Research on Building Energy Consumption Optimization Based on Improved Particle Swarm Optimization Algorithm

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Abstract. Aiming at the poor efficiency of traditional PSO algorithm in energy consumption optimization of office buildings in cold areas, a building energy consumption optimization method based on improved PSO was proposed. Firstly, the basic principle of PSO algorithm is analyzed, and then the PSO algorithm is improved by GE or AG operators. On the basis of the improvement, different test functions were used to optimize the algorithm, and then the maximum PSO parameters were verified. Finally, the above improvements are applied to a building example. The results show that the improved PSO energy consumption optimization method can not only improve the fast travel performance of the algorithm, but also reduce the overall search time.

Keywords: Parameter settings, PSO algorithm, Global optimization

1. Introduction
At present, the optimization of building energy consumption at home and abroad mainly adopts PSO, genetic algorithm and differential evolution algorithm, and has carried out a lot of academic research, such as Gaoyuelin (2020) differential evolution algorithm to optimize the energy consumption of buildings, which improves the optimization ability of some algorithms, but it is easy to fall into local optimum. Li Xinran (2019) optimizes building energy consumption in cold regions based on genetic algorithm. Although the global optimization ability is improved, the algorithm takes too long and the overall effect is unsatisfactory. However, most of the above studies only start from the perspective of algorithm optimization, and rarely consider the parameter optimization problem. For example, Deng Xiaohong and Zhu Mingya optimize the parameters of LSSVM algorithm by PSO algorithm. These do not consider PSO’s own parameter optimization problem. Therefore, this study aims to find an optimal PSO parameter of building energy consumption optimization method, so as to improve the effect of building energy consumption optimization.

2. Basic Principle and Improvement of PSO
PSO is an algorithm that selects random particles for initialization under a certain population number,
and then finds the optimal solution through iteration and update operations. Among them, in the
iterative operation, each particle will be updated according to two optimal values: first, in the process
of successive iterations, the optimal solution of the position of the particle is denoted as $P_{best}$; The
second is to find the global optimal position among all particles, referred to as the global optimal
denoted as $g_{best}$.

In this article, the traditional PSO algorithm is improved, which is mainly optimized by GA or DE
operators. The specific steps are as follows: when the constant $g_{best}$ exceeds $T_0$, PSO is considered to
fall into local optimum at this time, so the operator operation of GA or DE is run once. The operation
will retain particles that generally meet the requirements, and the other half will be re-discharged to
the complete search space, so as to increase the global search ability of the algorithm.

3. Parameters and Test Functions

3.1. Parameter selection and setting

3.1.1. Particle swarm optimization.
The position update and velocity update of particles are the key to the particle swarm optimization
algorithm, and the specific position and velocity update formula is:

$$v_i(t+1) = \omega v_i(t) + c_1 r_1 [p_{best,i}(t) - x_i(t)] + c_2 r_2 [g_{best}(t) - x_i(t)]$$

$$x_i(t+1) = x_i(t) + v_i(t+1)$$

In the formula above, $x_i(t)$ is the position of the $i$ individual in the $t$ iteration; $v_i(t)$ is the
speed of the $i$ individual in the $t$ iteration operation; $r_1$ or $r_2$ is a random constant between $[0,1]$; $\omega$
represents the speed of the previous generation, $c_1$ and $c_2$ respectively representing cognitive search
and social search.

3.1.2. Parameter selection. In this study, the commonly used parameter selection values of dPSO or
gPSO algorithms in the field of building energy consumption optimization are counted. Among them,
the values of $c_1$ and $c_2$ are usually 1.5 and 2.0; The value of $\omega$ is usually 0.8; DE operator and GA
operator $[C_R, F]$ usually value $[0.5, 0.4]$; The values of $p_c$ and $p_m$ are usually 0.9 and 0.1.

3.2. Test function experiments and results

3.2.1. Test Function Setting and Test. In this study, the test function is used to determine whether the
Set parameters are effective. Since the distribution characteristics of buildings are unknown, three
peak test functions with different distribution forms (Rastrig function, Ackle function, and Griewa
function)are needed to test the functions under the current parameter setting.

3.2.2. Test function test. The improved particle swarm algorithm is compared with the original particle
Swarm algorithm corresponding parameters to find the size and algebra of the optimal solution.
The optimized particle swarm algorithm is compared with the original particle swarm
algorithm to calculate the corresponding optimal solution and algebra, and the experimental
results in Table 1.
Table 1. Experimental results of test functions

| Parameter | Initial population randomness | Same initial population |
|-----------|------------------------------|-------------------------|
| DE or GA Parameter | $C_1=C_2$ | Rastrig | Ackle | Griewa | Rastrig | Ackle | Griewa |
| $C_R=0.5, F=0.4$ | 1.5 | 1.5 | 1.5 | 1.5 | 1.5 | 1.5 | 1.5 |
| | 2.0 | 2.0 | 2.0 | 2.0 | 2.0 | 2.0 | 2.0 |
| | 2.1 | 2.1 | 2.1 | 2.1 | 2.1 | 2.1 | 2.1 |
| $C_R=0.9, F=0.8$ | 1.5 | 1.5 | 1.5 | 1.5 | 1.5 | 1.5 | 1.5 |
| | 2.0 | 2.0 | 2.0 | 2.0 | 2.0 | 2.0 | 2.0 |
| | 2.1 | 2.1 | 2.1 | 2.1 | 2.1 | 2.1 | 2.1 |
| $C_R=0.9, F=1.6$ | 1.5 | 1.5 | 1.5 | 1.5 | 1.5 | 1.5 | 1.5 |
| | 2.0 | 2.0 | 2.0 | 2.0 | 2.0 | 2.0 | 2.0 |
| | 2.1 | 2.1 | 2.1 | 2.1 | 2.1 | 2.1 | 2.1 |
| $P_R=0.9, P_m=0.1$ | 1.5 | 1.5 | 1.5 | 1.5 | 1.5 | 1.5 | 1.5 |
| | 2.0 | 2.0 | 2.0 | 2.0 | 2.0 | 2.0 | 2.0 |
| | 2.1 | 2.1 | 2.1 | 2.1 | 2.1 | 2.1 | 2.1 |
| $P_R=0.9, P_m=0.1$ | 1.5 | 1.5 | 1.5 | 1.5 | 1.5 | 1.5 | 1.5 |
| | 2.0 | 2.0 | 2.0 | 2.0 | 2.0 | 2.0 | 2.0 |
| | 2.1 | 2.1 | 2.1 | 2.1 | 2.1 | 2.1 | 2.1 |

Note: Suppose that the original PSO algorithm finds the optimal solution 1.0 in the 30th generation. 'white' indicates that the optimization result is greater than 1.0; 'Grey' means that the optimization result is less than 1.0, and the algebra is greater than 30 generations; 'black' indicates that the result is less than 1.0, and the algebra is less than 30 generations.

Through Table 1, the initial population has a negligible impact on the performance of the algorithm, and the setting of parameters has a certain impact on the optimization ability of the algorithm to PSO. Through the results in Table 1, it is found that some parameter settings can improve the algorithm performance, but the other parameter settings may reduce the algorithm performance. The concrete embodiment is: the setting of some parameters makes the optimal solution less than the original algorithm. The main reason for the above problems is that when the initial population generated by the original algorithm is close to the global optimal solution, other populations will be preferentially captured by the local optimum, resulting in the illusion that the optimization ability of the original algorithm is higher than that of the improved algorithm. Although there are some problems that the performance of the improved algorithm corresponding to some parameters is poor, from the overall results of Table 1, some parameter optimization settings still have positive effects on
the algorithm. Therefore, in terms of building energy consumption, the PSO parameter optimization designed in this study has certain research value.

4. Application of Algorithm Examples

4.1. Architectural plan
This study selected the northern cold zone of Tianjin as an example for the geographical and climatic conditions. The standard floor of the central core tube office building is the building model.

4.2. Simulation result
Based on the above range of parameters, the building energy consumption in Fig. 2 is optimized by simulation, and the results in Fig. 2 and Fig. 3.
Figure 2. Experimental results of random initial population

Figure 3. Experimental results of initial population consistency

It can be found from Figure 2 that most optimization algorithms have stronger global optimization ability than the original algorithm. However, there is still a situation that the initial population generation position of the original algorithm is very close to the global optimal solution under some parameter settings, that is, the optimization ability of the improved algorithm is not as good as that of the original PSO algorithm, which again proves that the optimization results of the algorithm are largely dependent on the initial population distribution. Therefore, this part of the parameter setting unreasonable improved algorithm is not as good as the original algorithm, but most of the optimized parameters of the algorithm is better. The original algorithm is fast in the optimization speed, and it can have the optimization results and complete the convergence when the number of iterations reaches about 10 times. However, the latter iteration process is easy to fall into local optimum and cannot jump
out. The corresponding optimization algorithm, even if some parameter settings are unreasonable, but more likely to find the global optimal.

It can be found from Figure 3 that after the initial population is consistent, the optimization ability of the improved algorithm is much better than that of the random population, but the optimization and iteration time will increase by a part. The simulation calculation of a 25-storey central core tube office building consumes about 420 s, the number of population is 25, the number of iterations is 40, and the optimization time is about 3.78 d. Although time has increased somewhat, it is generally acceptable.

5. Conclusions

In this study, an optimized PSO algorithm based on parameter setting is proposed. Firstly, the principles of dPSO and gPSO algorithms are studied, and the algorithm flow is analyzed. Then, the parameters generally set by the original PSO algorithm are analyzed, and the test function is set. Next, the simulation experiment with the initial population as the reference condition is carried out. Compared with the experimental results of the real data in Tianjin cold region, the optimization ability of the optimization algorithm after resetting the parameters is higher than that of the original PSO algorithm. Therefore, the optimization algorithm based on the improved parameter setting in this study is superior to the original PSO algorithm in the energy consumption optimization of office buildings in cold regions.

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