Retraction

Retracted: Efficient Management and Application of Human Resources Based on Genetic Ant Colony Algorithm

Journal of Sensors

This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

(1) Discrepancies in scope

(2) Discrepancies in the description of the research reported

(3) Discrepancies between the availability of data and the research described

(4) Inappropriate citations

(5) Incoherent, meaningless and/or irrelevant content included in the article

(6) Manipulated or compromised peer review

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

[1] C. Cheng, Y. Xu, and G. Daniels, "Efficient Management and Application of Human Resources Based on Genetic Ant Colony Algorithm," *Journal of Sensors*, vol. 2022, Article ID 9903319, 13 pages, 2022.

Research Article

Efficient Management and Application of Human Resources Based on Genetic Ant Colony Algorithm

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With the increasing demand of human resources, the cost of staffing and management is increasing, and it is difficult to dynamically allocate and adjust personnel among different parts. It is the key of intelligent management technology to realize efficient application and mining in human resource management. In the aspect of human resource allocation and management, this paper puts forward the efficient management and application of human resource based on the genetic ant colony algorithm. Firstly, this paper describes the process management and parameter application of the genetic algorithm and ant colony algorithm and manages the resource allocation and management process under the two algorithms. Secondly, several current test functions are applied to the genetic algorithm and ant colony algorithm to test the efficiency of the algorithm, which has obvious advantages in convergence efficiency. Finally, the paper uses the efficient management configuration of human resources for comprehensive application and management and applies the system uploading and downloading services on human resumes, respectively. The genetic ant colony algorithm has obvious advantages in efficiency. In human resource data matching, the genetic algorithm is slightly better than the ant colony algorithm in the case of relatively few data in the early stage, and the accuracy of the ant colony algorithm is slightly better than the genetic algorithm in the later stage. The ACO-GA algorithm is more consistent with the actual value, which not only ensures the stability but also ensures the accuracy of prediction, which is more in line with the actual needs.

1. Introduction

The country and even the whole world are full of confidence in the future development of intelligent computing and vigorously recommend the integration of intelligent computing into people's lives. At the same time, they hope that intelligent computing can solve the problem of uneven distribution and mismatch of resources. The allocation of human resources is also included. When the allocation of human resources is not handled properly, it will lead to a series of problems such as cost increase and brain drain. Therefore, it is necessary to make the process of human resources allocation more digital and technical. Human resources need to have high-efficiency performance at the same time of low cost, which is the premise of rationalization of allocation. This can show respect for talents. Intelli-gent computing can be said to be its savior in this respect, and they complement each other, which not only solves problems but also makes intelligent computing involved more widely.

Traditional intelligent computing has not been broken through in the past. In today's important fields [1], such as big data computing, traditional intelligent computing needs high manpower and material costs to study. For the emerging intelligent computing, it can make up for the defects of the traditional one. According to the investiga-tion, in the aspect of quantum heuristics, the inclusion of intelligent computing brings advantages to this technology but also brings disadvantages and challenges to the future. It is necessary for researchers to study it further [2]. Because of its high efficiency in solving nonlinear problems, computational intelligence is proposed to solve such
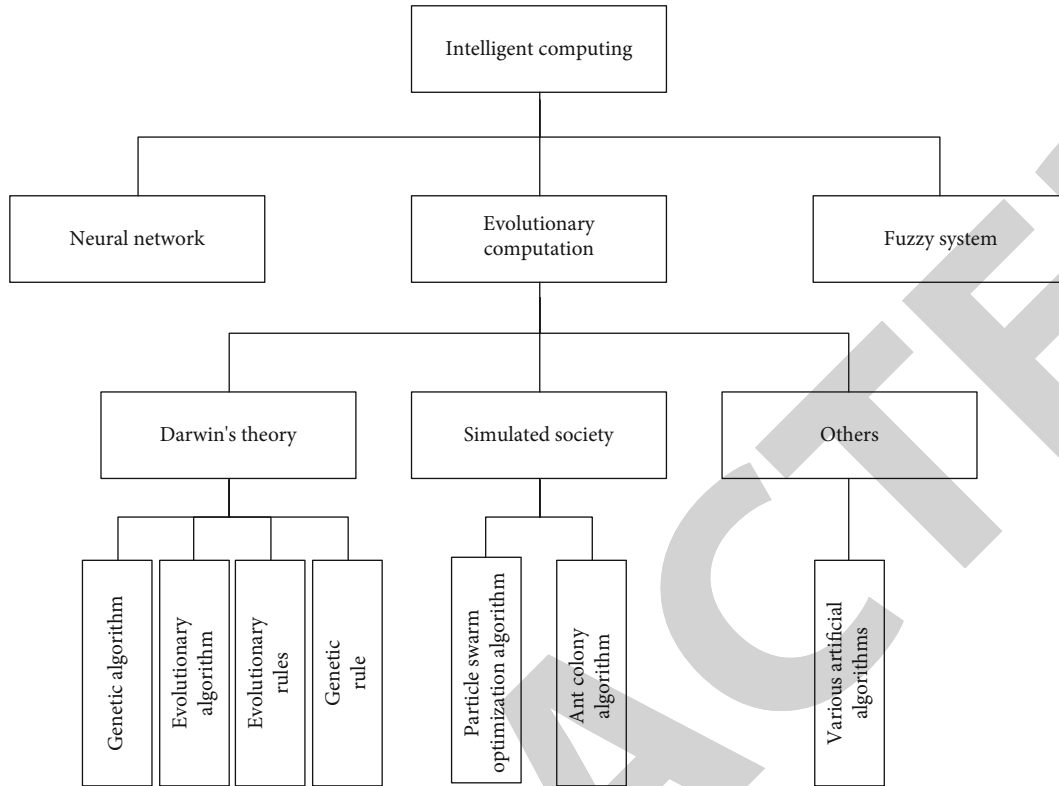
FIGURE 1: Classification diagram of intelligent computing.

problems as power outages, so that power can be quickly resupplied and redundant parts can be unloaded [3]. It contains most algorithms. In order to make these methods more efficient, it is necessary to further study these methods. Different from traditional technologies, intelligent computing has more advantages, but it also has its own limitations, which will lead to limited use. Intelligent computing [4] is also used in power load specialty, and because of its importance, it has attracted the attention of most relevant personnel. Some researchers put forward a method of using model-free technology to test power load based on NN and FL. Through a series of case studies, the advantages and special performance of this method are demonstrated to the public under geographical environment and other conditions. One part of intelligent computing, artificial neural networks, is good at solving the problem of air pollution modeling. It will simulate the ozone layer with pollution parameters. After putting this model into real life, experiments show that this model is very powerful in dealing with such problems [5]. Intelligent computing can also be applied to electrical islanding detection technology [6]. Because the electrical islanding detection technology is not very efficient in solving problems in nonlinear systems, intelligent computing is introduced to improve the accuracy of solving problems, which can provide accurate data and solutions for relevant researchers. Intelligent computing is also used in computer Go [7]. In the world-class computer Go competition held in Taiwan, many Go masters want to

compete with intelligent computing MoGo. MoGo, blessed by RAVE and UCT, has four high-performance attributes. From the outcome of the battle, we can see that intelligent computing can be used in computer Go to achieve a high level of Go battle, and its future development is immeasurable. Literature [8] at the same time, intelligent computing is getting higher and higher in solving problems related to biology, chemistry, and medicine, and its influence is getting bigger and bigger. Combining it with statistical methods, a new model is obtained. In the study of human resource allocation in large companies [9], it is found that human factors have the greatest impact. Generally speaking, in order to reduce the mismatch of resource allocation, personnel performance is generally controlled. Human resource allocation is the top priority in any project. In order to improve the allocation of human resources [10], a series of operations such as shortening project time and reducing costs have been taken. However, if the fundamental factors are not solved, these operations will be lost. The influence of human resource allocation on enterprises should not be underestimated [11]. However, although many schemes have been put forward, the problems still exist. Most of them are caused by not paying attention to the team. Therefore, some researchers have studied from various aspects and put forward a predictive model based on multilayer perceptron. Researchers put this model into practical experiments and finally get the conclusion that this model can improve the efficiency of human resource
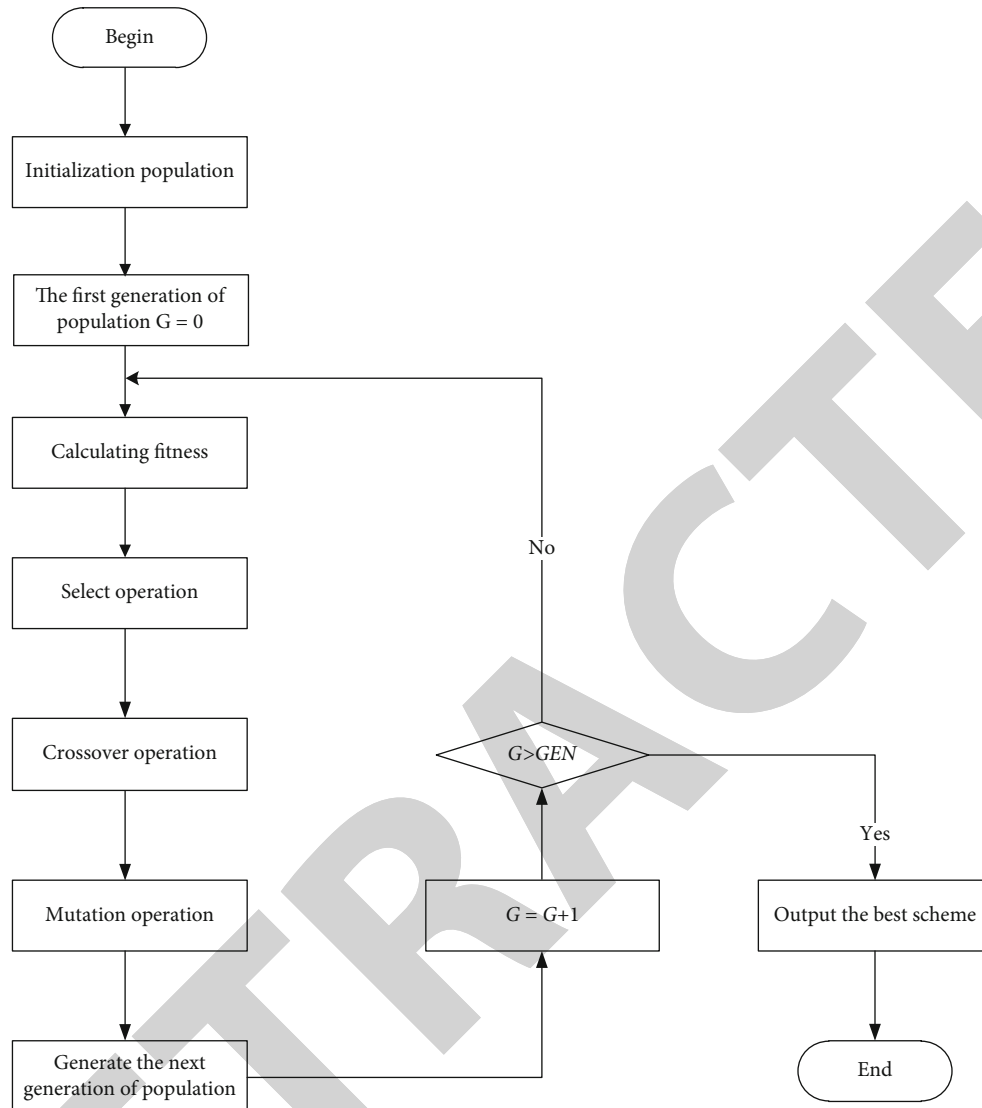
Figure 2: Flow chart of the genetic algorithm.

allocation. In the allocation of human resources, the most important criterion for the classification of personnel is personality, but the personality should be objective and complete [12]; otherwise, it is useless. Therefore, researchers propose to use high-performance algorithms to get more realistic data, which can minimize the error. In order to improve the utilization rate of scarce resources, researchers introduce decentralization factors and resource allocation with the help of software evaluation and portfolio planning and propose new allocation methods to solve the problem of improving the resource allocation of nonsmall R&D organizations [13]. In order to develop the human resource management of shelters, researchers propose to match the theory with people to get a model [14]. In this way, more influencing factors can be considered more comprehensively. The model is put into the experiment and finally found that there is a certain relationship between the working hours and the vacation time; so, in the shelter,

the human resources and vacation need to be set reasonably. The allocation of human resources has also brought troubles to the country. Therefore, the state also attaches great importance to optimizing its allocation and improving its utilization rate [15]. The intelligent method is quoted in human resources. Most researchers aim at the low utilization rate and unreasonable resource allocation in the process of human resources. In the process of algorithm implementation, there is slow convergence. Therefore, the paper proposed the ACO-GA algorithm to solve the above problems.

2. Intelligent Computing Analysis

2.1. Basic Concepts. Intelligent computing is a success for people to transform data into logic. At the same time, it can enable human beings to cultivate their ability to think independently. Most algorithms are its members, but it
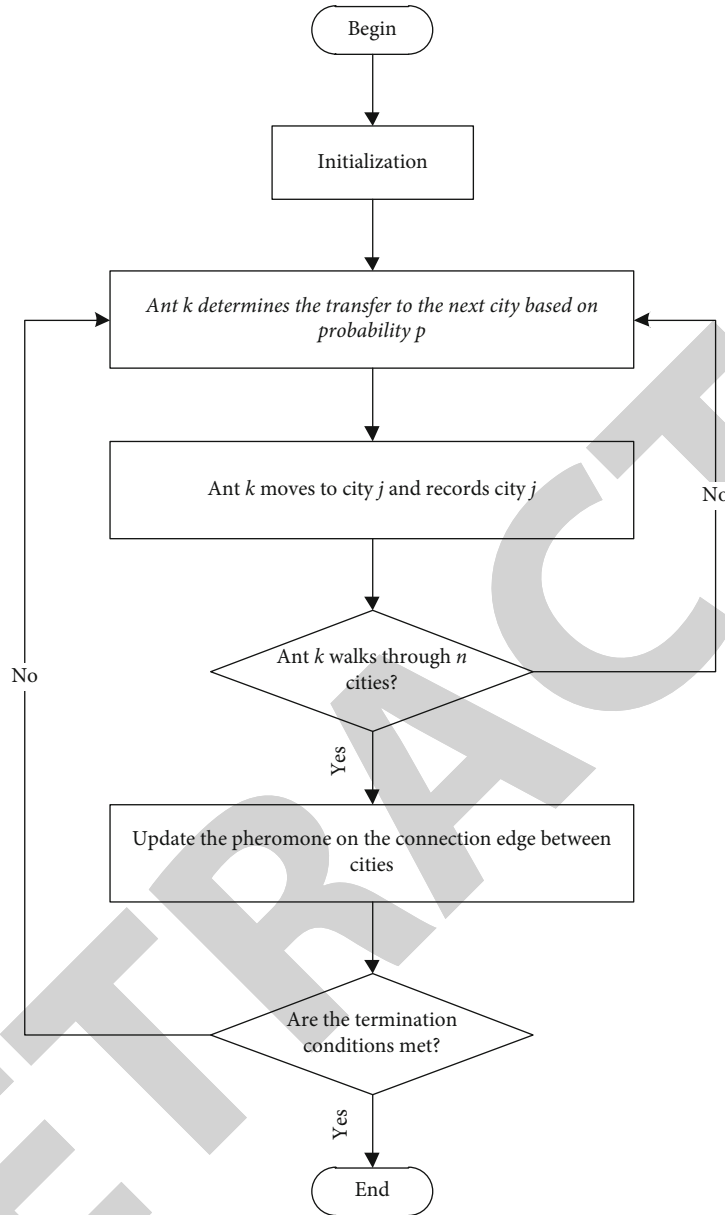
FIGURE 3: Flow chart of the ant colony algorithm.

does not go its own way but is based on calculation and continuously improved. The classification is shown in Figure 1.

2.2. Genetic Algorithm

2.2.1. Basic Concepts. Natural selection heredity is the foundation of this algorithm; that is, chromosomes are abstracted into body objects and then encoded. Only in this way can we search randomly and efficiently in this space. Among them, genetic operation is divided into selection, crossover, and variation.

After the formation of the first generation population, according to the law of the survival of the strong in the theory of biological evolution, a series of more and more excellent approximate solutions are produced through iteration. Moderate function is a strict judge, and excellent individuals can pass its selection. Then, these excellent people will choose, cross, and mutate. They have become completely different from before, and they are a brand-new population. The genetic algorithm flow is shown in Figure 2.

The genetic algorithm is divided into pattern H. The formula of general mathematical expression is as follows:

$$M[H(t+1)] \geq M[H(t)]\frac{f(H(t))}{f(t)}\left[1 - \frac{P_c \times \delta(H)}{L-1}\right](1-P_m)^{O(H)},$$
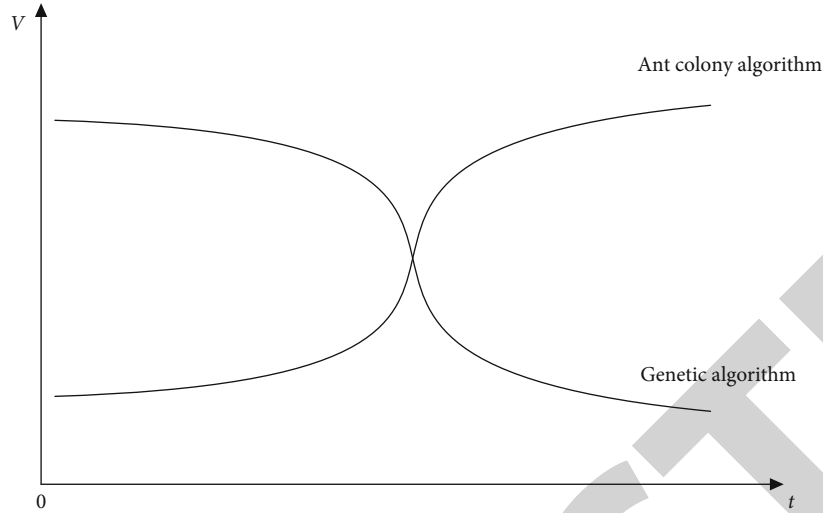
$$(1)$$

Figure 4: Time situation diagram of overall evolution rate.

$$f(H(t)) = \frac{\sum_{i \in H} f_i}{M[H(t)]}. \tag{2}$$

$M(H(t+1))$ is the expected number of pattern H in population after $t+1$ iteration, P_c is the crossing probability, P_m is the mutation probability, $f(t)$ is the average fitness value, $f(H(t))$ is the average fitness value of population model H, f_i is the i-th individual fitness value, and $\delta(H)$ is the pattern definition distance, that is, the distance between the initial and last determined positions in pattern H.

2.2.2. Related Issues. In the aspect of human resource allocation, the algorithm is not perfect. If the two are combined, the matching resources needed by the enterprise organization at first can have idealized results. The reason is that the convergence speed of the optimal solution is fast in the early stage of the algorithm. With the continuous operation, in the later stage of the algorithm, the efficiency of human resource allocation plummeted due to the increase of allocation times and the decrease of convergence speed. The two are not suitable and need to be improved.

2.3. Ant Colony Algorithm

2.3.1. Basic Concepts. When the number of ants is $k(k = 1, 2, \cdots, m)$ and the number of cities is $(i, j = 1, 2, \cdots, n)$, i and j, the distance between them is d. And set the initialization pheromone concentration $\tau_{ij}(0) = \tau_0$. The flow chart of the ant colony algorithm is shown in Figure 3.

After t iterations, the probability $P_{ij}^k(t)$ formula for the k-th ant to successfully move from city i to j is as follows:

$$P_{ij}^k(t) = \begin{cases} \dfrac{[\tau_{ij}(t)]^\alpha \cdot [\eta_{ij}(t)]^\beta}{\sum_{s \in J_k(i)}[\tau_{is}(t)]^\alpha \cdot [\eta_{is}(t)]^\beta} & j \in J_k(i), \\ 0 & j \notin J_k(i). \end{cases} \tag{3}$$

α is the relative importance of pheromone, β is the relative importance of heuristic factors, $\tau_{ij}(t)$ is the pheromone concentration of city i and j paths after t iterations, $\eta_{ij}(t)$ is the heuristic function, the heuristic degree that ants can smoothly from city i to j in the t iteration, and $J_k(i)$ is a collection of cities that ants can visit next.

The heuristic factor is calculated by the following formula:

$$\eta_{ij} = \frac{1}{d_{ij}}. \tag{4}$$

The update formula of pheromone concentration in intercity path is as follows:

$$\tau_{ij}(t+1) = (1 - \rho)\tau_{ij}(t) + \Delta\tau_{ij}, \tag{5}$$

$$\Delta\tau_{ij} = \sum_{k=1}^{n} \Delta\tau_{ij}^k. \tag{6}$$

ρ is the volatilization coefficient of pheromone, and the value range is (0, 1), $\Delta\tau_{ij}$ is the pheromone increment of edges i and j in this iteration, and $\Delta\tau_{ij}^k$: in this iteration, the amount of pheromones left on edges i and j is related to the k-th ant.

For $\Delta\tau_{ij}$, there are three calculation models:

The formula for the ant cycle system is as follows:

$$\Delta\tau_{ij}^k = \frac{Q}{L_k}. \tag{7}$$

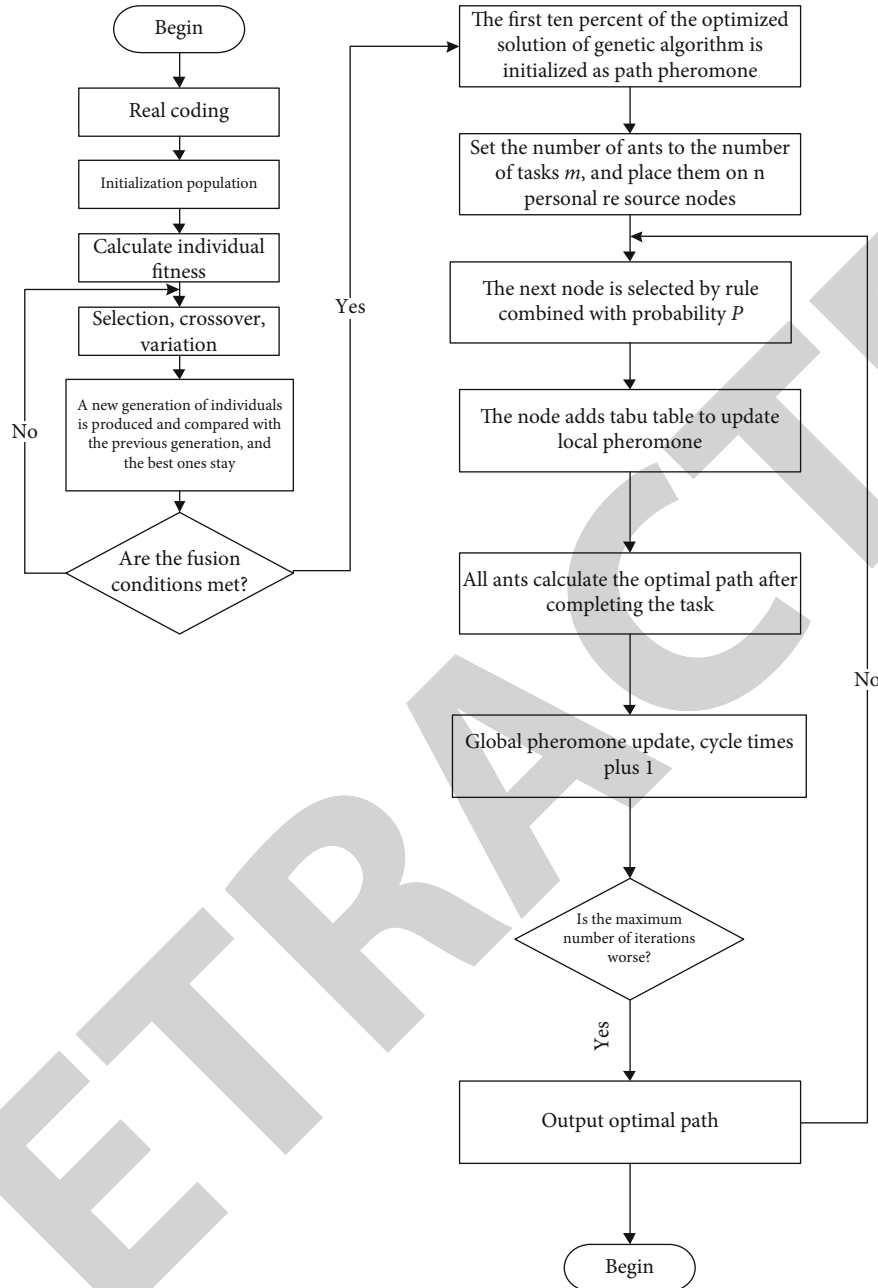L_k is the length of the path taken by ant k.

FIGURE 5: Flow chart of the genetic ant colony algorithm.

The formula for the ant quantity system is as follows:

$$\Delta\tau_{ij}^k = \frac{Q}{d_{ij}}. \qquad (8)$$

The formula for the ant density system is as follows:

$$\Delta\tau_{ij}^k = Q. \qquad (9)$$

Q is a normal number, which represents the total number of pheromones produced by ants after this iteration.

2.3.2. Related Issues. The influence of the ant colony algorithm on human resource allocation is just opposite to the new genetic algorithm. In the early stage of the algorithm, due to pheromone initialization, the ant's optimization ability is reduced. This means that in the allocation of human resources, in the early stage of allocation, human resource information cannot be rationalized, which will lead to reduced efficiency, increased costs, and brain drain. With many iterations, the pheromone concentration increases, which greatly increases the ant's optimization ability. This will greatly increase the matching efficiency in human resource allocation.

Table 1: Comparison of execution time and execution cost data.

Number of tasks	Type	Genetic algorithm	Ant colony algorithm	Genetic ant colony algorithm
30	Execution time	30	30	30
	Execution cost	45	45	25
60	Execution time	50	45	40
	Execution cost	76	75	52
90	Execution time	63	55	50
	Execution cost	100	101	88
120	Execution time	81	64	60
	Execution cost	162	161	109
150	Execution time	118	77	70
	Execution cost	177	177	146
180	Execution time	146	91	85
	Execution cost	220	221	175
210	Execution time	162	95	90
	Execution cost	250	248	208
240	Execution time	184	117	107
	Execution cost	288	290	247
270	Execution time	216	128	124
	Execution cost	321	323	268
300	Execution time	239	130	128
	Execution cost	361	360	300
330	Execution time	250	130	130
	Execution cost	426	425	339

3. Optimization Algorithm

The time trend of the overall evolution rate of the two algorithms is shown in Figure 4.

As can be seen from the figure, the disadvantages of the two are just the opposite. Therefore, this paper proposes to improve the two first and then combines them to complement each other. In this way, a new algorithm, namely, genetic ant colony algorithm, can be obtained. The algorithm can absorb the advantages of the former two, and ensure that the convergence speed does not decrease with iteration, and is more stable. The purpose of this algorithm for human resource allocation is to keep the efficiency of human resource allocation efficient and stable.

3.1. Improved Genetic Algorithm. For resource scheduling, assuming population size = popsize, subtasks = n, and schedulable resources = m, then the total length of parameters = n, then the range of each individual is $[1, m]$. The formula in the form of individual X is as follows:

$$X = (x_1, x_2, \cdots, x_n) \quad x_t \in R, i = 1, 2, \cdots n. \quad (10)$$

In order to compare the length of time required for information tasks in human resource allocation, the formula is as follows:

$$\text{totaltime}(I) = \max_{j=1}^{m} \sum_{i=1}^{n} T_{ij}, \quad (11)$$

$$T_{ij} = \frac{T_t(\text{length})}{\text{vm}_j(\text{mips})} + \frac{T_t(\text{inputfilesize})}{\text{vm}_j(\text{bw})} + \frac{T_t(\text{outputfilesize})}{\text{vm}_j(\text{bw})} + T_t(\text{wait\_time}), \quad (12)$$

$$\text{vm}_j(\text{mips}) = \text{pe\_num}_j \times \text{pe\_mips}. \quad (13)$$

$\text{vm}_j(\text{mips})$ is the CPU computing power, pe_num_j is the number of virtual machine processors, pe_mips is the virtual machine vm_j processor speed, $\text{vm}_j(\text{bw})$ is the wideband processing capability of virtual machine vm_j, and $T_t(\text{wait\_time})$ is the waiting time of subtask i.

In human resources, in order to get suitable resource information individuals, the formula of their fitness function is as follows:

$$f_1(j) = \frac{1}{\text{totaltime}(I)} \times u_{\text{LB}}, \quad (14)$$

$$u_{\text{LB}} = \frac{\sum_{j=1}^{m} \sum_{i=1}^{n} T_{ij}}{m \times \text{totaltime}(I)}. \quad (15)$$

u_{LB} is the balance the load factor, which is proportional to the utilization of resources.

$$f_2(j) = \frac{1}{\sqrt{\sum_{j=1}^{m} (\text{task}(i, j) - n/m)^2/m}} \quad 1 < i < \text{popsize}, \quad (16)$$

$$f(j) = \omega f_1(j) + (1 - \omega) f_2(j) \quad 0 < \omega < 1, \quad (17)$$
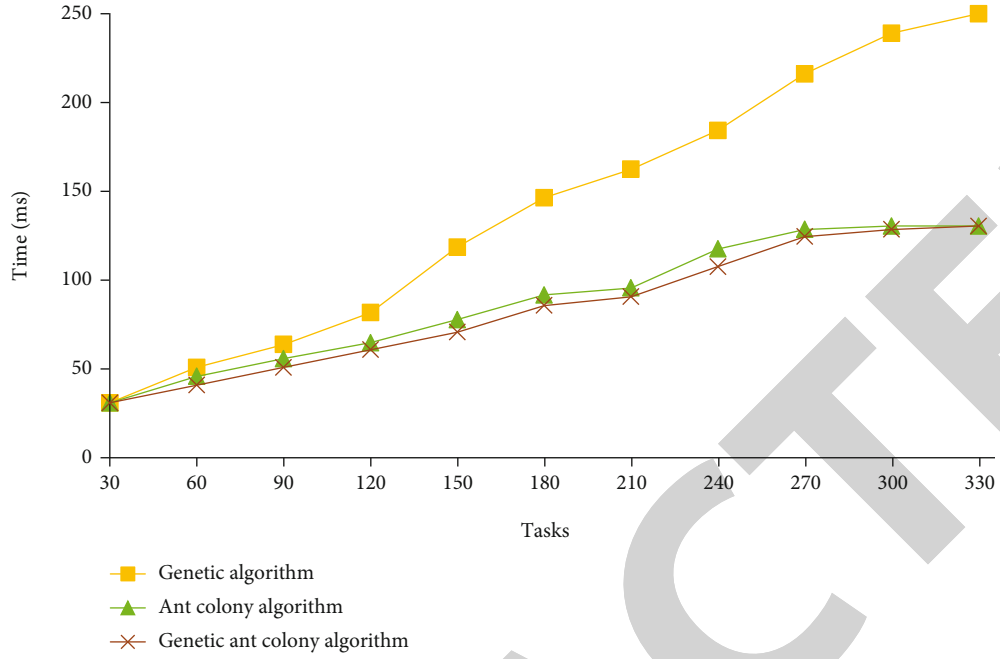
Figure 6: Comparison of the execution time length of the three algorithms.
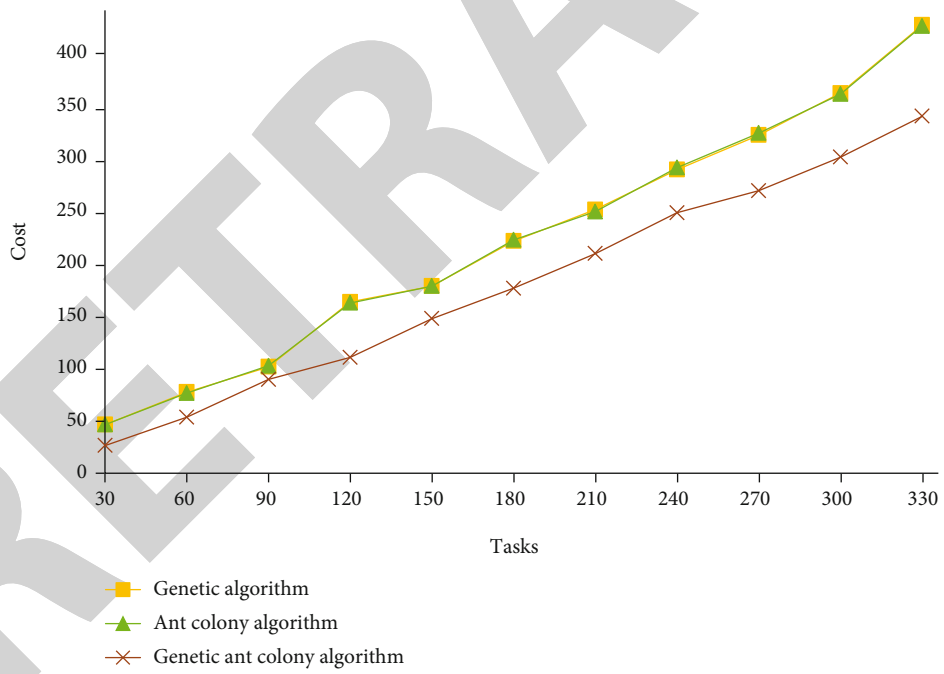

Figure 7: Comparison of the execution costs of the three algorithms.

in this which task(i, j) is the task to which the virtual machine j of the individual i is assigned.

The formula of selection probability is as follows:

$$P_i = \frac{f(i)}{\sum_{j=1}^{m} f(j)}. \tag{18}$$

The formula of crossover probability is as follows:

$$P_c = \begin{cases} P_{c1} - \dfrac{(P_{c1} - P_{c2})\left(f' - f_{\mathrm{ave}}\right)}{f_{\max} - f_{\mathrm{ave}}} & f' \geq f_{\mathrm{ave}}, \\ P_{c1} & f' < f_{\mathrm{ave}}, \end{cases} \tag{19}$$
$$P_{c1} = 0.9, P_{c2} = 0.6.$$

TABLE 2: Resume data size.

Number	Size
1	25 KB
2	30 KB
3	35 KB
4	40 KB
5	45 KB
6	50 KB
7	55 KB
8	60 KB
9	65 KB
10	70 KB

f_{max} is the maximum fitness value in the current population, f_{ave} is the average value of fitness in the current population, and f', compared with two cross individuals, is the maximum fitness value.

The mutation probability formula is as follows:

$$P_m = \begin{cases} P_{m1} - \dfrac{(P_{m1} - P_{m2})(f' - f_{ave})}{f_{max} - f_{ave}} & f' \geq f_{ave}, \\ P_{m1} & f' < f_{ave}, \end{cases}$$
$$P_{m1} = 0.1, P_{m2} = 0.001. \tag{20}$$

3.2. Improved Ant Colony Algorithm.
In conventional algorithms, the randomness of ants is not high when they move, which will lead to problems when ants search for similar optimal resource information. In order to solve this problem, new rules have been formulated. The formula is as follows:

$$j = \begin{cases} \arg\max \left\{ [\tau_{ij}(t)]^\alpha \cdot [\eta_{ij}(t)]^\beta \right\} & \rho \leq \rho_0, \\ P & \rho > \rho_0. \end{cases} \tag{21}$$

ρ is the uniformly distributed random values with a value range of [0, 1], and ρ_0 is the constant value.

The formula of HR multiservice quality requirement function related to pheromone update rule is as follows:

$$F(I) = \varphi_1 \frac{\text{totaltime}_{ij} - \text{totaltime}_{min}}{\text{totaltime}_{max} - \text{totaltime}_{min}} + \varphi_2 \frac{\cos t_{ij} - \cos t_{min}}{\cos t_{max} - \cos t_{min}}. \tag{22}$$

totaltime_{ij} is the expected task execution time, totaltime_{max} is the maximum expected task execution time, totaltime_{min} is the minimum expected task execution time, $\cos t_{ij}$ is the expected task execution cost, $\cos t_{max}$ is the Maximum cost of expected task execution, $\cos t_{min}$ is the minimum cost of expected task execution, and φ_1, φ_2 are the time weight coefficient and cost weight coefficient.

TABLE 3: Data on upload speed and operating cost.

Number	Type	Genetic algorithm	Ant colony algorithm	Genetic ant colony algorithm
1	Upload speed	90.3	85.3	98.7
	Operating cost	0.003	0.004	0.0008
2	Upload speed	64.2	83.2	95.2
	Operating cost	0.007	0.004	0.001
3	Upload speed	84.9	83.0	90.8
	Operating cost	0.005	0.005	0.003
4	Upload speed	69.1	74.8	88.4
	Operating cost	0.009	0.006	0.004
5	Upload speed	55.6	68.2	83.9
	Operating cost	0.012	0.008	0.005
6	Upload speed	67.1	51.3	80.7
	Operating cost	0.009	0.011	0.006
7	Upload speed	66.3	60.4	75.3
	Operating cost	0.010	0.013	0.006
8	Upload speed	55.6	56.9	72.6
	Operating cost	0.014	0.014	0.008
9	Upload speed	49.4	50.1	70.7
	Operating cost	0.017	0.016	0.008
10	Upload speed	45.8	47.9	70.2
	Operating cost	0.020	0.018	0.008

Time weight coefficient φ_1 and cost weight coefficient φ_2 are in [0, 1], and $\varphi_1 + \varphi_2 = 1$.

When calculating the local pheromone increment, the ant updates the resource every time it completes the resource allocation. The formula is as follows:

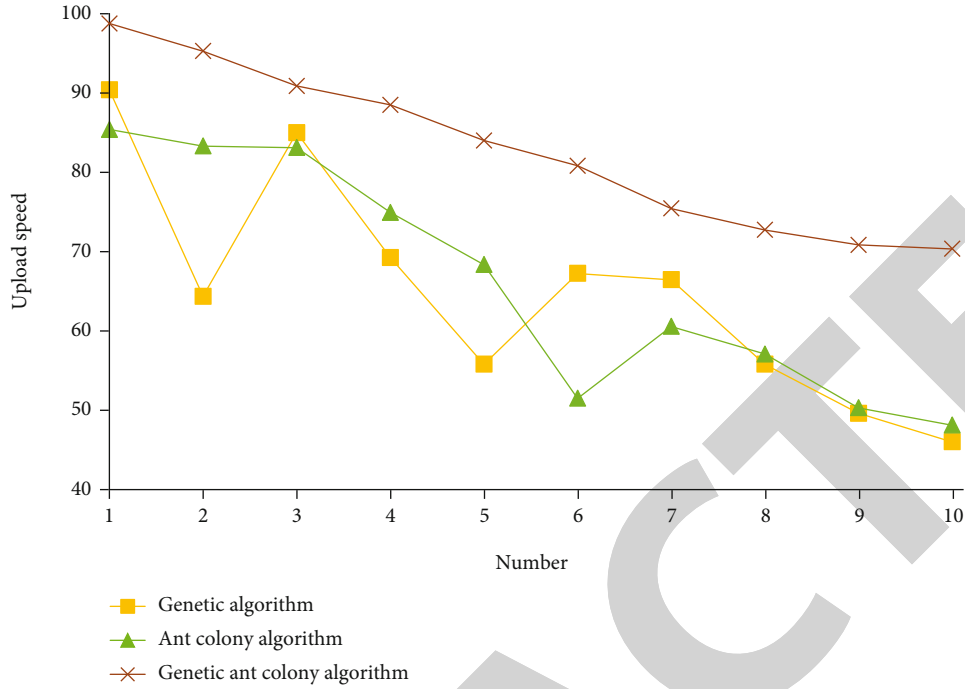$$\Delta\tau_{ij}(t) = \frac{\text{const}_1}{F(I)}. \tag{23}$$

FIGURE 8: Comparison of data upload speed.

When calculating the global pheromone increment, each ant completes the resource allocation once before updating. The formula is as follows:

$$\Delta\tau_{ij}(t) = \frac{\text{const}_2}{F(I)_{\text{best}}}. \qquad (24)$$

And $\tau_{\min} \leq \tau_{ij}(t) \leq \tau_{\max}$ is specified, so as to avoid the stagnation of the algorithm caused by the disparity of path pheromones.

In the ant colony algorithm, the distance between two cities is the same as heuristic information. However, this cannot guarantee the optimal solution; so, we need to refer to the load model to improve the expression of heuristic information. The heuristic factor function is expressed as follows:

$$\eta_{ij} = \frac{1}{\sum_{i=1}^{\text{task}} T_i(\text{length}) + T_i(\text{length})/\text{vm}_j(\text{mips})}. \qquad (25)$$

$T_i(\text{length})$ is the length of task i, and task is the number of tasks that have been run on virtual machine j.

3.3. Genetic Ant Colony Algorithm.
When $g_{\text{now}} < g_{\max}$, compare g_{ratio}, g_{pop}, and when the comparison result is $g_{\text{pop}} < g_{\text{radio}}$ and occurs many times, the algorithm begins to transform.

g_{now} is the current number of iterations, $g_{\max}$ is the maximum number of iterations $g_{\min}$ is the minimum number of iterations, g_{ratio} is the minimum evolution rate, and g_{pop} is the progeny evolution rate.

When the optimal solution of ant colony algorithm is = τ_G, the pheromone value of the ant colony algorithm is $\tau_S = \tau_{\min} + \tau_G$ at the initial stage. The algorithm flow is shown in Figure 5.

4. Simulation Experiment

4.1. Algorithm Testing.
Set popsize = 100, $g_{\max} = 150$, $g_{\max} = 50$, $g_{\text{radio}} = 0.5\%$, the maximum number of iterations is 120, and $\rho = 0.3$, $\alpha = \beta = 1$. The overall parameter sets the task length $\in [1000, 10000]$ and the total number of tasks $\in [30, 330]$ and $200 \leq \text{mips} \leq 1000$, bw = 1000Mb.

The data pairs obtained through experiments are shown in Table 1.

Execution cost index human resource allocation in the system uses the cost needed to reflect the human resource system allocation of scientific and optimal degree. The lower the execution cost, the higher the optimization degree of human resources allocation, and the relatively reasonable cost.

An alignment of execution times is shown in Figure 6.

The pair of execution costs is shown in Figure 7.

It can be seen from this that the GAACO algorithm is superior to the other two algorithms in terms of execution time and execution cost. It can be clearly seen that with the increase of the number of tasks, the execution time and cost of the ACO-GA algorithm are lower and lower than those of the other two algorithms, which shows that when the number of tasks increases gradually, the running speed of ACO-GA is better and better than those of the other two algorithms, that is, the ACO-GA algorithm has the characteristics of high efficiency, stability, and low cost.
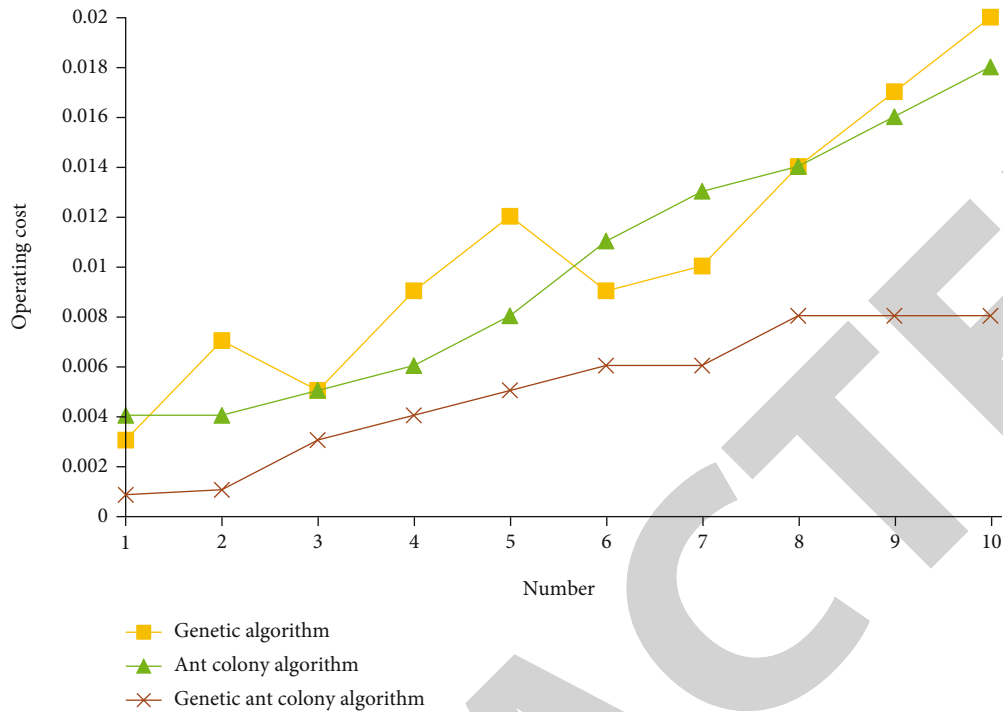
Figure 9: Comparison chart of data operation cost.

4.2. Experiments and Results

4.2.1. Establishing the Objective Function.
Establish the database of human resource allocation and digitize the resumes of relevant personnel, that is, change the characteristic attributes of personnel into vector features, such as transforming resumes A and B into $A = (a_1, a_2, a_3)$, $B = (b_1, b_2, b_3)$. The distance between the vectors they transform is the similarity between the two resumes, and the formula is as follows:

$$S = \sqrt{\sum_{i=1}^{n} (a_1 - b_1)^2}. \tag{26}$$

The formula for judging employee grades is as follows:

$$S(A, B, C) = \sum_{i=1}^{n} f(A, B) \times C_i. \tag{27}$$

$f(A, B)$ is the functional relationship between files A and B, that is, similarity, and C_i is the similarity distribution weight.

At the end, the formula for matching the similarity of data is as follows:

$$D = \left\{ \sum_{i=1}^{n} (S_{mn} - S_{11}) \times C_i \right\}^{1/2}. \tag{28}$$

S_{mn} is the maximum value of weight characteristic, and S_{11} is the minimum value of weight attribute,

Table 4: Comparison of similarity between predicted value and actual value of algorithm.

Number	Actual value	Genetic	Ant colony	Genetic ant colony
1	80%	70%	68%	75%
2	78%	67%	65%	75%
3	85%	71%	70%	83%
4	75%	68%	70%	77%
5	83%	75%	77%	81%
6	80%	65%	70%	83%
7	86%	70%	71%	85%
8	76%	65%	65%	77%
9	79%	64%	66%	80%
10	75%	60%	62%	77%

4.2.2. Simulation Experiment and Result Analysis.
Suppose a total of 10 resumes have been uploaded to the database, the data are uploaded and run in the order from small to small. Record the uploading speed and running cost of these 10 data under the three algorithms and compare them. The data sizes are shown in Table 2.

The data of upload speed and running cost obtained by experiments of the three algorithms are shown in Table 3.

The data upload speed pair is shown in Figure 8.

The data running cost pair is shown in Figure 9.

After testing and comparing the running speed and cost of the algorithms, this paper proposes to test the predicted values of the three algorithms and compare them with the
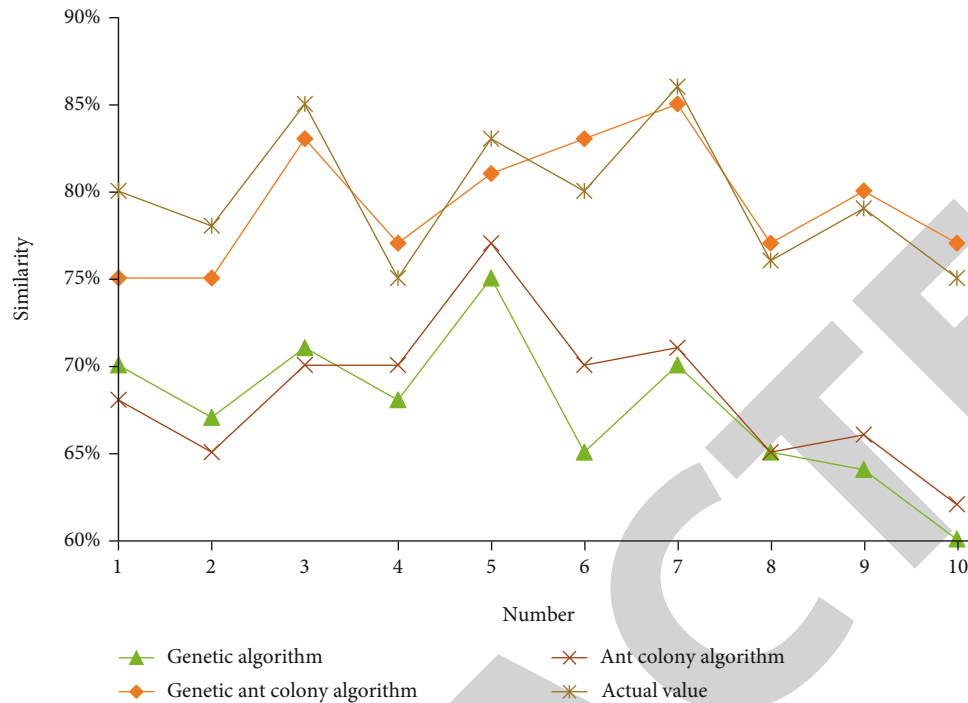
FIGURE 10: Similarity comparison data graph.

actual values according to the objective function of human resource allocation similarity set above. Set up each post standard information vector characterization, compare the above 10 human resources data with post standard data, calculate similar values, and compare them. Comparative data are shown in Table 4.

The similarity comparison data diagram is shown in Figure 10.

It can be seen that in human resource data matching, the accuracy of the first two is not ideal. When the data is relatively small in the early stage, it can be seen that the genetic algorithm is slightly better than the ant colony algorithm, and the accuracy of the ant colony algorithm is slightly better than the genetic algorithm in the later stage. On the other hand, the ACO-GA algorithm is more consistent with the actual value, which not only ensures the stability but also ensures the accuracy of prediction, which is more in line with the actual demand. The next research work needs to analyze the execution efficiency of the intelligent optimization algorithm in different stages, aiming at the problems of local convergence and insufficient execution in different stages. Further expand the human resource optimization program, from the implementation system and online analysis programs to analyze the problems in human resources.

5. Conclusion

The ACO-GA algorithm is improved and fused by the basic algorithm. At the beginning of the design, it was designed to make it take the strengths of the two and promote the weaknesses of the two. Through experiments, it is found that this

method can really keep the convergence speed at a high level in the early and late stages and keep a high stability. Therefore, in the human resource allocation module, the ACO-GA algorithm is a successful example of improvement.

Data Availability

The experimental data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declared that they have no conflicts of interest regarding this work.

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