Research on Agile Manufacturing Supply Chain Formation Based on Improved Ant Colony Algorithm

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Abstract: In view of the agile manufacturing supply chain formation strategy and the lack of initial information of traditional ant colony algorithm, this paper constructs a mathematical model of agile manufacturing supply chain formation. On the basis of analyzing the characteristics of traditional ant colony algorithm and genetic algorithm, the traditional ant colony algorithm is improved by introducing the 5 aspects: population initialization of genetic algorithm, initial value setting of pheromone, path selection strategy, value of ρ, and cross mutation of genetic algorithm. The improved ant colony algorithm is applied to the solution of agile manufacturing supply chain for sofa products. After verification, the convergence time and number of iterations of the algorithm are greatly reduced, and the ability of the algorithm to obtain an optimal solution at a certain search speed is improved.

1 INTRODUCTION

Agile manufacturing(AM) is the main mode of production in 21st Century. The degree of AM in a country directly determines the country's economic status in the world. The literature points out that AM is an advanced manufacturing technology with rapid response, high reliability and high flexibility. Katzy constructs a conceptual model of AM, and illustrates the feasibility of the model through an example of an enterprise. Chen Wen faces the problem of resource constraints in the selection of AM cooperative enterprises, and constructs a Bernardo group decision improvement model to solve the problem of partner selection under the constraint of resource constraints.

The core of AM is the establishment of AM supply chain, which is essentially the optimal combination of manufacturing enterprises. In solving the optimal combination problem, ant colony algorithm(ACA) can make good use of the positive feedback information of the system and solve the precision of the results. However, the efficiency of the algorithm is low because of the lack of the initial value information and the slow convergence speed of the traditional ACA. The genetic algorithm has the characteristics of fast, global search, parallel search and cross mutation in solving the optimal combination problem, which can make up for the defects of the traditional ACA.

On this basis, this paper makes an in-depth study on the formation of AM supply chain, gives a graphical representation of the formation of the AM supply chain, constructs its mathematical model, and improves the traditional ACA with the genetic algorithm, making the improved ACA to solve the problem of the establishment of the supply chain of AM. It is more efficient and accurate, and the effectiveness of the algorithm is verified through an example of AM supply chain in the furniture industry.

2 MATHEMATICAL MODEL OF AM SUPPLY CHAIN ESTABLISHMENT

The AM supply chain can make full use of the internal and external manufacturing resources of the customized enterprise, and build dynamic manufacturing alliance relations among many enterprises, and make collaborative manufacturing to meet the customer's personalized needs. The establishment of AM supply chain is essentially a partner selection problem. This section illustrates the cooperative relationship of multiple enterprises in supply chain by graphical representation of supply chain. By constructing the mathematical model of supply chain, it is the objective function chosen by cooperative enterprises.

2.1 Graphical Representation of the Supply Chain Establishment

The AM supply chain is carried out around the manufacturing task. Each module of the manufacturing task is undertaken by the manufacturing enterprises in the network, and the manufacturing enterprises are combined in a certain order to get the AM supply chain. Each node in the supply chain represents a manufacturing enterprise, and the connection order of each node represents the synergy relationship among enterprises. Therefore, it is necessary to consider the relevant factors from many candidate enterprises, select better enterprises, optimize the allocation of manufacturing chains, reduce costs and improve efficiency.

In order to solve the multi-objective optimization problem, it is assumed that when the supply chain is set up, the enterprise's target task M is divided into n branches, $M = \{m_i \mid i \in [1, n]\}$. Each branch task m_i has s_i candidates, $R_i = \{r_{ij} \mid i \in [1, n], j \in [1, s_i]\}$ represents the collection of candidate enterprises that can complete the branch task m_i. Each branch task selects a suitable manufacturing partner r_{ij} from s_i enterprises to select n manufacturing partners to complete the manufacturing task. From this, the problem of the establishment of AM chain can be transformed into a n level decision problem, that is, finding a set of optimal solutions in the solution space of $\prod_{i=1}^{n} m_i$ group. The graphical representation of the supply chain is shown in figure 1 below.

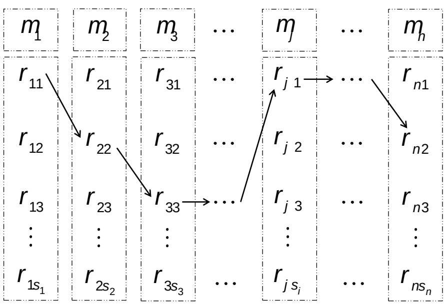

Figure 1: AM supply chain set up graphical representation.

2.2 Mathematical Model of Supply Chain Establishment

American scholar Dickson summed up 23 supplier selection criteria and their ranking and weighting. In this paper, based on the AM supply chain, the 6 selection criteria of quality Q, delivery time T, historical performance H, guarantee clause C, production capacity A and price P are selected as evaluation parameters to construct a mathematical model. The objective function of AM supply chain can be expressed as:

$$Z = w_1 Q + w_2 T + w_3 H + w_4 C + w_5 A + w_6 P \quad (1)$$

$$\sum_{k=1}^{6} w_k = 1 \quad (2)$$

$w_k (k = 1, 2, \cdots, 6)$ is the corresponding index weight. This paper uses entropy method to calculate. Suppose that $q_{r_{ij}}$, $t_{r_{ij}}$, $h_{r_{ij}}$, $c_{r_{ij}}$, $a_{r_{ij}}$, $p_{r_{ij}} (i \in [1, n], j \in [1, s_i])$ completes the sub task m_i quality, delivery time, historical performance, warranty terms, production capacity and price respectively for enterprise r_{ij}.

$$Q = \sum_{i=1}^{n} \sum_{i=1}^{s_i} \frac{q_{max} - q_{r_{ij}}}{q_{max} - q_{min}} u_{ij} \quad (3)$$

$$T = \sum_{i=1}^{n} \sum_{j=1}^{s_i} \frac{t_{r_{ij}} - t_{min}}{t_{max} - t_{min}} u_{ij} \quad (4)$$

$$H = \sum_{i=1}^{n} \sum_{j=1}^{s_i} \frac{h_{max} - h_{r_{ij}}}{h_{max} - h_{min}} u_{ij} \quad (5)$$

$$C = \sum_{i=1}^{n} \sum_{i=1}^{s_i} \frac{c_{max} - c_{r_{ij}}}{c_{max} - c_{min}} u_{ij} \quad (6)$$

$$A = \sum_{i=1}^{n} \sum_{j=1}^{s_i} \frac{a_{max} - a_{r_{ij}}}{a_{max} - a_{min}} u_{ij} \quad (7)$$

$$P = \sum_{i=1}^{n} \sum_{j=1}^{s_i} \frac{p_{r_{ij}} - p_{min}}{p_{max} - p_{min}} u_{ij} \quad (8)$$

The constraint conditions are:

$$\prod_{i=1}^{n} \prod_{j=1}^{s_i} q_{r_{ij}} u_{ij} \geq Q_{min} \quad (9)$$

$$\sum_{i=1}^{n} \sum_{j=1}^{s_i} t_{r_{ij}} u_{ij} \leq T_{max} \quad (10)$$

$$\prod_{i=1}^{n} \prod_{j=1}^{s_i} a_{r_{ij}} u_{ij} \geq A_{min} \quad (11)$$

$$\sum_{i=1}^{n}\sum_{j=1}^{s_i} p_{r_{ij}} u_{ij} \le P_{max} \tag{12}$$

$$s.t.\sum_{i=1}^{n} u_{ij} = 1 \tag{13}$$

$$u_{ij} = \begin{cases} 1, \text{ Select } r_{ij} \text{ for agile manufacturing} \\ 0, \quad \text{others} \end{cases} \tag{14}$$

Among them, q_{max}, t_{max}, h_{max}, c_{max}, a_{max}, p_{max} are the maximum value of the corresponding index when the candidate enterprise completes the manufacturing task. The minimum values for the candidate enterprises to complete the manufacturing tasks are q_{min}, t_{min}, h_{min}, c_{min}, a_{min}, p_{min}. u_{ij} is a decision variable. Q_{min}, T_{max}, A_{min}, P_{max} are the lowest quality, the longest delivery time, the minimum production capacity and the highest price for the whole AM chain, respectively.

Formula (9), (10), (11), (12) respectively indicate the constraints of quality, delivery time, production capacity and price. Constraints, as shown in formula (13) and (14), indicate that each sub task corresponds to the selection of a manufacturing enterprise. According to the meaning of each index, the mathematical expression of the optimal allocation of AM supply chain makes the objective function (1) obtain the minimum value.

3 THE IMPROVEMENT OF ACA

Combined with the accuracy of ACA and the rapidity of genetic algorithm, the ACA is integrated into the genetic algorithm to improve the ACA. And the improved ACA is used to solve the minimum value of the objective function in the supply chain mathematical model, and then the optimal combination of the AM supply chain is obtained.

3.1 Traditional ACA

ACA is a bionics algorithm, which simulates the interaction of pheromones through the pheromone of the ant colony in nature to find the shortest foraging path phenomenon, and a simulated evolutionary algorithm is proposed. The algorithm has the characteristics of distribution calculation, information feedback and heuristic search. It is proposed from the solution of the traveling salesman problem (TSP) and can be used for the precise solution of the combinatorial optimization problem.

Taking the TSP problem of n cities as an example, the traditional ACA is described as follows: m is the number of ants in the ant colony, n is the number of cities, and d_{ij} is the distance between city i and city j . $\tau_{ij}(t)$ represents the pheromone content of t on the edge $e(i, j)$.In the initial time, the pheromone content of each path is equal, so $\tau_{ij}(0) = C(C \text{ is constant})$, ant $k(k = 1, 2, \cdots , m)$ will choose the path according to the content of pheromone on each path, and at the time of t, the probability of the ant k to choose the city j by the ant of the city i is $p_{ij}^{k}(t)$:

$$p_{ij}^{k}(t) = \begin{cases} \dfrac{\tau_{ij}^{\alpha}(t) \cdot \eta_{ij}^{\beta}}{\sum\limits_{s \in allowed_k} \tau_{is}^{\alpha} \cdot \eta_{is}^{\beta}}, & j \in \text{allowed}_k \\ 0, & \text{others} \end{cases} \tag{15}$$

Among them, η_{ij} represents the visibility of the edge $e(i, j)$, calculated by the heuristic algorithm $\eta_{ij} = 1 / d_{ij}$; $allowed_k = \{0, 1, \cdots, m - 1\} - tabu_k$ represents the city set that ant k can choose; $tabu_k$ represents the city that the ant k has passed; α represents the relative importance of the trajectory; β represents the relative importance of visibility.

When the ant ends a cycle, the pheromone on the path will be updated according to the number of ants passing through. The update value will be used as the basis for the selection probability of the next ant cycle. The update formula is as follows:

$$\tau_{ij}(t + 1) = (1 - \rho)\tau_{ij}(t) + \Delta\tau_{ij}(t) \tag{16}$$

$$\Delta\tau_{ij}(t) = \sum_{k=1}^{m} \Delta\tau_{ij}^{k}(t) \tag{17}$$

$$\Delta\tau_{ij}^{k}(t) = \begin{cases} Q / L_k, & \text{k passes through } e(i, j) \\ 0, & \text{others} \end{cases} \tag{18}$$

Among them, $\rho \in (0, 1)$ represents pheromone volatility; while $1 - \rho$ represents the pheromone residual coefficient; $\Delta\tau_{ij}(t)$ represents the increment of information on the path $e(i, j)$; $\Delta\tau_{ij}^{k}(t)$ represents the amount of information released by ant

k on the path $e(i, j)$ in this cycle; Q is a constant, indicating the amount of information released by each ant in the cycle; L_k represents the path length of the ant k in this cycle. The optimal combination of parameters $Q, C, \alpha, \beta, \rho$ can be obtained by experiment.

3.2 The Improvement of ACA

Aiming at the shortcomings of traditional ACA, the paper improves the ACA as follows:

(1) The population initialization step of the genetic algorithm is introduced. Genetic algorithm is used to optimize the initial AM supply chain and generate the initial pheromone distribution. It avoids the inefficiency caused by the lack of initial information in traditional ACA. The X individual fitness function is set as:

$$\delta(X) = P_X Z(X) \tag{19}$$

$$P_X = w_1 P_{Xq} + w_2 P_{Xt} + w_3 + w_4 + w_5 P_{Xa} + w_6 P_{Xp} \tag{20}$$

$$P_{Xq} = \begin{cases} 1, & \text{Satisfying formula (9)} \\ (Q_{min} / \prod_{i=1}^{n} \prod_{j=1}^{s_i} q_{r_{ij}} u_{ij})^{\theta}, & \text{others} \end{cases} \tag{21}$$

$$P_{Xt} = \begin{cases} 1, & \text{Satisfying formula (10)} \\ (\sum_{i=1}^{n} \sum_{j=1}^{s_i} t_{r_{ij}} u_{ij} / T_{max})^{\theta}, & \text{others} \end{cases} \tag{22}$$

$$P_{Xa} = \begin{cases} 1, & \text{Satisfying formula (11)} \\ (A_{min} / \prod_{i=1}^{n} \prod_{j=1}^{s_i} a_{r_{ij}} u_{ij})^{\theta}, & \text{others} \end{cases} \tag{23}$$

$$P_{Xp} = \begin{cases} 1, & \text{Satisfying formula (12)} \\ (\sum_{i=1}^{n} \sum_{j=1}^{s_i} p_{r_{ij}} u_{ij} / P_{max})^{\theta}, & \text{others} \end{cases} \tag{24}$$

Among them, P_X, P_{Xq}, P_{Xt}, P_{Xa}, P_{Xp} are the total penalty function, the quality penalty function, the delivery penalty function, the production capacity penalty function, the price penalty function, and the θ as the penalty scale.

(2) The initial value of the pheromone is set. The maximum and minimum ant system (MMAS) is used here. In order to make the ant movement global and avoid the premature convergence of the algorithm, MMAS sets the minimum value of the pheromone content on the initial time path, and limits the value of the pheromone content to $[\tau_{min}, \tau_{max}]$. In this paper, the initial value of the pheromone is set to $\tau_{ij \cdot pq}^{S}$ based on the information quantity and the initial value of the information generated by the genetic algorithm.

$$\tau_{ij \cdot pq}^{S} = \tau_{ij \cdot pq}^{C} + \tau_{ij \cdot pq}^{G} \quad (i, p = 1, 2, \cdots, n \text{ and } |i - p| = 1) \tag{25}$$

Among them, $\tau_{ij \cdot pq}^{C}$ is equivalent to the τ_{min} in the MMAS algorithm for the given information constant given by the solution, and $\tau_{ij \cdot pq}^{G}$ is the pheromone content converted from the population initialization results of the genetic algorithm.

Therefore, the calculation results of the genetic algorithm are contained in the initial value setting of the pheromone solved by formula (25), which makes the ACA have a relatively optimized and complete initial path and improve the speed of the algorithm.

(3) The introduction of path selection strategy. In the ACA, the ant's mobile path selection is based on the pheromone content in the path to calculate the selection probability. The greater the pheromone content, the greater the probability of being selected. This will cause the high local pheromone path to be chosen by high frequency, thus losing the diversity of solutions. In order to avoid this problem, this paper sets a sensory threshold ρ_0 to the ant. When the pheromone content of the path is less than ρ_0, the ant ignores the existence of the original pheromone; when the content of the pheromone is greater than ρ_0, the ant tends to choose the path of high pheromone content according to the content of pheromone. That is, the state transition probability of ant k in the inter stage nodes can be expressed as:

$$P_{r_{ij} r_{pq}}^{k}(t) = \begin{cases} \max\left\{\tau_{r_{ij} r_{ps}}^{\alpha} \cdot \eta_{r_{ij} r_{pq}}^{\beta}\right\}, & r_{ps} \in J_k(r_{ij}),\ r \le \rho_0 \\ \dfrac{\tau_{r_{ij} r_{pq}}^{\alpha}(t) \cdot \eta_{r_{ij} r_{pq}}^{\beta}}{\sum_{r_{ps} \in J_k(r_{ij})} \tau_{r_{ij} r_{ps}}^{\alpha}(t) \cdot \eta_{r_{ij} r_{pq}}^{\beta}}, & r_{pq} \in J_k(r_{ij}),\ r > \rho_0 \\ 0, & \text{others} \end{cases} \tag{26}$$

$$\eta_{r_{ij} r_{pq}} = \tag{27}$$

$$1/\left(w_1\frac{q_{max}-q_{r_{ij}}}{q_{max}-q_{min}}+w_2\frac{t_{r_{ij}}-t_{min}}{t_{max}-t_{min}}+w_3\frac{h_{max}-h_{r_{ij}}}{h_{max}-h_{min}}\right.$$
$$\left.+w_4\frac{c_{max}-c_{r_{ij}}}{c_{max}-c_{min}}+w_5\frac{a_{max}-a_{r_{ij}}}{a_{max}-a_{min}}+w_6\frac{p_{r_{ij}}-p_{min}}{p_{max}-p_{min}}\right)$$

Among them, $\rho_0 \in (0, 1)$; r is the random number in $(0, 1)$; $J_k(r_{ij})$ refers to the set of lower nodes that ants k can choose at node r_{ij}. Thus, the diversity of algorithm solutions is increased, and the algorithm is avoided to fall into local optimum.

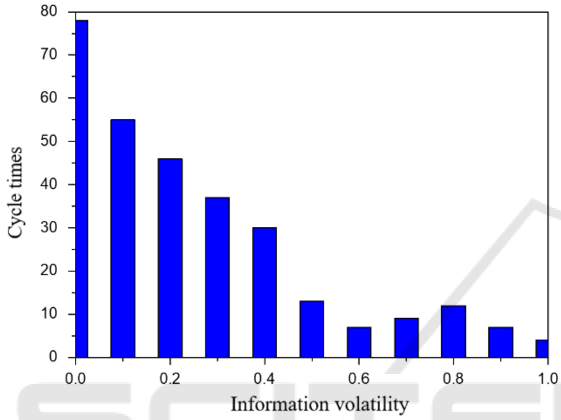

Figure 2: ρ and the optimal path length correspondence.

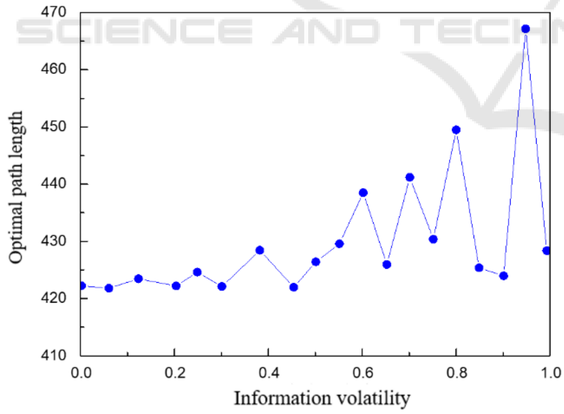

Figure 3: ρ and the correspondence between the number of iterations.

(4) The improvement of the value of ρ. In the ACA, the information is used to imitate human memory. With the operation of the algorithm, the volatilization of pheromones weakens the old information. The value of pheromone volatilization ρ controls the degree of pheromone content change, which will directly affect the content of pheromone and the selection of ants' path, thus affecting the global searching ability and convergence speed of the algorithm.

Next, we take the TSP30 problem as the research object and analyze the influence of ρ on the performance of the algorithm through computer simulation experiments. The parameters are set as: $n = 16$, $Q = 100$, $\alpha = 2$, $\beta = 4$, $Nc\_max = 100$, and stop condition is: the difference between the two adjacent loops is less than 0.01. Figures 2 and 3 denote the correspondence between Nc and the optimal path length and iteration number, respectively.

The experimental results show that the optimal path length and the number of cycles have a great dependence on the value of pheromone volatility in the case of certain other parameters. On the one hand, if the ρ value is too large, the algorithm cycle number is less, the convergence speed will be faster, but in the initial search, the initial pheromone content in the initial time path is less, and the initial pheromone content of the selected path will not be selected again after the initial pheromone content volatilization. This will lower the global performance of the algorithm search, and the algorithm gets the most. The optimal path length is only local optimal value, which has randomness and inaccurate results. On the other hand, if the ρ value is too small, the change amount of pheromone on the path after each cycle is small, the algorithm is global and the result is relatively accurate, but the feedback effect of the algorithm is not very good, which makes the cycle times larger and the convergence speed is slow. In order to solve these problems, this paper adaptively changes the method of ρ value. Set the initial time $\rho = \rho_{min} = 0.30$; when the cycle is a certain number, if the optimal value of the algorithm does not change significantly, then increase the ρ value, and the value function of ρ is:

$$\rho(t+1) = \begin{cases} (0.9 + rand()/10*(RAND\_MAX+1))\rho(t), & \rho(t+1) \geq \rho_{min} \\ \rho_{min}, & \text{others} \end{cases} \tag{28}$$

Among them, ρ_{min} is the minimum value of ρ; $rand()$ is a random function. The above method adaptively changes the ρ value in the search process, which guarantees the global search ability and the convergence speed of the algorithm.

(5) Cross genetic manipulation by introducing genetic algorithms. In this paper, a new path is generated by introducing the cross genetic operation of genetic algorithm to expand the path selection strategy of ACA and optimize the ACA. When the ant colony completes one traversal after a crossover operation, the specific cross process is that two mating nodes are selected randomly in the two result parent string, the two parent string is mutated in two points, then the sequence number of the sub task is modified, and the cross process schematic diagram is shown in figure 4 below.

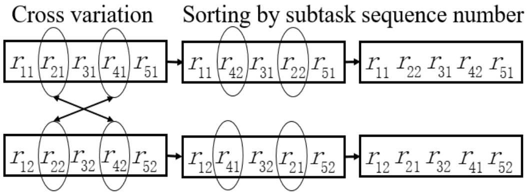

Figure 4: ρ and the optimal path length correspondence.

3.3 The Execution Flow and Description of the Improved ACA

The execution process of the improved ACA is shown in figure 5. The algorithm is described as follows:

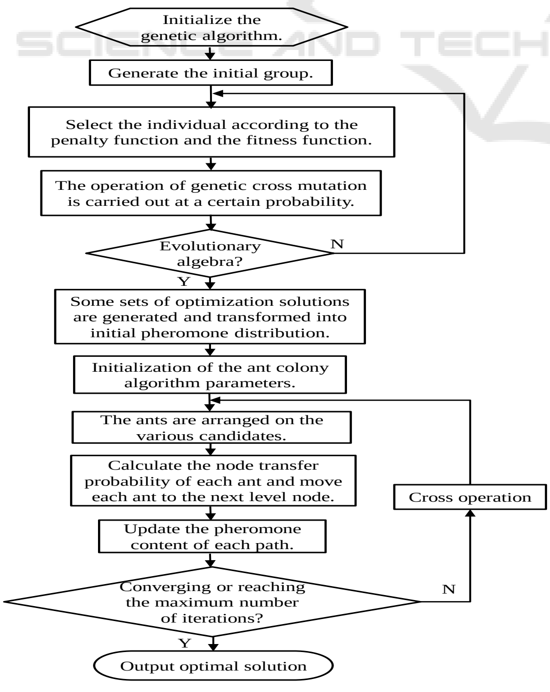

Figure 5: ImprovedACAflow chart.

① Initialize the genetic algorithm. The probability of setting crossover is P, and the number of genetic iterations is n. In the feasible region of the solution space, N individuals satisfying the constraint conditions are randomly generated to form the initial population $S = \{X_l \mid l = 1, 2, \cdots, N\}$.

② The formula (20) is used as a penalty function to deal with constraints.

③ Taking the formula (1) as fitness function, a certain number of highly adaptive individuals are screened from $X_1, X_2, \cdots, X_{N_p}$.

④ The genetic cross mutation operation was performed with the probability of P.

⑤ The genetic algorithm terminates the genetic algorithm after operation, and converts the better combination solution of the genetic algorithm into pheromone $\tau^{G}_{ij \cdot pq}$.

⑥ACA is introduced to initialize the parameters of ACA. The relative importance of the trajectory is α, the relative importance of visibility is β, the pheromone volatilization is ρ, the ant number is N_{ant}, and the largest ant iteration number is N_{Cmax}.

⑦ The N_{ant} ants are assigned to $\sum_{i=1}^{n} s_i$ candidates.

⑧ For $k = 1, 2, \cdots, N_{ant}$, the probability of ant node transfer is calculated according to formula (26), and the supply chain Z_k formed by ant k is calculated according to formula (1).

⑨ The content of pheromone was updated according to formula (25).

⑩ If the algorithm converges or reaches the maximum number of iterations, the optimal supply information is output; otherwise, a cross operation is carried out and the cycle of ACA is continued.

4 SOFA PRODUCT AM SUPPLY CHAIN FORMATION EXAMPLE

A furniture enterprise needs to set up the AM supply chain to complete the manufacture of a batch of sofa products. The manufacturing task is divided into five modules: backrest, armrest, sitting frame, lying position and corner. The constraints of the enterprise on this manufacturing task are: quality constraint $Q_{min} = 0.9$; delivery time constraint $T_{max} = 20$ days;

production capacity constraint $A_{min} = 0.85$; price constraint $P_{max} = 180{,}000$ yuan. After market research and bidding, the enterprise selected four backrest module manufacturing enterprises (r_{11}, r_{12}, r_{13}, r_{14}); three armrest module manufacturing enterprises (r_{21}, r_{22}, r_{23}); three sitting frame module manufacturing enterprise (r_{31}, r_{32}, r_{33}); three lying module manufacturing enterprise (r_{41}, r_{42}, r_{43}), four corner module manufacturing enterprises (r_{51}, r_{52}, r_{53}, r_{54}). The quality, delivery time, historical performance, warranty terms, production capacity and price data of each candidate are shown in table 1.

In this paper, the Java language is used to encode the algorithm. There is no theoretical basis for setting the parameters in the algorithm. It can only be determined by experiment. According to the algorithm several experiments, the parameters are determined as follows: $n = 45$; $p = 0.8$; $N = 100$; $N_{ant} = 20$; $N_{Cmax} = 200$; $Q = 100$; $\rho = 0.6$; $\alpha = 0.4$; $\beta = 4$; $\rho_0 = 0.1$. The improved ACA is compared with the traditional ACA, and the convergence relationship between the number of iterations and the objective function is obtained, as shown in figure 6.

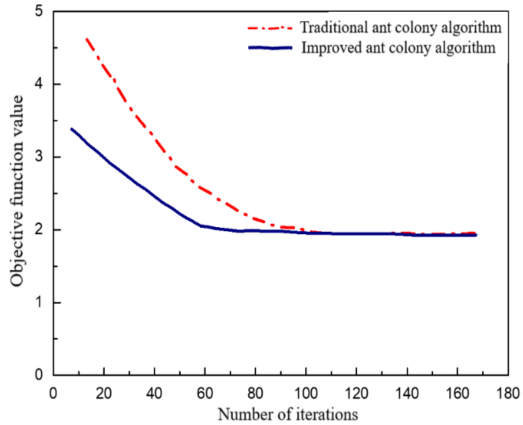

Figure 6: Contrast improved ACA before and after the convergence.

For the same parameter setting, the improved ACA and the traditional ACA run 50 times each. The average iteration times and the convergence time of the improved ant colony algorithm, as well as the final output results are calculated, and the table 2 is summed up, and the performance of the improved algorithm is compared.

Table 1: Candidate manufacturing companies' related data.

		$q_{r_{ij}}$	$t_{r_{ij}}$	$h_{r_{ij}}$	$c_{r_{ij}}$	$a_{r_{ij}}$	$p_{r_{ij}}$
Backrest module	r_{11}	0.96	6.2	0.92	0.95	0.93	4.1
	r_{12}	0.91	5.5	0.86	0.79	0.76	4.9
	r_{13}	0.94	5.9	0.88	0.87	0.84	4.3
	r_{14}	0.89	7.3	0.92	0.89	0.95	4.0
Armrest module	r_{21}	0.96	5.7	0.83	0.85	0.90	6.1
	r_{22}	0.95	5.3	0.89	0.94	0.88	6.3
	r_{23}	0.94	4.8	0.86	0.89	0.86	6.6
Sitting frame module	r_{31}	0.94	4.0	0.82	0.87	0.93	6.2
	r_{32}	0.96	3.8	0.92	0.91	0.90	6.9
	r_{33}	0.92	4.2	0.81	0.89	0.86	6.8
Lying module	r_{41}	0.97	5.8	0.90	0.90	0.90	4.6
	r_{42}	0.88	4.9	0.86	0.81	0.87	4.5
	r_{43}	0.96	5.5	0.95	0.89	0.88	4.3
Corner module	r_{51}	0.95	5.7	0.93	0.95	0.92	5.0
	r_{52}	0.93	5.1	0.87	0.80	0.87	5.7
	r_{53}	0.96	5.4	0.88	0.73	0.76	5.1
	r_{54}	0.98	7.1	0.81	0.90	0.88	5.7

Table 2: Comparison between improved ACA and traditional ACA.

Algorithm	Number of iterations	Convergence time (s)	Optimal solution of objective function	Corresponding optimal combination
Traditional ACA	105.7	16.4	1.90	$r_{11}, r_{22}, r_{32}, r_{43}, r_{51}$
Improved ACA	58.5	9.6	1.90	$r_{11}, r_{22}, r_{32}, r_{43}, r_{51}$

The results of the simulation analysis and the experimental summary show that the results of the improved ACA are all: the optimal solution of the target function is 1.90, and the combination of the corresponding AM supply chain is (r_{11}, r_{22}, r_{32}, r_{43}, r_{51}), as shown in figure 7. But the improved ACA has converged at about 60 times and reached the optimal solution. Compared with the traditional ACA, the number of iterations and the time of convergence have been reduced to a great extent, which ensures the ability of the algorithm to obtain the global search optimal solution at a certain speed. Therefore, the improvement of the traditional ACA is an effective improvement algorithm, which improves the running speed of the algorithm significantly.

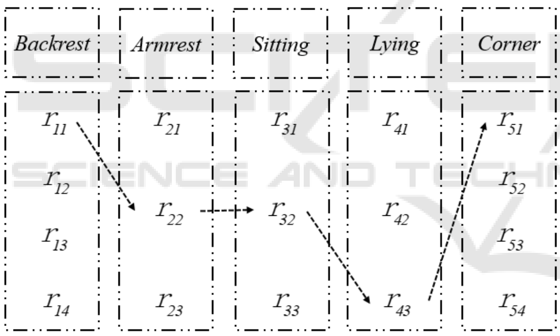

Figure 7: The best combination of candidate manufacturers.

5 CONCLUSIONS

In this paper, the strategy of improving the ACA in the AM supply chain is described, and a graphical representation of the establishment of the AM supply chain is made and its mathematical model is constructed. It is pointed out that the essence of AM supply chain is the optimal combination of manufacturing enterprises. On the basis of analyzing the characteristics of the traditional ACA and genetic algorithm, the traditional ACA is modified from 5 aspects, including the introduction of the population initialization of the genetic algorithm, the initial setting of pheromone, the introduction of the path selection strategy, the value of ρ, and the introduction of the cross mutation of the genetic algorithm. The improved ACA and its execution process are described in detail. By comparing the traditional ACA with the improved ACA, the advantages of the improved ACA in solving the optimization combination problem of the AM supply chain are verified by the example of the AM supply chain of sofa products.

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REFERENCES

1. Jiang Xinsong. 1996, *The main mode of enterprise in twenty-first Century - agile manufacturing enterprise*, Computer integrated manufacturing system,2 (4): 3-8.
2. Katzy, B. R., 1998, *Design and implementation of virtual organizations*, Hawaii International Conference on System Sciences. IEEE Computer Society, 142.
3. Zhang Qiang, Chen Wen, 2004, *A method of selecting partners in dynamic alliance based on fuzzy multi-attribute group decision making*, Fuzzy system and Mathematics, 18 (S1): 332-336.
4. Dong Jingfeng, Wang Gang and Lu Min, 2007, *Multi supplier selection problem based on improved ant colony algorithm*, Computer integrated manufacturing system, 13 (8): 1639-1644.
5. Dickson, G. W., 1996, *An analysis of vendor selection systems and decision*, Materials Science Forum. 1377-1382.
6. Weber, C. A., Current J R and Benton W C, 1991, *Vendor selection criteria and methods*, European Journal of Operational Research, 50(1):2-18.
7. Liu Jin, Guo Jinchao, 2018, *Supplier selection in supply chain environment based on entropy method and TOPSIS method*, Business economy research, (06): 34-36.
8. Reed, M., Yiannakou A. and Evering R., 2014, *An ant colony algorithm for the multi-compartment vehicle*

routing problem, Applied Soft Computing, 15(2):169-176.

9. Ghafurian, S., Javadian N, 2011, *An ant colony algorithm for solving fixed destination multi-depot multiple traveling salesmen problems*, Applied Soft Computing, 11(1):1256-1262.
10. Lai Xuewei, 2017, *Research on TSP problem based on ant colony algorithm*, Journal of Foshan University (NATURAL SCIENCE EDITION), 35 (3): 72-74.
11. Kang Lanlan, 2008, *Hybrid ant colony algorithm based on genetic algorithm*, Jiangxi University of Science and Technology.