Research on Optimization Model of Power Grid Project Investment

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Abstract. For the multi-criteria decision-making problem of portfolio investment in power grid construction projects, the modern portfolio theory is used to construct a portfolio optimization model based on adaptive particle swarm optimization algorithm under the constraints of power demand, grid enterprise investment capability and reliability level in this paper. For the shortcomings of slow convergence and long operation time of particle swarm optimization, the change of inertia weight is used to change the update mode of particle position, which improves the convergence speed of the algorithm. The portfolio optimization model provides an applicable decision-making method for complex grid optimization investment decisions, and builds a complex grid optimization investment decision management process based on power demand and investment capability.

Keywords: optimization model; power grid project investment; particle swarm optimization algorithm.

1. Introduction

The investment decision-making is an important step in the rational placement of corporate funds, which is always reflected in the process of business management. The correct and reasonable investment decision-making of enterprises is an important condition for improving the economic benefits of enterprises, and it is also an important guarantee for enterprises to accelerate the turnover of funds [1-2]. The investment decision of the power grid is to build the project in stages according to the power grid planning, investment capacity, the project importance and construction timing requirements. Therefore, grid investment project decision-making is particularly important [3-4].

The traditional methods for solving grid investment decision-making target planning problems usually include discrete approximation iterative method [5] and inverse induction method [6]. In Ref [7] the inverse induction method is used to solve the grid investment decision-making model. Through the empirical simulation study, it provides the optimal portfolio strategy, investment scale and investment timing of the grid company, which is solved from the micro level of the project investment decision.

The intelligent optimization algorithms such as genetic algorithm [8 9], particle swarm optimization algorithm [10], ant colony algorithm [11] are widely used to solve optimization problems. Ref [8] considers the advantages and disadvantages of the scheme itself, and uses genetic algorithms to find the best matching combination to achieve the optimal goal of the overall investment scheme. In Ref [9] the investment amount, construction period and other factors are considered from the perspective of the overall project optimization, and the cost minimization model of the overall decision-making scheme of the project is established. In addition, the technology maturity theory [6], the Markowitz model [12], the expert group decision feature root method [1] and other methods are also applied to grid investment decision optimization.

In summary, investment decision-making of power grid construction projects in domestic and foreign research is still in a stage of continuous development [13]. At present, the common problems in investment decision-making research are as follows: the simplification of objective function and constraints. In the research process, only one of the project's income indicators is used as the objective function for decision-making, and the constraints are considered one-sided. It is difficult to accurately solve the problem of multi-criteria decision-making for portfolio investment in power grid construction projects. At the same time, there is very little literature on the investment capacity of enterprises as a constraint on investment decisions. In general, the objective function and constraints of studies are not comprehensive and systematic, and lack of constraints on investment ability. The investment plan obtained is not reasonable and scientific, and further research is needed.

Compared to existing literature, contributions of this work include: (1) A portfolio optimization model based under the constraints of power demand, grid enterprise investment capability and reliability level is proposed. (2) The change of inertia weight is used to change the update mode of particle position, which improves the convergence speed of the algorithm. (3) A complex grid optimization investment decision management process based on power demand and investment capability is constructed.

2. Grid Optimization Portfolio Decision Model

The problem of grid optimization investment decision can be expressed as: under limited capital constraints (investment capacity), decision makers need to select the optimal portfolio from the alternative grid construction projects to invest in meeting the power needs of the regional grid.

In the current power grid construction, it is often the simultaneous investment and construction of multiple projects. Therefore, combined with the theory of portfolios, under the premise of meeting the demand, the constraints such as capital are introduced to optimize the investment portfolio.

2.1 Objective Function

According to the above analysis, the objective function of comprehensively considering the economic benefits, safety benefits and energy saving benefits after grid optimization investment is as follows.

$$\max F(x) = \frac{E(x) - S(x) + D(x)}{Q(x)} \tag{1}$$

where F(x) represents the maximum benefit function of the investment; E(x) represents the economic benefit function; S(x) represents the safety benefit function; D(x) represents the energy saving benefit function; n(x) represents the investment ability penalty function.

the economic benefit function: The economic benefit function can be obtained by calculating the investment cost, annual income, and operating cost of each project as shown below [14].

$$E(x) = \sum_{i=1}^{n} a_i \left[\sum_{t=1}^{T} (S_{it} - C_{it}) - Q_i \right] \tag{2}$$

where S_{it} represents the sales income of the i-th construction project in the t-year; C_{it} represents the operating cost of the i-th construction project in the t-year; a_i represents the investment variable, when its value is 1, it means that the project can invest, when its value is 0, it means that the project cannot invest; T represents the life cycle of the project; Q_i represents the construction cost of the i-th project .

the safety benefit function: The capacity-load ratio is used to measure the reliability of project investment. When the capacity-load ratio is too high, more equipment will be idle, resulting in lower investment efficiency. Conversely, if it is too low, it will inhibit the consumption of electricity and is not conducive to the development of economy. Therefore, under the premise of meeting the demand and reliability of power consumption, the value of the capacity-load ratio should be gradually reduced and controlled within a certain range [14].

$$S(x)=\begin{cases} c_1(\sum_{i=1}^{n}a_ib_i+b-2L), \frac{\sum_{i=1}^{n}a_ib_i+b}{L}>2 \\ 0, 1.8<\frac{\sum_{i=1}^{n}a_ib_i+b}{L}<2 \\ c_2(\sum_{i=1}^{n}1.8L-a_ib_i-b), \frac{\sum_{i=1}^{n}a_ib_i+b}{L}<1.8 \end{cases} \quad (3)$$

where c_1 represents the influence coefficient of the remaining capacity of the grid; c_2 represents the influence coefficient of the insufficient capacity; L represents the average load the entire grid system; b_i represents the new capacity of the i-th project; b represents the capacity of the original grid.

the energy saving benefit function: the energy saving benefit function can be obtained by calculating the amount of power generated by the distributed power source and the network loss reduced after the project construction.

$$D(x)=\sum_{i=1}^{n}a_i * \mathrm{A}(W_{h-i} * \Delta\eta_{loss-i}+\sum_{k=1}^{l}T_k * P_k) \quad (4)$$
$$\mathrm{A}=\mathrm{m}_1\lambda_1+\mathrm{m}_2\lambda_2+\mathrm{m}_3\lambda_3+\mathrm{m}_4\lambda_4+\mathrm{m}_5\lambda_5$$

where W_{h-i} represents the amount of electricity for the i-th construction project; $\Delta\eta_{loss-i}$ represents network loss rate for the i-th construction project; P_k represents the k-th clean energy power generation rated power; T_k represents the maximum utilization hours of the clean energy generation of the type; l represents the type number of clean energy power generation; A represents the emission reduction benefit per kWh; m_1 represents the coal price per ton of standard coal; m_2, m_3, m_4 and m_5 represent the environmental treatment costs per ton of carbon dioxide, sulfur dioxide, nitrogen oxides and dust, respectively; λ_1 represents the weight of standard coal saved per kWh; λ_2, λ_3, λ_4 and λ_5 represent emissions of carbon dioxide, sulfur dioxide, nitrogen oxides, and dust that are reduced by one degree of electricity reduction, respectively.

the construction cost function: the construction cost function can be obtained by calculating the sum of project investment.

$$Q(x)=\sum_{i=1}^{n}a_iQ_i \quad (5)$$

where Q_i represents the construction cost of the i-th project.

2.2 Constraints

Investment capacity constraints: The total investment amount after optimizing the investment should not exceed the investment capacity of the grid enterprise.

$$\sum_{i=1}^{N}Q_i * a_i \le Q \quad (6)$$

where Q_i represents the investment amount of the i-th project, and Q represents the investment ability of the grid enterprise.

Power demand constraints: In addition, constrained by investment capacity, the added capacity of the grid needs to meet the electricity demand of the society.

$$\sum_{i=1}^{N}b_i * a_i \ge B \quad (7)$$

where B represents the electricity demand in the area,

Investment project relationship constraints: Assuming there are n projects in the grid, there are several relationship constraints between these projects [14].

a) If the projects are independent of each other, the constraint relationship is as follows:

$$\sum_{i=1}^{N} a_i \le N \tag{8}$$

b) If the projects are mutually exclusive, the constraint relationship is as follows

$$\sum_{i=1}^{N} a_i \le 1 \tag{9}$$

c) If the projects are interdependent, that is, only if Project 1 is selected, Project 2 may be selected; otherwise, if Project 1 is not selected, Project 2 may not be selected, the constraint relationship is as follows

$$a_1 - a_2 \ge 0 \tag{10}$$

d) If the projects are closely related, that is, the two projects must be selected at the same time or not selected at the same time. Then the constraint relationship is as follows

$$a_1 - a_2 = 0 \tag{11}$$

3. Improved Particle Swarm Optimization Algorithm

The particle swarm optimization algorithm is an intelligent evolutionary algorithm that simulates the behavior of biological populations such as flocks. The collective cooperation between birds makes the group reach the optimal value. The algorithm iteratively updates the position and velocity of particles by the velocity and displacement of the particles.

$$\begin{aligned} v_{Id}^{k+1} &= wv_{Id}^{k} + c_1 r_{and1}^{k}(p_{bestId}^{k} - x_{Id}^{k}) + c_2 r_{and2}^{k}(g_{bestId}^{k} - x_{Id}^{k}) \\ x_{Id}^{k+1} &= x_{Id}^{k} + v_{Id}^{k+1} \end{aligned} \tag{12}$$

The search performance is excellent, and has the following characteristics: clear concept, simple formula, few parameters, easy programming, no special requirements for initial values, efficient hidden parallelism, suitable for processing non-differentiable, non-convex functions.

The parameters in the particle swarm algorithm are mainly as follows:

1) Inertia weight w: Inertia weight w has a great influence on the convergence performance of the particle swarm algorithm. When the value is large, the global optimization and exploration ability is strong, otherwise, the local optimization and exploration ability is strong.

2) Learning factors c_1, c_2: Learning factors c_1, c_2 reflect the strength of the particle's own thinking and information exchange between particles.

3) Maximum speed v_{max}: Maximum speed v_{max} can balance global and local search ability, effectively control the search range, and set the value to know the problem to be optimized in advance.

4) Population size N: It indicates the number of particles to be searched at the same time, and determines the minimum number of times that each iteration needs to be updated;

5) Maximum number of iterations I_{tera}: It determines the amount of calculation, which indirectly affects the convergence accuracy, because when the number of iterations is small, the population will not have enough time to find the global optimum.

Therefore, according to the above parameters of the particle swarm optimization algorithm, the following parameters can be improved to overcome the premature problem on the particle swarm algorithm:

1) Improvement of inertia weight: This paper uses an adaptive inertia weight adjustment strategy based on average granularity, as follows:

a) Average grain distance. It is used to reflect the degree of dispersion between particles within the population. The calculation formula of the "average grain distance" of the k-th iteration population is as follows:

$$\begin{cases} Dis(k) = \dfrac{1}{N*L}\sum_{i=1}^{N}\sqrt{\sum_{j=1}^{D}(x_{ij}^{k} - \bar{x}_{j}^{k})^2} \\ L = \sqrt{\sum_{j=1}^{D}(x_{j,\max} - x_{j,\min})^2} \end{cases} \tag{13}$$

where L represents the diagonal length of the search space; N represents population size; D represents solution space dimension; x_{ij}^k represents the coordinate value of the i-th particle at the k-th iteration with respect to the j-th dimension;

x_j^k represents the average of the k-th iteration with respect to the j-th dimensional coordinate values; $x_{j,\max}$ and $x_{j,\min}$ represent the upper and lower limits of the j-th dimension of the feasible domain space.

b) Adaptive adjustment of inertia weight. The adaptive inertia weight adjustment strategy adopted is as follows:

$$w(k) = 0.8 + \frac{1}{12}\ln\left(\frac{Dis(k)}{1 - Dis(k)}\right) \tag{14}$$

where Dis(k) represents the average grain distance; w(k) represents the k-th iteration inertia weight. The upper and lower limits can be set to prevent the inertia weight from crossing the boundary. When the average grain distance is larger, the inertia weight is larger and the global search is realized. When the average grain size is smaller, the inertia weight is smaller and the regional fine search is realized.

2) Improvement of learning factors. This paper uses a linear adjustment learning factor strategy with the following formula:

$$\begin{aligned} c_1 &= c_{1,\max} - (c_{1,\max} - c_{1,\min})\frac{k}{I_{tera}} \\ c_2 &= c_{2,\min} + (c_{2,\max} - c_{2,\min})\frac{k}{I_{tera}} \end{aligned} \tag{15}$$

where $c_{1,\max}$, $c_{1,\min}$, $c_{2,\max}$, $c_{2,\min}$ represent the upper and lower limits of c_1 and c_2, respectively. At the beginning of the iteration, c_1 is large and c_2 is small. The iterative update of the particles in the population is mainly based on the experience of the particle itself. Then c_1 becomes smaller and c_2 becomes larger. The cooperation between the particles is strengthened, so that the population flies to the global optimum.

4. Case Study

Grid enterprises construct an optimized portfolio decision model, and adopt an improved adaptive particle swarm optimization algorithm to obtain the optimal project portfolio based on combined with grid construction projects to optimize portfolio decision-making methods, analyzed and collated the required data. Through the collection, analysis and collation of data, five grid investment projects are selected for analysis. The relevant data of each scheme are shown in Table 1.

To simplify the calculation, each grid construction project has a life expectancy of 30 years, and the annual net income and operating costs of each project will never change over the next 30 years. The parameter values for c_1 and c_2 are 0.1 and 0.2. The investment capacity of power grid enterprises in the year is 180 million yuan. The sum of the selected project capacity is the added capacity of the system.

Table 1. Relevant Data of Each Investment Project

Project	Investment demand (million yuan)	Capacity (MVA)	Profit (million yuan)
A	29.43	765	2.61
B	23.88	590	2.27
C	13.03	310	1.05
D	27.01	635	2.48
E	80.94	1980	7.61
F	42.28	1025	3.92
G	72.08	1880	6.82

Based on the optimization model constructed above and the corresponding assumptions, the optimization analysis of the seven selected investment projects. The improved adaptive particle swarm optimization algorithm in this paper uses Matlab software to solve the model.

In the model, the parameters are set as follows: the population size N is 50; the maximum number of iterations is 150; the maximum speed v_{max} is 10; the learning factors $c_{1,max}$, $c_{1,min}$, $c_{2,max}$, $c_{2,min}$ are respectively 2.75, 1.25, 2.25 and 1.05; the inertia weight initial value w_{max} is 0.8; the inertia weight final value w_{min} is 0.3. The optimization process of this algorithm is shown in figure 1.

Combined with the optimization model of formula (1), aiming at the economic, social and reliability of power grid construction projects, the investment capability constraints are transformed into an optimized investment model established by the target penalty function. the improved PSO algorithm is optimized to get the final optimization results as shown below.

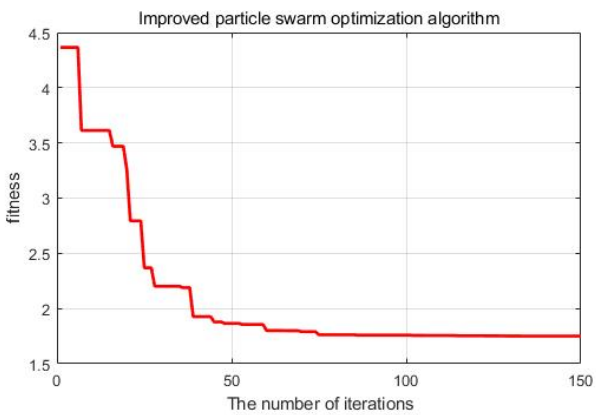

Fig 1. Optimization Process

Table 2. The Main Indicators of the Regional 220kv Power Grid Construction SCALE

Project	A	B	C	D	E	F	G	Investment	F(x)
Result	0	1	0	1	1	1	0	174.11	56.8

In Table 2, The final portfolio of the final grid construction project based on the mproved particle swarm optimization algorithm is the project B, D, E, F. The expected return value of the portfolio project is 56.8 million yuan.

5. Conclusion

The investment optimization combination between construction projects is studied in this paper. The model takes the investment utility maximization as the objective function, considering the constraints of power demand and investment ability. Aiming at the shortcomings of slow convergence and long operation time, the improved PSO algorithm improves the convergence speed of the algorithm. In the empirical example, the improved algorithm proposed in this paper improves the convergence speed and shortens the computation time to some extent, and obtains better optimization results, which verifies the effectiveness of the method.

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