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ORIGINAL ARTICLE

Distributed manufacturing resource selection strategy in cloud manufacturing

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Abstract With the development of the information technology and logistics industry, industrial production models are more likely to be innovated than ever before. Therefore, there is a tendency for a large number of manufacturing enterprises to start outsourcing their manufacturing activities to more professional subcontractors so they could pay more attention to their core business. Cloud manufacturing (CMfg), as a supplement to cloud computing and big data, is also a new network manufacturing mode that is service-oriented. This mode makes it even more complex and impractical to organize and optimize manufacturing resources. Considering this problem, this paper proposes a manufacturing resource selection strategy based on an improved distributed genetic algorithm (DGA) for manufacturing resource combinatorial optimization (MRCO) in CMfg. We divided the DGA into several sections and distributed and optimized the process, which not only guaranteed algorithm speed but also expanded the search range and improved the accuracy. A case study, a performance comparison between a simple genetic algorithm (SGA) and a working procedure priority-based algorithm (WPPBA) is presented later in this paper. Experimental results showed that the proposed method is preferable and a more effective choice for searching for the optimal solution.

Keywords Cloud manufacturing · Manufacturing resource combinatorial optimization · Distributed genetic algorithm · Parallel optimization

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1 Introduction

In recent years, driven by the development and application of information technology and the logistics industry [1, 2], there is a tendency for the manufacturing industry to begin outsourcing its manufacturing activities. Therefore, it is significantly important for core manufacturing enterprises (CMEs) to effectively select the external manufacturing resources and collaborate with other business partners [3, 4]. Even though three typical cooperative manufacturing modes, i.e., computer-integrated manufacturing [5], network manufacturing [6], and manufacturing grid [7–10], have been introduced in recent years, there still exist some issues, such as flexibility, security, and coverage that limit higher-level manufacturing collaboration [11]. At the same time, the rapid development of cloud computing and big data has been identified as the key technology and development trend, as they can offer operational models for the manufacturing industry to resolve the problems they are faced with [12–14]. In this background, the concept of cloud manufacturing (CMfg) has been proposed.

CMfg is a new service-oriented network manufacturing paradigm, which derives from, but is not limited to, traditional manufacturing modes [15–18]. It provides a third-party CMfg service platform and collects various types of manufacturing resources (MRs) in a virtual resource pool [19, 20]. To realize a rapid and personalized manufacturing mode, we can consider the manufacturing resource optimal selection to be one of the key technologies for CMfg, which mainly refers to optimization issues at the time of selecting the suitable outsourcing suppliers and component suppliers for the purpose of strategic cooperation and reducing the cost incurred from production and improving product quality [21–23].

Manufacturing resource combinatorial optimization (MRCO) is a traditional problem, and it has been studied by many researchers using different manufacturing theories. However, with the development of advanced manufacturing systems, especially the CMfg system, it was found that the existing models lack flexibility and practicality, which can be explained by the fact that certain studies only collect limited resources or processes (one-stage or two-stage). Other studies only consider the time and/or cost, and there are other studies that do not even take logistics time and the cost of resource provider nodes into account. In addition to this, MRCO has become more complicated under the conditions of CMfg owing to the increasing number of MRs, the extensive distribution of MRs, and the advanced logistics industry, which imposes a great challenge for the models with respect to computational speed, convergence, searching ability, flexibility, etc. Therefore, it is necessary to build a modified mathematical model and algorithm to accommodate new manufacturing modes in CMfg. An MRCO model based on a novel encoding scheme and a modified distributed genetic algorithm (DGA) in CMfg are presented in this paper, and corresponding solutions are introduced in detail.

The rest of this paper is organized as follows. Related research studies are presented in Sect. 2. The problem description and mathematical model are detailed in Sect. 3. The algorithm design is explained in Sect. 4. The simulation experiment and discussion are presented in Sect. 5. Especially, the comparison results are provided to demonstrate how our model can be better applied to CMfg. Finally, Sect. 6 provides the conclusion of this paper and indicates the research direction to a further extent.

2 Literature review

At present, many scholars have carried out many research studies on the manufacturing resource selection problems of the manufacturing industry and have come to valuable results [24–30]. For example, Araz et al. presented a fuzzy goal programming approach to improve the methods of evaluating and selecting outsourcing suppliers [31]. Adiel and de Almeida established a multi-criteria decision model for outsourcing contract selection programs by using the ELECTRE method [32]. Cheng proposed an automated outsourcing selection and order tracking system (OSOTS) for alliance members within a particular supply chain [33]. The OSOTS could assist the central factory to find suitable outsourcers and track among outsourcers for a particular customer order. Chaharsooghi proposed a modified version of the ant colony optimization (ACO) to solve multi-objective resource allocation problems [34]. Wang selected suppliers in a quantity discount environment by using multi-objective linear programming, analytical hierarchy process, and fuzzy compromise programming [35]. Wu et al. proposed a fuzzy multi-objective programming model to decide supplier selection involving multiple criteria and risk factors [36]. Wang and Ma proposed a cost optimization model based on supply cost, flexible ability, and service integration to deal with the logistics optimization problem under demand changes and supply restrictions [37]. Zhou et al. established job scheduling problems on the basis of an N-person non-cooperative game theory in networked manufacturing, and the optimal result for each job is derived from the Nash equilibrium point of the game [38]. Ivan et al. developed a hybrid evolutionary algorithm combining priority-dispatching rules with a genetic algorithm (GA) to address the issue of efficient scheduling routine and proposed the application service provider paradigm [39]. Tao et al. presented a new manufacturing grid resource service composition and optimal selection method based on the principles of particle swam optimization (PSO) algorithm [3, 40]. Liu et al. proposed a time, quality, cost, and service (TQCS)-based multi-objective integer programming algorithm by analyzing the self-organization manufacturing grid and the characteristics of a self-organization manufacturing system [41]. Guo et al. proposed a multi-objective optimization model and an improved cluster-based genetic algorithm to solve the MRCO problem for large complex equipment in group manufacturing [42]. Du et al. proposed a supplier optimal selection model that considers the operating stage of a complex product system to balance the procurement and operating cost [43].

Significant research efforts in the modeling of resource selection and production scheduling approaches have been made. However, the selection objective and parameters are quite different in the environment of CMfg. The changes are mainly reflected in several aspects such as the amount and distance of MRs, the transparency of data, the personalized production, the criteria of optimization (quality of service (QoS), energy, utility, and trust), etc. Studies on resource selection and application in CMfg have been conducted only in recent years, and most of them mainly focus on the theoretical model. Wu and Yang studied resource sharing in a CMfg environment and developed a cloud manufacturing service platform by combining theory with practice [44]. Yin et al. resolved the interoperability and combination problem of heterogeneous outsourcing resources with one stage; however, the proposed model could not be applied in a complex production environment [45]. Yang et al. focused on the need of the large equipment manufacturing industry to adopt collaborative operations to transform the industry to cloud manufacturing services and developed a multi-level cloud manufacturing service platform by combining theory with practice [12]. For the problem of dynamic migration of virtual machines in the cloud computing platform, Tao et al. established a triple-objective optimization model that takes energy consumption, communication between virtual machines, and migration cost into account [22]. Wang proposed an optimal selection of a machining equipment model, which considered the logistics effectivity not only among the service suppliers but also from the client to the first service supplier as well as from the last service supplier to the client [46]. Cao et al. proposed a novel part manufacturing service combined with a working procedure manufacturing service (PMS + WPMS) prime collaboration mode, which was considered as an essential guide for CMfg applications [47]. Tao et al. proposed several intelligent models and algorithms to deal with service composition optimal-selection problems in CMfg environment, such as full connection-based parallel adaptive chaos optimization with reflex migration, chaos quantum group leader algorithm, the design preference-based QoS description model combined with the PSO algorithm, etc. [21, 24, 26, 48, 49]. Considering the correlation of QoS, Xu proposed a correlation-aware QoS model of aggregation service and an improved discrete bees algorithm based on Pareto in a CMfg environment [23]. Cao et al. established a service selection and scheduling model that considers the TQCS criteria [2].

The problems of MRCO in CMfg are more complicated than traditional resource optimization models. Many factors need to be considered for new models, such as the logistics time and cost of workpiece from one device to another. Moreover, the traditional model of shop scheduling or resource selection is usually solved by a heuristic algorithm such as GA), simulated annealing, PSO, ACO, etc. [50–63]. However, under the environment of CMfg and big data, the traditional model is not appropriate in the following aspects:

(1) The vast resources in different regions could easily lead to divergence of the algorithm.
(2) There are some new factors needing to be considered such as logistics time and cost, etc [64–65].
(3) Under the trend of cooperative manufacturing, the occupation and conflict of resources must be considered.
(4) The requirements on calculation speed are higher than before because of the increasing number of resources.

According to the above problems, this paper provides a DGA, which has a good effect on the response speed, the rate of convergence, and the ability to search for the global optimal solution.

3 Problem description and mathematical model

3.1 Problem description

On the basis of the current MRCO and shop scheduling problems in a CMfg environment, this paper presents a multi-agent and multi-objective manufacturing resource optimal selection model, shown in Fig. 1. Let us assume that a CME submits some manufacturing tasks to the cloud manufacturing platform (CMP), which is called n orders $\{O_1, O_2, \ldots, O_n\}$. Each of the orders is split into several different operations $\{O_{i1}, O_{i2}, \ldots, O_{im}\}$. The CMP selects a vast amount of MRs $\{R_{i1}, R_{i2}, \ldots, R_{iq}\}$ from different suppliers $\{S_1, S_2, \ldots, S_k\}$. Meanwhile, the corresponding candidate resources of O_{ij} are marked as $U_{ij} = \{R_{ab}, R_{cd}, \ldots, R_{ef}\}$. The processing time, processing cost, logistics time, logistics cost, and quality of each resource are pre-known. The optimal goal of the resource selection and scheduling process is to find the processing route among MRs from different areas according to the demand of customers. The assumptions of our problem are as follows:

(1) The sequence of operation in the orders is fixed and immutable.
(2) Each machine can process several operations, and the process cost and processing time of each operation are different.
(3) All the machines are available from time zero.
(4) One machine can only process one operation at a time; if there are more than two operations to be processed by the same machine, the subsequent operation needs to wait for the previous one to finish.

To formulate the mathematical model of the problem, we summarize the related parameters and variables as follows:

i	the sequence of the order
j	the sequence of an operation
m	the sequence of the supplier
n	the sequence of the resource
O_i	the order i
O_{ij}	the jth operation of O_i.
S_m	the supplier m
R_{mn}	the nth resource of supplier m
n_i	the number of O_i
Q_i	the unit loading quantity for O_i
$pc(i, j, m, n)$	the processing unit cost of operation O_{ij} on resource R_{mn}.
$pt(i, j, m, n)$	the processing time of operation O_{ij} on resource R_{mn}.
$lt(ijmn, i(j+1)uv)$	the logistics time of O_i from the supplier where O_{ij} is processed by R_{mn} to the supplier where $O_{i(j+1)}$ is processed by R_{uv}.
$lt(i0rs, i1rs)$	the logistics time of O_i from the CME to R_{rs}, if O_{i1} is the first operation.
$lt(imrs, i(m+1)rs)$	the logistics time of O_i from R_{rs} to CME, if m is the last operation of O_i.
$lc(ijmn, i(j+1)uv)$	the unit logistics cost of O_i from the supplier where O_{ij} is processed by R_{mn} to the supplier where $O_{i(j+1)}$ is processed by R_{uv}.

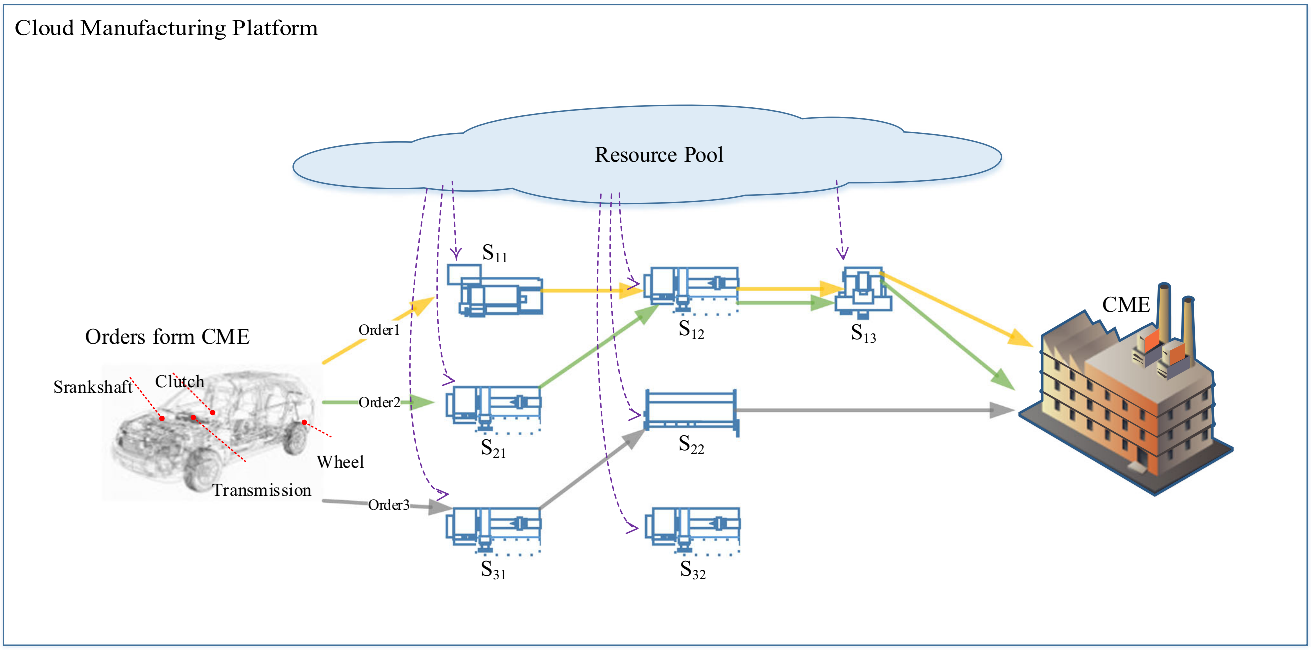

Fig. 1 Schematic diagram of the MRCO problem

$lc(i0rs,i1rs)$	the logistics cost of O_i from the CME to R_{rs}, if O_{i1} is the first operation.
$lc(imrs, i(m+1)rs)$	the unit logistics cost of O_i from R_{rs} to CME, if m is the last operation of O_i.
S_{ij}	the start time of operation O_{ij} on resource R_{mn}.
E_{ij}	the end time of operation O_{ij} on resource R_{mn}.
W_{ij}	the waiting time of operation O_{ij}.
$q(rs)$	the pass rate of R_{rs}.
U_{ij}	the set of resources which can process the operation O_{ij}。
T_i	the total time of O_i.

3.2 Mathematical model

The most important optimization criteria of resource optimal selection in a CMfg environment can be summarized as the QoS. In consideration of the dynamic and service-oriented character of CMfg, this paper proposes five QoS properties, i.e., CTQRS = (C, T, Q, A, S), where C, T, Q, A, and S represent the use-cost, trading period, pass rate, anti-risk ability, and satisfaction degree of customers, respectively. Accordingly, we formulate the mathematical optimization model of resource selection in CMfg as follows.

Set the binary decision variable as:

$$\alpha_i = \begin{cases} 1 & \text{if the first operation of } O_i \text{ starts from CME} \\ 0 & \text{if the first operation of } O_i \text{ starts from the first supplier} \end{cases} \tag{1}$$

$$\beta_{ij,i(j+1)} = \begin{cases} 1 & \text{if } O_{ij} \text{ and } O_{i(j+1)} \text{ are outsourced by different subcontractors} \\ 0 & \text{if } O_{ij} \text{ and } O_{i(j+1)} \text{ are outsourced by the same subcontractor} \end{cases} \tag{2}$$

$$x_{ijmn} = \begin{cases} 1 & \text{if } O_{ij} \text{ is processed by } \mathrm{R}_{mn} \\ 0 & \text{if } O_{ij} \text{ is not processed by } \mathrm{R}_{mn} \end{cases} \tag{3}$$

$$r_{ij} = \begin{cases} 0 & \text{if } R_{ij} \text{ is not occupied at time t} \\ 1 & \text{if } R_{ij} \text{ is occupied at time t} \end{cases} \tag{4}$$

(1) The time mathematical model is

$$T_i = E_{im} + lt(im, i(m+1)) \tag{5}$$

$$E_{ij} = S_{ij} + \sum_{i=1}^{n}\sum_{j=1}^{m}\sum_{s=1}^{k}\sum_{r=1}^{q} pt(i,j,s,r)x_{ijsr} \tag{6}$$

$$S_{ij} = \begin{cases} E_{i(j-1)} + lt(i(j-1)mn, \mathrm{ijuv}) & \text{if } O_{ij} \text{ is processed by } R_{uv} \text{ and } R_{uv} \text{ is free when } O_i \text{ arrives at } S_u \\ E_{rs} & \text{if } O_{ij} \text{ is processed by } R_{rs} \text{ and } O_{ij} \text{ is being processed by } R_{rs} \text{ when } O_i \text{ arrives at } S_r \end{cases} \tag{7}$$

$$S_{i1} = \alpha_i lt(i0rs, i1rs) \tag{8}$$

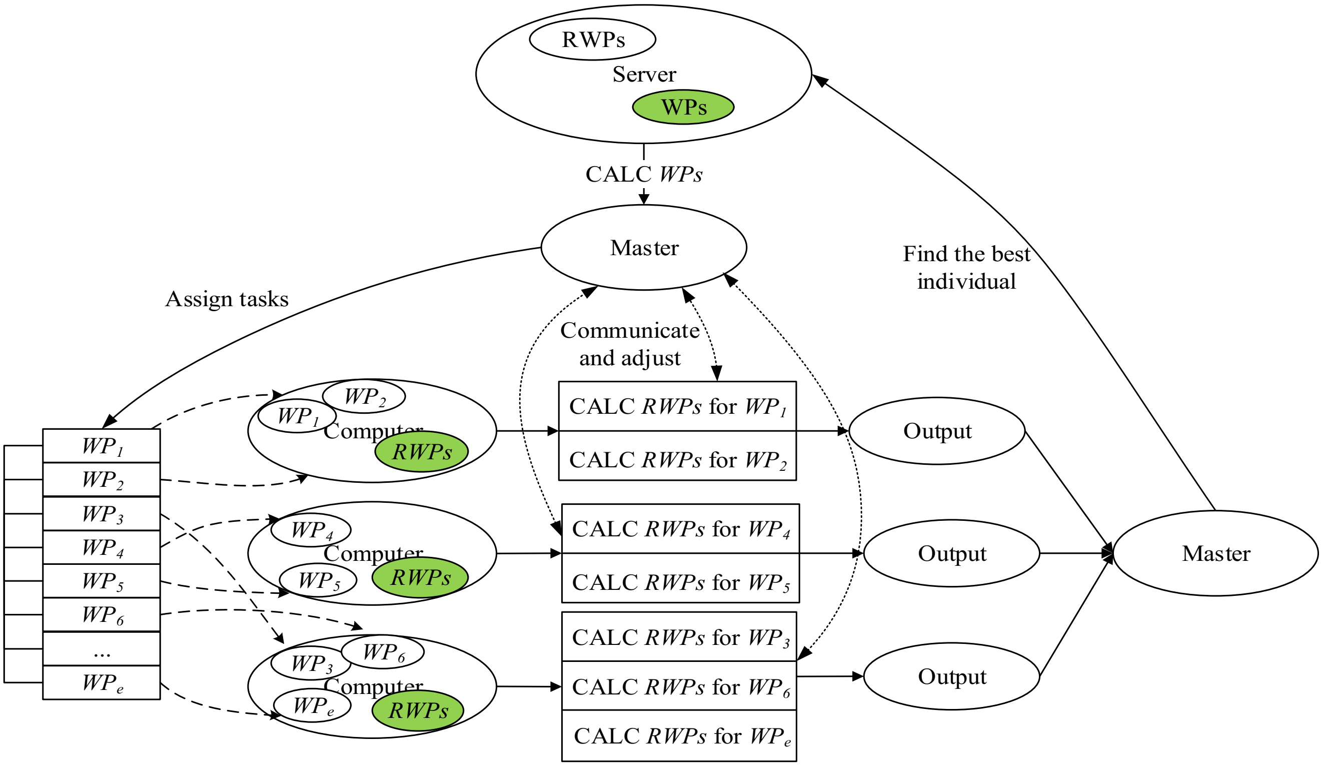

Fig. 2 Process of the DGA

Here, formula (5) is the total time objective function of order O_i, including the end time and logistics time of the last operation of O_i.

(2) The cost mathematical model is

$$C = C_t + C_s \tag{9}$$

$$C_s = \sum_{i=1}^{n}\sum_{j=1}^{m}\sum_{s=1}^{k}\sum_{r=1}^{q} x_{ijsr} pc(i,j,s,r) pt(i,j,s,r) \tag{10}$$

$$C_t = \sum_{i=1}^{n} ceil\left({}^{n_i}/_{Q_i}\right)\Bigg(\sum_{s=1}^{k}\sum_{r=1}^{q}\alpha_i x_{i1sr} lc(i0sr, i1sr) + \sum_{j=1}^{m-1}\sum_{s=1}^{k}\sum_{r=1}^{q}\sum_{u=1}^{k}\sum_{v=1}^{q} x_{ijsr}x_{ijuv} lc(ijsr, i(j+1)uv) + \sum_{s=1}^{k}\sum_{r=1}^{q} x_{\mathrm{imsr}} lc(imsr, i(m+1)sr)\Bigg) \tag{11}$$

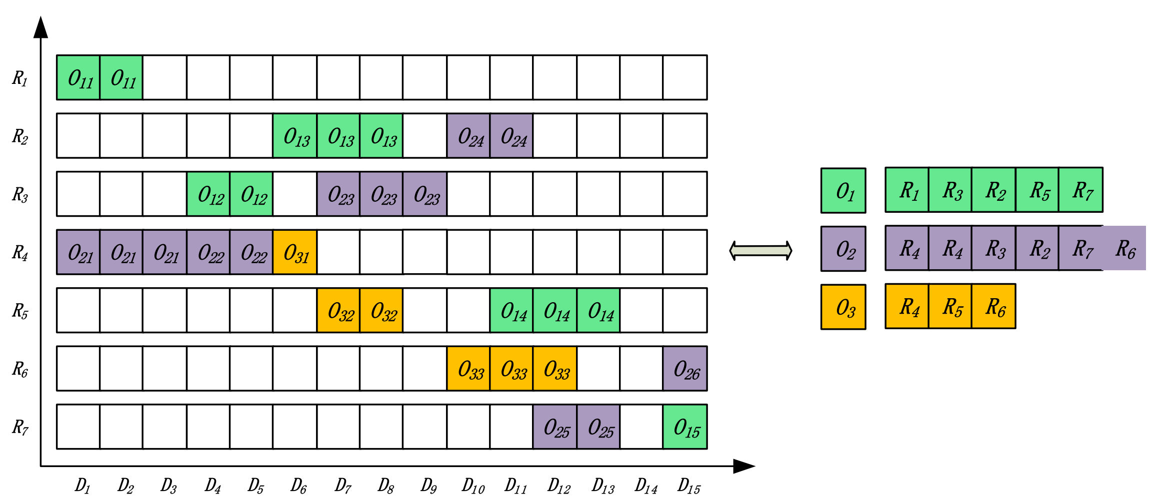

Fig. 3 Encoding method of the algorithm

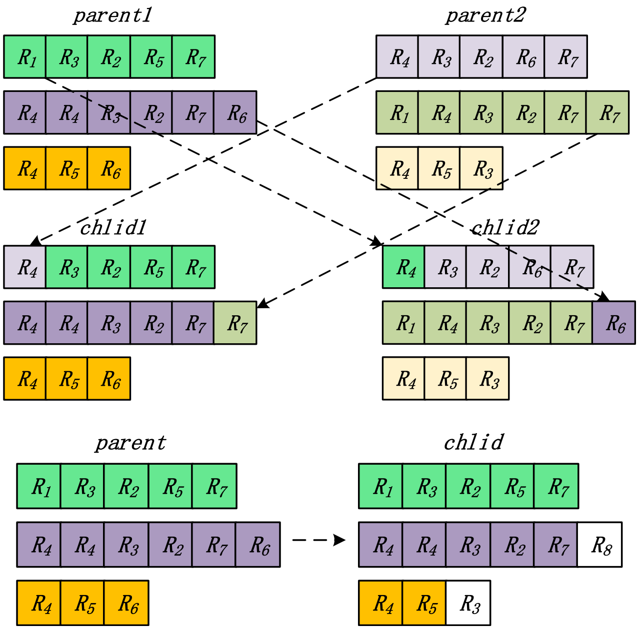

Fig. 4 Crossover and mutation operation of the algorithm

Here, formula (9) is the total cost objective function, including logistics cost C_t and processing cost C_s; formula (10) is the total processing cost objective function, and formula (11) is the logistics cost objective function, which consists of three parts: $\mathrm{ceil}\left({}^{n_i}/_{Q_i}\right)\sum\limits_{s=1}^{k}\sum\limits_{r=1}^{q}\alpha_i x_{i1sr} lc(i0sr, i1sr)$ denotes the logistics cost from the CME to the first supplier of O_i $ceil\left({}^{n_i}/_{Q_i}\right)\sum\limits_{j=1}^{m-1}\sum\limits_{s=1}^{k}\sum\limits_{r=1}^{q}\sum\limits_{u=1}^{k}\sum\limits_{v=1}^{q} x_{ijsr}x_{ijuv} lc(\mathrm{ijsr}, i(j+1)\ uv)$ denotes the logistics cost of two adjacent suppliers of O_i; and $ceil\left({}^{n_i}/_{Q_i}\right)\sum\limits_{s=1}^{k}\sum\limits_{r=1}^{q} x_{imsr} lc(imsr, i(m+1)\ sr)$ denotes the logistics cost of the last supplier to the CME of O_i.

(3) The pass rate of O_i is

$$P_i = \sum_{j=1}^{m}\sum_{s=1}^{k}\sum_{r=1}^{q} x_{ijsr} q(s,r) \tag{12}$$

Table 1 Basic information about the tasks

Task	n_i	Q_i	α_i	Resource/number of processing per day/cost for every operations						
				O_{i1}	O_{i2}	O_{i3}	O_{i4}	O_{i5}	O_{i6}	O_{i7}
O_1	500	100	1	$R_{1,1}$/200/17.3 $R_{2,1}$/250/18.6 $R_{10,1}$/150/17.2 $R_{11,1}$/180/17	$R_{3,1}$/200/20.6 $R_{4,1}$/140/23.6 $R_{6,1}$/150/22 $R_{7,1}$/180/21.6 $R_{12,1}$/300/21.8	$R_{3,2}$/100/5.8 $R_{4,2}$/150/6.2 $R_{6,2}$/180/6.6 $R_{7,2}$/250/6 $R_{12,3}$/260/5.4	$R_{1,2}$/200/17.2 $R_{2,2}$/250/17.1 $R_{10,2}$/150/16.2 $R_{11,2}$/180/15.6	$R_{5,1}$/180/30 $R_{8,1}$/150/28.2 $R_{9,1}$/230/28 $R_{13,1}$/160/27.8	$R_{5,2}$/300/8.6 $R_{8,2}$/260/9 $R_{9,2}$/250/9.2 $R_{13,2}$/250/8.2	$R_{1,3}$/230/13 $R_{2,3}$/180/12.6 $R_{10,3}$/140/13 $R_{11,3}$/180/12.2
O_2	800	200	1	$R_{1,1}$/300/5.4 $R_{2,1}$/300/5.2 $R_{10,1}$/250/4.4 $R_{11,1}$/280/4.8	$R_{3,3}$/180/8.6 $R_{4,2}$/160/9 $R_{6,2}$/180/8.4 $R_{7,2}$/200/7.8 $R_{12,2}$/250/7.4	$R_{1,2}$/300/5.4 $R_{2,2}$/300/5 $R_{10,2}$/250/4.4 $R_{11,2}$/280/4.6	$R_{5,3}$/170/18.4 $R_{8,3}$/200/18 $R_{9,3}$/160/17.4 $R_{13,3}$/150/18.6	$R_{5,5}$/180/26.6 $R_{8,5}$/250/28 $R_{9,5}$/200/27 $R_{13,5}$/200/26	$R_{1,3}$/200/5.6 $R_{2,3}$/250/5.4 $R_{10,3}$/180/5.2 $R_{11,3}$/260/6	
O_3	500	100	0	$R_{3,3}$/80/13 $R_{4,3}$/60/14 $R_{6,3}$/80/12.6 $R_{7,3}$/70/14.4 $R_{12,2}$/50/12.8	$R_{3,2}$/200/4.2 $R_{4,2}$/180/4.6 $R_{6,2}$/180/3.8 $R_{7,2}$/250/3.8 $R_{13,3}$/260/3.6	$R_{5,3}$/120/14.4 $R_{8,3}$/100/14.8 $R_{9,3}$/100/15.2 $R_{13,3}$/100/13.8	$R_{5,2}$/80/10.6 $R_{8,2}$/135/10.8 $R_{9,2}$/100/10.8 $R_{13,2}$/100/10	$R_{5,5}$/80/16.6 $R_{8,5}$/100/16.4 $R_{9,5}$/120/15.8 $R_{13,5}$/120/16		
O_4	200	200	1	$R_{3,3}$/200/7 $R_{4,3}$/150/8.4 $R_{6,3}$/150/7.6 $R_{7,3}$/180/8.2 $R_{12,2}$/300/7.4	$R_{5,4}$/60/30.8 $R_{8,4}$/50/29.2 $R_{9,4}$/60/29.6 $R_{13,4}$/55/29	$R_{5,5}$/50/64 $R_{8,5}$/40/66 $R_{9,5}$/40/62 $R_{13,5}$/40/64				
O_5	300	300	0	$R_{3,1}$/100/16 $R_{4,1}$/150/17 $R_{6,1}$/80/14 $R_{7,1}$/150/16 $R_{12,1}$/180/15.6	$R_{3,2}$/100/6 $R_{4,2}$/150/6.4 $R_{6,2}$/80/5.2 $R_{7,2}$/150/6 $R_{12,3}$/180/5.8	$R_{1,2}$/200/4.6 $R_{2,2}$/150/4.8 $R_{10,2}$/160/4.2 $R_{11,2}$/180/4.6	$R_{5,1}$/80/32.2 $R_{8,1}$/100/33.6 $R_{9,1}$/60/31.6 $R_{13,1}$/80/31.4	$R_{5,5}$/80/28.4 $R_{8,5}$/90/27.8 $R_{9,5}$/50/29.6 $R_{13,5}$/60/30	$R_{1,3}$/200/16.8 $R_{2,3}$/150/16.8 $R_{10,3}$/160/15.2 $R_{11,3}$/180/17.8	
O_6	400	260	1	$R_{3,2}$/50/40 $R_{4,2}$/45/42 $R_{6,2}$/40/38.4 $R_{7,2}$/40/39.2 $R_{12,3}$/50/42.4	$R_{5,4}$/35/66.8 $R_{8,4}$/45/69.6 $R_{9,4}$/40/66.2 $R_{13,4}$/45/68					

Table 2 Time (t) and logistics cost (Lc) among suppliers

$t,Lc=$	0	320,0	340,0	280,0	350,0	330,0	480,1	540,1	570,1	480,1	820,2	850,2	780,2	820,2
		0	320,0	350,0	320,0	320,0	450,1	460,1	500,1	480,1	800,2	850,2	820,2	780,2
			0	300,0	300,0	330,0	470,1	480,1	510,1	450,1	800,2	820,2	810,2	780,2
				0	320,0	310,0	480,1	500,1	470,1	520,1	850,2	860,2	780,2	850,2
					0	300,0	470,1	490,1	500,1	460,1	890,2	880,2	850,2	840,2
						0	480,1	470,1	500,1	520,1	780,2	770,2	800,2	850,2
							0	200,0	250,0	230,0	1000,2	1050,2	980,2	1000,2
								0	200,0	200,0	950,2	920,2	1000,2	900,2
									0	210,0	1020,2	980,2	1000,2	1080,2
										0	880,2	1000,2	920,2	970,2
											0	320,0	330,0	270,0
												0	310,0	250,0
													0	180,0
														0

(4) The anti-risk ability of O_i is

$$A_i = \sum_{j=1}^{m} \sum_{s=1}^{k} \sum_{r=1}^{q} x_{ijsr} \min\left\{ {}^{\zeta_s A_s}\!/_{Ad_s}, a_s \right\} \tag{13}$$

In the process of task execution, there are many risks caused by different reasons, such as delay of upstream suppliers, mistake in their own production scheduling, and so on. Consequently, the anti-risk ability of the suppliers is one of the key signs of the implementation in a CMfg environment. In this paper, A_s represents the maximum processing capacity per day, Ad_s is the quantity of the orders for the day when O_{ij} is processed, and ζ_s and a_s, respectively, represent a factor and a threshold value depending on the size of subcontractor s.

Table 3 Pass rate of the resources

Resource	$q(rs)$	Resource	$q(rs)$	Resource	$q(rs)$	Resource	$q(rs)$
$R_{1,1}$	98	$R_{1,2}$	97.2	$R_{1,3}$	98.1	$R_{2,1}$	96
$R_{2,2}$	96.2	$R_{2,3}$	92.1	$R_{3,1}$	93.5	$R_{3,2}$	96.3
$R_{3,3}$	93	$R_{4,1}$	95	$R_{4,2}$	98	$R_{4,3}$	95
$R_{5,1}$	96	$R_{5,2}$	97	$R_{5,3}$	94	$R_{5,4}$	93
$R_{5,5}$	99	$R_{6,1}$	96	$R_{6,2}$	98	$R_{6,3}$	96
$R_{7,1}$	98	$R_{7,2}$	94	$R_{7,3}$	93	$R_{8,1}$	92.5
$R_{8,2}$	96.5	$R_{8,3}$	98.2	$R_{8,4}$	97.3	$R_{8,5}$	95.1
$R_{9,1}$	89.8	$R_{9,2}$	95.3	$R_{9,3}$	96.3	$R_{9,4}$	98.1
$R_{9,5}$	92.3	$R_{10,1}$	96	$R_{10,2}$	95.3	$R_{10,3}$	96.2
$R_{11,1}$	98	$R_{11,2}$	98.1	$R_{11,3}$	99.1	$R_{12,1}$	96.2
$R_{12,2}$	96.3	$R_{12,3}$	98.2	$R_{13,1}$	98	$R_{13,2}$	97.5
$R_{13,3}$	97.2	$R_{13,4}$	97.3	$R_{13,5}$	99.1		

(5) The satisfaction degree

The satisfaction degree of O_i is a service evaluation of an order calculated by the satisfaction degree summation of all the selected resources.

$$G_i = \sum_{j=1}^{m} \sum_{s=1}^{k} \sum_{r=1}^{q} x_{ijsr} g_s \tag{14}$$

Here, g_s is the service evaluation of resource S_s evaluated by the customers.

Therefore, the MRCO model is as follows:

$$\begin{cases} \min(T_i) \\ \min(C) \\ \min(1-Q_i) \\ \min(A_i) \\ \min(G_i) \end{cases} \tag{15}$$

Table 4 ξ_s, A_s, and g_s of supplier s

Supplier	ξ_s	a_s	g_s	Supplier	ξ_s	A_s	g_s
S_1	1.2	1.6	4.85	S_2	1.13	1.55	4.43
S_3	1.15	1.48	4.67	S_4	1.08	1.43	4.86
S_5	0.98	1.62	4.35	S_6	1.23	1.48	4.82
S_7	1.07	1.47	4.12	S_8	0.95	1.58	3.95
S_9	1.16	1.53	4.47	S_{10}	0.85	1.37	4.46
S_{11}	1.27	1.58	4.56	S_{12}	0.94	1.46	4.83
S_{13}	1.03	1.62	4.58				

Table 5 Algorithm parameters of the DAG, SGA, and WPPBA

Algorithm	Crossover probability(k_1)	Mutation probability(k_2)	α	β	γ	δ	ε	e	P_n	G
SGA	0.4	0.2	0.55	0.2	0.1	0.08	0.07			
WPPBA	0.4	0.2	0.55	0.2	0.1	0.08	0.07		*75%*	
DGA	0.4	0.2	0.55	0.2	0.1	0.08	0.07	*8*	*75%*	*100*

$$\begin{cases} T_i < T_{\max} \\ \forall i, j, \sum_{s=1}^{k} \sum_{r=1}^{q} x_{\text{ijsr}} = 1 \\ \sum_{s=1}^{k} \sum_{r=1}^{q} x_{ijsr} q(r,s) > Q_{\min}(i) \end{cases} \tag{16}$$

Minimizing the total cost and the total time while maximizing the total pass rate, anti-risk ability, and satisfaction degree is a multi-objective optimization problem. This paper converts those different objectives into a single objective by a linear weighted method, as follows:

$$f(X) = \sum_{i=1}^{n} \left(\alpha \frac{T_{\max} - T_i}{T_{\max} - T_{\min}} + \beta \frac{C_{\max} - C_i}{C_{\max} - C_{\min}} + \gamma \frac{Q_i - Q_{\min}}{Q_{\max} - Q_{\min}} + \delta \frac{R_i - R_{\min}}{R_{\max} - R_{\min}} + \varepsilon \frac{G_i - G_{\min}}{G_{\max} - G_{\min}} \right) \tag{17}$$

4 Algorithm design

Compared with other factors, processing cost is the most important factor in resource allocation. Normally, a mechanical part includes several major work procedures (WPs), which account for most of the processing cost [47]. In [47], Cao et al. proposed a PMS + WPMS prime machining service mode and an algorithm called working procedure priority-based algorithm (WPPBA) to solve the MRCO problem in a CMfg environment. In the PMS + WPMS mode, they first calculated the optimal combination of major WPs and then optimized the rest of the WPs (RWPs). However, the model only obtained one set of solutions in the first phase of the algorithm, and it was easy to lose the optimal solution.

This paper provides a DGA, which has a good effect on the response speed, the rate of convergence, and the ability to search for the global optimal solution. Similar to the algorithm in Ref. [47], the DGA is divided into two phases. The method in the first phase is the same as in the WPPBA. In the second phase, the DGA divides the procedure into several parts, which are completed by different computers. In the process of calculation, every computer continuously keeps an interaction with the primary server and the server can adjust the parameters according to the current result. In this way, the algorithm not only enhances the search ability and search scope but also guarantees the convergence speed.

The essentials of the DGA are as follows: preferentially determining several optimal processing routes of major WPs, choosing the top e results in the first phase, and then optimizing in parallel the processing routes of the RWPs by using several distributed computers.

To select the major WPs of an order O_i, we use $\overline{c}(O_{ij})$ as the reference price of operation O_{ij}.

$$\overline{c}(O_{ij}) = average\{pc(i,j,m,n) | R_{mn} \in U_{ij}\} \tag{18}$$

Table 6 Results of the comparison experiment

Algorithm	Population size	Stopping generation	Best fitness	Worst fitness	Average fitness	Rate of best fitness (%)	Average elapsed time(s)	Average generations
SGA	50	100	0.7614	0.5543	0.6918	5	10.28	143.24
	100	100	0.7723	0.5956	0.7218	5	38.50	183.1
WPPBA	50	100	0.7881	0.7745	0.7815	10	19.32	312.75
	100	100	0.7935	0.7814	0.7882	10	79.45	389.28
DGA	50	100	0.7962	0.7825	0.7936	60	27.38	532.12
	100	100	0.7962	0.7919	0.7955	80	117.21	567.21

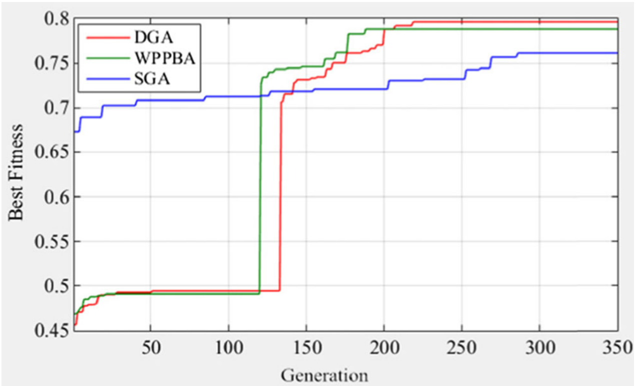

Fig. 5 Evolutionary curves of best fitness with 50 populations

Then, we sort the WPs of O_i in descending order of $\overline{c}\left(O_{ij}\right)$ to get the WP order (WPO):

$$WPO = \left\{O_{ia}, O_{ib}, O_{ic}, ...|\overline{c}(O_{ia}) > \overline{c}(O_{ib}) > \overline{c}(O_{ic}) > ...\right\} \quad (19)$$

Thereby, we get the major WPs (MWPS_i) of O_i whose sum processing cost accounts for more than P_n of the total processing cost:

$$MWPS_i = \left\{ \begin{array}{l} O_{ia}, O_{ib}, O_{ic}, ...|\overline{c}(O_{ia}) + \overline{c}(O_{ib}) \\ + \overline{c}(O_{ic}) + ... \geq P_n \sum_{j=0}^{n} \overline{c}\left(O_{ij}\right) \end{array} \right\} \quad (20)$$

As shown in Fig. 2, the steps of the DGA are listed as follows:

Step 1: Calculate $\overline{c}\left(O_{ij}\right)$ according to formula (16).

Step 2: Determine the major WPs on the basis of formulas (17) and (18).

Step 3: Optimize the processing route of the major WPs and select the top e schemes in the result set.

Step 4: Begin e parallel threads by several computers and optimize the processing route of the minor WPs of each scheme using the same method above.

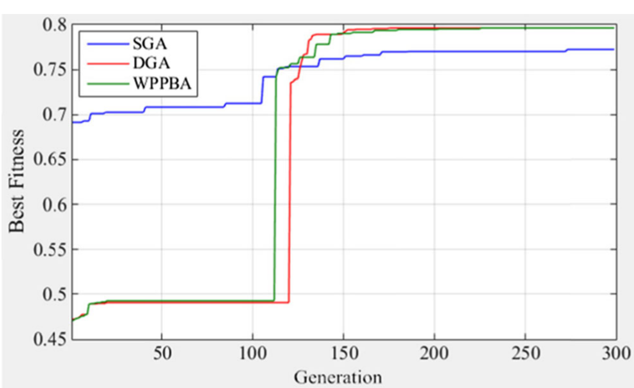

Fig. 6 Evolutionary curves of best fitness with 100 populations

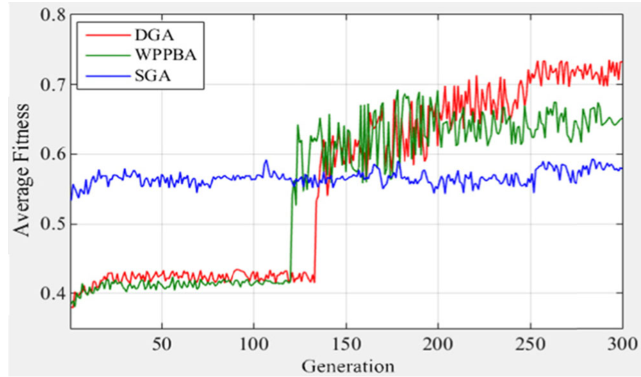

Fig. 7 Evolutionary curves of average fitness with 50 populations

Step 5: After the crossover and mutation operation, check all the orders whether they meet the constraint or not (16); otherwise, cross and mutate again.

Step 6: For every G generation, stop all the threads and send their best individuals to the server. The server will recalculate the probabilities of the crossover and mutation operation for every thread according to the fitness value. The probabilities of the crossover and mutation operation can be set as follows:

$$P_c = \begin{cases} k_1 & f \geq f_{avg} \\ k_1\left(1 + 0.1\dfrac{f_{\max} - f}{f_{\max} - f_{avg}}\right) & f < f_{avg} \end{cases} \quad (21)$$

$$P_m = \begin{cases} k_2 & f \geq f_{avg} \\ k_2\left(1 + 0.1\dfrac{f_{\max} - f}{f_{\max} - f_{avg}}\right) & f < f_{avg} \end{cases} \quad (22)$$

Here, f_{max} is the largest fitness of the group, f_{avg} is the average fitness of the group, f is the fitness of the current individual of a specific thread, k_1 is the initial crossover probability, and k_2 is the initial mutation probability.

Step 7: Find the combinations of RWPs of e individuals and join them into every thread to expand the diversity of the populations.

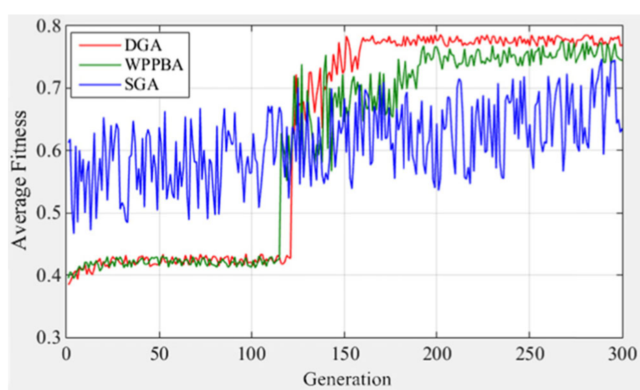

Fig. 8 Evolutionary curves of average fitness with 100 populations

Table 7 The best individuals of the SGA, WPPBA, and DGA

Algorithm	Populations	C	T	Q	A	S
SGA	50	253,780	26, 31, 21, 13, 31, 30	95.915	229.86	131.13
WPPBA	50	251,590	22, 31, 32, 14, 38, 31	96.126	238.16	138.21
DGA	50	250,900	22, 31, 23, 22, 17, 30	96.318	236.74	139.43

Step 8: When all the threads stop working, mix the results of every generation and choose the best individual as the result of the DGA among e threads.

4.1 Chromosome encoding

The model proposed in this paper is a multi-task and multi-stage problem in a complex external environment. Compared with the traditional MRCO problem, more factors need to be taken into consideration, including logistics factors, interference of different processes belonging to different tasks, occupation among different resources, etc. Therefore, this paper proposes a complicated encoding method. As shown in Fig. 3, with the candidate resources as the vertical coordinate and the unit time as the horizontal coordinate, they can be formulated as a matrix. The elements in the matrix denote the processing route of the tasks. The distance between two operations of a task is the transportation time or queuing time. The time in this paper mainly denotes days. The matrix on the right is the simplified version of the left one, and the two matrixes can transform each other.

4.2 Crossover and mutation operation

As shown in Fig. 4, when an operation can be processed by different resources, the processing route will be different. The crossover is used for exchanging the position of resources that process the same operation. Mutation is achieved by using a new resource to replace an old one for a specific operation. For the two algorithms, either one-point or multi-point operation is available.

4.3 Stopping criterion

To compare the rate of convergence of the algorithms, we set a parameter as the stopping generation (Sg). When the fitness value remains the same in the Sg, the algorithm will be considered to be convergent or will fall into the local optimum.

5 Simulation experiments and discussion

5.1 Initial data

To demonstrate the effectiveness of the proposed method, we investigated the outsourcing process in a group manufacturing enterprise (http://www.sinoma-tec.com.cn/en/default.aspx) named SINOMA. With reference to part of the outsourcing data in the company, six tasks were taken as examples to test the performance of the DGA. Every task consisted of several operations that needed to be outsourced. Table 1 shows the information about the tasks, including the mass, loading quantity (starting from CME or not), outsourcing resource, processing days, and processing cost. An operation can be outsourced by different resources; therefore, $R_{i,j}$ denotes the jth resource from the ith supplier. Table 2 shows the logistics cost (C_t) and logistics time (C_s). The 1st row and column denote the CME, and the 2nd to the 13th denote the 13 suppliers. Table 3 shows the pass rate of the

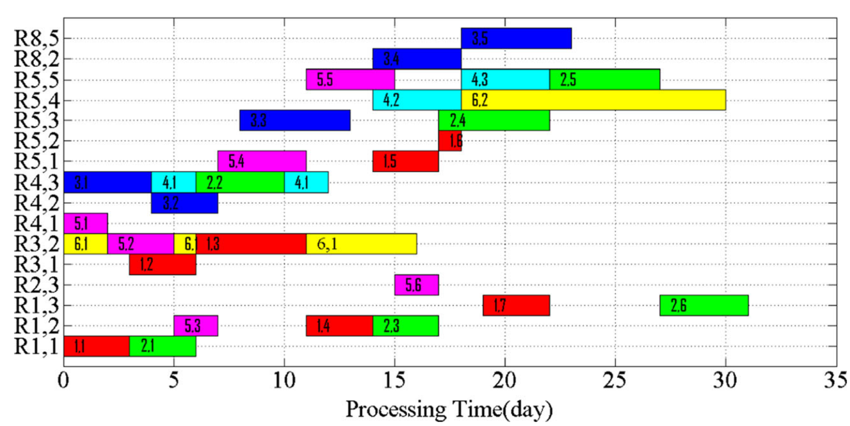

Fig. 9 Gantt chart of the best result

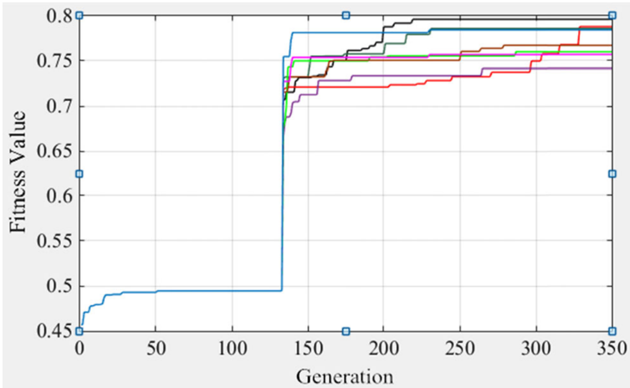

Fig. 10 Evolutionary curves with best fitness of DGA

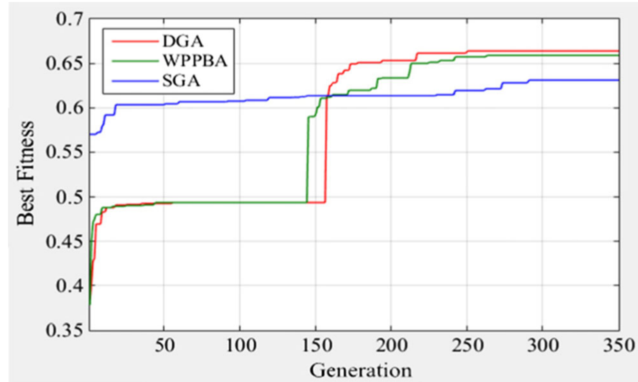

Fig. 11 Evolutionary curves with the best fitness of scene 1

resources. Table 4 shows the anti-ability and satisfaction degree of the suppliers, which refer to the statistical data evaluated by SINOMA.

5.2 Experiment results

The parameters for the hardware and software platforms are listed as follows: Windows 7, Intel® Core™ i7-4700MQ CPU, 2.40 GHz, 8 GB of RAM, and the Hadoop platform. For the DGA, we used three computers as the subservers to simulate the distributed calculation.

To verify the advantages of the DGA over other algorithms, we performed a comparison experiment between a simple genetic algorithm (SGA), a working procedure priority-based algorithm (WPPBA) proposed by Cao et al. (2015), and the DGA. All the algorithms adopted the same operation strategies: roulette, elite strategy, multi-point cross, and multi-point mutation. The parameters of the DGA, SGA, and WPPBA are listed in Table 5. Here, α, β, γ, δ, ε, e, P_n, and G are the constants mentioned before.

All the algorithms with different populations ran for 20 times, and the results are shown in Table 6. It can be clearly observed that the DGA has advantages in solving efficiency and quality. The DGA has the best quality in the best fitness and average fitness, and the highest rate of best fitness with an acceptable elapsed time after running for 20 times. The results of the experiment can be described as follows:

(1) The divergence of data caused the SGA to incur difficult in obtaining the global optimal solution.
(2) The WPPBA had a good effect on the MRCO problem in this paper. However, if the algorithm does not obtain the optimal solution in the first stage, it will fall into the local optimum all the time.
(3) The DGA had the best quality in the best fitness and average fitness and also the highest rate of best fitness with an acceptable elapsed time.

The evolutionary process of the best and average fitness of the algorithms is shown in Figs. 5, 6, 7, and 8, respectively. Because of the different operations in two stages, the curves of the WPPBA and DGA are divided into two sections. It can be analyzed from the diagrams that the SGA had difficulty in obtaining convergence with the increase in the amount of data and that the DGA had a higher convergence than the WPPBA and SGA in the big data environment. In terms of the average solution value, the DGA was more stable than the WPPBA and SGA. As a result, the DGA had the better effect on the search for the optimal solution than the other two in handling massive amount of concurrent data in the CMfg environment. The contrast figures of optimization results for CTQRS = (C, T, Q, A, S) are shown in Table 7, where the DGA solution had a relative optimal solution. Figure 9 shows a Gantt chart of the optimal solution of the DGA, and Fig. 10 shows the evolutionary curves with the best fitness of the DGA containing all the threads. As shown in

Table 8 Different optimization criteria of 3 scenes

	α	β	γ	δ	ε
Scene 1	0.2	0.1	0.1	0.05	0.55
Scene 2	0.2	0.1	0.5	0.1	0.1
Scene 3	0.2	0.2	0.2	0.2	0.2

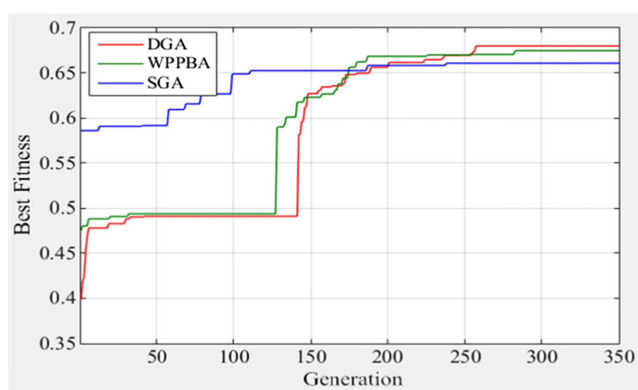

Fig. 12 Evolutionary curves with the best fitness of scene 2

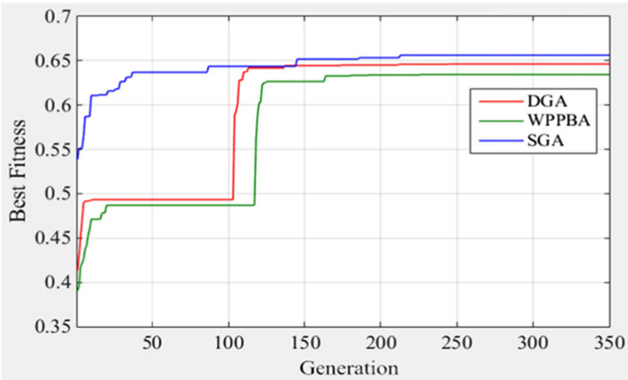

Fig. 13 Evolutionary curves with the best fitness of scene 3

Fig. 10, the left of the curve denotes the first stage of the algorithm and it ran in the central server first. The right of the curve denotes the second stage, and it ran in the distributed subservers. Because of the different standards of fitness, the curve had a great leap between the two stages.

5.3 Weight simulation

Simulation of the different criteria models of CTQRS = (C, T, Q, A, S) is applied in this section. According to different optimization requirements, we assume three scenes in Table 8: service-oriented, quality-oriented, and non-oriented. Figures 11, 12, and 13 separately show the best fitness of the three scenes, respectively. The DGA had a good performance in scenes 1 and 2 but fell into the local optimal solution quickly in scene 3. This was because the weight of optimization objective was quite average, and the algorithm could not look for the main optimization goals in the first phase. Consequently, the DGA is suitable for models that have a certain optimal tendency.

6 Conclusions and future work

Because of the complexity and diversity of a CMfg environment, the MRCO problem should take into consideration more factors such as the transportation time, transportation cost, occupation of resources, increasing amount of data, etc. To ensure the computing speed and optimal result, this paper proposed a distributed manufacturing resource selection strategy in a CMfg environment. The method of distributed computing greatly shortens the calculation time of the algorithm, and real-time data exchange among distributed computers accelerates the convergence speed and enhances the global searching ability. A set of experiments were carried out to verify the efficiency of the proposed DGA. The simulation results demonstrated the effectiveness, high efficiency, and superiority of the DGA compared to the SGA and WPPBA. Consequently, with the development of cloud computing and distributed technology, the DGA could be applied to more scenes and provide significant methods for the optimal selection of a resource service in a CMfg environment. In the future, it will be interesting to investigate the following issues:

The DGA should be used in a big data environment to verify its performance. A resource allocation prototype platform system of CMfg will be established on the basis of resource selection strategies. Existing combinatorial optimization algorithms should be extended to dynamically resource allocation problems.

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