SCIENCE CHINA
Technological Sciences

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https://doi.org/10.1007/s11431-020-1577-0

Human resource allocation for multiple scientific research projects via improved pigeon-inspired optimization algorithm

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Received January 14, 2020; accepted March 23, 2020; published online June 10, 2020

Aiming at the complex and restrictive characteristics of human resource allocation in multiple scientific university research projects, an improved pigeon-inspired optimization (IPIO) algorithm is proposed wherein loss minimization and the shortest project delay time are considered as optimization goals. Firstly, mathematical modelling of the problem is carried out, and the multi-objective optimization problem is transformed into a single-objective optimization problem by means of a weighted solution. In the second step, the traditional pigeon-inspired optimization (PIO) algorithm is discretized, and an adaptive parameter strategy is adopted to improve the shortcomings of the algorithm itself. Finally, by comparing the simulation results with the original algorithm and the genetic algorithm in the optimization of human resource allocation in multiple projects, the feasibility and superiority of the proposed algorithm in the optimization of human resource allocation in multi-scientific research projects is verified.

human resource allocation, multiple scientific research projects, improved pigeon-inspired optimization (IPIO) algorithm, parameter adaptation

Citation: Liu C B, Ma Y H, Yin H, et al. Human resource allocation for multiple scientific research projects via improved pigeon-inspired optimization algorithm. Sci China Tech Sci, 2020, 63, https://doi.org/10.1007/s11431-020-1577-0

1 Introduction

Colleges and universities are both sources of national science and technology innovation, and most scientific research projects do not take place in isolation, being rather either divided into several sub-projects or run concurrently with other research and development projects. When multiple scientific research projects are implemented, universities often meet the problem of resource conflicts in projects at the same time [1]. In ref. [2], various problems in multi-project management were investigated and studied, and several factors affecting multi-project collaboration were analyzed. The results showed that the unreasonable allocation of resources, such as human resources, funds, and equipment, greatly increased the difficulty and complexity of project management [3,4].

Recently, human resources have become a very critical resource, especially for universities with science and technology as the main tasks [5–9]. The allocation of key human resources will affect the progress and quality of scientific research projects. Therefore, key human resource allocation in colleges and universities has become a practical problem for universities to decrease the period of scientific research projects as much as possible, to reduce losses in scientific research projects, and to minimize cost and maximize benefits urgently.

In 1989, the American scholar Gareis proposed the concept of “management by project” on the basis of traditional single

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project management, that is, the concept of multi-project management. Since then, multi-project management has been widely discussed and studied [10]. Steyn [11] analyzed human resource allocation in a multi-project environment based on limit theory, and Hendriks et al. [12] considered the scale and priority of each project and, based on this, allocated various resources for similar work in multiple projects. Grundy [13] emphasized the management of human resources, the adjustment of organization structure, and the selection of projects. Chen et al. [14] proposed an allocation method to solve the problem of high subjectivity and low efficiency of multi-project human resources. Based on simulations, a multi-dimensional model (molecular dynamics model) method was presented. Weng et al. [15] proposed a multi-project human resource allocation method and designed a set of input and output indicators that can reflect the performance of human resource allocation. This method mainly used a data envelopment analysis model to evaluate the progress of parallel multi-projects, and then dynamically adjusted human resource allocation schemes to improve the resource utilization efficiency and the multi-project success rate. Chien et al. [16] proposed that a matrix-based organizational structure met the total cost constraint requirements of multi-projects and was an effective human resource allocation model. They also designed a multi-project personnel information resource communication and negotiation mechanism for distributed environments. Chen et al. [17] established a project evaluation system using a multi-level fuzzy comprehensive evaluation method and then utilized a multi-dimensional model and the Fleischman analysis system to achieve a quantitative evaluation of employee capabilities and employee work efficiency. Moreover, a multi-project human resource allocation model was designed based on the backpack problem principle.

Intelligent algorithms are widely applicable to complex optimization and other problems due to their versatility, high execution efficiency, and easy implementation. Examples of this kind of algorithm include genetic algorithms (GAs) [18], particle swarm optimization algorithms [19], and ant colony optimization algorithms [20]. Debels and Vanhoucke [21] developed a decomposition-based GA to solve the resource-constrained project-scheduling problem. Tchomté et al. [22] proposed an improved particle swarm optimization algorithm to solve the combinatorial optimization problem with precedence constraints in general and the resource-constrained project scheduling problem in particular. Deng et al. [23] used a hybrid and colony optimization to solve the resource-constrained project scheduling problem. Although these algorithms had some research value in optimization, the parameter settings of these algorithms were crucial to the results, and there were also learning strategies, such as genetic cross, which made application of these algorithms cumbersome. Therefore, if the parameter settings could be reduced and tedious learning strategies avoided, the algorithms could be made simple and practical. In 2014, Duan and Qiao [24], inspired by pigeons' homing behavior in nature, first proposed a new group intelligent optimization algorithm, namely the pigeon-inspired optimization (PIO) algorithm. This algorithm has the advantages of fast convergence speed, strong optimization ability, and fewer parameters, and it has achieved fruitful results in unmanned aerial vehicles' formation, optimal control parameters, image processing, and other fields. A cooperative control method for unmanned aerial vehicle based on predatory escaping PIO is proposed in ref. [25]. In ref. [26] a novel control parameter design method was proposed, which transformed the parameter design problem into a parameter optimization problem through PIO to overcome the difficulty of manually adjusting the parameters in the automatic landing system. Li and Duan [27] improved the herd optimization through the simulated annealing mechanism and applied it to the aerial image target detection method based on contour matching, which improved the efficiency and accuracy of target detection.

In this paper, we first present a human resource allocation model for multi-scientific research projects in universities mathematically, and then improve the PIO algorithm. Based on the traditional PIO algorithm, adaptive control is applied to avoid the disadvantage of iterative results being local instead of global optima. Finally, by comparison with the traditional PIO algorithm and GA, we verify the superiority of the method on the human resource allocation of multi-scientific research projects.

2 Establishment of a human resource optimal allocation model for multi-scientific research projects

2.1 Problem description

An event-based scheduler is a representational scheme. It is the combination of a task list [28] and an employee allocation matrix [29]. Assume that there are N independent scientific research projects and that a resource scramble for R researchers occurs in a certain period, with each researcher having a different knowledge level in different research fields. Each research project has several sub-projects, and each sub-project has a certain workload, which requires the different knowledge and skills of researchers to complete. After entering a project, researchers cannot withdraw from the original project and enter other projects before the completion of tasks. Based on the above background, a multi-objective human resource allocation optimization model is established, the goal of which is to minimize the weight of delay losses for multiple scientific research projects. The most important research projects, i.e., those with highest priority, should have the shortest delays.

2.2 Model definitions

(1) In a certain period of time, N parallel and independent scientific research projects of colleges and universities fall into a conflict of human resources. We use N_i to represent each such project. Every research project N_i has S sub-projects, with N_{is} indicating the ith sub-project of the sth research project, and i=1, 2, …, N, s=1, 2, …, S.

(2) The priority of each scientific research project is known, and the priority factor of scientific project N_i is noted as ω, i=1, 2, …, N.

(3) The total amount of researcher resources allocated by universities for each project is denoted as R, and each researcher is represented by R_j, j=1, 2, …, R.

(4) We use θ_{ji} to indicate personnel distribution (θ_{ji}=either 1 or 0). When θ_{ji}=1, R_j is assigned to the ith scientific research project.

(5) We assume that a scientific research project starts to compete for human resources at time t and that the project N_i has formulated a networking plan based on human resources. The time required to complete the task according to the networking plan is denoted as T_i. We also assume that the human resource needs of the projects can be satisfied fully. Because each project competes for resources, after allocation, the time required to complete a task of project N_i after the time t is marked as T'_i.

(6) According to the mandate, if project N_i is delayed, the unit loss cost of the delay is Δc_i. Delays in scientific research projects bring not only direct cost losses to universities but also qualitative losses, such as credibility. To simplify the model, this article will not consider them here.

(7) Due to the limited resources of team members, projects compete for shared resources. After resource allocation, the difference between the actual completion time and the estimated completion time of a task of the scientific research project after time t is noted as ΔT_i=T'_i−T_i.

(8) The lateness cost of project N_i is recorded as C_i=ΔT_i −Δc_i.

(9) The duration of a task activity of project N_i can be expressed as a function of the project task workload and the allocated resources. In scientific research project tasks, each sub-topic has a certain logical sequence, which may be sequential or side-by-side. Therefore, the activity task duration function should be set according to the specific task, marked as T'_i=$f(Q_{is})$, where Q_{is} represents the amount of human resources and technology assigned to research project N_i sub-projects s (person-days), and $Q_{is}=\sum_{i=1}^{\pi}\theta_{ji}\times P_{js}$. As each researcher has several knowledge skills, one researcher can contribute to several sub-projects in a research project. Let P_{js} be the ability coefficient of the knowledge and skills that researcher j has to complete the sth sub-project, with P_{js}={0, 1, 2} representing poor, medium, and good levels of knowledge and skills.

To simplify the model, in this paper we assume that the task of each scientific research project has a logical sequence of sub-projects. Therefore, T'_i is equal to the sum of the ratio of the workload of each sub-topic of the project task to the amount of human resources and technology allocated. If μ_{is} indicates the workload (person-day) of research project N_i sub-project s, then T'_i can be expressed as

$$T'_i=\sum_{s=1}^{S}\frac{\mu_{is}}{Q_{is}}=\sum_{s=1}^{S}\frac{\mu_{is}}{\sum_{j=1}^{R}\theta_{ji}\times P_{js}}. \tag{1}$$

2.3 Model building

Based on the above assumptions, the following human resource allocation optimization models for multiple scientific research projects can be established:

$$\begin{aligned}F_1&=\min Z_1=\min\sum_{i=1}^{N}\omega_i\times C_i\\&=\min\sum_{i=1}^{N}\omega_i\times(T_i'-T_i)\times\Delta c_i\\&=\min\sum_{i=1}^{N}\omega_i\times\left(\sum_{s=1}^{S}\frac{\mu_{is}}{\sum_{j=1}^{R}\theta_{ji}\times P_{js}}-T_i\right)\times\Delta c_i,\end{aligned} \tag{2}$$

$$F_2=\min Z_2=\min\left(\sum_{s=1}^{S}\frac{\mu_{ms}}{\sum_{j=1}^{R}\theta_{jm}\times P_{js}}-T_m\right), \tag{3}$$

$$\text{s.t.}\quad \omega_m=\max\{\omega_i\}\ \ (i=1,2,\dots,N), \tag{4}$$

$$0\le\sum_{i=1}^{N}\sum_{j=1}^{R}\theta_{ji}\le R, \tag{5}$$

$$0\le\sum_{i=1}^{N}\theta_{ji}\le 1\ (i=1,2,\dots,R), \tag{6}$$

$$\theta_{ji}\in 0,\ 1. \tag{7}$$

Eq. (2) is the first objective function, and it means that multiple projects with known priorities have the lowest delay losses.

Eq. (3) is the second objective function, which indicates that the project with the highest priority has the shortest delay time.

As high-priority research projects are of the highest importance to universities, failure to complete a project within the scheduled time will not only cause direct losses for the university, such as delaying compensation for breach of contract, but also negatively affect the reputation and development prospects of the university. These hidden and difficult-to-measure losses are even more serious for colleges and universities. Therefore, it is necessary to ensure that the projects with the highest priority avoid delay due to competition for resources.

Eq. (5) describes the constraint on human resources. Eq. (6) states that each researcher can be assigned to at most one research project. Eq. (7) is the constraint of the 0–1 variable θ_{ji}.

2.4 Multi-objective optimization problem solving

The Pareto optimal solution of a multi-objective optimization problem is simply an attainable solution; such problems usually have multiple Pareto optimal solutions, which form a Pareto solution set. When solving practical problems in colleges and universities, the optimal solution in the Pareto solution set should be chosen according to the information held by the decision maker and the personal preferences of the decision maker.

In the field of scientific research, multi-objective optimization problems are not uncommon [30–33]. In general, each optimization target can be regarded as one of multiple subtargets under a general target. The actual situation can be applied to determine the weight of each target and then obtain the optimal solution of the total target. In weighted solution methods, it is assumed that if the weights corresponding to two optimization objective functions are α and β, then $\alpha+\beta=1$. The total goal after weighting is $F=\alpha F_1+\beta F_2$. After determining the weights of the two optimization objective functions, the overall objective is determined, and the search direction is determined accordingly.

There are usually two methods to solve this problem. One is to generate the weights of each target randomly, use the randomly generated weights to solve the problem iteratively, and then obtain the optimal solutions in different directions. The other is to update the weights continuously and change the search direction during the operation. In this paper, when solving the model, the weighted sum of the objective functions is used as the evaluation function of the multi-objective optimization problem, so the problem is transformed into a single-objective optimization problem. Then, we use the IPIO algorithm to analyze the model.

3 Pigeon-inspired optimization algorithm

The PIO algorithm is a swarm intelligence optimization algorithm. This algorithm is inspired by the mathematical model of pigeon swarms using geomagnetism and landmark homing. A survey examining the ability of pigeons to detect different magnetic fields shows that pigeons have a strong homing ability because iron crystals in their beaks help them confirm directions based on the strength of the geomagnetic field. It has been known since ancient Roman times that pigeons have a homing instinct, and carrier pigeons have been used for communication. When a pigeon is far from its destination, it uses the geomagnetic field to navigate, and it uses local landmarks for the same purpose when it is closer to the destination. Carrier pigeons can easily find their destination using geomagnetic fields and landmarks. In the PIO algorithm, the guide operator model is proposed based on the geomagnetic field and the sun, whereas the landmark operator model is proposed based on landmarks.

3.1 Guide operator

The guide operator is based on the geomagnetic field. We use X_i and V_i to represent the position and velocity of the ith pigeon. In 2D space, the position and velocity are updated during each iteration. The velocity and position of the ith pigeon will be calculated iteratively using the following equation:

$$V_i(t) = V_i(t-1)\cdot \mathrm{e}^{-Rt} + \mathrm{rand}\cdot (X_g - X_i(t-1)), \tag{8}$$

$$X_i(t) = X_i(t-1) + V_i(t). \tag{9}$$

The velocity of the ith pigeon is determined by its last iteration velocity and its current best position, where R is the compass factor, "rand" is a random number, and t is the iteration number. The position of the ith pigeon is determined by its previous position and its current speed. The best position of the pigeons can be obtained by comparison and is denoted as X_g. Each pigeon will adjust and fly to the pigeon with the best position according to eq. (8), and eq. (9) will adjust the position.

3.2 Landmark operator

The landmark operator is established based on the pigeons' use of landmarks for navigation. When using landmark navigation, the distance to the destination is closer than when using the guide operator. If a pigeon is not familiar with a landmark of its current location, it will fly under the leadership of a nearby pigeon. When an iconic building or familiar location is found, then it flies freely based on its own experience. In the landmark model, N_p is used to denote half of the pigeons in each generation. $X_c(t)$ is the center position of all pigeons in generation t. If each pigeon flies straight to its destination, there will be the following equation:

$$N_p(t) = \frac{N_p(t-1)}{2}, \tag{10}$$

$$X_c(t) = \frac{\sum X_i(t)\cdot \mathrm{fitness}(X_i(t))}{N_p\cdot \sum \mathrm{fitness}(X_i(t))}, \tag{11}$$

$$X_i(t) = X_i(t-1) + \mathrm{rand}\cdot (X_c(t) - X_c(t-1)), \tag{12}$$

where fitness(X) is the mass of each pigeon. When fitness($X_i(t)$) $=1/[f_{\min}(X_i(t))+\varepsilon]$, the minimum optimization problem is targeted; when fitness($X_i(t)$)=$f_{max}(X_i(t))$, the maximum optimization problem is targeted. The center of all pigeons is the position at each iteration, and pigeons outside N_p will follow those that are close to the destination. Pigeons closer to their destination will fly there faster.

4 Improved strategy of pigeon-inspired optimization algorithm

The traditional PIO algorithm is aimed at the optimization of continuous functions. Although its convergence speed is fast, it is easy to fall into local optima. This section aims at creating a discrete mathematical model of the human resource allocation problem of multiple scientific research projects established in the second subsection. The traditional PIO algorithm is improved to ensure that the iteration results meet the actual requirements and avoid finding local optima.

4.1 Adaptive parameter strategy

In the PIO algorithm, the compass factor R is an important parameter, which can affect the speed of the pigeon and plays a key role in the algorithm's convergence. As can be found from eq. (8): when R is small, the value of e^{-Rt} is large, and the pigeon assumes a greater speed, which is conducive to rapid convergence and better global search capabilities; when R becomes larger, the e^{-Rt} has a smaller value, which corresponds to a lower pigeon speed and is more conducive to searching in detail. Therefore, an adaptive approach is adopted: in the beginning, the parameter value is small and changes slowly, whereas, in the final stages, the parameter value increases quickly to reach the preset value. From experience, eq. (13) meets this requirement.

$$f(x) = \frac{1}{a + b \cdot e^{-x}}, \tag{13}$$

$$x = -10 + \frac{\mathrm{ITER} \cdot 20}{Nc1max}. \tag{14}$$

The range of $f(x)$ is [0, $1/a$], and the parameter b controls the fast-changing position. Specifically, we transform the number of iterations ITER to the interval [−10, 10] as the independent variable x input, as shown in eq. (14). It is known that R is more effective when it lies in the range [0, 1], so the value of a is 1, and the value of b is 80. The variation trend of adaptive parameters is shown in Figure 1.

In summary, instead of using the fixed compass factor R of the basic PIO algorithm, adaptive parameter control is applied. Eqs. (13) and (14) are used to control the parameter changes dynamically, so R, which is small initially, becomes larger gradually and approaches 1 after a full global search for a more accurate local search. This adaptive parameter strategy balances global and local search capabilities well and has strong adaptability and robustness.

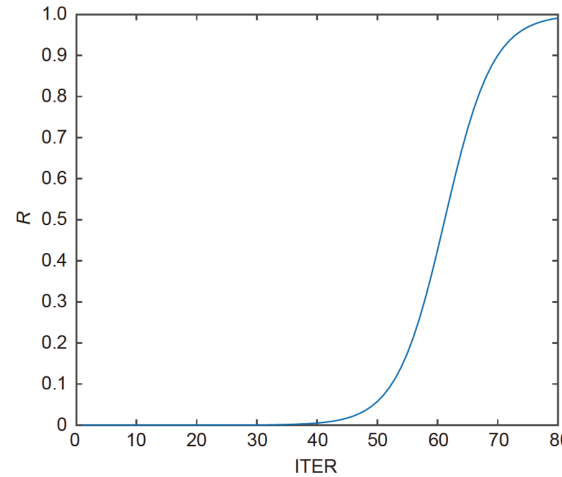

Figure 1 (Color online) The variation trend of adaptive parameters.

4.2 Algorithm discretization

Due to the fragmented nature of the variables, the problem of human resource allocation for multiple scientific research projects is a discrete problem. In addition, during the algorithm iterations, it is impossible to have unrealistic situations such as projects without researchers being assigned. Therefore, the PIO algorithm needs to be modified to be more applicable to the problem at hand.

For the position X_i of each pigeon, its dimension is the total number of researchers R, and the solution space of each dimension is {1, …, N} corresponding to N different scientific research projects. Therefore, each pigeon's position represents R researchers assigned to each research project. In the process of algorithm iteration, the PIO algorithm needs to be processed discretely. In this paper, we use the method of taking integers to change eqs. (9) and (12) to eqs. (15) and (16), respectively:

$$X_i(t) = \mathrm{round}\big(X_i(t-1) + V_i(t)\big), \tag{15}$$

$$X_i(t) = \mathrm{round}\big(X_i(t-1) + \mathrm{rand} \cdot (X_c(t) - X_c(t-1))\big). \tag{16}$$

Eliminating pigeons that do not meet all the requirements during the iteration process can ensure that the iteration results are reasonable and optimal. Based on the above IPIO algorithm, the basic framework is as shown in Algorithm 1.

5 Numerical simulation experiment

5.1 Basic information

A university has four independent research projects being implemented at the same time. It is known that these four research projects have the same network structure and that each project has only one key research objective. These

Algorithm 1 The basic framework of IPIO

Begin

1 Initialization

Set initial values for $Nc1max$, $Nc2max$, N_p, D and the search range.

Set initial path $X_i = [x_{i1}, x_{i2}, \ldots, x_{iD}]$ and velocity $V_i = [v_{i1}, v_{i2}, \ldots, v_{iD}]$ for each individual pigeon randomly.

Remove pigeons that do not meet the requirements.

Set $X_{pi}=X_i$, ITER=1.

Calculate fitness values of different individual pigeons.

$X_g=\text{argmin}[F(X_{pi})]$.

2 Compass operations

For ITER=1 to *Nc1max* do

Remove pigeons that do not meet the requirements.

Update R with eqs. (13) and (14).

For *i*=1 to N_p do

Calculate V_i and X_i according to eqs. (8) and (15).

End for

Evaluate X_i and update X_{pi} and X_g.

End for

3 Landmark operations

For ITER=*Nc1max*+1 to *Nc2max* do

Remove pigeons that do not meet the requirements.

Rank all the available individual pigeons according to their fitness values.

$N_p=N_p/2$.

Keep half of the individuals with better fitness values, and abandon the other half.

Calculate X_i according to eqs. (11) and (16).

Evaluate X_i and update X_{pi} and X_g.

End for

4 Output

X_g is output as the global optima of the F.

End

projects will require the cooperation of researchers with expertise in different fields, and we assume that the total number of researchers available in the university is 20. In a certain period of time, these four projects will compete for these human resources. Each project has two sub-topics, A and B, which need to be completed in each period, and sub-topic B must be completed after sub-topic A has been completed. Each researcher has the corresponding knowledge skills to complete these two sub-topics with different knowledge ability coefficients. Each researcher can only be assigned to one research project. Colleges and universities have determined the priority of these four research projects, and the relevant data of each research project are shown in Table 1. The corresponding knowledge skills ability coefficients of the researchers are shown in Table 2.

5.2 Simulation

We use MATLAB to mathematically model the human resource allocation problem for multiple projects and use the IPIO algorithm shown in Algorithm 1 to find an optimal solution to the problem. The algorithm parameters are shown

Table 1 The relevant data of each research project

N_i	ω_i	T_i (d)	Δc_i (hundred dollars/d)	μ_{i1} (person-day)	μ_{i2} (person-day)
1	0.38	14	120	80	60
2	0.27	9	160	40	50
3	0.21	12	80	70	50
4	0.14	9	100	50	40

Table 2 The corresponding knowledge skills ability coefficients of the researchers

Researcher	P_{j1}	P_{j2}	Researcher	P_{j1}	P_{j2}
1	0.7	1.2	11	0.7	1
2	1	0.8	12	1.3	0.6
3	1	1	13	1	1
4	1.1	0.9	14	1.2	0.7
5	1	0.9	15	0.8	1.1
6	0.8	1.2	16	0.7	1.3
7	1.3	0.7	17	1.1	0.8
8	1.2	0.8	18	1	1.2
9	1	1.1	19	0.9	1.1
10	1	0.8	20	1	1.1

in Table 3 below.

To demonstrate the superiority of the IPIO algorithm in the optimization of human resources' allocation in multiple research projects, the GA and the traditional PIO algorithm are compared with the IPIO algorithm. We compare without loss of generality under the weight coefficients α=0.7, β=0.3 and α=0.5, β=0.5, respectively. Table 4 and Figure 2 show the comparison of the three algorithms for the first weight combination, whereas Table 5 and Figure 3 show the comparison for the second combination.

Figures 2 and 3 show the convergence curves of GA, PIO, and IPIO. IPIO has stronger ability to search for the minima of objective function F. It has the advantages of fast convergence speed and strong optimization ability. In 15 to 20 iterations of first weight combination, IPIO reaches a value of 823.1369, which is both faster and smaller than either PIO or GA. In the second weight combination, IPIO find the smallest value in 40 to 50 iterations, whereas PIO and GA seem to fall into a local optimum before 20 iterations, as shown in Figure 3.

Tables 4 and 5 show the iteration results of different algorithms. IPIO can obtain the minimum value of F and the most reasonable personnel allocation results. It can be seen from the simulation experiments that the traditional PIO algorithm has a fast convergence speed and falls into a local optimum easily. This is because the value of the compass factor has a great influence on the search ability of the algorithm. After improving the PIO algorithm and adding parameter adaptation, it can be clearly seen that IPIO can overcome the problem of local optimization to find the globally optimal solution. Compared with GA, IPIO has faster convergence speed and a better ability to find the optimal solution.

Table 3 Algorithm test parameters

Parameter	Value
N_p	200
D	20
$Nc1max$	80
$Nc2max$	20

6 Conclusion

In this paper, we use mathematical modeling to transform the multi-objective optimization problem into a single-objective optimization problem to solve the issue of human resource allocation for multiple scientific research projects in universities. The traditional PIO algorithm is discretized and combined with adaptive control technology to deal with some of its shortcomings. The simulation and verification of a practical case using MATLAB prove the feasibility and effectiveness of the proposed scheme. At the same time, the results are compared with the GA and the traditional PIO algorithm, showing that the IPIO algorithm has the characteristics of fast early stage convergence, strong optimization ability, and accelerated convergence in later stages.

Table 4 When α=0.7, β=0.3, the results of different algorithms

Output data	IPIO	PIO	GA
Researchers in project 1	4, 9, 12, 14, 15, 17, 19	1, 5, 13, 14, 16, 17, 19	2, 6, 10, 11, 13, 15, 17, 19
Researchers in project 2	1, 5, 10, 11, 13, 16	6, 9, 10, 11, 15, 20	5, 9, 12, 18, 20
Researchers in project 3	2, 3, 8, 18	3, 7, 12, 18	3, 4, 8, 16
Researchers in project 4	6, 7, 20	2, 4, 8	1, 7, 14
The final value of F	823.1369	834.5620	841.8741

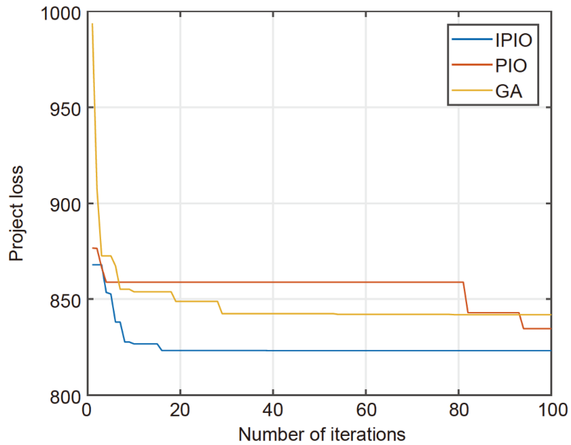

Figure 2 When α=0.7, β=0.3, the results of different algorithms.

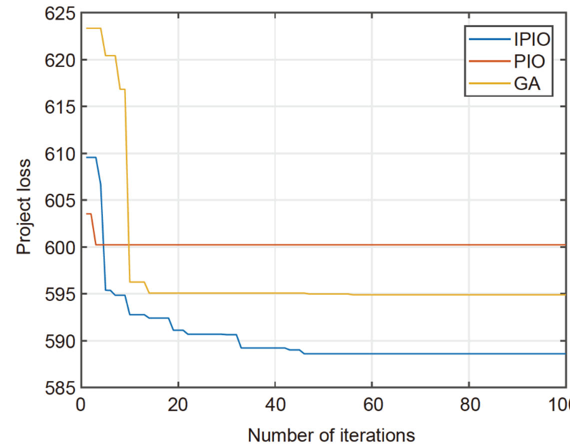

Figure 3 When α=0.5, β=0.5, the results of different algorithms.

Table 5 When α=0.5, β=0.5, the results of different algorithms

Output data	IPIO	PIO	GA
Researchers in project 1	4, 8, 13, 14, 16, 17, 18	2, 4, 9, 10, 11, 15, 18	2, 9, 10, 13, 17, 19, 20
Researchers in project 2	1, 2, 3, 6, 10, 11	5, 13, 16, 17, 19, 20	1, 3, 4, 5, 12, 15
Researchers in project 3	5, 9, 12, 15	1, 6, 7, 14	7, 11, 14, 16
Researchers in project 4	7, 19, 20	3, 8, 12	6, 8, 18
The final value of F	588.6079	600.2310	594.9062

Therefore, the IPIO algorithm can provide a better allocation scheme for multi-project human resource allocation and has wider applicability in engineering problems.

This work was supported by the Fundamental Research Funds for the Central Scientific Research Institutes (Grant No. 20200306).

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