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Article

Research on Efficient Model of Enterprise Human Resource Planning and Scheduling under Intelligent Management Framework

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Abstract: Aiming at the complex problems of human resource scheduling in enterprise multi-project management, this paper constructs a multi-objective scheduling model. Adaptive pheromone updating strategy is introduced to dynamically adjust the volatility coefficient and increment, and a dynamic candidate list mechanism based on multi-attribute evaluation is designed. Combined with local search optimization, an improved ant colony algorithm is proposed. A case study is conducted to verify the effectiveness of the proposed algorithm. The results show that the improved algorithm can converge to the Pareto optimal solution set after about 50 iterations, and the shortest working time is 23 days. Compared with the improved ACO algorithm in this paper, the SW+Random algorithm has a total cost ratio of 156.34% and a duration ratio of 124.45%. After testing, the proposed scheme can effectively predict the comprehensive execution value of enterprise human resource planning and scheduling, and large enterprises can use it to evaluate various programs in advance and then choose the optimal personnel scheduling strategy.

Keywords: human resource scheduling; multi-objective scheduling model; improved ant colony algorithm; adaptive strategy; dynamic candidate list mechanism

1. Introduction

In the wave of digital transformation, artificial intelligence is profoundly changing the mode of various industries, and human resource management is no exception, which shows unique advantages in talent recruitment, employee training, performance evaluation and other aspects [1-2]. Human resources can promote social and economic development, and the quality and quantity of human resources determine the level of social and national development [3]. In the process of enterprise operation, there are many projects at the same time, the project contains many activities, the enterprise needs to implement good personnel scheduling for different activities of different projects to improve efficiency [4]. With the powerful data processing and analysis capabilities of artificial intelligence, it has brought many changes to the enterprise human resources scheduling, and is likely to reshape the overall pattern of human resources management [5]. From realizing accurate job matching to providing a scientific basis for enterprise decision-making, AI shows great potential [6-7]. With the continuous maturity and development of big data and artificial intelligence technology, enterprise projects have become more and more complex, and accordingly the enterprise project human resource scheduling problem also presents an increasingly large challenge [8].

Currently, there are more studies on human resource scheduling, Dong, W et al. [9] improved the utilization rate of enterprise human resources by mining the potential personal skills of enterprise employees, splitting and reorganizing workflows according to the concepts of computable dependencies and clustering, and sequencing the change process, and determining the enterprise human resource scheduling strategy by business constraints. CAI et al. [10] investigated a decision support system for human resource file information based on cloud computing decision support system optimization method for human resource file information, the design adopts a 7-layer architecture based on data collection layer, network service support layer, cloud computing support layer, data standardization conversion layer, etc., discusses the characteristics and functions of each layer structure, and describes in detail the working mode and working mode of the decision support system. Zhang et al. [11] used artificial intelligence and terrestrial wireless sensor networks to pushed forward the information exchange between project employers and enterprise employees, in which the human resource scheduling model based on Fordful Carson method achieved 99.12% accuracy in scheduling. Dong, F [12] established an intelligent scheduling model for enterprise human resources, used the model to test the business performance project, and the quizzes passed the spherical test to realize the enterprise human resource dynamic planning and improve internal human resource utilization. Huang [13] created a human resource dynamic planning model based on big data, which successfully broke through the technical bottleneck of imperfect dynamic planning and computation time process of traditional model, and the average computing time was reduced by 6.96s, which effectively alleviated the burden of the enterprise caused by the human resource scheduling problem. Lin et al [14] proposed a cloud environment in a novel autoencoder neural network-based approach to improve the efficiency of human resource management and the match between jobs and personnel by modeling the semi-automatic human resource allocation process.

In recent years, researchers have begun to explore the use of intelligent algorithms to solve the problem of project human resource scheduling, and heuristic optimization algorithms have been used to find the optimal solution of complex resource scheduling problems [15-16]. Zhang et al. [17] optimized the current human resource scheduling model by an intelligent algorithm, which was combined with the collected historical data of the enterprise, and successfully mined the relationship between the enterprise problems and human resource relationship, and the new scheduling model can stably find the optimal human resource scheduling scheme suitable for different enterprise problems. Chen [18] developed a human resource scheduling model for disadvantaged groups in enterprises, taking the minimization of human resource cost and the shortest project completion cycle length as the objectives while adding some constraints, introducing the second generation of non-dominated sorting genetic algorithms for optimal solution, and experimentally confirming the reliability of the used method in human resource scheduling for disadvantaged groups. Chen, J et al [19] used a genetic algorithm based on a heuristic labor allocation method to solve a resource-constrained multi-project scheduling model for a large-scale equipment manufacturing enterprise and optimized the comprehensive cost by 10.34%. Zuo et al. [20] designed a hybrid meta-heuristic algorithm combining the forbidden search algorithm and simulated annealing algorithm, which aimed to solve the problem of shortage of human resources and multi-skilled employees of an enterprise resulting in the enterprise's project operations could not run smoothly, and developed a mathematical planning model to reduce the organizational cost of human resource scheduling. Liu et al. [21] in order to improve the efficiency of problem solving, constraint planning to deal with complex combinatorial scheduling problems including single skilled and multi-skilled personnel, demonstrated how multi-skilled constraints can be utilized to optimize the project duration and to improve the continuity and efficiency of the work in the construction company and used genetic algorithms for solving multi-skilled worker scheduling problems. Dong, Y et al. [22] successfully embedded a multi-objective differential evolutionary algorithm and a learning curve model in a human resource management system to achieve accurate scheduling of multi-skilled personnel and project efficiency optimization in an enterprise, and in the test the optimized model completed an enterprise project with the lowest manpower cost within the constraints of the project duration. Chen, T [23] tested the performance of collaborative filtering algorithm, content-based recommendation algorithm and rule-based scheduling algorithm in terms of HR scheduling matching accuracy, scheduling response time, and employee satisfaction on a home-grown dataset containing employees' skills, historical scheduling records, and task requirements. The performance of collaborative filtering algorithm, content-based recommendation algorithm and rule-based scheduling algorithm in terms of human resource scheduling matching accuracy, scheduling response time and employee satisfaction was tested in a dataset containing self-generated data containing employee skills, historical scheduling records and task requirements, in which the collaborative filtering algorithm had the best overall performance and was able to respond quickly to emergency situations of manpower shortages in the enterprise.

Previous studies have shown that human resource scheduling based on intelligent frameworks can help to improve employee satisfaction and achieve win-win situation for people and enterprises while guaranteeing the achievement of multiple objectives of project groups [24]. However, like other emerging technologies, artificial intelligence is not a straight path in the process of practical application. In the practice of intelligent HR scheduling, it may face serious challenges in data security, employee adaptation, management model conflict, and ethics [25-26]. Therefore, in-depth exploration of these issues and actively explore innovative paths are of vital practical significance for promoting the transformation of enterprise human resource management to intelligence and enhancing enterprise competitiveness.

In this paper, firstly, for the human resource problems in project management, the problem of human resource multi-objective scheduling model and the definition of parameter variables are elaborated. Clarify the parameter definitions and constraints, and construct a multi-objective scheduling model. An improved ant colony algorithm is proposed to optimize the multi-project human resource scheduling scheme. Rely on the adaptive pheromone updating strategy and dynamic candidate list mechanism to improve the global search capability of the algorithm. The actual data of Company A is selected as a case study, and the improved ACO algorithm is used to optimize the model solution. The performance level of the algorithm is quantitatively analyzed through parameter sensitivity and comparison experiments.

2. Multi-objective scheduling of human resources based on improved ant colony algorithm

With the wide application of intelligent project management model in enterprises, the parallel implementation of multiple projects has become the norm, and the human resource scheduling problem has become more and more prominent. Multi-project human resource scheduling is a NP-hard problem, and traditional optimization methods are difficult to obtain the ideal solution within a reasonable time. Ant colony algorithm shows unique advantages in solving combinatorial optimization problems due to its good group intelligence characteristics.

2.1. Human resources multi-objective movement model

2.1.1. Description of the problem

Multiple projects are developed in parallel in an iteration cycle, sharing development human resources, and there are resource grabbing, conflict, and a single project are composed of multiple requirements, there are sequential logical constraints between different requirements, and each requirement is composed of different tasks.

The problem assumptions are as follows:

(1) The number of human resources remains constant throughout the iteration cycle;

(2) The project development process does not take into account the situation of task imposition and time lag, the personnel in the different tasks between the conversion does not need to consume time, the task of the immediately after the requirements in the case of immediately before the completion of the task of the requirements can be started immediately;

(3) Once a task is assigned to a staff member, it cannot be interrupted, and the assigned staff member can only participate in the next task after finishing the current task;

(4) Each developer can only be responsible for one task at the same time and cannot be responsible for multiple tasks at the same time;

(5) There are multiple skills in this model, and the skills required for a single task are single skills, and the staff can be responsible for the corresponding task if their skills meet the task skill requirements.

2.1.2. Parameter and variable definitions

I denotes the total number of employees, i denotes the i th employee $\left(1 \le i \le I\right)$.

J denotes the total number of skills, j denotes the j th skill $\left(1 \le j \le J\right)$.

M denotes the total number of items, m denotes the m th item $\left(1 \le m \le M\right)$.

N_m denotes the total number of tasks in project m , and n denotes the n th task of the project $\left(1 \le n \le N_m\right)$.

R_{mnj} indicates whether the project m task n requires skill j or not, and a value of 1 indicates that the project m task n requires skill j , while a value of 0 indicates that the project m task n does not require skill j .

E_{ij} denotes the level of skill j mastered by employee i , $0 \le E_{ij} \le 1$, if the value is 0, it means that the employee i does not have the skill j ; the closer it is to 1, it means that the employee i masters the level of skill j the higher the level of skill j ; when the value is 1, it means that the level of employee i masters the level of skill j is the highest among the personnel.

C_i denotes the salary of employee i.

U_{h_p} denotes the set of tasks with high priority requirements.

T_{ijmn} denotes the duration for employee i to complete project m tasks n using skill j.

ST_{mn} denotes the start time of the project m task n.

FT_{mn} denotes the completion time of the project m task n.

P_{mn} denotes the set of tasks that are required immediately prior to the project's m tasks n.

d is any of the tasks in P_{mn}.

$FT_{P_{mn}}$ denotes the completion time of the set of tasks for the immediate prior requirements of project m -task n.

x_{ijmn} denotes a 0-1 auxiliary variable, where a 1 indicates that employee i uses skill j to be responsible for project m task n, and a 0 indicates that employee i does not use skill j to be responsible for project m task n.

y_{ijtmn} denotes a 0-1 auxiliary variable, where a 1 indicates that employee i uses skill j to be responsible for project m task n at time t and a 0 indicates that employee i does not use skill j to be responsible for project m task n at time t.

2.1.3. Objective function

This model takes the comprehensive duration, employee task balance, and project cost of multiple projects as the objective function, which needs to be optimized for multiple objectives.

In the process of software project development, the actual time required for different tasks is not only affected by the difficulty of the task itself, but also by the skill level of the employee in charge. The higher the value of the employee's skill level, the higher the level of mastery and use of their skills, the time required to complete the task is also shortened accordingly, while combining the priority of the demand situation, the high priority demand completion time is also taken into account. The integrated project time objective function is shown in equation (1), which indicates the sum of the minimized overall duration and the duration of high-priority requirements:

$$\min T = T_{total} + T_{hp} \tag{1}$$

Among them:

$$T_{total} = \max FT_{mn} \quad \forall\ m, n \tag{2}$$

$$T_{hp} = \max FT_{mn} \quad \forall\ mn \in U_{h_p} \tag{3}$$

Different task arrangements may cause differences in the workload of different members, and too large a gap in the workload during the same period of time is likely to cause internal imbalance and dissatisfaction among employees, and task balancing is conducive to enhancing the job satisfaction of employees. The goal of employee task balancing is shown in Equation (4), which indicates that the differences in the working time of different employees will be minimized:

$$\min R = \sum_{i=1}^{I} \left| \sum_{j=1}^{J} \sum_{m=1}^{M} \sum_{n=1}^{N_m} x_{ijmn} T_{ijmn} - \frac{\sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{m=1}^{M} \sum_{n=1}^{N_m} x_{ijmn} T_{ijmn}}{I} \right| \tag{4}$$

Project cost is an important consideration for task scheduling, only labor cost is considered in this model, employees with higher skill levels have higher salary levels and the longer the scheduling time the project cost increases. The project cost objective is shown in equation (5), which indicates minimizing the project cost:

$$\min C = \sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{m=1}^{M} \sum_{n=1}^{N_m} C_i T_{ijmn} x_{ijmn} \tag{5}$$

2.1.4. Constraints

(1) Scheduling constraint relationships for each task in the overall project:

$$FT_{mn} = ST_{mn} + T_{ijmn} \quad \forall\, m,n \tag{6}$$

$$ST_{mn} \geq FT_{P_{mn}} \quad \forall\, m,n \tag{7}$$

$$FT_{P_{mn}} = \max_{d \in P_{mn}} FT_d \quad \forall\, m,n \tag{8}$$

$$ST_{mn} \geq 0 \quad \forall\, m,n \tag{9}$$

Equation (6) means that the end time of project m -task n is the sum of the start time and the actual duration; Equation (7) means that the start time of project m -task n is to be no earlier than the end time of the immediately required task; Equation (8) means that the end time of the immediately required task is the largest end time in the set of tasks in the immediately required task; and Equation (9) means that the start time of any task is more than equal to 0.

(2) Personnel allocation constraints

$$R_{mnj} = \{0,1\} \tag{10}$$

$$\sum_{j=1}^{J} R_{mnj} = 1 \quad \forall\, m,n \tag{11}$$

$$\sum_{i=1}^{I} \sum_{j=1}^{J} x_{ijmn} = 1 \quad \forall\, m,n \tag{12}$$

$$\sum_{i=1}^{I} x_{ijmn} = R_{mnj} \quad \forall\, m,n,j \tag{13}$$

Tasks have skill requirements, the person in charge needs to have the skills required for the task, and cannot be in charge of the corresponding task without the required skills. Equation (10) indicates that R_{mnj} is a 0-1 variable, which is used to indicate the demand for skills in the task; Equation (11) indicates that each task in this model requires only a single skill; Equation (12) indicates that each task will only have an employee responsible for using a single skill; Equation (13) indicates that each task is responsible for the use of the skills of the employee and the task of the skills required to be consistent.

$$\sum_{j=1}^{J} \sum_{m=1}^{M} \sum_{n=1}^{N_m} y_{ijtmn} \leq 1 \quad \forall\, i,t \tag{14}$$

$$x_{ijmn} = \begin{cases} 1 & \forall t, \exists y_{ijtmn} = 1 \\ 0 & \forall t, \forall y_{ijtmn} = 0 \end{cases} \tag{15}$$

$$x_{ijmn} = \{0,1\} \tag{16}$$

$$y_{ijtmn} = \{0,1\} \tag{17}$$

Personnel can not be responsible for multiple tasks at the same time, can only be responsible for new tasks after the completion of the current task, and there is a limit to the number of personnel can be dispatched at a single moment. Equation (14) indicates that each employee can only use one skill to be responsible for one task at most at any moment; Equation (15) indicates that if employee i uses skill j to participate in project m activity n at time t, employee i uses skill j to be in charge of project m activity n, i.e., if there exists $y_{ijtmn} = 1$, then $x_{ijmn} = 1$. Otherwise $x_{ijmn} = 0$; Eq. (16) and Eq. (17) indicate that x_{ijmn} and y_{ijtmn} are 0-1 variables.

2.2. Design of Improved Ant Colony Algorithm

2.2.1. Multi-objective ant colony algorithm

Ant colony algorithm realizes local search by using the rules related to state transfer. While performing the TSP problem solving, the ants move from city r (current path point) to city s (next path point), and the rules of state transfer can be expressed as:

$$s=\begin{cases}\arg\max_{u\in J_k(r)}\{[\tau(r,u)]\times[\eta(r,u)]\} & if\ \ (q\le q_0)\\ S & other\end{cases} \tag{18}$$

In the above equation: $J_k(r)$ refers to the set of cities that ant k has started from city r but has not yet visited; τ refers to all pheromones contained in the path R_{ru} between city u and r;

$$\eta(r,u)=1/L_{ru} \tag{19}$$

refers to the inverse of the path R_{ru}, which is introduced into the algorithm in the sense that it serves as heuristic information; q_0 refers to a predefined parameter $\left(0\le q_0\le 1\right)$; s refers to a random city selected based on the probability distribution defined in equation (20); and q refers to a random city that realizes a distribution of random numbers between the $\left[0,1\right]$ the size of a uniformly distributed random number.

$$P_k(r,s)=\begin{cases}\dfrac{[\tau(r,s)]\times[\eta(r,s)]^{\beta}}{\sum\limits_{u\in J_k(r)}[\tau(r,s)]\times[\eta(r,s)]^{\beta}} & if\left(s\in J_k(r)\right)\\ 0 & other\end{cases} \tag{20}$$

When the ants realize a search and successfully construct some feasible solution, the ants realize the globalized pheromone. Specifically, the globalized pheromone update rule can be expressed as follows:

$$\tau(r,s)=(1-\alpha)\times\tau(r,s)+\alpha\times\Delta\tau[r,s] \tag{21}$$

In the above equation:

$$\Delta\tau(r,s)=\begin{cases}\left(L_{gb}\right)^{-1} & if\left(R_{rs}\in R_{gb}\right)\\ 0 & other\end{cases} \tag{22}$$

L_{gb} refers to the length size of the optimal path R_{gb} obtained from the current search; $0<\alpha<1$ refers to the volatility coefficient of the globalized pheromone. When the globally optimal ant realizes pheromone release, its main purpose is to guide the subsequent ants, that is, to make the search better guided, based on the current optimal path, to realize the relevant search in the neighborhood. When the ants realize the path search, whenever a path point determination is realized, the relevant update can be realized by the update rule of the local pheromone. Specifically, the update rule of the local pheromone can be expressed as:

$$\tau(r,s)=(1-\rho)\times\tau(r,s)+\rho\Delta\tau(r,s) \tag{23}$$

In the above equation: $\Delta\tau=(r,s)=\tau_0$, τ_0 refers to the correlation level of the initial pheromone; $0<\rho<1$ refers to the volatility coefficient of the localized pheromone. After relevant experimental studies, it is found that if $\tau_0=(n\times L_{nn})^{-1}$, better results can be obtained. In the above equation: L_{nn} refers to the length prediction of the optimal path (the calculation method is arbitrary); n refers to the number of cities. If the ants move from city r toward city s, it will cause the pheromone shrinkage on the relevant trajectory, so that it can give avoidance to the situation that all the ants are concentrated in the optimal solution area search.

For the ant colony algorithm, its most important feature is to realize the creative use of heuristic information, that is to say, through the introduction of pheromone broadcasting mechanism, to realize the guidance of the optimal solution to the subsequent search. Improving the pheromone broadcasting mechanism is the most popular problem among the related operations of ACO algorithm. One of the important ways of improvement is to combine other search algorithms with ACO algorithm.

In summary, the pheromone seeding amount and the state transition rule are both correlated functions of the path length. Among them, the minimized path length is exactly the only optimization objective of TSP. Therefore, in this paper, for the optimization problem related to the two objectives, the pheromone seeding amount function and the state transition rule are reconstructed, which are transformed into a binary function of threat intensity and path length. The heuristic information of the multi-objective ACO algorithm can be calculated according to the following equation:

$$\eta(r,s) = 1/\left(l_{rs} \times t_{rs}\right) \tag{24}$$

Represent the local pheromone update rule (in the multi-objective ACO algorithm) as:

$$\tau_0 = \left(n \times L_{p0} \times T_{p0}\right)^{-1} \tag{25}$$

In the above equation: n refers to the number of path points; L_{p0} and T_{p0} refer to the size of the length of the time-minimum path and the size of the prediction of the minimum threat intensity, respectively. The global pheromone update rule (in the multi-objective ACO algorithm) can be expressed as:

$$\Delta\tau(r,s) = \sum_{k=1}^{k_0} \Delta\tau_k(r,s) \tag{26}$$

In the above equation: k_0 refers to the number of solutions in the Pareto set obtained from the current search. In addition:

$$\Delta\tau_k\left(rs\right) = \left(L_k T_k\right)^{-1} \tag{27}$$

In the above equation, L_k and T_k refer to the total length of the optimal path of the k th Pareto and the associated strength of the total threat. In the multi-objective ACO algorithm, the path length of the optimal solution and the strength of the threat are used together as a guide for the next search to achieve the simultaneous optimization of the two objectives.

2.2.2. Adaptive Pheromone Update Strategy

Adaptive pheromone updating mechanism is designed for the complexity of multi-project human resource scheduling problem, which dynamically adjusts the volatility coefficient and increment of pheromone. The overall process of the improved algorithm contains three core modules: pheromone update, dynamic candidate list and local search. The pheromone updating rules are as follows:

$$\tau ij\left(t+1\right) = \left(1-\rho\left\{t\right\}\right) \cdot \tau ij\left(t\right) + \Delta\tau ij\left(t\right) \tag{28}$$

where the pheromone volatilization coefficient $\rho(t)$ changes dynamically with the iterative process:

$$\rho\left(t\right) = \rho_{\min} + \left(\rho_{\max} - \rho_{\min}\right) \cdot \left(1 - \exp\left\{-\lambda t\right\}\right) \tag{29}$$

where λ is a regulating factor to control the rate of change of the volatilization coefficient. The pheromone updating mechanism is shown in Fig. 1, where the pheromone concentration is constrained by upper and lower limits during the iteration process to prevent over-concentration or over-diffusion.

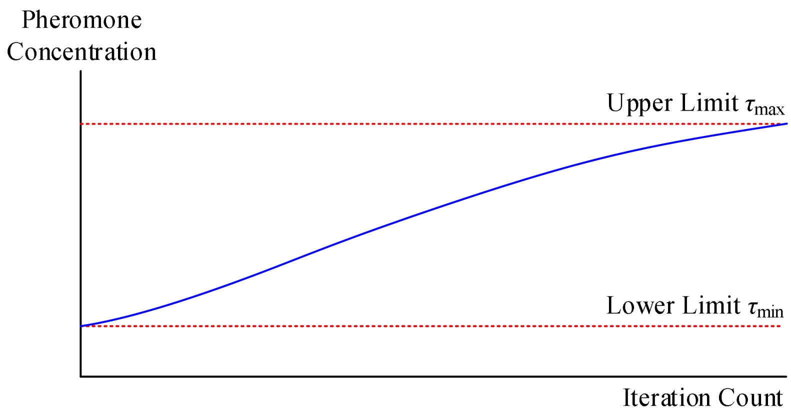

Figure 1. Information pheromone update mechanism.

The pheromone increment $\Delta\tau ij(t)$ is expressed as a segmented function:

$$\Delta\tau ij(t)=\begin{cases}\dfrac{Q}{Lbest}, \text{If } (i,j) \text{ belongs to the current optimal solution } \dfrac{Q}{Lgb} \\ \text{If } (i,j) \text{ belongs to the global optimal solution 0, otherwise}\end{cases} \tag{30}$$

where Q is the pheromone intensity coefficient, $Lbest$ and Lgb denote the objective function values of the current iterative optimal solution and the global optimal solution, respectively. In order to prevent the pheromone from being over-concentrated or over-sparse, the upper and lower limits of the pheromone concentration are set as $[\tau_{\min}, \tau_{\max}]$, and truncation is performed when τij is out of the range. The experimental results show that this adaptive updating strategy can maintain a large exploration range at the initial stage of the search, and gradually strengthen the exploitation of high-quality solutions at the later stage, effectively balancing the global search and local search capabilities of the algorithm.

2.2.3. Dynamic candidate list mechanism

A dynamic candidate list mechanism based on multi-attribute evaluation is designed to dynamically construct and update the candidate resource list by considering resource availability, skill matching and workload balance. The scope of the candidate list is gradually contracted with the algorithm to improve the search efficiency. The formula for calculating the resource evaluation score is:

$$\begin{aligned} Score(k) &= w1 \cdot Availability(k) + w2 \cdot Skill\ Match(k) \\ &+ w3 \cdot Load\ Balance(k) \end{aligned} \tag{31}$$

where the weighting coefficients $(w1, w2, w3)$ are determined by fuzzy hierarchical analysis. The resource availability indicator reflects the degree of availability of resource k in the target time period:

$$Availability(k)=\frac{Free\ Days(k)}{Total\ Days} \tag{32}$$

Skill matching adopts a fuzzy evaluation method to establish an evaluation index system, including professional skill level, project experience, and teamwork ability. Workload balance is measured by calculating the deviation between the current load of resources and the average load of the team:

$$Load\ Balance(k)=1-\frac{|Load(k)-Avg\ Load|}{\max Load} \tag{33}$$

The dynamic update mechanism sets the candidate list length $L(t)$ to vary with the iteration process:

$$L(t)=L_{\max}-\left(L_{\max}-L_{\min}\right)\left(\frac{t}{T}\right)^{\alpha} \tag{34}$$

where α is the adjustment coefficient. This mechanism can adaptively adjust the search range according to the search stage to improve the convergence efficiency of the algorithm.

2.2.4. Local Search Optimization

The local search module is embedded in the basic algorithmic framework, and three kinds of neighborhood search operators are designed: resource exchange, time shift and task reorganization. The resource exchange operator randomly selects two resource allocation schemes within a time window to be interchanged, and calculates the degree of improvement of the objective function after the exchange:

$$\Delta F = F(S') - F(S) \tag{35}$$

If $\Delta F < 0$, the new solution is accepted, otherwise it is accepted with probability p:

$$p=\exp\left(-\frac{\Delta F}{T(t)}\right) \tag{36}$$

$$T(t)=T_0 \cdot \gamma t \tag{37}$$

where $T(t)$ is the simulated annealing temperature function.

The time-shift operator locally adjusts the activity start time while ensuring the activity dependencies. The task reorganization operator explores new scheduling schemes by decomposing and reorganizing the sequence of activities on the critical path. These three operators are used alternately and their frequency of use is dynamically adjusted with the search process:

$$Pi(t) = Pi\_base + \Delta Pi \cdot \left(1 - \frac{t}{T}\right)^{\beta} \tag{38}$$

where Pi_base is the usage frequency, ΔPi is the adjustment amplitude, and β is the frequency adjustment coefficient. The experimental results show that the local search strategy can significantly improve the solution optimization ability of the algorithm.

3. Human resources multi-objective scheduling model application cases

3.1. Example analysis

A large enterprise, Company A, needs to synchronize the promotion of three projects within 30 days, which are recorded as R1, R2 and R3, and their corresponding weights are 0.35, 0.25 and 0.4. The number of project tasks is small, respectively 5, 6 and 4, and the basic situation of the data of multi-project parallel promotion is shown in Table 1. There is a significant difference between the number of tasks and the planned duration of the three parallel projects, in which the number of tasks of Project 2 reaches 6, and some tasks have the shortest planned duration, indicating that the complexity and urgency of its tasks are higher.

Table 1. Basic information on the data of multi-project parallel progression.

	Project	Task 1	Task 2	Task 3	Task 4	Task 5	Task 6
Number of personnel required for the project	Project 1	3	2	4	4	1	
	Project 2	5	3	4	2	4	2
	Project 3	5	4	4	3		
Completion time of the task plan	Project 1	15	12	16	9	9	
	Project 2	9	11	9	16	16	8
	Project 3	12	9	11	18		
Task skill requirements	Project 1	1	1	2	2	2	
	Project 2	2	2	1	3	2	2
	Project 3	2	3	2	2		

The enterprise deployed 10 employees for the above tasks, all the tasks involve four job skills, and the results of each employee's scores on the four skills are shown in Table 2. It can be seen that the distribution of employee skills is uneven, all employees have a skill shortcomings, and human resources have a significant skill bias.

Table 2. Employee skill evaluation results.

	Skill 1	Skill 2	Skill 3	Skill 4
1	0	0.8	0.5	0.4
2	0.7	1.0	0.8	0
3	0.9	0	0.7	0.5
4	0.4	0.6	0.8	0.2
5	0.6	0.9	0.5	0
6	0	0.8	0.1	0.5

7	0.8	0.5	1.0	0
8	0.5	0	0.8	0.4
9	1.0	0.7	0.8	0
10	0.9	1.0	0	0.6

3.2. Model solving

In the solution process, each task in the project is regarded as a node in the network graph, and a directed connection is constructed based on the logical relationship between the tasks immediately before and immediately after the task to form a scheduling task network with constraints, and the weight of each path is determined by the multidimensional factors such as the task duration, the employee skill match, the task priority and the personnel's current workload. Based on the route of the improved ant colony algorithm, the solution process of the improved ant colony algorithm convergence process shown in Figure 2, the objective function value at the beginning of the iteration there is a certain degree of fluctuation, with the increase in the number of iterations gradually tends to stabilize, and ultimately in about 50 iterations the algorithm converges and outputs a set of Pareto optimal solution, at this time, the duration of the work period of 23 days.

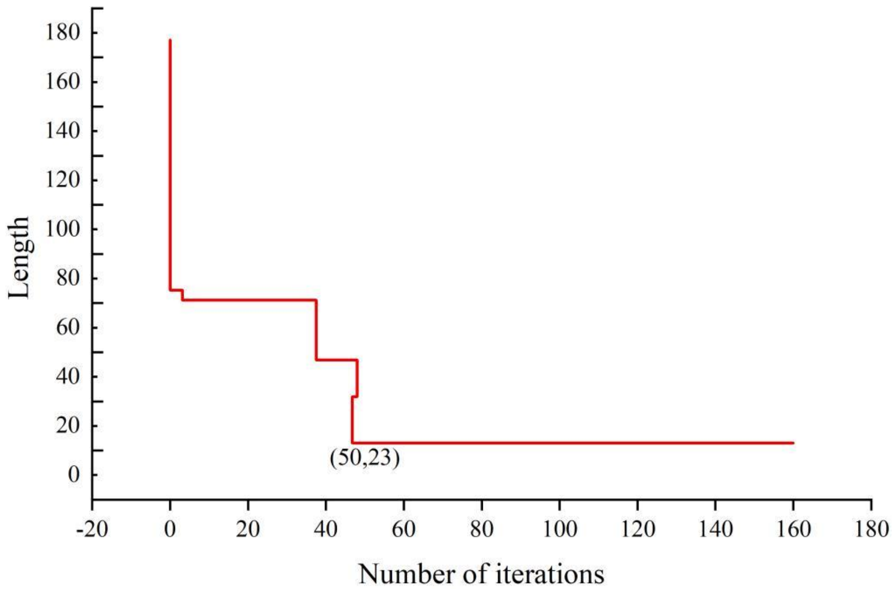

Figure 2. Convergence process of improved ant colony algorithm.

The solution route of the improved ACO algorithm is required: the employee skills match the task requirements and there is no resource conflict phenomenon. According to the project weight, the number of tasks and skill requirements will be 3 projects with a total of 15 tasks are numbered, the final solution route is shown in Figure 3. Where the horizontal coordinate indicates the time and the vertical coordinate indicates the task node number. After the convergence process of Fig. 2, the final order of the coordinates of the optimal route is found: (0,1)→(3,2)→(3,3)→(5,4)→(5,5)→(8,6)→(9,7)→(9,8)→(11,9)→(12,10)→(13,11)→(16,12)→(16,13)→(18,14)→(21,15). Each coordinate point (x,y) in this coordinate sequence indicates that task node y is scheduled for execution on day x of time. The ability of the improved ACO algorithm to generate high-quality scheduling solutions in the multi-project human resource scheduling problem is verified by the fact that each task follows the completion constraints of its immediate preceding task according to the route, and that employees with the appropriate skills are responsible for its implementation within the allowed time window.

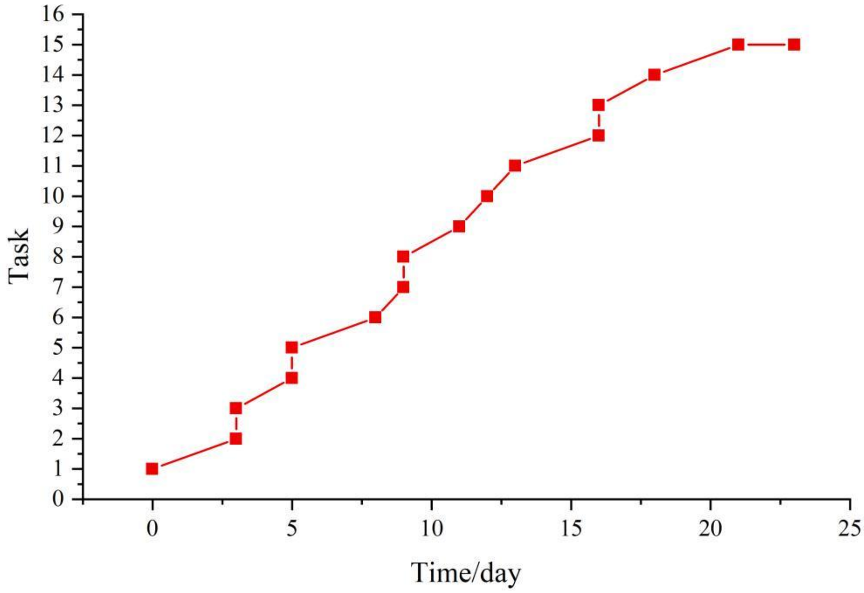

Figure 3. The optimal route obtained through the solution process.

3.3. Performance experiments

3.3.1. Model parameters

The parameter settings in the improved ant colony algorithm have a relatively large impact on the results, and now simulation experiments are carried out for multiple groups of values of the pheromone volatility intensity ρ, an important parameter in the algorithm. The results of the experiments on multiple values of parameters are shown in Fig. 4. If the pheromone volatilization strength is too large, the algorithm will converge too fast, and if the pheromone volatilization strength is too small, the positive feedback on the pheromone in each iteration is weak, which affects the algorithm search efficiency. In this paper, the parameter is set to $\rho = 0.35$ and the number of iterations at convergence is 50.

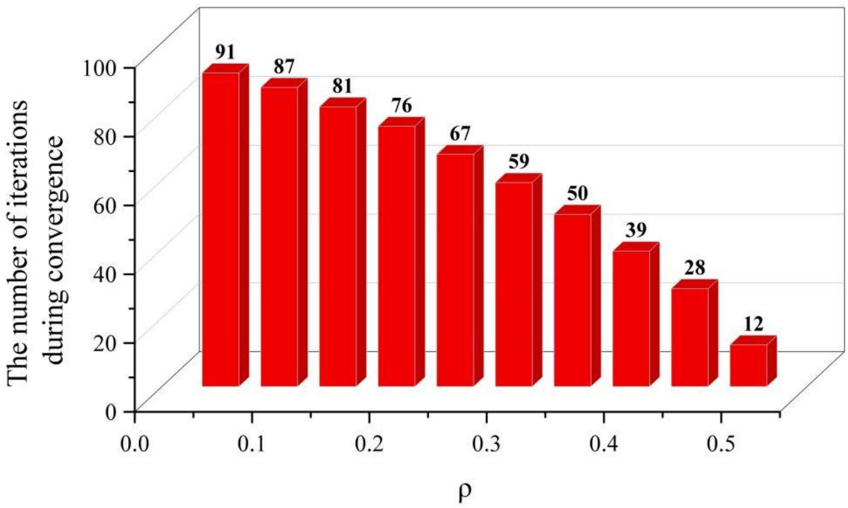

Figure 4. Experimental results of multiple parameter value groups.

3.3.2. Comparative analysis

In order to verify the effectiveness of the proposed algorithm, the same set of data is selected and run 20 times respectively, and the results of this algorithm are compared with those of the algorithm using several mainstream heuristic rules. With this paper's algorithm as a benchmark, several other groups of values and its division to obtain the relative proportion of the comparative experimental data results are shown in Table 3. The proposed improved algorithm does not reduce the running time but obtains better results, and overall shows better search performance. In particular, compared with the improved ACO algorithm in this paper, the SW+Random algorithm has a total cost ratio of 156.34% and a duration ratio of 124.45%.

Table 3. Results of comparative experiment data.

	Average running time ratio	Average total cost ratio	Average duration ratio
The proposed	1	1	1
SW+Random	96.45%	156.34%	124.45%
ME+Random	92.57%	140.37%	128.77%
Random+SFT	91.22%	142.82%	115.62%
FA+MTS	106.48%	109.63%	167.29%
SW+EDD	114.27%	99.21%	145.43%

4. Conclusion

This paper focuses on the multi-objective scheduling problem of enterprise human resources under the framework of intelligent management, proposes an improved multi-objective ant colony algorithm for model solving, and further develops case study analysis by taking a large-scale enterprise, Company A, as an example.

The objective function value finally converges after about 50 iterations, and the shortest duration is 23 days. The optimal route is: (0,1)→(3,2)→(3,3)→(5,4)→(5,5)→(8,6)→(9,7)→(9,8)→(11,9)→(12,10)→(13,11)→(16,12)→(16,13)→(18,14)→(21,15). The performance test shows that the parameter is set to ρ=0.35 and the number of iterations at convergence is 50. The improved algorithm in this paper does not reduce the running time but obtains better results, and the total cost and duration are only 63.96% and 80.35% of the SW+Random algorithm, which shows a better performance overall.

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