Application of particle swarm optimization in multi-resource leveling optimization of engineering projects

Tang Jian[1,a], *Lu Lai[1,b]

[a]176024108@qq.com, [b*]1309046724@qq.com

[1]Architectural and Civil Engineering Institute, Jiangxi Science and Technology Normal University, Nanchang, China

Abstract: The purpose of this study is to use Particle Swarm 0ptimization (PSO) calculation to make the multiple resources in engineering projects reach global equilibrium after calculation. From the single-resource equilibrium optimization theory to the multi-resource optimization problem, the importance of engineering project resources is evaluated, appropriate evaluation indexes are selected, and a multi-resource equilibrium optimization mathematical model is established. Following that, the PSO solves the mathematical model, and the actual start time of activities (i.e., particle position) is constrained and rounded, subject to logical constraints between activities and time constraints. Finally, using the model to solve the case, the obtained results reduce the variance of resource intensity by 89.69% compared to the original solution, and the experimental results show that the PSO can effectively solve this kind of complex problem.

Keywords: Particle Swarm Optimization; Relative weights; Multiple resources; Balanced optimization

1 INTRODUCTION

As the field of engineering construction continues to develop and expand in scale, it has to a certain extent promoted the growth of the social economy, but the country implements the concept of green development as well as the backwardness of construction organization and excessive consumption of energy and resources during the implementation of engineering projects. Construction units must take various forms of measures to improve the utilization rate of resources in order to obtain higher profits， and how to achieve a foothold in the highly competitive market. How to achieve a foothold in the competitive construction market and achieve sustainable development is also a problem in front of each construction unit. Resource balancing optimization refers to the rational use of resources and the planned adjustment of the actual start-up time of non-critical actions within the specified period, thus smoothing the dynamic curve of resource requirements [5]. Using resource balance optimization for engineering projects can increase labor productivity, work efficiency, and overall project profitability in addition to improving the project's construction organization plan. Optimizing the balance of resources is therefore very important.

EMIS 2023, February 24-26, Chengdu, People's Republic of China

DOI 10.4108/eai.24-2-2023.2330669

The resource balance problem is a typical NP-hard problem, whose solution difficulty and computational effort grow exponentially with the increase of the problem size[4]. Traditional computational methods are inefficient, their applicability is limited, and the accuracy of their solution results is not ideal[7], Genetic Algorithms[10], ant Colony Algorithms[6] and a large number of other intelligent algorithms are applied to the study of this problem, avoiding the tedious computational process of traditional algorithms. Compared to the premature and complex genetic operations of genetic algorithms, ant colony algorithms have the issues of slow convergence and tendency to drop into local optimal solution. The PSO has the characteristics of not being affected by the size of the result, powerful search, better robustness and portability and the nature of random-based search.Based on this, this paper will use PSO to optimize the multi-resource balancing problem in engineering projects.

2 CONSTRUCTION OF A MULTI-RESOURCE BALANCED OPTIMIZATION MODEL

There are three key issues that need to be addressed when constructing a multi-resource balance optimization model: One is the evaluation of the importance of resources, various resources to the project optimization of varying degrees of importance, and the project for network planning arrangements, which limit the effect of multi-resource balanced optimization to some extent. The second is the correlation analysis of resources. The aim of multi-resource equilibrium is to achieve an overall equilibrium of multiple resources, and the correlation of resources means that when one resource reaches relative equilibrium, another resource also reaches relative equilibrium, and the demand curves of the two resources are often the same in this case. Therefore, the correlation of such resources cannot be ignored when performing multi-resource equilibrium optimization. This paper does not deal with resource correlation analysis. The third is the choice of the optimization objective. In order to achieve a certain degree of relative equilibrium in multi-resource equilibrium optimization, a comprehensive evaluation function needs to be determined.

2.1 Evaluation of resource importance

The longer the construction period, the greater the type and amount of resources used, plus the fact that each resource has a distinct degree of effect on the optimization goal. For example, if a resource with high cost or scarcity is compared with a resource with low cost or abundance, the former has a greater influence on the optimization goal. It is therefore necessary to assess the importance of each resource in order to determine the relative importance of each resource to each other.

This paper establishes a multi-resource importance index system in conjunction with engineering projects. There are three evaluation indexes: Cost Importance Index, Process Importance Index and Total Time Difference Importance Index. The cost importance index is the ratio of the cost of a resource to the cost of all resources. Reducing the cost of construction projects is one of the goals of resource balancing optimization, and how well this goal is achieved is one of the metrics used to measure the performance of the strategy. Therefore, the definition of this metric is relevant for multi-resource balanced optimization. The sequence of work importance index is the ratio of the number of activities requiring this resource to the total number of project activities. When a resource is needed for every activity in an engineering project and that resource is more likely to result in a resource conflict while the project is being built, that resource has a stronger impact on the project and is of greater importance. The total time difference importance index is the ratio of the sum of the time differences in the work occupying a resource to the sum of the time differences in the activities involved in all resources. Time difference is the amount of maneuvering time available for an activity. When more maneuvering time is available for an activity, it means that its potential to work within that time frame is greater and the likelihood of achieving resource balance without affecting other activities is greater. Then the relative weights of the three important indicators are calculated using hierarchical analysis, and the three indicators in the resource importance evaluation index system are compared by means of a questionnaire to derive the judgment matrix of the resource importance indicators:

$$A=\begin{array}{cc} & \begin{array}{ccc} C_k & A_k & F_k \end{array} \\ \begin{array}{c} C_k \\ A_k \\ F_k \end{array} & \begin{bmatrix} 1 & 4 & 3 \\ 1/4 & 1 & 1/2 \\ 1/3 & 2 & 1 \end{bmatrix} \end{array}$$

After using the square root method to calculate the judgment matrix and solve the weights of the three importance indicators, we can obtain the weight of the cost importance indicator as 0.625, the weight of the process importance indicator as 0.136, and the weight of the total time difference importance indicator as 0.239. Finally, the three indicators are weighted and summarized to obtain a comprehensive evaluation index of resource importance, expressed as

$$\omega_k = 0.625\times C_k + 0.136\times A_k + 0.239\times F_k \tag{1}$$

The study in this paper does not involve resource correlation analysis, and the comprehensive resource importance index sought by each resource is the relative weight of each resource.

2.2 Selection of multi-resource equilibrium optimization objectives and optimization methods

In the study of multi-resource equilibrium optimization, it is not reasonable to use the minimum sum of the total variance of each resource as the evaluation criterion due to the different magnitudes and importance of the demand for each resource in each time period [3]. The solution to the optimization problem of multi-resource equilibrium is to establish a comprehensive evaluation function to measure the overall equilibrium achieved by multiple resources due to its many constraints and complexity. There are two methods for representing the comprehensive evaluation function: one is to transform the multi-resource optimization problem into a single-resource optimization problem through homogenization; the other is to transform the idea of simplifying the objective of the multi-objective optimal solution into a single-objective optimal solution.

2.2.1 Multi-resource optimization problem into a single-resource optimization problem

This method converts the resource requirements for an engineering project into a single resource through the homogenization process, and then uses the single resource balancing optimization problem method to carry out a balancing optimization process. Assume that there are a total of a activities, requiring b resources, and that due to the different types, orders of magnitude, and units of resources, making the various resources comparable, resources need to be homogenized, expressed as:

$$r_{(i,j)\ k}{}' = \frac{r_{(i,j)\ k}}{\sum_{j=1}^{a}\left[r_{(i,j)\ k}\right]} \tag{2}$$

Where denotes the demand for resource i at activity j, i = 1, 2, ..., b, j = 1, 2, ..., a.

After dimensionless treatment, the demand for various resources at each time period is changed from dimensionless to dimensionless and within the range of 0 to 1. Homogenized resources are then weighted and summarized and treated as one resource. Assuming that the relative weight of resources k is ω_k, the equivalent resource requirements for each activity are expressed as:

$$r_{(i,j)\ k} = \sum_{k=1}^{b} \omega_k r_{(i,j)\ k}{}' \tag{3}$$

2.2.2 Multi-objective optimization problems into single-objective optimization problems

This approach treats each resource in the project as a single object to be optimized, i.e. a single-objective optimization problem. Thus, the optimization problem for multiple resources can be seen as an optimization problem with multiple objectives. In the single resource equilibrium optimization problem, the variance evaluation metric is used as the objective function of the optimization problem, expressed as:

$$\min \sigma^2 = \frac{1}{T}\sum_{t=1}^{T}\left[R(t) - R_m\right]^2 \tag{4}$$

If resource balancing optimization is performed for b resources at the same time, the optimization problem has b objectives, i.e. a multi-objective optimal solution. The idea of solving the multi-objective optimization problem for multiple resources is to convert the combination of several goals into a single goal by assigning a weight factor to each single objective problem function, which is then optimized. The objective function of multi-resource balancing optimization can then be expressed as:

$$\min \sigma^2 = \sum_{k=1}^{b} \omega_k \sigma_k^2 \tag{5}$$

where ω_k is the weighting factor for resource k; σ_k^2 is the variance of resource k.

The first method converts multi resource equilibrium optimization into single resource equilibrium optimization, which eliminates errors caused by different levels and units of resource size, but treats the demand amounts of multiple resources as one resource after weighted average equivalence, which does not effectively reflect the actual equilibrium of various resources, and its equivalent demand curve is actually a superposition of various resources. With the second method, single objective optimization multi objective optimization, the equilibrium of a single resource is extended to a comprehensive equilibrium of multiple resources, which is more reasonable than the first method and closer to the essence of the research problem. Therefore, this paper selects the solution idea of the second method to determine the objective function of multi-resource equilibrium optimization.

2.3 Multi-resource balanced optimization mathematical model

Based on the above, the multi-resource equilibrium optimization model can be expressed as:

$$\min E = \min \sigma^2 = \sum_{k=1}^{s} \omega_k \sigma_k^2 = \sum_{k=1}^{s} \omega_k \left[\frac{1}{T} \sum_{t=1}^{T} R_k^2(t) - R_{k,m}^2 \right] \tag{6}$$

$$\text{s.t.} \begin{cases} R_{ki}(t) = \begin{cases} R_{ki} & TS_i \le t \le TS_i + D_i \\ 0 & t \le TS_i \text{ or } t \ge TS_i + D_i \end{cases} \\ S_i = LS_i - ES_i \end{cases}$$

Where ω_k is the relative weight coefficient of resource k; E is the resource intensity value of the resource; $R_k(t)$ is the total amount of resources consumed by resource k in the project at time t; and $R_{k,m}$ is the average resource consumption during the construction phase of resource k. R_{ki} is the amount of resources consumed by resource k on activity i. Under the condition that the constraints are satisfied, the corresponding solution is the best solution for the problem when E is the smallest.

3 MULTI-RESOURCE BALANCED OPTIMIZATION BASED ON THE PARTICLE SWARM OPTIMIZATION

3.1 Fundamentals of the Particle Swarm optimization

The basic idea of the PSO algorithm is to consider each particle as a feasible solution to the optimization problem and determine the best position of the particle by judging the goodness of the current position of the particle through its fitness and then calculating the merit of the objective function. Suppose that in the N-dimensional search space, a population of s particles is formed, in which the spatial position of the Ith particle can be denoted as $X_i = (x_{i1}, x_{i2}, \dots, x_{in})^T (i = 1,2,\dots,s)$, and the coordinate value of the Ith particle on the

N-dimensional search space is noted as x_{in}. The flight speed of particle i in the search space is denoted as $V_i = (v_{i1}, v_{i2}, \cdots v_{in})^T (i = 1, 2, \ldots, s)$, V_i needs to be bounded, V_i and bounded can effectively balance the spatial search capability and the exploitation capability of the algorithm. The evaluation function is set up to calculate the fitness value to judge the good position of the particle, i.e. to evaluate the feasible solution of the target problem to which the particle corresponds. The individual historical best position is the optimal position of the Ith particle found so far and is denoted as $P_{best} = (p_{i1}, p_{i2}, \cdots, p_{in})$. The optimal flight position of all particles in space is called the best global historical position and is denoted as $g_{besti} = (p_{i1}, p_{i2}, \ldots p_{in})$, g = 1, 2, ..., n. G is the maximum number of iterations that ensures the optimal solution of the particle with the number of iterations t = 1, 2, ..., G. The PSO advances through the following evolutionary equations for velocity and position update[1]:

$$v_{ij}(t+1) = w \cdot v_{ij}(t) + c_1 rand_1(t)(p_{ij}(t) - x_{ij}(t)) + c_2 rand_2(t)(p_{gj}(t) - x_{ij}(t)) \tag{7}$$

$$x_{ij}(t+1) = x_{ij}(t) + v_{ij}(t+1) \tag{8}$$

The velocity update formula shows that three components work together to determine the particle's spatial search capability. The first component ensures the global search capability of the particle; the second and third components ensure the global search capability of the particle. With the three parts working together, the particle can search for the optimal position in the search space.

3.2 Constraints

The goal of multi-resource balance optimization for engineering projects is to smooth out the resource requirements of an engineering project within a specified period by adjusting the actual start-up time （$S_i(i = 1, 2, \cdots, N)$）) of non-critical activities. As demonstrated by the objective function of resource balancing optimization, activities are not only constrained by logical relationships, but also by temporal relationships. Similarly, the precise time that an activity takes place is not limited to the moment when the activity begins and ends, but is also limited to the effect of the time completed by any action taken just before the activity, so that the total time difference of the activity will be affected.

Ensuring that the logical relationships between the activities and the total project duration remain unchanged, the duration of each activity is D_i and the actual time that each activity is S_i, and adding the logical relationships between the activities to the range of values taken for the actual time that the activities, the actual start time of the activities needs to satisfy the following constraints:

$$\begin{cases} ES_i \le S_i \le LS_i \qquad i = 1, 2, \cdots, n \\ \max\limits_{h \in F} \{S_h + D_h\} \le S_i \end{cases} \tag{9}$$

where ES_i is the earliest start time of activity i; LS_i is the latest start time of activity i; and F_i is the set of action i's directly preceding activities.

Considering the logical and temporal constraints on the activity and thus assigning a range to when the activity starts, not only ensures the feasibility of the result, but also avoids the generation of non-feasible solutions.

3.3 Evolutionary design

In an actual engineering project, the particle's position, which is when the activity began in the project, is an integer. However, equations (3) and (4) show that the velocity of the particle is not exactly an integer during the evolutionary process, resulting in the position of the particle not being exactly an integer either, so the evolutionary equation needs to be corrected.

The first part $w \cdot v_{ij}(t)$ of equation (3) is rounded, i.e. $\mathrm{int}(w \cdot v_{ij}(t))$. For the second and third parts of equation (3), since rand() is taken randomly in the range [0, 1], it is only necessary to allow the second and third parts to be rounded within their minimum to maximum value ranges. Thus, the evolution after adjustment is as follows:

$$\begin{aligned} v_{ij}(t+1) = {} & \mathrm{int}(w \cdot v_{ij}(t)) + \mathrm{int}\, random(c_1 rand_1(t)(p_{ij}(t) - x_{ij}(t))) \\ & + \mathrm{int}\, random(c_2 rand_2(t)(p_{gj}(t) - x_{ij}(t))) \end{aligned} \tag{10}$$

$$x_{ij}(t+1) = x_{ij}(t) + v_{ij}(t+1) \tag{12}$$

3.4 Parameter setting

In PSO, the choice of control parameters can affect the performance and efficiency of the algorithm. Therefore, the setting parameters is important and depends mainly on the specific engineering project. The particle population size, M, depends on the specific problem; the spatial dimension, N, the number of activities; the range of values of particles can be set differently for each dimension; research has shown [8] that inertia weights are generally taken to be a number between 0.8 and 1.2, and that by enhancing the inertia weights, the overall performance of the algorithm can be enhanced, and by decreasing the inertia weights, the local performance of the algorithm can be improved; the acceleration constants c1, c2, represents the weighting of the statistical acceleration of each particle, if the value is low, then the particle can wander outside the target zone, if the value is high, the value will cause the particle to jerk towards or beyond that target zone[9], the value is usually c1=c2=2; the maximum velocity of the particle $V_{\max}$, sets the greatest distance the particle can go in one flight, Choosing a value that is too high or too little can limit the particle's search range and cause a local optimum, usually set to the particle's range width $v_{\max} = k \cdot x_{\max}$, where 0.1 ≤ k ≤ 1, which can be set in the same way for each dimension.

4 CASE ANALYSIS

A project requires three of these resources: cement, manpower, and tipper trucks（indicated by R1, R2, R3 in the table）. By calculating the relative weights of cement resources, manpower, and tipper as $\omega = [0.478, 0.353, 0.169]$. The network plan for the project is shown in Figure 1, with the data above the arrow showing the names of the activities and the daily requirements of the three resources corresponding to the activities. The relevant parameters of the initial plan according to the network plan are shown in Table 1.

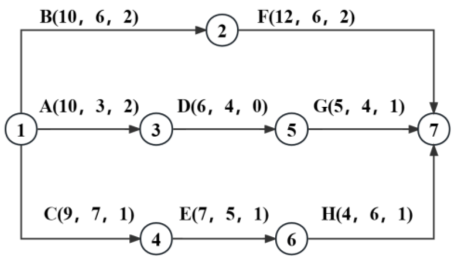

Figure 1: Example network plan diagram

Table 1: Initial parameters of the algorithm

process	D	ES	LS	TF	R1	R2	R3
A	5	1	1	0	10	3	2
B	4	1	6	5	10	6	2
C	5	1	1	0	9	7	1
D	6	6	8	2	6	4	0
E	8	6	6	0	7	5	1
F	10	5	10	5	12	6	2
G	6	12	14	2	5	4	1
H	6	14	14	0	4	6	1

Because there are 8 activities in the case and each particle represents an arrangement scheme, each particle is equivalent to a point in an 8-dimensional space, i.e., N = 8, with a population size of 10 such particles, i.e., M = 10, and a maximum number of iterations, G = 500. Table 2 shows the results of the calculation.

Table 2: Calculation results

process	A	B	C	D	E	F	G	H
Initial programme	1	1	1	6	6	5	12	14
Optimun solution	1	6	1	6	6	10	14	14

Intensity variance	E	E_{R1}	E_{R2}	E_{R3}
Initial programme	41.316	77.88	10.77	1.69
Optimun solution	4.259	3.99	6.56	0.22

As shown in the table, the overall resource intensity value of the original scheme of the case is 41.316, and following the calculation of the PSO, the resource intensity value drops to 4.259, a decrease in resource intensity of 89.69%, resulting in a very clear overall balanced optimization. Compared to the original scheme, the results show that the intensity value of cement resources decreases from 77.88 to 3.99, a decrease of 94.88%; the intensity value of human resources decreases from 10.77 to 6.56, a decrease of 39.09%; and the intensity value of dump truck resources decreases from 1.69 to 0.22, a decrease of 86.98%.

According to the data, cement and dump truck resources have higher levels of optimization than human resources, which is due to the type of evaluation function used. Multi-resource balancing means that while resources as a whole are relatively balanced, not every resource is balanced at the same time. From Figures 2, 3 and 4, it can be seen that after optimization, the fluctuation of the intensity value of each resource becomes smaller, and to a certain extent, the balanced optimization of resources is achieved.

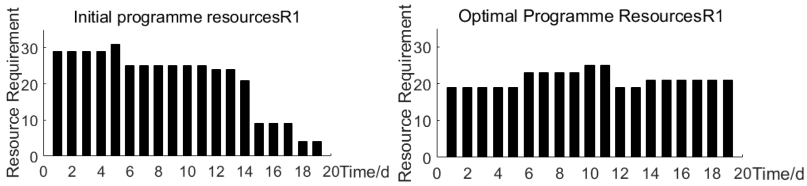

Figure 2: Resource R1

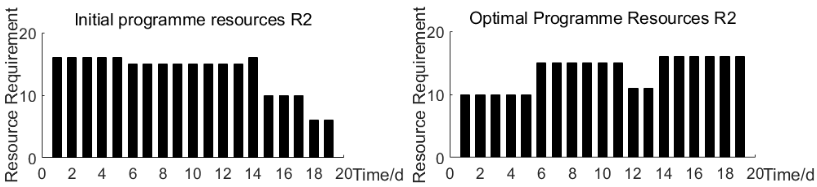

Figure 3: Resource R2

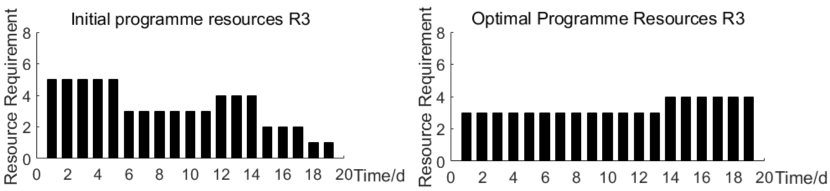

Figure 4: Resource R3

5 CONCLUSIONS

The PSO is applied to the "schedule fixed-resource balancing" problem. This work constructs a multi-resource importance evaluation index system, calculates the weights of each index, weights and sums each index to obtain the comprehensive resource importance evaluation index, then calculates the relative weights of each resource, and establishes a mathematical model of multi-resource balance optimization by analyzing the importance of multiple resources to the optimization target and the choice of the objective function.

When using the PSO to solve the problem, the range of the actual start-up time of the activity is constrained, and the speed and position formulas are adjusted by considering the time as an integer. Finally, through strength verification, the optimization model designed in this paper can make the overall resources reach equilibrium, and the calculation results are more satisfactory, which shows the effectiveness and practical significance of the PSO in the multi-resource equilibrium optimization.

Acknowledgements: This work is supported by the "2020 Ministry of Education Industry-University-Research Cooperation Collaborative Education Project "Construction of Teaching Practice Base of "Big Civil Engineering" Courses Based on BIM Technology" (Project No. 2022002256012) and the university-level postgraduate project "Research on an Interdisciplinary Cultivation Model for Graduate Students of Management Science and Engineering (Engineering)" (Project No. KSDYJG-2020-05) is the Teaching Reform Research Project.

REFERENCES

[1] Bao Ziyan,Yu Jizhou,Yang Bin.Intelligent optimization algorithms and Its MATLAB examples. Beijing: Electronic Industry Press,2021.

[2] Cun Zhihua,Zeng Jianhuo.Particle Swarm Optimization. Beijing:Science Press,2011.

[3] Cai Qianfen,Wang Junwu.Variance Minimization Method Improvement for Construction Project Labor Resource Optimization.Statistics Decision,2019,35(13):181-184.

[4] D.Savin,S.Alkass,P.Fazio.Constrction resource leveling using neural networks. Canadian Journal of Civil Engineering,1993,23(4):917-920.

[5] He Lihua,Zhang Lianying.Resource balance optimization of engineering projects based on resource fluctuation cost.Journal of Industrial Engineering and Engineering Management,2015，29(,02):167-174.

[6] He Lijuan,Li Xin.Resource Balancing Optimization Decision Based on Ant Colony Algorithm and Its MATLAB Implementation.Industrial Engineering Journal,2016,18(06):125-129.

[7] Li Hongbo,Xiong Li,Liu Yanbing.A Review of Project Resource Balancing Studies[J].Journal of Control and Decision，2019,35(13): 769-779.

[8] Shi Y,Eberharrt R C. A modified particle swarm optimizer.Proceedings of 1998 IEEE Internaational Conference on Evolutionary Computation,1998:69-73.

[9] Yang Yingjie.Particle Swarm Optimization and Its Application.Beijing University of Technology Press, 2017.

[10] Zhao Gongxun,Guo Haibin,Su Li.Genetic Algorithm-based Resource Balancing Optimization for Engineering Projects and its MATLAB Implementation.Engineering Economy,2016,26(12): 59-64.