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Research on Multidimensional Computational Optimization of Enterprise Organizational Structure Supported by PSACO Algorithm in the Era of Digital Economy

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ABSTRACT

The purpose of this paper is to study the multidimensional computational optimization problem of enterprise organization structure. Based on the value dimension, this paper designs a kind of enterprise organizational structure which contains six dimensions such as demand definition, sales and so on. And the optimization model of enterprise organizational structure is studied by taking a demand-pull enterprise as an example. In the iterative process of the algorithm, the particle swarm optimization (PSO) algorithm and ant colony optimization (ACO) algorithm are run alternately to form the PSACO algorithm to solve the optimization model of enterprise organizational structure constructed in this paper. The experimental results show that the PSACO algorithm used in this paper can maintain stable and good convergence performance under different demand sizes. The enterprise organizational structure optimization model and solving algorithm in this paper can achieve ideal resource allocation scheme and effect, and can still achieve good solving effect in large-scale enterprise organizational structure optimization adjustment. It provides good decision support for the optimization and improvement of enterprise organizational structure in the era of digital economy, and has important application value.

Keywords: PSO algorithm, ACO algorithm, PSACO algorithm, enterprise organizational structure

1. Introduction

With the rapid development of digital economy, enterprises are facing the pressure of structural adjustment and change [1]. The rapid development and wide application of digital technology has changed the way of traditional enterprise business model and organizational structure, bringing greater development opportunities and challenges for enterprises [2-3]. In the era of digital economy,

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enterprises need to adjust and change their traditional organizational structure to meet the requirements of the times and market demand [4-5].

The rapid development of the digital economy provides a new opportunity for the change of enterprise organizational structure, and the traditional enterprise organizational model usually has the problems of information asymmetry and centralized decision-making control, while the emergence of the digital economy makes it more convenient to obtain and transfer information and reduces the degree of information asymmetry [6-9]. Enterprises can achieve timely access to and sharing of internal and external information through digital platforms and big data analysis technology, thus improving the efficiency of collaboration within the organization and the accuracy of decision-making [10-11]. The prerequisite for enterprises to optimize their organizational structure is the need to establish a talent team that meets the requirements of digital transformation, including talents with digital transformation thinking and talents who are good at the application of intelligent technology and data analysis [12-14]. In addition, better exploring the potential of talents is also an important factor for enterprises to carry out the optimization of the organizational structure, and provide a strong organizational foundation and talent support for digital transformation through diversified training and promotion programs [15-18]. Moreover, in the process of digital transformation, enterprises should also focus on the redesign of workflow and resource sharing of information to achieve the sharing and flow of information, and create an open, efficient and collaborative digitized organization [19-22].

In this paper, the enterprise value dimension is divided into six dimensions, including demand definition, sales, design, manufacturing, logistics and service, etc. Based on the value dimension, an enterprise organizational structure model is designed to optimize the work unit configuration of each value dimension based on the data. With the objective function of maximizing total revenue and the constraints of delivery time and allocation cost, we construct an enterprise organizational structure optimization model with optimal allocation of work units under multiple constraints. According to the characteristics of particle swarm optimization algorithm and ant colony optimization algorithm, the two algorithms are run alternately in the iterative process, and the PSACO algorithm is implemented for solving the enterprise organizational structure optimization model in this paper. Simulation experiments are used to verify the performance of the PSACO algorithm and the effectiveness of the enterprise organizational structure optimization model in different enterprise sizes, so as to highlight the effectiveness of the method proposed in this paper, and to provide scientific references for enterprises to formulate organizational structure optimization strategies.

2. Enterprise organizational design and optimization

2.1. Enterprise organizational design

In the era of digital economy, big data, Internet of Things and other emerging technologies have greatly contributed to the change of enterprises, and only by constantly adapting to the digital economy and relying on data to adjust the organizational structure, can we face the market competition. Compared with the traditional organizational structure of centralized, hierarchical, closed, low efficiency and other characteristics, this paper proposes an organizational structure model based on the value dimension, aiming to form a production and organization model that combines the value objective and the optimization objective of the production factors through the organizational form of work unit which does not need to be subdivided, and to link the overall organizational structure through the dimension of value creation, optimize the configuration of work unit based on the data for each value dimension, and construct the optimization model. Optimize the configuration of each value dimension based on the data, and construct the optimization model algorithm.

Considering the direction of demand-pull enterprise data flow, this paper divides the enterprise value dimension into six dimensions: demand definition, sales, design, manufacturing, logistics and service. Among them, design includes 2 sub-dimensions of product design and process design; manufacturing includes 10 sub-dimensions such as production planning and scheduling, purchasing, internal warehousing 01, material scheduling, internal distribution, production operation, quality inspection, safety production, environmental protection production, and internal warehousing 02. Service includes 2 sub-dimensions of product service and customer service. Considering the data form, correlation relationship and workload of each sub-dimension, it forms the enterprise organization structure management model based on the value dimension.

2.2. Enterprise organizational structure optimization model

2.2.1. Model assumptions and parameter definitions. In order to facilitate the model construction and solution and combined with the actual enterprise, this paper makes the following assumptions:

1) This model studies demand-pull enterprises, assuming that everything starts from the market demand, according to the market demand pull each value dimension work.

2) It is assumed that the demand reaches the enterprise randomly, independent of each other and obeying Poisson distribution.

3) Assume that in the context of digitalization, the service capacity of all work units can be accurately measured.

4) It is assumed that the service capabilities of uniform sub-dimension work units are homogeneous and the service time obeys a negative exponential distribution.

The related parameters are described as follows:

$i \in \{1,2,3,\cdots,17\}$: set of 17 value sub-dimensions. N : desired demand arrival rate. M : number of products per unit of demand. x : production lot size. s_i : number of work units in the i th sub-dimension. s_i^* : number of optimal work units in the i th sub-dimension. $best\_s$: optimal configuration scheme. λ_i: i th sub-dimension work arrival rate. μ_i: i th sub-dimension work unit service rate. ρ_i: i th sub-dimension work unit service intensity. L_{qi}: i th sub-dimension queue length. L_i: i th sub-dimension captain. W_i: i th sub-dimension average length of stay. W_{qi}: i th sub-dimension average waiting time. P_{ni} : probability that any moment of the i th sub-dimension steady state system is n. P_{0i} : probability that all work units of the i th sub-dimension steady state system are idle. W : the firm's committed delivery time. $W_{\lim}$: finite time for value creation in the sub-dimension. T_{cycle} : total number of working days in a cycle. C : the total cost of allocating work units in the cycle for the firm. c_i : the cost of configuring a unit of work in the i th sub-dimension for the firm. s : the maximum number of work units that can be configured in each sub-dimension. P_{fi} : probability of a busy unit of work in the i th sub-dimension. $P_{\max}, P_{\min}$: upper and lower bounds of the work cell busy probability. π : total return on value creation.

2.2.2. Modeling. In this paper, the objective function is to maximize the total revenue, and the work unit configuration scheme takes into account the constraints of delivery time and configuration cost, aiming to provide a design solution for the optimal configuration of the organizational structure in a cycle, and the total configuration cost of work units in each dimension is more in line with the reality as a constraint. The optimal work unit configuration scheme under multiple constraints can be derived from the following planning:

$$\pi = p\lambda_1 M T_{cycle} - \sum_{i=2}^{17} s_i c_i \tag{1}$$

s.t.:

$$\sum_{i=2}^{17} W_i \le W \tag{2}$$

$$W_i < W_{Limit} \tag{3}$$

$$\sum_{i=2}^{17} s_i c_i \le C \tag{4}$$

$$s_i \le s \tag{5}$$

$$P_{\min} \le P_{f_i} \le P_{\max} \tag{6}$$

In this case, the service intensity, captain, queue length, busy probability and length of stay formulas are as follows:

$$\rho_i = \frac{\lambda_i}{s_i \mu_i} \tag{7}$$

$$L_i = L_{qi} + \frac{\lambda_i}{\mu_i} \tag{8}$$

$$L_{qi} = \frac{\lambda_i^{s_i} \rho_i P_{bi}}{\mu_i^{s_i} s_i !(1-\rho_i)^2} \tag{9}$$

$$P_{fi} = 1 - \left[\sum_{n=0}^{s_i-1} \frac{\lambda_i^n}{\mu_i^n n!} + \frac{1}{s_i !} \left(\frac{\lambda_i}{\mu_i} \right)^{s_i} \frac{1}{1-\rho_i} \right]^{-1} \tag{10}$$

$$W_i = \frac{L_i}{\lambda_i} \tag{11}$$

3. PSACO-based model solving algorithm

3.1. PSO algorithm

In Particle Swarm Optimization (PSO) algorithm solution, the candidate solutions of the population are called particles, which share experience with neighboring particles while coexisting and evolving [23]. The position and velocity update of a particle can be expressed as:

$$x_i^{(m+1)} = x_i^{(m)} + v_i^{(m+1)} \tag{12}$$

$$v_i^{(m+1)} = w_m v_i^{(m)} + c_1 r_1 \left[P_i^{(m)} - x_i^{(m)} \right] + c_2 r_2 \left[P_g^{(m)} - x_i^{(m)} \right] \tag{13}$$

where: $x_i^{(m)}$ is the position in the solution space for the ith particle, the mth search. $P_i^{(m)}$ is the best position for the ith particle, for the first m searches. $\mathbf{v}_i^{(m)}$ denotes the velocity of the ith particle, the first m searches, and its value is controlled at $[-v_{\max}, v_{\max}]$ to avoid excessive roaming of particles outside the search space. $P_g^{(m)}$ is the global optimal solution among all particles at the mth search. r_1, r_2 are random numbers uniformly distributed in $(0,1)$. c_1, c_2 are acceleration coefficients, which are used to adjust the convergence strategy of the algorithm and accelerate the search for the global optimum. w_m is the inertia weight coefficient. w_m is defined as:

$$w_m = \begin{cases} -\left(\dfrac{m}{M}\right)^2 + w_s & 1 \le m \le \dfrac{M}{2} \\ \left(\dfrac{m}{M} - 1\right)^2 + w_e & \dfrac{M}{2} < m \le M \end{cases} \tag{14}$$

where: M is the maximum number of iterations. w_s and w_e are the initial and termination inertia weight coefficients, respectively.

3.2. ACO Algorithm

Ant Colony Optimization (ACO) algorithm simulates the foraging behavior of ants [24]. When ants are traveling back and forth from the food source to the nest, they release pheromone on the ground and form pheromone trails. The ants can sense the odor and concentration of the pheromone, and when they are choosing a path, they will choose the path with strong (shorter) pheromone concentration. The algorithm can solve complex combinatorial optimization problems, such as the Traveling Provider (TSP) problem and the quadratic allocation problem. Taking the classical TSP problem as an example, the ant operator's mobile search strategy follows:

$$\begin{cases} A_{ij}^k = \dfrac{\left[\tau_{ij}(t)\right]^\alpha \left[\eta_{ij}(t)\right]^\beta}{\sum\limits_s \left[\tau_{is}(t)\right]^\alpha \left[\eta_{is}(t)\right]^\beta} \\ \eta_{ij}(t) = \dfrac{1}{D_{ij}} \end{cases} \tag{15}$$

where: i and j denote the two target cities. s denotes the unreached location of ant k between city i and city j. $\tau_{ij}(t)$ denotes the pheromone located on the path (i,j) at moment t. The $\eta_{ij}(t)$ is the heuristic function. The indices α as well as β denote the influence factors, respectively. A_{ij}^k denotes the probability that the k th ant selects from city i to city j based on the pheromone concentration and the size of the heuristic function. The pheromone will be updated when all ants reach the node:

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

where: ρ is the pheromone volatilization coefficient, the empirical value is generally about 0.9. $\Delta\tau_{ij}(t)$ is the increment of pheromone on the current loop path (i,j), which denotes the sum of pheromone content of each ant operator staying on the path in this loop.

3.3. PSACO algorithm

The PSACO algorithm is realized by running the PSO algorithm and the ACO algorithm alternately during one total iteration [25]. Each ant generates the corresponding particle around the global optimal position according to the following equation:

$$z_i^{(m)} \sim N\left[P_g^{(m)}, \sigma_m\right] \tag{17}$$

Equation (17) indicates that the generated solution vector $z_i^{(m)}$ satisfies a Gaussian distribution with $P_g^{(m)}$ as the expectation and σ_m as the standard deviation. When $m=1$, $\sigma_1 = 1$ and update $\sigma_{m+1} = \sigma_m \times d$ at the end of each search, where the parameter d satisfies $0.250 \le d \le 0.997$. Let $10^{-4} \le \sigma_{\min} \le 10^{-2}$, if $\sigma_m < \sigma_{\min}$, then $\sigma_m = \sigma_{\min}$. Then the fitness of the particle $z_i^{(m)}$ is calculated, and the position is replaced by comparing the magnitude of the ant colony and particle swarm fitness f. If $f[z_i^{(m)}] < f[x_i^{(m)}]$, then $z_i^{(m)}$ is replaced by $x_i^{(m)}$ and $f[z_i^{(m)}]$ replaces $f[x_i^{(m)}]$.

3.4. Steps for solving the optimization model of enterprise organization structure

The essence of enterprise organizational structure optimization model solution is a process of finding the global optimal solution to the objective function. The most direct factor to measure the advantages and disadvantages of the solution result is the size of the objective function of the solution. In this paper, the objective function (fitness) of the enterprise organizational structure optimization model solution is defined as shown in equation (1), and will not be repeated here.

The PSACO algorithm solution process is as follows:

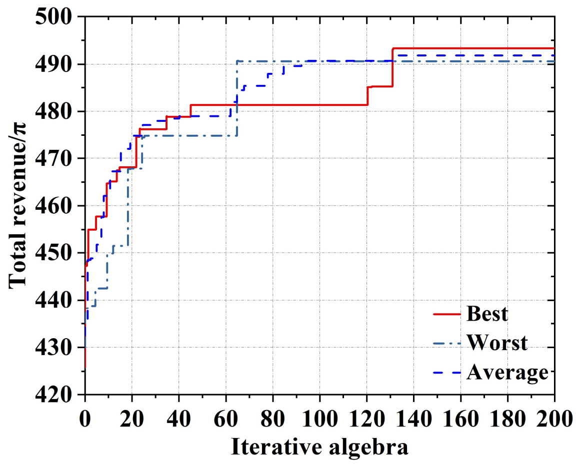
1) Initialization. Set parameters such as the number of particles I, the maximum number of iterations.
2) Pick up the enterprise organizational structure model and value sub-dimension information and determine the search boundary, and then randomly generate I particles within the search range.
3) Calculate the objective function of each solution, and make the particle corresponding to the maximum objective function value as the global optimal solution, and a single particle as the local optimal solution.
4) Use particle swarm optimization algorithm to update the particles and calculate the fitness, if it is better than the local optimal solution and the global optimal solution, then the particles will be replaced.
5) Generate I ants (possible solutions) near the global optimal solution using the ant colony algorithm and calculate the fitness of each solution.
6) Compare the fitness of the ants with the particles and replace the particles with ants if the ant solution is better.
7) If the fitness of the global optimal solution is greater than the accuracy requirement or the maximum number of iterations is not reached, return to step 4).
8) Output the global optimal solution.

4. Simulation experiments and analysis

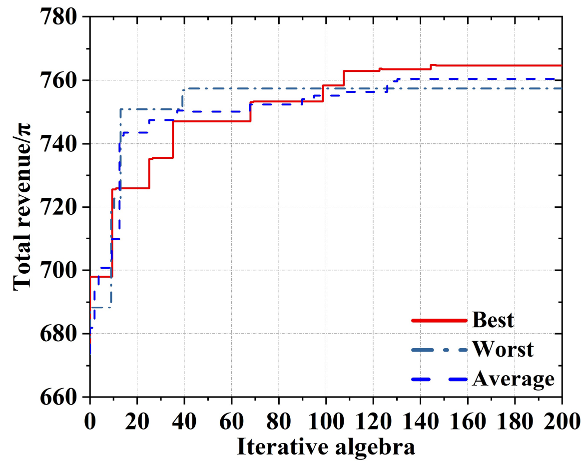
4.1. Performance analysis of PSACO algorithm

4.1.1. Convergence analysis. In this section, the PSACO algorithm will be used to conduct 50 experiments for each of the problems with different demand sizes ($D = 100, 200, 500$) in the corporate organizational structure optimization model, and the cases of the optimal iteration process, the worst iteration process, and the average of the iteration process of the 50 experiments will be recorded for each of them to examine the convergence of the algorithms.

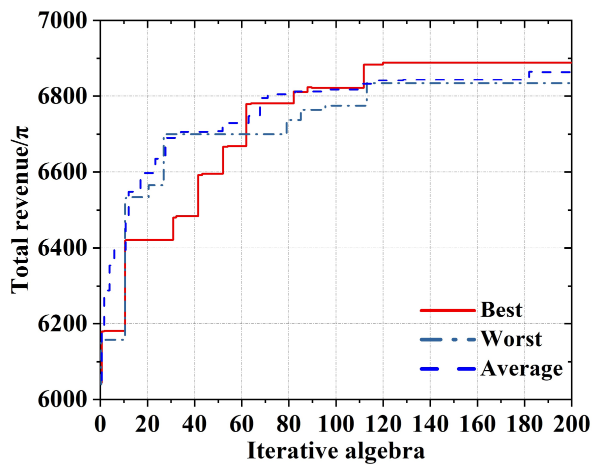
The cases of the optimal iteration process, the worst iteration process, and the average value of the iteration process for the three problems in their respective 50 experiments are shown in Fig. 1, with (a)-(c) denoting the algorithm's convergence under $D = 100$, $D = 200$, and $D = 500$ problem sizes, respectively. As can be seen from the figures, the PSACO algorithm has similar performance for different problem sizes. One is a stable case of convergence, i.e., the final results do not differ much in this experiment, are stable, and approach the known optimum of the problem. The other is that in the case of rapid convergence in the early stage, the algorithm can gradually and slowly approach the known optimal value in the later stage of the algorithm, that is to say, the addition of the predatory search makes the ant colony algorithm able to jump between various local optimal points, so that the overall performance of the ant colony's search for the optimal performance has been improved, so that the optimal solution can be found more easily.



(a) $D = 100$



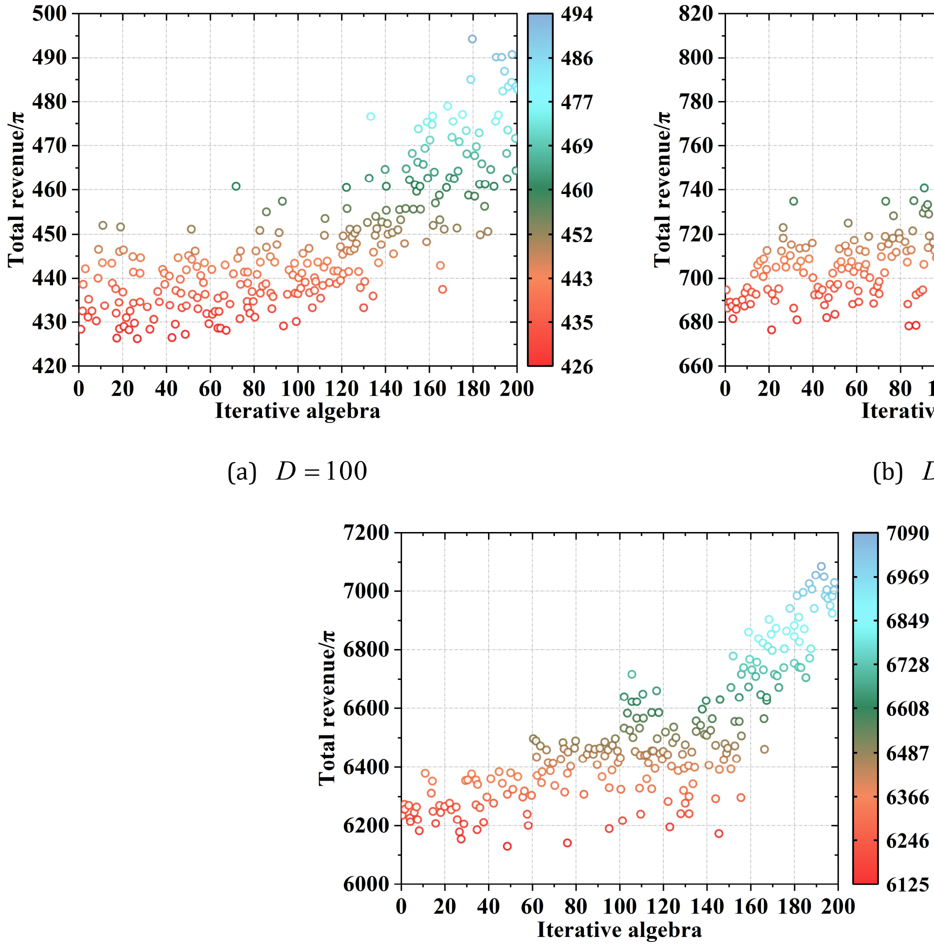
(b) $D = 200$



(c) $D = 500$

Fig. 1. Algorithm convergence analysis

4.1.2. Analysis of the effects of adjustments to the pheromone matrix. One of the more important steps in the algorithm of this paper is to adjust the pheromone matrix according to the results after the predation search is completed, in order to optimize the overall performance of the ant colony in finding the optimum. Fig. 2 shows the change of local optimal value of an experiment iteration randomly selected from 50 experiments of three problems, (a)-(c) denote $D = 100$, $D = 200$ and $D = 500$ respectively. From the figure, it can be seen that the iterative local optimum value of PSACO algorithm has an obvious upward convergence trend and carries out Eq. It indicates that the adjustment of the pheromone matrix by the predatory search makes the new and better paths effectively attract the attention of the ants so that the ants can search around the new paths, which results in better local optimum solutions than the previous ones, and the pheromone adjustment strategy achieves a good effect.



(a) $D = 100$ (b) $D = 200$

(c) $D = 500$

Fig. 2. Adjustment effect analysis

4.1.3. Algorithm performance comparison. The following experiments are conducted to test the effectiveness of the PSACO algorithm solution in this paper by comparing PSACO with the Combined Local Search and ACO algorithm (Opt-ACO) and the Simulated Annealing-based Dynamic Ant Colony Algorithm (SAACO) on a number of demand scales.

The idea of the Opt-ACO algorithm is to optimize the search results of the ACO algorithm using local search in the ACO algorithm and in this way influencing the update of the pheromone matrix. And the idea of SAACO's algorithm is to use simulated annealing to optimize the ant colony algorithm search results and adjust the pheromone matrix according to the optimized results.

The experimental platform for this section is Intel Cerlon(r) 2.4GHz CPU and 768M DDR RAM, Visual Studio 2005, programming language C#, and running platform Windows XP Professional. The experimental results are shown in Table 1, each experiment is run 50 times each, and the optimal and worst values are taken. From the table, it can be seen that the algorithm of this paper is the best in finding the optimum, and it can reach or approach the known optimal solution of the problem in all kinds of demand sizes, in addition, the number of ants in the PSACO algorithm is fixed and small, 15, and the number of iterations is fixed at 200. Various parameters are used that are use-case independent, especially those in the ACO algorithm part of it, which is set to reduce a lot of parameter tuning work and improve the efficiency of the algorithm running and solving.

Table 1. Comparison experiment results

Demand scale	Known best value	Algorithms	Best	Worst
$D = 100$	491	PSACO	491	487
		Opt-ACO	491	472
		SAACO	486	463
$D = 200$	762	PSACO	762	761
		Opt-ACO	751	738
		SAACO	709	689
$D = 300$	1128	PSACO	1128	1128
		Opt-ACO	1046	1024
		SAACO	1008	983
$D = 400$	3587	PSACO	3587	3587
		Opt-ACO	3378	3326
		SAACO	3041	3025
$D = 500$	6874	PSACO	6874	6874
		Opt-ACO	6538	6012
		SAACO	6291	6007
$D = 600$	8396	PSACO	8396	8396
		Opt-ACO	8271	8063
		SAACO	7984	7781

4.2. Case Studies

This section uses the figured and data from the design experiment of organizational structure relationship in teamwork behavior of Company A to verify the validity of the enterprise organizational structure optimization model and solution algorithm in this paper. The wanting of the case contains 20 tasks, 25 resource individuals, and 10 different resources. The algorithm runs with 5 subjects selected, and firstly, the Gantt chart of enterprise subject organization structure and task execution is obtained by ACO algorithm as shown in Figure 3. Figure 4 shows the solution results using the PSACO algorithm, from the comparison of the results of the two methods, it can be seen that under the optimization of the enterprise organizational structure, the amount of inter-subject collaboration is reduced through the optimal allocation of resources and tasks, reducing unnecessary collaboration. Resource allocation within the optimized enterprise organizational structure makes the execution of the task more compact under the premise of meeting the task requirements, reduces the time for the completion of the whole mission, and improves the utilization rate of resources at the same time. The results show that the solution method based on the PSACO algorithm utilizes the global search capability of the ant colony algorithm for all possible solution spaces, while the inner layer is further optimized for the size as well as the reduced resource allocation using the particle swarm algorithm, to obtain the optimal resource allocation scheme relative to the results of each population. The PSACO-based algorithm proposed in this paper avoids the solution by the ACO algorithm falling into local optimization, and achieves more ideal results.

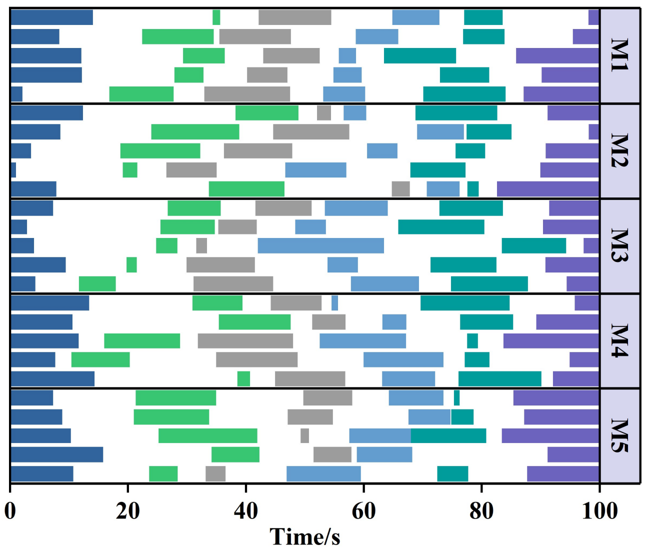


Fig. 3. Gantt diagram based on the ACO algorithm

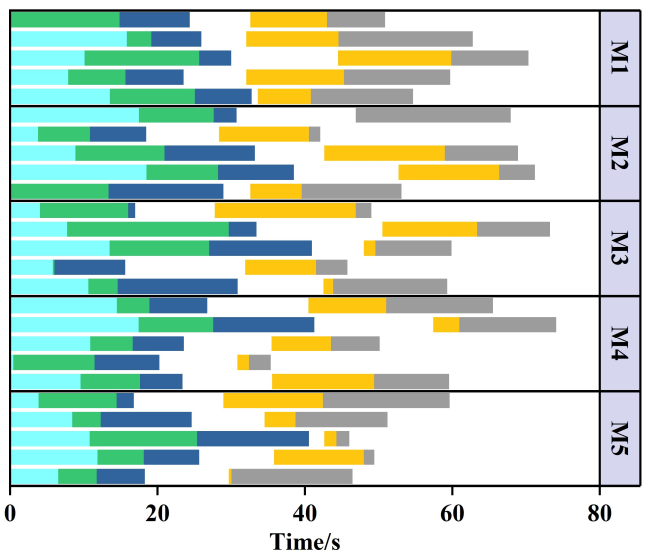


Fig. 4. Gantt diagram based on the PSACO algorithm

4.3. Additional cases

The cases in the above examples are small in scale and cannot well represent the algorithm's solution performance, so this section generates a large-scale team staff replenishment scenario in the company's organizational structure optimization problem according to a specific rule, and then solves the problem based on the PSACO algorithm in order to test the performance of the algorithm.

4.3.1. Case Description and Generation:

1) Case Description. Assuming that a large technology company plans to enter a new artificial intelligence field, the technical team needs to recruit and select a large number of high-tech talents. The team has 150 employees, and there are 50 vacant positions that need to be filled. As a whole, the skills of the new additions to the team need to cover 10 skills related to the emerging AI field, denoted as A to J. The rigid constraints that need to be satisfied by the composition of the technology team include: (1) Among the new additions to the team, there are at least 5 people who have mastered each skill from A to J. (2) There are at least 20 women in the team, and at least 5 women in the team. (2) At

least 20 women. (3) At least 40 people with 2 years of experience in the relevant field. (4) At least 30 people with master's and doctoral degrees.

2) Case Generation. For each vacant position, the number of candidates is randomly generated in the [10,50] integer interval, the generation probability of candidate gender is 1:1, the generation probability of education of bachelor's degree, master's degree, and Ph.D. is 0.4, 0.3, and 0.3 respectively, and the generation probability of candidate's work experience in the related field of no experience, 1 year, 2 years, and more than 2 years is 0.1, 0.1, 0.7, and 0.1 respectively. The generation probability of each candidate mastering a particular skill is 0.1, and if a candidate does not master any skill after data generation, a skill is randomly assigned to that candidate. In other words, each candidate masters at least one of the skills A through J, and may master more than one. The person-job match value of each candidate was randomly generated in the interval [5,10], retaining 2 decimals, and the personality traits of the candidates were generated based on the probability distribution of the MBTI assessment results, with each attribute of the candidates being independent of each other.

4.3.2. Case Solution and Result Analysis:

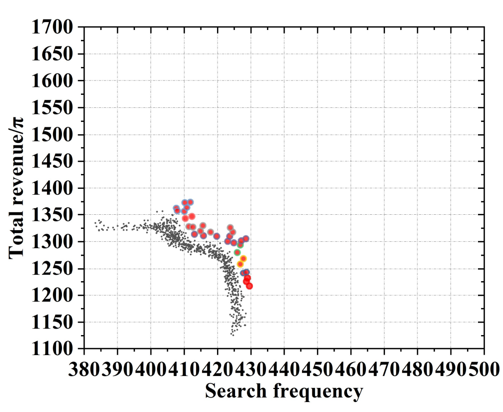
1) Algorithm parameter settings and evaluation indexes. The initial population size of the PSACO algorithm is set to be 1000 in the experiment, the number of iterations of the algorithm is 1000 generations, the crossover probability is 0.2, and the variance probability is 0.2.

In enterprise organization optimization problems, the goodness of the solution obtained by the algorithm is usually measured by the convergence of the Pareto front and the distribution of the solution. In this paper, we adopt the index of hypervolume (HV) to evaluate the algorithm's solution effect, which can obtain the search effect of the solution on the objective function through the "volume", thus reflecting the algorithm's ability to solve the problem, which is calculated as shown in the following formula:

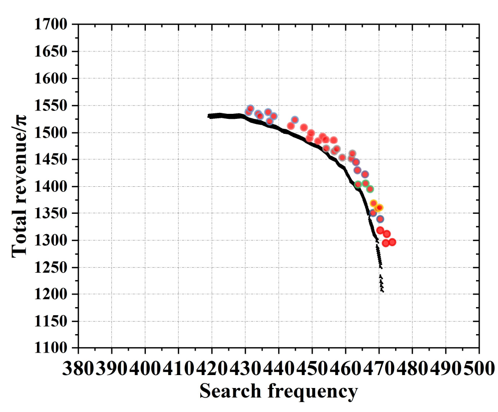
$$HV = volume(\bigcup_{i=1}^{|ND|} v_i) \tag{18}$$

where $|ND|$ is the number of solutions obtained by searching the space of the objective function and v_i is the hypercube containing the far point of the coordinate space.

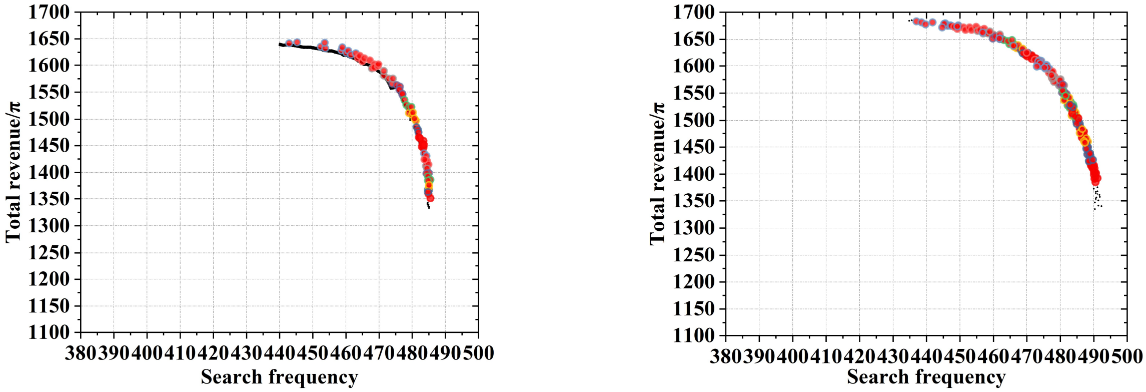
2) Solution process and result analysis. The solution results of PSACO algorithm under the scenario of large-scale team staff replenishment in enterprise organizational structure optimization at each iteration number are shown in Fig. 5. Figures (a)-(d) show the solution results of PSACO algorithm at 10, 100, 500, and 800 generations, respectively, where the red dots are labeled as Pareto frontiers.



(a) 10 generation



(b) 100 generation

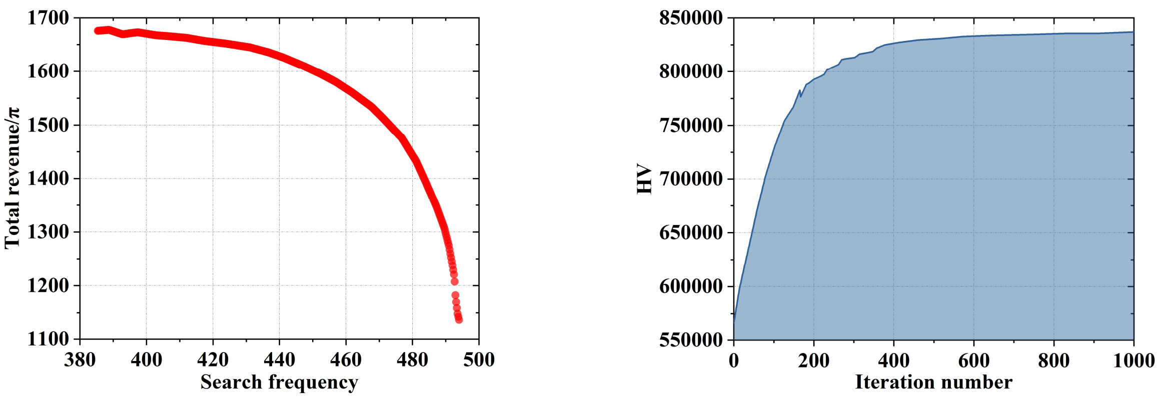


(c) 200 generations

(d) 800 generations

Fig. 5. Solution results of PSACO

The final Pareto front and the convergence curve of the algorithm obtained based on the algorithm are shown in Fig. 6, and (a) and (b) are the solution result and the convergence curve of the algorithm in 1000 generations, respectively. From the iterative process of the algorithm, it can be seen that the Pareto frontier is constantly changing and finally converges and stabilizes. The value of the hypervolume of the algorithm is 844573.48 after executing 1000 generations.



(a) 1000 generations

(b) Convergence curve

Fig. 6. Solution results of PSACO in 1000 generations

The above experiments show that the algorithm in this paper is able to search the Pareto optimal solution even in the large-scale enterprise organizational structure optimization problem, which indicates that the algorithm in this paper has good solution performance.

5. Conclusion

In this paper, we design the enterprise organizational structure based on the value dimension and optimize the structure, and combine the PSO algorithm and the ACO algorithm to implement the PSACO algorithm to solve the enterprise organizational structure optimization model. Simulation results show that for problems of different sizes, the PSACO algorithm can approximate the known optimal value of the problem while maintaining high stability. The addition of PSO algorithm makes it easier for ACO algorithm to avoid falling into local optimization and find the global optimal solution in the process of solving. At the same time, the PSACO algorithm, compared with other algorithms, is able to reach or approach the known optimal solution of the problem in a variety of demand size problems.

Using the enterprise organizational structure optimization model and solution algorithm in this paper, the tasks and resources of each work unit can be optimally allocated to achieve the desired results. And the model can also successfully search for the Pareto optimal solution in the large-scale team staff replenishment scenario of the enterprise organizational structure optimization problem, which provides theoretical and data support for enterprises of different sizes to optimize their own organizational structure.

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