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Functional objectives decision-making of discrete manufacturing system based on integrated ant colony optimization and particle swarm optimization approach

Xu, W.[a], **Yin, Y.**[b,*]

[a]School of Management, Shenyang University of Technology, Shenyang, P.R. China
[b]ANU College of Business and Economics, The Australian National University, Australia

ABSTRACT

In order to obtain a decision model with universality, the manufacturing unit was regarded as the most basic carrier for the functional objectives of the manufacturing system. This paper has established the functional objective decision model of discrete manufacturing system by characterizing the manufacturing objectives of cost, efficiency, quality, time, agility and greenness, and has introduced the concept of coordination degree between manufacturing units. In weight calculation, the model could balance the importance of the functional objectives required by the customer and the producer. Moreover, according to the NP-hard characteristics of the model, ant colony algorithm and particle swarm optimization (ACO-PSO) algorithm was designed to solve the problem. The feasibility and validity of the algorithm were verified by simulation examples, which could promise the experimental results more satisfactory than the traditional genetic algorithm. In addition, the model can provide more choices for decision-making of functional objectives in discrete manufacturing systems by adjusting the fitness value.

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**Corresponding author:*
lu6400269@anu.edu.au
(Yin, Y.)

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1. Introduction

Manufacturing system is the core subsystem of enterprises and the fundamental driving force for sustainable development of enterprises [1]. Its competitiveness directly determines the competitiveness of product market, so enterprises have to improve the manufacturing system to meet the fluctuation of market and customer demand. The companies can ensure their competitive advantages and their continued effectiveness in a complex market environment through this method [2]. In previous investigations, the manufacturing, in which only 5 % of the total man-hour cost was invested, was used in enterprises, but the total cost of the product was increased by 12 times [3-4]. Therefore, good adaptability and competitiveness of enterprises cannot do without flexible adjustment of the manufacturing system [5]. Besides, practice has proved that, the main way to improve the flexible adaptability and competitiveness of enterprises is to build a manufacturing system, and it could meet market demands [6-7]. Furthermore, in order to ensure the realization of environmental needs, enterprises should constantly adjust their manufacturing systems with the competition environment changing [8].

Objective decision-making function of the manufacturing system is to obtain the ideal products for users through a good manufacturing system, fundamentally provide strategic competitiveness, leverage manufacturing system functions, meet multiple technical and economic indicators, and identify the best comprehensive solution among series of scenarios [9]. And at the core stage of forming enterprise competitiveness, the objective of manufacturing system function is the ultimate source of ensuring product and service quality, because its advantages and disadvantages directly determine the intrinsic quality of products and the external level of service, which mainly manifested in manufacturing, use and maintenance process, simultaneously, its advantages and disadvantages affect the production and service capabilities of products as well as follow-up behaviours [10-11]. In recent years, industrial technology has flourished, and users had higher requirements for products and equipment, which include quality, function, structure, etc. [12]. So, enterprises have been inseparable from the objective of manufacturing system functions during operation [13].

2. Problem descriptions and hypothesis

2.1 Problem descriptions

It can be concluded that the main functional objectives of discrete manufacturing systems include cost, efficiency, quality, time, agility and green attributes, furthermore, in order to meet customer demand and corporate competitive strategies, these may also be expanded in real-world builds [6]. Therefore, the decision-making factors are complicated. And on the other hand, in the case of limited enterprise resources, various functional objectives may be modified according to certain principles to meet the focus shifts in the production process, and there may even be serious conflicts between functional objectives. Therefore, enterprises must make scientific and effective decisions. When companies pursue the following objectives that include high efficiency, low cost, good quality, prompt delivery, high agility, greenness and coordination among the above objectives, for any of the manufacturing subtasks in the manufacturing unit of Fig. 1, each candidate unit is equivalent to a selection in D. That is, the manufacturing unit has to select a certain direction in each two-way arc in D. and if it is directed acyclic, it corresponds to an optimal service configuration that belongs to the k-th manufacturing subtask; Similarly, when the service execution nodes are all determined which correspond to the subtasks in the manufacturing task chain, a complete directed acyclic graph called Hamilton loop can be obtained.

There are four structures in the model which include series, parallel, selection and cycle, as shown in Fig. 2.

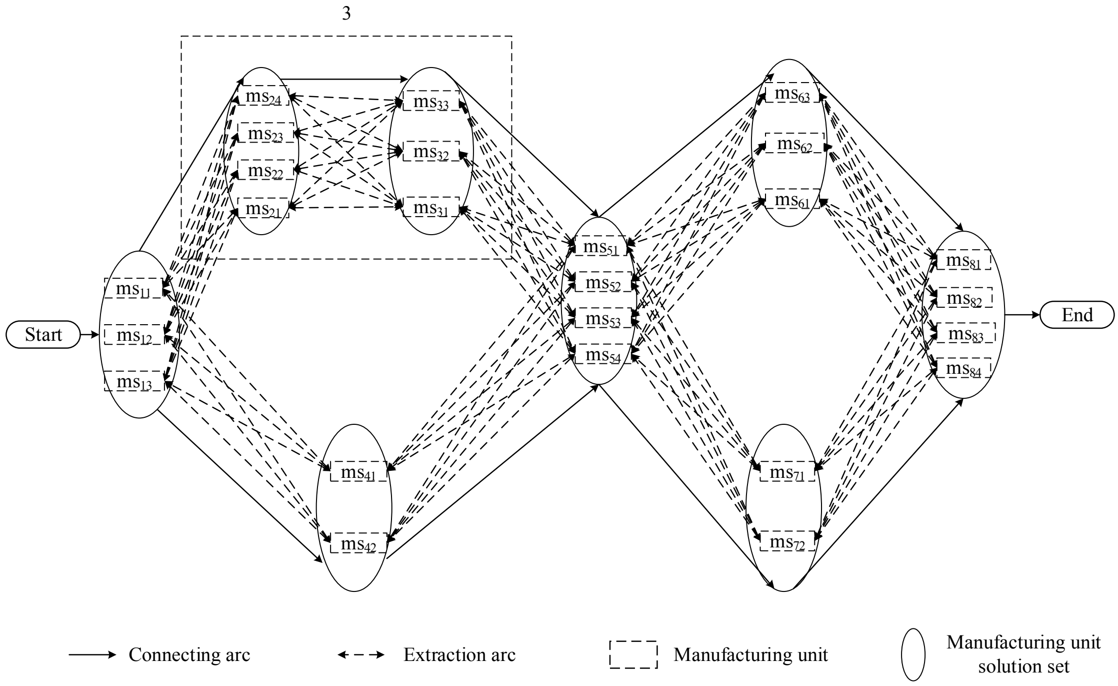
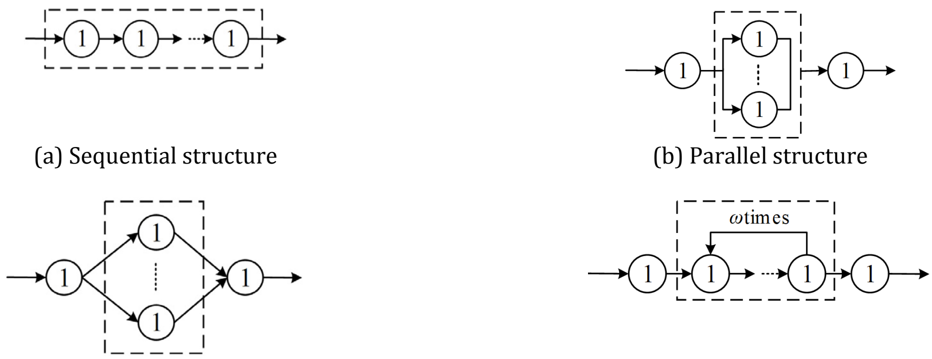


Fig. 1 Disjunctive graph of function decision making for discrete manufacturing system



(a) Sequential structure (b) Parallel structure

(c) Branch structure (d) Cyclic structure

Fig. 2 Four kinds of subtask combination structures

There is a cyclic structure in sub-task 2 and 3 which cannot meet Hamilton loop requirements, while in order to meet the requirements, three cycles need to be converted into three series. In fact, both branch selection structure and parallel structure can be converted into series structure. And it was expressed as $\{st_1 \rightarrow st_2/st_3 \rightarrow st_4 \rightarrow 3[st_5 \rightarrow st_6] \cup st_7 \rightarrow st_8\}$.

2.2 Problem hypothesis

The manufacturing unit could optimize the functional objective direction and strength of the decomposable task in a certain predictable time, and which is called discrete manufacturing system function objective decision. However, the manufacturing unit may also be self-interested, exclusive, and competitive in the actual operation process, which may cause damage to the organic whole of the functional objectives of the manufacturing system. So in order to construct a functional objective decision model with certain universality, we give such simplifications and assumptions:

- Each sub-task in the manufacturing task chain could be realized by the same type of manufacturing unit, but the premise is that it has the same processing capability, processing technology and processing method. However, each manufacturing unit has its own characteristics, which are mainly reflected in the functional objectives not in manufacturing process. Besides, a sub task could only be finished by one of the best manufacturing units.
- The manufacturing unit has differences in time, quality, cost, agility, efficiency, and green functionality, each of which can be independently measured within the optimal range of objectives. Moreover, we can comprehensively measure the functional objectives of manufacturing units by using the relevant duplicate weights, which called comprehensive evaluation, and it could provide quantitative support for the final multi-objective decision-making.
- The calculation of transportation costs and transfer time between manufacturing units is defined by a coordination factor, and it could be obtained by experts or engineering designers with reference to transportation costs and transfer times.
- There are four kinds of interconnection among manufacturing units: serial, parallel, selective and cyclic, and all of them can be expressed in series.
- The manufacturing unit function has certain robustness, and which indicates that the manufacturing system has sufficient resources and capabilities within a certain range, and it can avoid time conflicts for multiple manufacturing subtasks in the use of manufacturing units.

3. Model establishment

3.1 Objective functions

Cost objective function

For discrete manufacturing enterprises, manufacturing is the creative process of enterprise value, and the cost of manufacturing directly affects the profit and core competitiveness of discrete manufacturing enterprises. Therefore, the cost factor most concerned is manufacturing cost generated by production activities in workshops. Thus the total cost objective function of discrete manufacturing system is defined as:

$$E = \sum_{i=1}^{a}\sum_{j=1}^{k_j} H_{ij}e_{ij} + \sum_{l=1}^{b} max\left(\sum_{j=1}^{k_j} H_{ij}e_{ij}, \sum_{j=1}^{k_j} H_{(i+1)j}c_{(i+1)j}\right) + p_i\sum_{i=1}^{c}\sum_{j=1}^{k_j} H_{ij}e_{ij} + \lambda\sum_{i=1}^{d}\sum_{j=1}^{k_j} H_{ij}e_{ij} \tag{1}$$

$$H_{ij} = \begin{cases} 1 & \text{The } i\text{- th sub task is made by the manufacturing unit } ms_j \\ 0 & \text{The } i\text{- th sub task is not made by the manufacturing unit } ms_j \end{cases}$$

In Eq. 1, c_{ij} is the manufacturing cost of the *j*-th manufacturing unit in the *i*-th subtask in the manufacturing system, a is the number of serial tasks in the manufacturing unit, b is the number of parallel manufacturing units in a manufacturing system, c is the number of manufacturing units in the manufacturing system, d is the number of circulating manufacturing units in the manufacturing system, k_p is the number of manufacturing unit subtasks in the four manufacturing categories, p_i is selection probability, λ is the number of cycles for manufacturing subtasks.

Manufacturing efficiency objective function

Manufacturing efficiency generally refers to the quantity of qualified products produced per unit of time (such as one hour, one day and night), per unit of capacity of a manufacturing unit (such as a machine tool or an automated production line) or equipment (such as per cubic meter of blast furnace volume). So the increase in manufacturing efficiency showed that the manufacturing system makes full use of resources. Thus the efficiency objective function in the function objective of discrete manufacturing system is defined as:

$$E = \frac{1}{a}\sum_{i=1}^{a}\sum_{j=1}^{k_j} H_{ij}e_{ij} + \frac{1}{b}\sum_{l=1}^{b}\left(\sum_{j=1}^{k_j} H_{ij}e_{ij}, \sum_{j=1}^{k_j} H_{(i+1)j}e_{(i+1)j}\right) + p_i\frac{1}{c}\sum_{i=1}^{c}\sum_{j=1}^{k_j} H_{ij}e_{ij} + \frac{1}{d}\lambda\sum_{i=1}^{d}\sum_{j=1}^{k_j} H_{ij}e_{ij} \tag{2}$$

$$H_{ij} = \begin{cases} 1 & \text{The } i\text{- th sub task is made by the manufacturing unit } ms_j \\ 0 & \text{The } i\text{- th sub task is not made by the manufacturing unit } ms_j \end{cases}$$

In Eq. 2, e_{ij} is the manufacturing efficiency of the *j*-th manufacturing unit in the *i*-th sub-task in the discrete manufacturing system.

Manufacturing quality objective function

Manufacturing quality index is mainly used to evaluate the production capacity of machine tools equipment and the level of machining accuracy, such as production processing accuracy, product qualification rate, surface roughness and so on. Manufacturing quality of a manufacturing unit should be the product of the qualified rate of each process within the unit, that is, the manufacturing quality should be optimized as far as possible. Thus the objective function of manufacturing quality of discrete manufacturing system is defined as:

$$Q = \prod_{i=1}^{a}\prod_{j=1}^{k_j} H_{ij}q_{ij} + min\prod_{i=1}^{b}\left(\prod_{j=1}^{k_j} H_{ij}q_{ij}\,, \prod_{j=1}^{k_j} H_{(i+1)j}q_{(i+1)j}\right) + p_i\prod_{i=1}^{c}\prod_{j=1}^{k_j} H_{ij}q_{ij} + \left(\prod_{i=1}^{d}\prod_{j=1}^{k_j} H_{ij}q_{ij}\right) \tag{3}$$

$$H_{ij} = \begin{cases} 1 & \text{The } i\text{- th sub task is made by the manufacturing unit } ms_j \\ 0 & \text{The } i\text{- th sub task is not made by the manufacturing unit } ms_j \end{cases}$$

In Eq. 3, q_{ij} is the quality pass rate of the *j*-th manufacturing unit in the *i*-th subtask of a discrete manufacturing system.

Time objective function

The technological process for each order is fixed. The raw materials have gone through several processes in the workshop before becoming end products. And the processing cycle is sum of the process time of each manufacturing, in which involves handling time, waiting time, and processing time. Thus the total running time objective function of the discrete manufacturing system functional objective is defined as:

$$T = \sum_{i=1}^{a}\sum_{j=1}^{k_j} H_{ij}t_{ij} + \sum_{l=1}^{b} max\left(\sum_{j=1}^{k_j} H_{ij}t_{ij}\,, \sum_{j=1}^{k_j} H_{(i+1)j}t_{(i+1)j}\right) + p_i\sum_{i=1}^{c}\sum_{j=1}^{k_j} H_{ij}t_{ij} + \lambda\sum_{i=1}^{d}\sum_{j=1}^{k_j} H_{ij}t_{ij} \tag{4}$$

$$H_{ij} = \begin{cases} 1 & \text{The } i\text{- th service node selects service } ms_j \text{ to provide services} \\ 0 & \text{The } i\text{- th service node doesn't select service } ms_j \text{ to provide services} \end{cases}$$

In Eq. 4, t_{ij} is the execution time of the *j*-th manufacturing unit of the *i*-th subtask in the discrete manufacturing system.

Manufacturing agility objective function

The manufacturing agility of discrete manufacturing systems is primarily measured by the average level of agility of each manufacturing unit, which is to make the overall agility of the manufacturing system optimal as far as possible. So the objective function of manufacturing agility of discrete manufacturing system is defined as:

$$A = \left(\prod_{i=1}^{a}\prod_{j=1}^{k_j} H_{ij}a_{ij}{}'\right)^{\frac{1}{a}} + \sum_{l=1}^{b} min\left(\prod_{j=1}^{k_i} H_{ij}q_{ij}\,, \prod_{j=1}^{k_j} H_{(i+1)j}a'_{(i+1)j}\right)^{\frac{1}{b}} + p_i\left(\prod_{i=1}^{c}\prod_{j=1}^{k_j} H_{ij}a'_{ij}\right)^{\frac{1}{c}} + \left(\prod_{1}^{\lambda}\prod_{i=1}^{d}\prod_{j=1}^{k_j} H_{ij}a'_{ij}\right)^{\frac{1}{d}} \tag{6}$$

$$H_{ij} = \begin{cases} 1 & \text{The } i\text{- th sub task is made by the manufacturing unit } ms_j \\ 0 & \text{The } i\text{- th sub task is not made by the manufacturing unit } ms_j \end{cases}$$

In Eq. 5, a'_{ij} is the agility of the *j*-th manufacturing unit in the *i*-th subtask in a discrete manufacturing system.

Green function

The greenness of the manufacturing unit refers to the evaluation of environmental indicators in the manufacturing process under current environmental requirements, such as carbon emissions and material loss. So the objective function of manufacturing agility of discrete manufacturing system is defined as:

$$T = \frac{1}{a}\sum_{i=1}^{a}\sum_{j=1}^{k_j} H_{ij}g_{ij} + \sum_{l=1}^{b} max\left(\sum_{j=1}^{k_j} H_{ij}t_{ij}, \sum_{j=1}^{k_j} H_{(i+1)j}e'_{(i+1)j}\right) + p_i\frac{1}{c}\sum_{i=1}^{c}\sum_{j=1}^{k_j} H_{ij}g_{ij} + \frac{1}{d}\prod_{1}^{\lambda}\prod_{i=1}^{d}\prod_{j=1}^{k_j} H_{ij}g_{ij} \tag{6}$$

$$H_{ij} = \begin{cases} 1 & \text{The } i\text{- th sub task is made by the manufacturing unit } ms_j \\ 0 & \text{The } i\text{- th sub task is not made by the manufacturing unit } ms_j \end{cases}$$

In Eq. 6, e'_{ij} is the greenness of the j-th manufacturing unit in the i-th subtask in the discrete manufacturing system.

Manufacturing unit function objective total objective function

In actual production and operation, enterprise pursued such objectives which include low cost, high efficiency, perfect quality, short time, agility and strong green. However, these objectives are often interrelated and conflict with each other. When a manufacturing unit was selected, each sub-objective has its own optimization criteria, and they could also restrict each other, so it is almost impossible to find a group of manufacturing units that can satisfy these requirements simultaneously, which includes Min T, Max Q, Min C, Max F, Max E, Max G. Thus the corresponding weights should be assigned according to the relative importance of each sub objective.

$$minZ = w_1\,T + w_2\,C + w_3\,(1-Q) + w_4\,(1-A) + w_5\,(1-E) + w_6(1-G) \tag{7}$$

Coordination function between manufacturing units

$$R = \sum_{i=1}^{n-1}\sum_{j=1}^{k_j}\sum_{q=1}^{k_{j+1}} H_{ij}\,H_{(i+1)g}r_{ij,(i+1)q} \tag{8}$$

$$H_{ij} = \begin{cases} 1 & \text{The } i\text{- th sub task is made by the manufacturing unit } ms_j \\ 0 & \text{The } i\text{- th sub task is not made by the manufacturing unit } ms_j \end{cases}$$

In Eq. 8, $r_{ij,(i+1)q}$ is the coordination relationship between the j-th manufacturing unit in the i-th subtask in the discrete manufacturing system and the q-th manufacturing unit in the (i+1)-th subtask, and the value range is [0,1], and the greater the figure, the higher the coordination.

Functional objective decision model of discrete manufacturing system

Discrete manufacturing system function objective decision model is equivalent to the sum of the coordination values between the manufacturing unit functional objective and the manufacturing unit, as shown in Eq. 9.

$$minZ' = w_1\,T + w_2\,C + w_3\,(1-Q) + w_4\,(1-A) + w_5\,(1-E) + w_6(1-G) + w_7(1-R) \tag{9}$$

In Eq. 9, W is used as a weight vector, determined by both customers and producers.

The importance of cost (C), efficiency (E), quality (Q), time (T), agility (A), greenness (G) and coordination (R) has different dimensions and scales, so it is impossible to compare these indicators directly. Therefore, it is necessary to normalize them to eliminate the dimensional differences and obtain comparable scales. And T and C are the cost indicators z, and Q, A, E and R are benefit indicators y. Besides, different indicators are treated differently in the normalization process, as follows:

$$Z_{ij} = \frac{V_{ij} - \min\limits_{1\le j\le k}\{V_{ij}\}}{\max\limits_{1\le j\le k}\{V_{ij}\} - \min\limits_{1\le j\le k}\{V_{ij}\}} \tag{10}$$

$$Z_{ij} = \frac{\max\limits_{1\le j\le k}\{V_{ij}\} - V_{ij}}{\max\limits_{1\le j\le k}\{V_{ij}\} - \min\limits_{1\le j\le k}\{V_{ij}\}} \tag{11}$$

After normalizing the time (T), quality (Q), cost, (C), agility (A), efficiency (E), green (G) and coordinated (R), the general objective function of discrete manufacturing system is defined as follows in Eq. 12:

$$\begin{aligned} minZ'' = {} & w_1\, T + w_2\, C' + w_3\, (1 - Q') + w_4\, (1 - A') + w_5\, (1 - E') + w_6 (1 - G') \\ & + w_7 (1 - R') \end{aligned} \tag{12}$$

$$w_1 + w_2 + w_3 + w_4 + w_5 + w_6 + w_7 = 1$$

Weights $w_1, w_2, w_3, w_4, w_5, w_6$, and w_7 are the importance of cost (C), efficiency (E), quality (Q), time (T), agility (A), greenness (G), and coordination (R), respectively.

3.2 Constraints and decision variables

The decision-making process is that each manufacturing unit provides a functional objective carrier and integrates the discrete manufacturing system, which has the most coordination of manufacturing units. Therefore, the decision has the following corresponding constraints:

Manufacturing time constraint

The total manufacturing time of the manufacturing system cannot be greater than the latest delivery time, which is:

$$T_{max} \ge T$$

T_{max} is the latest delivery time in the manufacturing system.

Manufacturing quality constraint

The manufacturing quality of the manufacturing system cannot be less than the minimum quality requirement:

$$Q_{max} \le Q$$

Q_{max} is the minimum manufacturing quality acceptable to the manufacturing system.

Manufacturing cost constraint

The manufacturing quality of the manufacturing system cannot be higher than the maximum cost requirement.

$$C_{max} \ge C$$

C_{max} is the highest cost that a manufacturing system can afford.

Manufacturing agility constraint

The agility of manufacturing system must be higher than the minimum system agile requirement, as follows:

$$A_{min} \le A$$

R_{min} is the minimum system agility acceptable to a manufacturing system

Manufacturing efficiency constraint

The manufacturing efficiency of the manufacturing system cannot be less than the minimum efficiency, as follows:

$$E_{min} \leq E$$

E_{min} is the minimum efficiency acceptable to the manufacturing system.

Green constraint

The greenness of the manufacturing system cannot be less than the minimum greenness, as follows:

$$G_{min} \leq G$$

G_{min} is the minimum greenness requirements acceptable to the manufacturing system

Decision variable constraint

The decision variable constraint is represented by a manufacturing sub task, and which can only be completed by one type of manufacturing unit, one has the following expression:

$$\forall_i \in \{1,2,\cdots,n\}, j \in \{1,2,\cdots,g_j\}$$

$$H_{ij} = \begin{cases} 1 & \text{The } i\text{- th sub task is made by the manufacturing unit } ms_j \\ 0 & \text{The } i\text{- th sub task is not made by the manufacturing unit } ms_j \end{cases}$$

4. Solution of model

4.1 Part of ACO

We set the number of manufacturing units to N, the total number of ants to N, and the degree of coordination between unit i and unit j is $R_{ij}(i \neq j)$. The objective function can be described that the sum of the functional objectives of each unit and the degree of coordination between different units, such as Eq. 9. The bigger the value, the better. Where the manufacturing system task sequence is expressed as $\{st_1, st_2, ..., st_n\}$, which gives a full array of all tasks.

The basic idea of ant colony algorithm: ants find the path randomly at first time, and release the same amount of pheromone on the path. We define $\tau_{ij}(t)$ to represent the residual pheromone content on the line unit i and unit j at time t. The pheromone content of each path at the initial moment is $\tau_{ij}(0) = \tau_0$. During the crawling process, ant $ant_k(k = 1, 2, \dots, N)$ uses the Tabu Table $tabu_k$ to record the currently traversed unit, and uses the set $allowed_k$ to record the next alternative unit, i.e. $allowed_k = \{C - tabu_k\}$.

$p_{ij}^k(t)$ represents the state transition probability that ant ant_k is transferred from unit i to unit j at time t, where η_{ij} indicates the heuristic information from unit i to unit j (generally, $\eta_{ij} = 1/R_{ij}$. The parameter α represents the relative importance of the amount of residual information on the path from i to j, and the parameter β is the relative importance of the heuristic information, as shown by the Eq. 13.

$$p_{ij}^k(t) = \begin{cases} \dfrac{[\tau_{ij}(t)]^\alpha [\eta_{ij}]^\beta}{\sum_{s \in allowed_k} [\tau_{is}(t)]^\alpha [\eta_{is}]^\beta}, & \text{if } j \in allowed_k \\ 0\,, & j \in tabu_k \end{cases} \tag{13}$$

Eq. 14 represents the pheromone volatilization rate over time N; $\Delta\tau_{ij}$ represents the sum of the pheromone increments on path from i to j in this iteration, as shown in Eq. 15; Q represents the total pheromone content released by the ant cycle; L_k indicates the length of the path taken by ant_k in this tour; $\Delta\tau_{ij}^k$ represents the pheromone content left by ant_k on path in this iteration, as shown in Eq. 16.

$$\tau_{ij}(t+n) = \rho \cdot \tau_{ij}(t) + \Delta\tau_{ij} \tag{14}$$

$$\Delta\tau_{ij} \sum_{k=1}^{m} \Delta\tau_{ij}^{k} \tag{15}$$

$$\Delta\tau_{ij}^{k} = \begin{cases} \dfrac{Q}{L}, & \text{if } ant_k \text{ pass path } i \text{ to } j \text{ from time } t \text{ to } t+1 \\ 0, & \text{others} \end{cases} \tag{16}$$

4.2 Part of PSO

Particle swarm optimization is a swarm intelligence algorithm that simulates the predation behavior of flocks. In the process of optimization, each potential best solution is related to the velocity of particle motion. According to the historical experience of the particle and the experience of neighbors, the velocity and direction are adjusted to approach the best solution.

We set the position and velocity of the *i*-th particle in the particle group are $x_i(x_{i1}, x_{i2})$ and $v_i(v_{i1}, v_{i2})$ respectively. $pbest_i(p_{i1}, p_{i2})$ represents the best position searched by the *i*-th particle. $gbest_i(p_{i1}, p_{i2})$ represents the best position of all particles searched. according to Eqs. 17 and 18, we can update the velocity and position of the particles:

$$v_{i+1} = \omega * v_i + c_1 * \zeta_1(pbest_i - x_i) + c_2 * \zeta_2(gbest_i - x_i) \tag{17}$$

$$x_{i+1} = x_i + v_{i+1} \tag{18}$$

where the learning factors c_1 and c_2, respectively, indicate that the particles have self-optimizing ability and swarm intelligence ability to approximate the individual and group optimal solutions. ζ_1 and ζ_2 are the random numbers between [0, 1]. Particle velocity needs to be limited, if $|v_i| > v_{max}$, then $|v_i| = v_{max}$. ω is the inertia weight, which indicates how much the particle continues the current velocity, and its value is reasonably selected so that the particle has balanced local and global search ability.

4.3 Algorithm flow

The ACO-PSO hybrid algorithm model overcomes the shortcomings of both Ant Colony Optimization (ACO) and Particle Swarm Optimization (PSO) algorithms, and it combines the advantages of the two algorithms. Furthermore, its basic construction ideas are as follows: The first step is to generate an initial solution set of the problem by the strong global search ability of the particle swarm algorithm and its randomness. And then according to the primary selection result, the initial pheromone matrix of the ant colony algorithm is constructed. Next, it is to find the optimal solution of the problem, which applies the strong optimization ability and positive feedback of the ant colony algorithm. Moreover, in the optimal configuration model, in order to alleviate the occurrence of ant colony and stagnation, limited ant resources should be allocated to populations, and it has higher search rates. The algorithm structure is shown in Fig. 3.

4.4 The steps of algorithm

Step 1: Set the particle swarm parameters and initialize the particle swarm, that is, randomly generate N_p particle velocities and positions.

Step 2: Initialize the pheromone and parameters of each ant; randomly place N_{sa} ants on *N* units.

Step 3: Set each ant traverse all the units. The ant selects the passing unit by the concept of (13), updates the path length of N_{sa} ants, and calculates the optimal path of each ant as the fitness value of N_p particles.

Step 4: According to the fitness value of the particle, we update each particle's individual optimal solution and group optimal solution according to Eqs. 17 and 18, and obtain the velocity and position of the particle.

Step 5: Apply the global pheromone update rule.

Step 6: If the maximum number of iterations is reached, then the process ends. Otherwise, return to step 4.

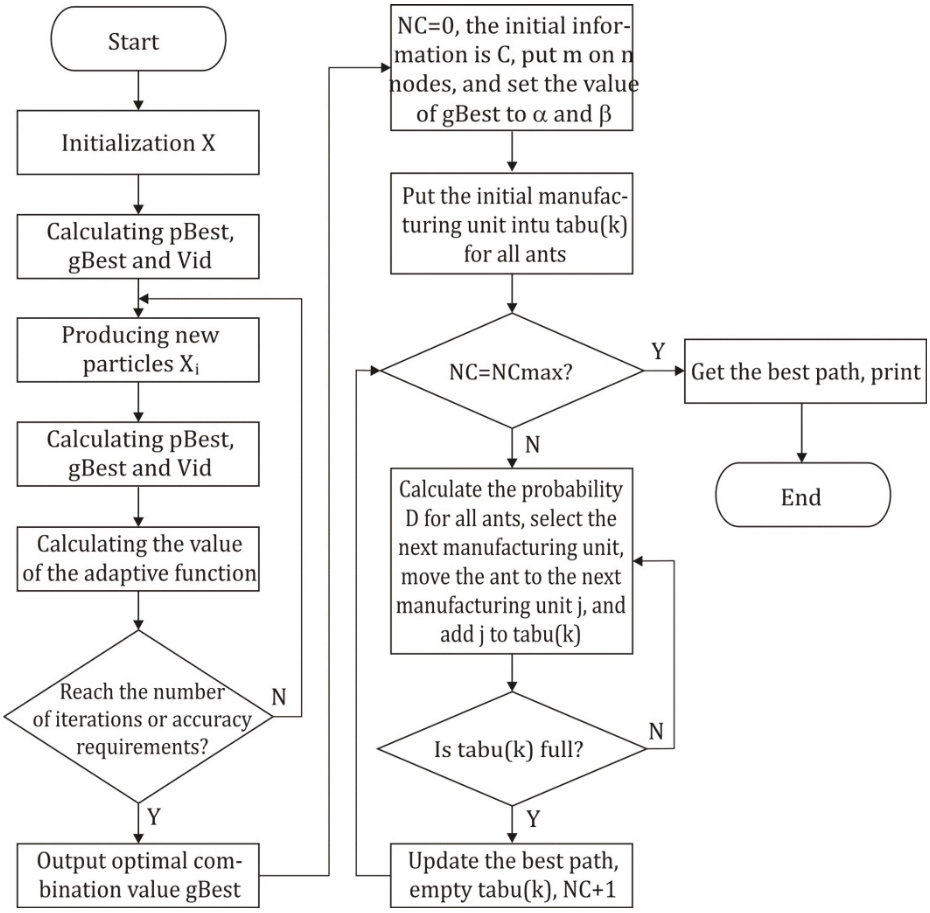


Fig. 3 Hybrid PSO-ACO algorithm flow

5. Results and discussion

5.1 The initial data

The process of functional objective decision making for discrete manufacturing systems is as follows: Starting from the upstream sub-task st_1, each sub-task st_1 passes through the downstream sub-task st_1 in the direction of directed connection arc, input and output connection arc r_{ij}. We select variable function allocate (ms_{ij}) respectively according to the rules of adjacency combination from the corresponding manufacturing units. A manufacturing unit is selected to participate in the formation of a discrete manufacturing system, which has formed satisfactory functional objectives, as shown in Fig 4. The result of discrete manufacturing system decision is that, the preferred manufacturing units has been selected from each sub-task, and then combined them to form a complete organic whole E^*, which can be formally expressed as:

$$E^* = \{\bar{P}(ms_{ij}),\ ms_{ij},\ \bar{N}(ms_{ij})\}$$

According to Fig. 4, an optimal decision-making scheme can be established, and it is corresponded to the task chain which consists of manufacturing unit, as shown in Table 1.

Functional objective decision-making of manufacturing system is the process of screening and integrating manufacturing units for each manufacturing sub-task in the manufacturing task chain. Besides it can make full use of manufacturing units based on the specific manufacturing system construction scheme, meanwhile it could optimize the allocation of resources within enterprises, and then achieve the organic combination of various manufacturing units under different manufacturing modes which can help form the dynamic core competitiveness, and at last maximize the functional objectives of manufacturing resources utility.

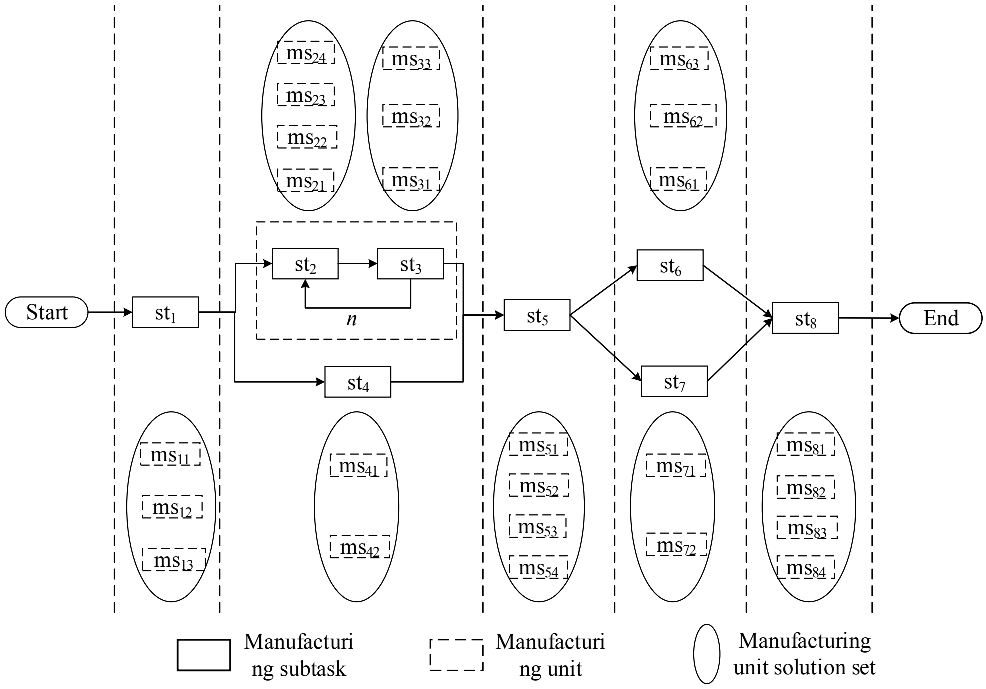


Fig. 4 Sketch map of function decision of discrete manufacturing system

Table 1 Functional components of discrete manufacturing system

Subtask	Manufacturing unit	C	E	T	Q	A	G
	ms_{11}	23.4	10	13.4	17.5	8.9	7.1
ts_1	ms_{12}	25.6	12.5	16.5	11.5	8.9	14.1
	ms_{13}	24.5	9.8	21.5	8.7	14.5	6.8
	ms_{21}	25.4	18.5	9.8	15.2	9.8	13.8
ts_2	ms_{22}	22.4	11.1	9.8	10.2	9.7	9.2
	ms_{23}	20.4	11.5	10.5	12.2	10.1	7.8
	ms_{24}	26.5	13.4	9.8	14.5	9.8	14.5
	ms_{31}	19.4	15.6	15.2	12.1	10.9	8.6
ts_3	ms_{32}	24.8	9.6	15.2	9.4	10.3	8.7
	ms_{33}	27.5	14.5	6.7	18.4	9.2	9.5
ts_4	ms_{41}	26.5	13.6	16.5	7.5	14.2	6.4
	ms_{42}	25.3	18.5	14.5	10.2	11.2	9.8
	ms_{51}	35	15.3	7.1	11.2	16.5	9.8
ts_5	ms_{52}	25.5	14.2	12.3	14.2	12.2	9.8
	ms_{53}	27.8	15.8	10.7	13	9.9	11
	ms_{54}	25.6	10.2	17.8	9.8	16.3	7.5
	ms_{61}	26.4	12.1	14.2	9.4	13.4	9.8
ts_6	ms_{62}	32.1	10.3	10.2	15.2	14.5	7.8
	ms_{63}	22.6	9.2	15.4	18.2	10.2	7.8
$ts7$	ms_{71}	24.5	10.5	14.4	9.4	11.2	10.5
	ms_{72}	28	9.8	15.4	16.4	9.2	9.6
	ms_{81}	22.2	13.4	18.8	12.3	11.8	9.6
ts_8	ms_{82}	27.7	7.4	13.1	16.3	13.8	6.4
	ms_{83}	22.4	6.9	22.3	7.8	14.8	6.5
	ms_{84}	27.6	16.6	14.8	16.5	7.9	11.2

The coordination data among manufacturing units were generated through random digits, as shown in Table 2. Then the disjunction graph model becomes a combinatorial optimization model, and it has met the coordination degree of the connection arc of each manufacturing unit. Besides, the manufacturing unit is selected by the following method, that is, One of the three designs in the manufacturing unit set 1 is selected, one of the four designs in the manufacturing unit set 1 is selected, and one of the three designs in the manufacturing unit set 3 is selected, one of the two designs in the manufacturing unit set 4 is selected, one of the four designs in the manufacturing unit set 5 is selected, and one of the three designs in the manufacturing unit set 6 is selected, One of the two designs in the manufacturing unit set 7 is selected, and one of the four designs in the manufacturing unit set 8 is selected. Furthermore, each manufacturing unit has its own characteristics, and which has reflected in cost, efficiency, quality, time, agility, and greenness, besides, its degree of coordination between units is different as well.

Table 2 Degree of coordination between units

	ms_{21}	ms_{22}	ms_{23}	ms_{24}		ms_{41}	ms_{42}				ms_{31}	ms_{32}	ms_{33}
ms_{11}	0.81	0.8	0.79	0.91	ms_{11}	0.45	0.56			ms_{21}	0.91	0.68	0.73
ms_{12}	0.65	0.85	0.65	0.56	ms_{12}	0.64	0.65			ms_{22}	0.89	0.75	0.64
ms_{13}	0.65	0.45	0.83	0.81	ms_{13}	0.53	0.68			ms_{23}	0.79	0.72	0.86
										ms_{24}	0.95	0.86	0.56
	ms_{51}	ms_{52}	ms_{53}	ms_{54}		ms_{51}	ms_{52}	ms_{53}	ms_{54}				
ms_{31}	0.88	0.76	0.87	0.89	ms_{41}	0.65	0.67	0.71	0.69				
ms_{32}	0.66	0.79	0.88	0.92	ms_{42}	0.95	0.66	0.86	0.83				
ms_{33}	0.68	0.69	0.86	0.84									
	ms_{61}	ms_{62}	ms_{63}			ms_{71}	ms_{72}						
ms_{51}	0.65	0.87	0.56		ms_{51}	0.81	0.78						
ms_{52}	0.86	0.89	0.64		ms_{52}	0.79	0.72						
ms_{53}	0.63	0.91	0.92		ms_{53}	0.67	0.86						
ms_{54}	0.65	0.75	0.45		ms_{54}	0.69	0.72						
	ms_{81}	ms_{82}	ms_{83}	ms_{84}		ms_{81}	ms_{82}	ms_{83}	ms_{74}				
ms_{61}	0.64	0.56	0.62	0.53	ms_{71}	0.91	0.75	0.61	0.85				
ms_{62}	0.81	0.72	0.65	0.58	ms_{72}	0.89	0.78	0.89	0.87				
ms_{63}	0.82	0.78	0.8	0.81									

5.2 The results

In this example, on the case of the discrete manufacturing system function objective decision model and algorithm (ACO-PSO), combined with MATLAB 7.0 simulation tool programming, the set of manufacturing units and the possible set of link arcs in the table are optimized and solved to obtain the functional objective combination of discrete manufacturing system. Parameter setting for programming solution was as follows. Particle swarm optimization part: population size1 = 20, ω = 1, $c_1 = c_2 = 2$, the number of iterations 500. Ant colony algorithm part: ants size2 = 10，α = 1，β = 1，ρ = 0，Q = 1, the number of iterations 60. The whole process is realized on the computer of Intel (R) Core (TM) i3 CPU550 @ 3.2 GHz ZN-2, RAM 2.O GB and Windows XP operating system. In the solving process, when the customer and the manufacturer have different requirements for the manufacturing task, which mainly reflected in the weight requirements for each objective, the decision-making results of the discrete manufacturing system functional objectives, which reflect the specific requirements of the combination optimization scheme. Decision-making schemes shown in Table 3 can be separately calculated to meet different requirements of the customer and the producer when they have own demand for each objective in the evaluation of the functional objectives. Taking the uniform weight as an example, each objective weight is 1/7, in which the fitness function value is the total objective value, that is Z'', meanwhile, the discrete manufacturing system function objective decision-making scheme is shown in Fig. 5.

As shown in Fig. 6, when PSO algorithm was employed alone, the initial convergence of the algorithm was faster. While with the number of iterations increased, the performance of local search ability was insufficient, and the convergence curve tended to level gradually, and which had resulted in that the solution was easy to fall into local optimum. Similarly, when the ACO algorithm was used alone, although the quality of the solution was higher than PSO, and it was also better at searching for the optimal solution. But its initial pheromone was relatively scarce, and which had resulted that its initial search is blind, time-consuming and slower. In short, this paper has designed a PSO-ACO algorithm for the functional decision making of discrete manufacturing systems, which fully circumvented the shortcomings of PSO and ACO algorithms and combined their advantages. Besides, it has greatly improved the accuracy and speed of the problem solved. Furthermore, both the GA algorithm and the proposed algorithm had the same minimum fitness value, and they could also avoid the premature and stagnant phenomenon of the solving process. However, obviously the GA algorithm took more time.

Table 3 Functional objective decision making of discrete manufacturing system under different weights

Objective weight							Fitness	Manufacturing unit combination
Cost	Efficiency	Quality	Time	Agility	Green	Coordination		
1/7	1/7	1/7	1/7	1/7	1/7	1/7	0.265	$ms_{12}ms_{22}ms_{32}ms_{41}$ $ms_{52}ms_{63}ms_{84}$
0.2	0.2	0.2	0.1	0.1	0.1	0.1	0.312	$ms_{14}ms_{22}ms_{33}ms_{42}$ $ms_{53}ms_{62}ms_{82}$
0.3	0.2	0.1	0.1	0.1	0.1	0.1	0.327	$ms_{11}ms_{23}ms_{33}ms_{42}$ $ms_{54}ms_{72}ms_{81}$
0.4	0.1	0.1	0.1	0.1	0.1	0.1	0.295	$ms_{13}ms_{22}ms_{32}ms_{42}$ $ms_{53}ms_{62}ms_{84}$
0.1	0.1	0.2	0.2	0.2	0.1	0.1	0.276	$ms_{14}ms_{22}ms_{31}ms_{42}$ $ms_{51}ms_{72}ms_{84}$
0.1	0.1	0.1	0.1	0.2	0.2	0.2	0.267	$ms_{12}ms_{21}ms_{32}ms_{41}$ $ms_{53}ms_{72}ms_{82}$
0.1	0.1	0.1	0.1	0.1	0.1	0.4	0.253	$ms_{14}ms_{24}ms_{32}ms_{42}$ $ms_{53}ms_{63}ms_{83}$

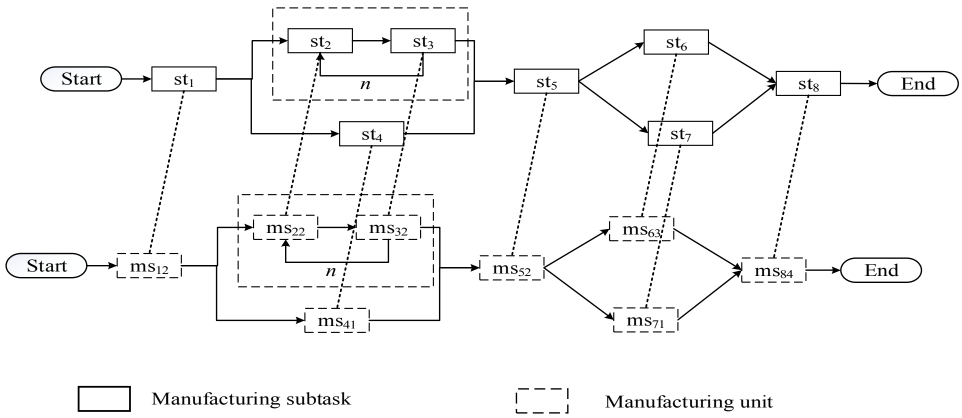


Fig. 5 Function objective decision making of discrete manufacturing system under uniform weight

In addition, the initial data at different scales are solved respectively. And the results have shown that, when the number of link arcs between the alternatives in the manufacturing unit set and the unit increased, the performance of the proposed algorithm was better.

As shown in Table 4 that the PSO-ACO algorithm proposed is the most accurate solution to the minimum of the objective function, followed by the ACO algorithm and GA algorithm, and the PSO algorithm is the worst. Besides, by analyzing the solutions obtained by running the three algorithms repeatedly, we found that the optimal solution obtained by PSO-ACO algorithm proposed has been floating around 0.387, and finally stabilized at 0.387. However, the results of the other two algorithms floated greatly and were not better than 0.387, which has shown that when PSO and ACO algorithms are used alone, their solutions tended to be limited due to their shortcomings and defects. Furthermore, it also indicated that the PSO-ACO algorithm had good solution performance.

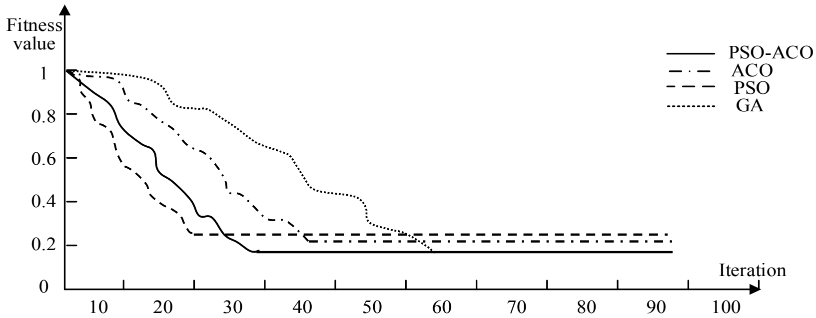


Fig. 6 Algorithm convergence curve

Table 4 Comparison of the results of four algorithms

Algorithm	Optimal solution objective function value	Optimum solution
PSOACO	0.387	$ms_{11}ms_{21}ms_{32}ms_{41}$ $ms_{53}ms_{62}ms_{83}$
ACO	0.418	$ms_{12}ms_{21}ms_{32}ms_{42}$ $ms_{53}ms_{71}ms_{83}$
PSO	0.463	$ms_{11}ms_{22}ms_{32}ms_{41}$ $ms_{52}ms_{71}ms_{81}$
GA	0.387	$ms_{11}ms_{21}ms_{32}ms_{41}$ $ms_{53}ms_{71}ms_{83}$

As shown in Table 5, the PSO-ACO algorithm had high search efficiency for three indexes on average value, worst value and average time, and these indicators were obtained from 30 consecutive runs. So it could be concluded that PSO-ACO algorithm is feasible and effective in discrete manufacturing system function objective decision-making.

In the functional objective decision of discrete manufacturing system shown in Table 6, the one-way optimal combination schemes has been given respectively, which was in cost, efficiency, quality, time, agility, greenness and coordination, meanwhile, and the overall optimal decision scheme was given in the last row, as shown in Table 6. Therefore, the decision-making scheme can be described as Fig. 7.

Table 5 Comparison of four algorithms

Algorithm	Optimal value	Average value	Worst value	Average time
PSACO	0.372	0.407	0.498	32
ACO	0.421	0.492	0.585	40
PSO	0.477	0.533	0.614	27
GA	0.374	0.451	0.570	43

Table 6 The best solution set of different objectives in discrete manufacturing system

Objective	Set of Solutions	Cost	Productivity	Quality	Time	Agility	Green	Coordination	Comprehensive satisfaction
Low cost	$ms_{11}ms_{22}$ $ms_{32}ms_{41}$ $ms_{52}ms_{63}$ ms_{84}	172.8	84.3	97.4	93.5	73.4	60.2	0.51	0.580
High productivity	$ms_{12}ms_{22}$ $ms_{31}ms_{42}$ $ms_{54}ms_{62}$ ms_{82}	178.1	85.6	97.1	85.3	85.3	63.4	0.54	0.582
High quality	$ms_{11}ms_{24}$ $ms_{33}ms_{41}$ ms_{54} $ms_{72}ms_{81}$	179.7	84.9	98.4	96.4	79.4	64.2	0.55	0.593
Short time	$ms_{13}ms_{22}$ $ms_{33}ms_{42}$ $ms_{52}ms_{62}$ ms_{83}	179.7	85.3	97.3	84.7	86.1	59.4	0.57	0.607
Great agility	$ms_{13}ms_{22}$ $ms_{33}ms_{42}$ $ms_{51}ms_{63}$ ms_{81}	183.4	85.2	98.0	87.2	89.2	58.5	0.58	0.602
Good greenness	$ms_{12}ms_{22}$ $ms_{33}ms_{42}$ ms_{54} $ms_{72}ms_{83}$	176.8	86.5	103	85.3	79.3	66.2	0.61	0.558
coordination	$ms_{12}ms_{24}$ $ms_{31}ms_{42}$ ms_{52} $ms_{72}ms_{83}$	181.5	84.6	98.1	88.7	80.3	57.9	0.65	0.589
Comprehensive satisfaction	$ms_{11}ms_{21}$ $ms_{32}ms_{41}$ $ms_{53}ms_{62}$ ms_{83}	182.4	84.7	98.1	85.6	82.4	61.3	0.62	0.613

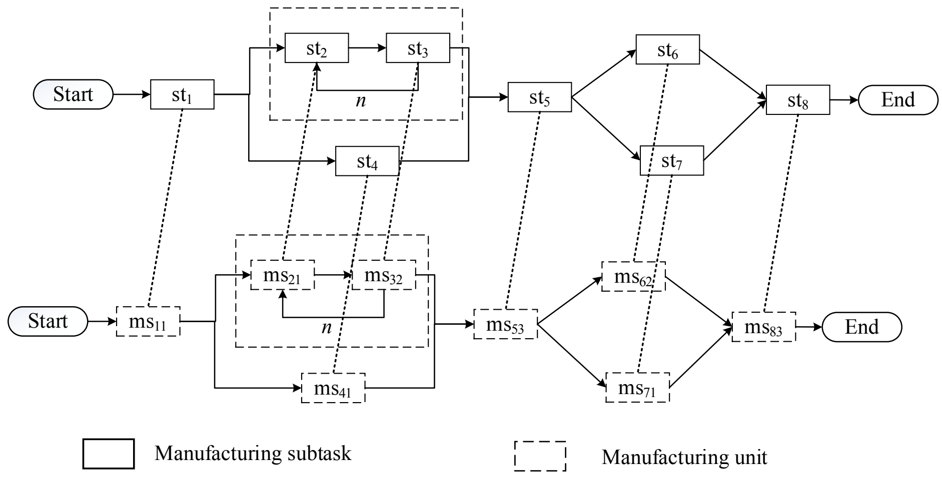


Fig. 7 The overall optimal solution of discrete manufacturing system functional objectives

This method could satisfy the preference of the functional objectives of discrete manufacturing system for different sub-tasks. Besides, when using the functional objective optimization combination method and PSO-ACO method, we could obtain the Pareto optimal state solution set of the discrete manufacturing system function objective decision and the optimal scheme in a specific aspect. At the same time, the optimal synthesis scheme could be given, which was helpful for decision-makers and customers to choose the optimal scheme and improve the environmental adaptability of manufacturing system.

6. Conclusion

This paper has established a decision model, and in which manufacturing unit was considered as a discrete manufacturing system function objective carrier. And it had different characteristics, such as cost, efficiency, quality, time, agility and green, and the coordination degree between units was also fluctuating. Besides, the decision-making model, production capacity, resource constraints and objective thresholds have constituted to a decision-making system for functional objectives of discrete manufacturing systems, and it also has quantified the data. The PSO-ACO method is used to solve the problem, and the preference of the combination of customer weight and enterprise weight was given as the combination weight. Finally, an example was given to verify the proposed method, which also proved the practicability of the algorithm.

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