration, otherwise, return step 4

Step 7: According to the results, output optimum particle position components, decode and convert to the candidate resource number

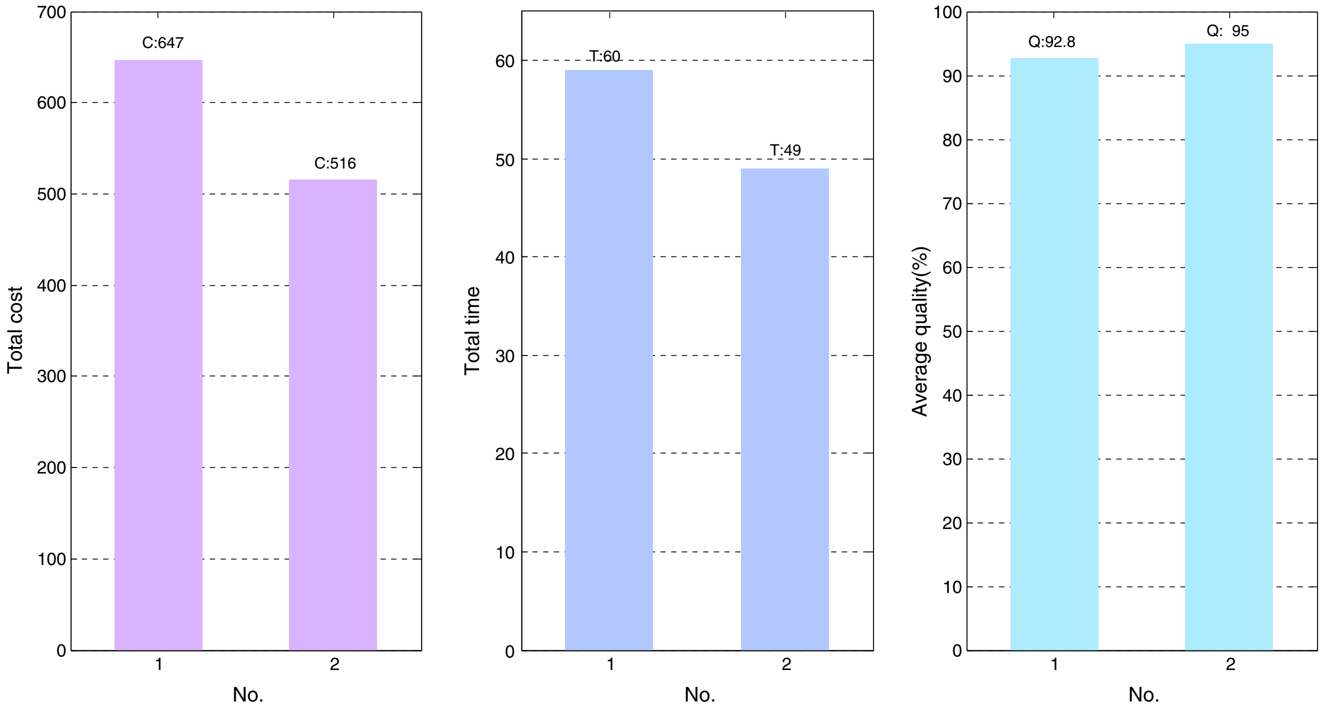

Fig. 8 Comparison of whether consider logistic effect between suppliers and client A

5 Simulation experiment and discussion

5.1 Experimental preparation

In the section, we first verify that the proposed IPSO algorithm is feasible and effective to solve the above model. Second, the effect on solving the optimal selection of machining equipment is analyzed by using the proposed model with current model.

In order to verify the feasibility and superiority of the proposed algorithm, the improved particle swarm algorithm is analyzed firstly, then comprising with the genetic algorithm. The experimental environment is Intel (R) Core (TM) 2 Quad CPU Q800, 2.33GHz; RAM 2GB, 32-bit window 7 operating system. The experimental tool is Matlab2012 software. Assume a client named *A* submits five successive process of certain machine part to the CMP, and the client *A* provides rough part. Five kind of machining equipment (relevant services suppliers) have been found through the resources discovery. And the relevant data are shown in Tables 1, 2, and 3 below.

In addition, the $T_{\max}$=60, the maximum penalty coefficient r_c=500, r_t=100. Set the IPSO population size as 10 and 20, respectively, c_1=c_2=2, the maximum number of iterations is 50. Set genetic algorithm population size as 10 and 20 respectively, crossover probability P_c=0.5, mutation probability P_m=0.005, the maximum number of iterations is 50.

Table 6 Changed logistics time data

Name	Logistics time (unit time) *i*				
	1	2	3	4	5
Client A—service supplier R1i	10	5	8	2	2
Service supplier R5i—client A	10	7	10	14	10

5.2 Experimental discussion

5.2.1 IPSO test

First, the improved particle swarm algorithm is tested 20 times, due to space limitations four test results picture are shown in Fig. 2. The more data information can be seen in Table 4.

Figure 2 illustrates when the population size is set at 10 and 20, respectively, all the particles are obtained at each IPSO iteration. The fitness value converged to 2,516, the optimization is R14-R22-R31-R43-R53, the total cost is 516, total time is 49, and the average quality is 95 %. In addition, from the change trend of individual fitness in Fig. 2, it is shown that the maximum number of iteration is appropriate. (As this test problem size is 5×5, it is not the large-scale combination problem). From Table 5, we can know the IPSO algorithm parameter setting is reasonable and effective, all iterations converge between 10 and 46 times (average is 26.2) and the fitness value converges to 2516.

In comparison with the genetic algorithm, it is found when the population size is 10 in Fig. 3a. the GA exist precocious situation and do not converge to the optimum value, which solution is R15-R24-R31-R43-R53, the total cost is 700, the total time is 53, and the average quality is 92 %. More progress difference can be found in Fig. 4. Both GA and IPSO are almost the same run time to solve the problem (between 2.5 and 2.7 in Fig. 4a), but the total cost and time of GA are more 84 (unit of cost) and 4 (unit of time) than IPSO, respectively. From the comparison we can see, the IPSO could help the client save machine part outsourcing cost and reduce the overall outsourcing time.

What's more, when the population size is set into 20, Fig. 3b illustrates the genetic algorithm and the improved particle swarm algorithm all converge to the optimal solution. However, the IPSO converge when the iteration is set as 30, the GA converged when the iteration is 35. In the 6×6 scale test, the performance of GA and IPSO is more obvious (the population size is set as 20). From the above comparison showed that the proposed IPSO algorithm had better solution quality.

5.2.2 Comparison and discussion

The feasibility and superiority of the IPSO is proved by a lot of test experiments and comparative experiments based on the above simulation. Using the IPSO algorithm based on its configuration parameters and the above experimental data (Tables 1, 2, and 3), this paper further studied the practicality effect of the proposed model with the similar model. In the literature [16, 41], there are similar resource optimal selection problems, but the logistic effect is not be considered in the actual modeling, making this model similar to shop schedule. If the selection of machining equipment in CM uses their model, the result can see in Figs. 5 and 6. The fineness value is 141 in Fig. 5. The combination no. is R14-R22-R31-R45-R54. The results can be computed according the combination number, which is shown in the Fig. 6. But these are just the model solution results, the client need to pay the actual part logistics cost and will longer time to receive the outsourcing part in the real-world operation, which is marked by red dotted line in Fig. 6.

Figure 6a shows the comparison of total cost. Bar graph 1 is the total cost of not considering the logistics effect; bar graph 2 is the total cost of adding actual spending in real world; bar graph 3 is the total cost of considering the logistics effect (our model). Figure 6b shows the comparison of total time. Figure 6c shows the comparison of quality (pass rate), and the corresponding bar graph number has a similar meaning.

From Fig. 6 we can see, when the model does not consider logistics cost under the above test data (Tables 1, 2, and 3), the actual total cost is less than the logistics cost is considered. However, from the comparison of total time, we can see that the actual total time is larger than considering logistics time,

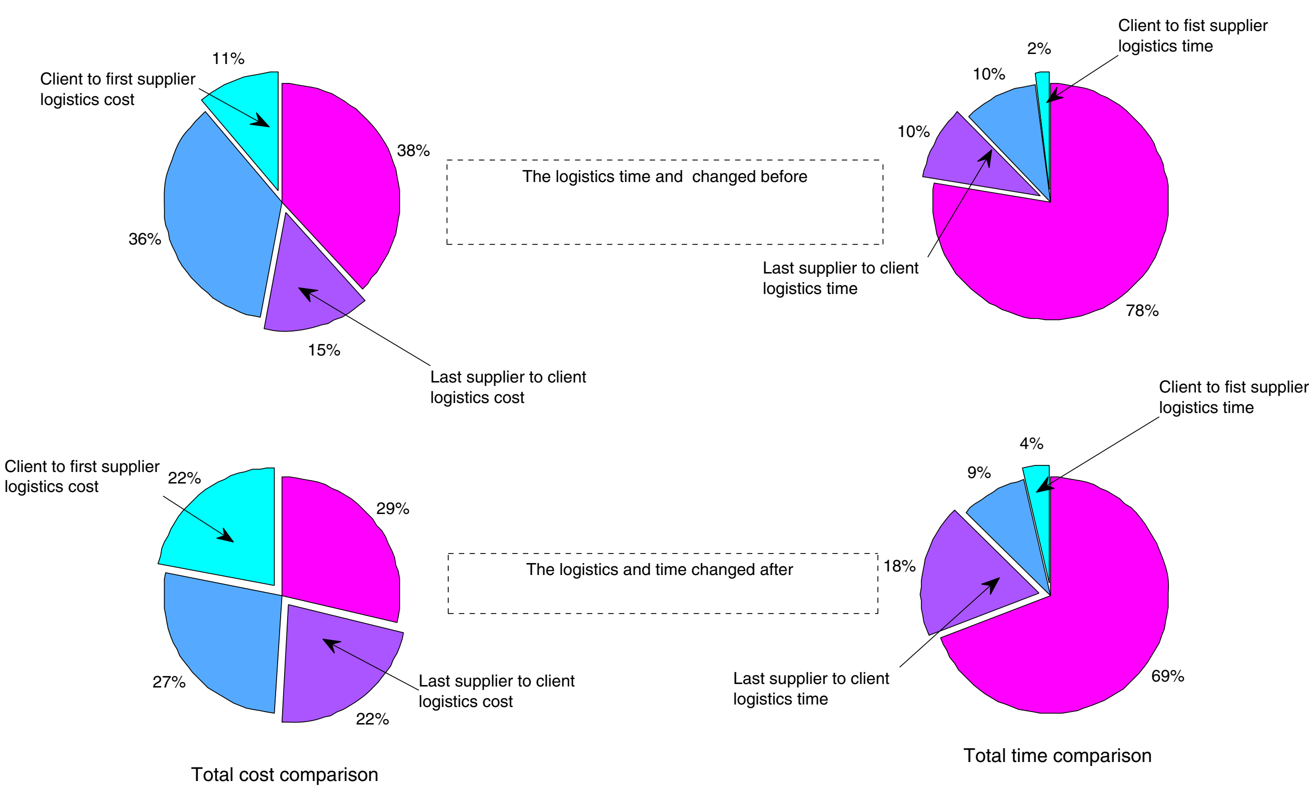

Fig. 9 Comparison of logistic cost and time

but it beyond the time limit set by the client, which is 60 (unit of time). What's more, the average quality is lower than combination of resources when considering logistics. In general, the total cost is minimal when logistics effect is not considered, but from the overall optimization goal (*t, c, q*), considering the logistics effect meet client all requirements, only the *c* satisfy when without considering the logistics.

Furthermore, the literature [17] considered the logistics cost and time between supplies, but the logistics time and cost between the client to first task suppliers and the last suppliers to the client is ignored in many models, but it cannot be neglected in CM. Figures 7 and 8 show the effect of not considering the logistics effect from the client to the first service suppliers and from the last service suppliers to the client.

The fineness value is 1,782 from the Fig. 7, the combination is R14-R22-R33-R45-R54. The model solution is C=516, T=49, and Q=92.8, but the actual total cost and time comparison can be seen from Fig. 8.

In Fig. 8, the bar graph 1 presents the actual result of not considering logistic effect between suppliers and client *A* in model. The bar graph 2 presents the result of using our paper model. From Fig. 8 we can see, when the logistic effect between suppliers and client A is not considered, the solving quality is less than considering it. What's more, when the client provides rough material, the selection of machining in CM is usually multiple regions. Therefore, the logistic effect between suppliers and client *A* will increase with the distance of suppliers and client *A*. Assuming the address of candidate suppliers have changed, the logistics cost and time of the first suppliers R1i and the final suppliers R5i are increased. The change data is shown in Tables 5 and 6.

Using the same data, the new combination number is still R14-R22-R31-R43-R53 coincidently, but the total cost is 684, the total time is 55, the average quality is same as before. But the significant changes can be seen from Fig. 9.

In Fig. 9, the two fan diagram in the first line denote the distribution of the logistic cost and time before logistic cost and time changed, the two fan diagram in the second denote the distribution of the logistic cost and time after their changed. All the meaning is marked in Fig. 9. From the comparison of two figures on the left, we can see that because of the logistics effect the cost proportion from the client to first supplier and the last supplier to client has increased. The similar can be seen from total time comparison. However, if the model does not consider this effect, the client will spend more money for total cost, and will wait more days to receive the outscoring part. Especially, when the above two kinds of total logistics proportion increase or decrease, this effect will be enlarged. Through the contrast research, the proposed model is more correspond to the objective reality, which can be more close to the actual situation, and providing the optimal selection of machining equipment in CM.

6 Conclusions

In this paper, we studied the selection strategy of machining equipment in CM. An optimal selection of machining equipment model is proposed, which not only considers the logistics effect between the service suppliers, but also considers it between the client to the first service supplier as well as the last service supplier to the client in the model. The mathematical model is established on the basis of problem description. In order to solve the multi-objective programming, we use the priority method as conversion method and presented the priority order of $t\backslash c\backslash q$ after analyzing the practical problem, and improve the PSO algorithm including two components: vector segmented random coding and multilevel constraint conversion based on penalty function. The simulation experiment indicates that the proposed IPSO is more practical and superior than the prevalent GA. The comparison simulation experiment indicates that our model is more objectively reflect the selection of machining equipment. When clients submit process-level manufacturing task to the CMP, it would make the actual total cost and time lower, average quality higher.

In the further, we will continue to model other level manufacturing task of relevant resources optimal selection and design corresponding algorithm. Ultimately, they will be used in CMP.

Acknowledgments The authors would like to thank the anonymous reviewers and the associate editor for their constructive comments and suggestions to our paper. In addition, we also acknowledge the support from the Youth Science Foundation of National Natural Science Foundation, China (no.51005260), the Foundation of National Outstanding Youth Science, China (no. 50925518), the National Science and Technology Support Plan Subsidization Project, China (no. 2012BAF12B09), and the Innovative Talent Training Project of "211 Project" (no. S-09106).

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