An improved particle swarm optimization algorithm and its application in energy saving optimization of central air conditioning

YuTing Liu¹, XiangDong Wang², ShuJiang Li³
Shenyang University of Technology, Shenyang Liaoning 110870
Email: 1379021040@qq.com

Abstracts: In order to solve the problem that the traditional particle swarm algorithm is difficult to converge to the optimal solution in the late iteration, and enhance the global search ability of traditional particle swarm algorithm, the inertial weights of the random perturbation sine adjustment particles were added at the initial and end of the search. At the same time, some Benchmark functions are used to test the improved particle swarm algorithm, and the results show that the improved particle swarm algorithm has obtained remarkable progress on convergence speed and precision. In this paper, the improved particle swarm optimization algorithm is utilized to optimize the whole system of central air conditioning and the optimal working point corresponding to minimum system energy consumption can be confirmed.

1. Typing Instructions
Particle swarm optimization, PSO algorithm is a swarm intelligence optimization algorithm except ant colony algorithm and fish swarm algorithm. The algorithm was first proposed by Kennedy and Eberhart in 1995. The PSO algorithm is based on the study of bird feeding behavior, and the simplest and most effective strategy for finding food is to search the surrounding area of the nearest bird. The PSO algorithm derived from the behavior characteristics of the biological population and is used to solve the optimization problem[1][2]. Current improvements on particle swarm algorithm are mainly use linear regressive strategy to make the inertia weight and learning factor of the fixed value change to their own learning and learn from other particles learning in the iteration early and later times were adjusted in a timely manner. Although the improved algorithm has some improvements on performance and efficiency, it is difficult to avoid premature convergence and improve the local search capability of the algorithm simultaneously[3][4]. Also some scholars have proposed the particle swarm optimization algorithm of quantum behavior using the potential well model in quantum mechanics. Although this algorithm has achieved better results than the traditional particle swarm algorithm in various fields, in this algorithm, the particle is still trapped near the local extreme point in the search process[5]. And other scholars have proposed particle swarm optimization particle filter algorithm, this algorithm has the phenomenon of particle degradation and particle poverty, and the problem of premature convergence[6].

In this paper, a new improved particle swarm optimization algorithm is proposed for the precocious convergence of particle swarm algorithm and its convergence accuracy and searching ability. This method mainly introduces gaussian weighting to global extremum, and the inertial weights of the particle swarm are adjusted by the random perturbation sine wave as for the self-learning of particle.
2. Optimization Method

2.1 Improved Particle Swarm Optimization

In the traditional PSO algorithm, each particle represents a potential optimal solution for the optimization problem of extremum, and the characteristics of the particle are represented by three indicators: location, speed and fitness. It is assumed that in a d-dimensional search space, a population of n particles \( X = (X_1, X_2, \ldots, X_n) \) is a swarm with a population of n particles and the ith particle is represented as a vector of D dimensions \( x_i = (x_{i1}, x_{i2}, \ldots, x_{id}) \), represents the position of the ith particle in the d-dimensional search space and represents a potential solution to the problem. The fitness value of each particle location \( i \) can be calculated according to the objective function. The velocity of the ith particle is \( v_i = (v_{i1}, v_{i2}, \ldots, v_{id}) \), and the individual extremal value is \( P_i = (P_{i1}, P_{i2}, \ldots, P_{id}) \), the population group’s extreme value is \( G = (G_{1}, G_{2}, \ldots, G_{d}) \).

In each iteration, the particle updates its own speed and position through the individual extremum and the group extremum, and its mathematical expression is:

\[
\begin{align*}
V_{id}^{k+1} &= \omega V_{id}^{k} + c_1 r_1 (P_{id}^{k} - X_{id}^{k}) + c_2 r_2 (G_{id}^{k} - X_{id}^{k}) \\
X_{id}^{k+1} &= X_{id}^{k} + V_{id}^{k+1}
\end{align*}
\]

Among them, \( \omega \) is the inertial weight; \( d=1,2,\ldots,n \); \( K \) is the current iteration number; \( v_i \) is the velocity of a particle; \( c1 \) and \( c2 \) are non-negative constants, which are the accelerators; \( r1 \) and \( r2 \) are random numbers distributed in the \([0,1]\) range. In order to prevent the blind searching of particles, it is recommended to limit its position and speed to a certain range. 

The improvement of particle swarm optimization algorithm proposed in this paper includes the following two aspects.

1. Inertia weight improvement

   The size of the inertial weight determines how much of the current particle velocity is inherited. The larger inertial weights can make the particles have a greater speed and thus have a strong exploration ability; The smaller inertial weights can slow down the particles and thus have a strong development capacity [6]. To balance and enhance the algorithm’s searching ability, the random disturbance sine is added at the time of early and late searching stage which can adapt the inertia weight of particle swarm, and its mathematical expression is:

   \[
   \begin{align*}
   \omega^{k+1} &= \omega^{k} \times (1 - \sin(a)) + \omega_{\text{min}} \times \sin(a) \\
   a &= \pi / 2 \tau_{\text{max}}
   \end{align*}
   \]

Among them, \( a = \pi / 2 \tau_{\text{max}} \), the introduction of sine function makes the particle swarm have sinusoidal adjustment at the early and late stage of the search, in this process, the dynamic nonlinearity of particle swarm search is demonstrated.

2. Introdution of gaussian weighted global extremum

   In order to solve the problem that the traditional particle swarm algorithm is not easy to converge to the optimal solution in the late iteration, the global extremum of gaussian weight is introduced. The mean of the gaussian weight is the mean of the fitness function of all the particles, and the variance of the mean is the gaussian weighted variance, and its mathematical expression is:

   \[
   \begin{align*}
   E[f(x)] &= \frac{1}{m} \sum_{i=1}^{m} f(x_i) \\
   \sigma^2 &= \frac{1}{m-1} \sum_{i=1}^{m} (f(x_i) - E[f(x_i)])^2
   \end{align*}
   \]

Among them, \( f(x_i) \) is the fitness value of the ith particle, \( E[f(x_i)] \) is the average fitness of all particles, \( \sigma^2 \) is the variance of the mean.

The global factor of Gaussian weight is the minimum fitness value \( \text{fitness}_{\text{min}} \) of the current particle group as the center of gaussian weighting, and its mathematical expression is:
\[ \Delta(x_i) = \exp\left(-\left(f(x_i) - f_{\text{min}}\right)^2/(2\sigma)^2\right) \]

At last, the global extremum is weighted average for the individual extremum of all particles and the global factors above gaussian weighting, and its mathematical expression is:

\[ P_t = \frac{\sum_{i=1}^{n}(P_{\text{max}} \times \Delta(x_i))}{\sum_{i=1}^{n} \Delta(x_i)} \]

The introduction of gaussian weighting is beneficial for the convergence of global extremum to obtain the optimal solution.

In conclusion, the improvement of the traditional particle swarm optimization algorithm includes both the convergence speed and the accuracy.

The following three benchmark functions are selected to verify the improved particle swarm optimization algorithm, and the three functions are shown in table 1:

| name       | Test function                                                                 |
|------------|-------------------------------------------------------------------------------|
| Sphere     | \[ f_1 = \sum_{i=1}^{n} x_i^2 \]                                          |
| Rastrigrin | \[ f_2 = \sum_{i=1}^{n} \left[x_i^2 - 10 \cos(2\pi x_i) + 10\right] \]   |
| Ackley     | \[ f_3 = 20 + e - 20 \exp\left(-0.2\sqrt{\frac{1}{n} \sum_{i=1}^{n} x_i^2}\right) - \exp\left(\frac{1}{n} \sum_{i=1}^{n} \cos(2\pi x_i)\right) \] |

Among them, the Sphere function is a nonlinear symmetric single mode function, its search range is \(-100 \leq x_i \leq 100\), it is mainly used to test the optimization precision of the algorithm. The Rastrigrin function is a typical complex multimode function with a large number of local advantages, and its search scope is: \(-5.12 \leq x_i \leq 5.12\); The Ackley function is a continuous, rotating, non-separable multimode function, its search scope is: \(-30 \leq x_i \leq 30\).

The optimal solutions of these three test functions are 0, each function is tested for 50 times respectively, and each function selects 100 individuals and iterates 500 times. The results are shown in table 2.

| function | Optimal solution | Optimal value | Average value | Worst value   |
|----------|-----------------|---------------|---------------|--------------|
| Function 1 | 0 | PSO | 2.2245 \times 10^{-28} | -1.3043 \times 10^{-26} | -2.3394 \times 10^{-25} |
|          | 0 | improve PSO | 8.1976 \times 10^{-58} | -2.5704 \times 10^{-38} | -1.2468 \times 10^{-56} |
| Function 2 | 0 | PSO | 1.5139 \times 10^{-11} | 4.052 \times 10^{-11} | -1.593 \times 10^{-9} |
|          | 0 | Improve PSO | -8.822 \times 10^{-11} | 4.0244 \times 10^{-12} | -2.1512 \times 10^{-10} |
| Function 3 | 0 | PSO | 0.4863 | -0.0584 | -0.4863 |
|          | 0 | Improve PSO | 0.3042 | -0.0101 | 0.4855 |

Through the comparison of table 2, it can be seen that the improved particle swarm optimization algorithm is superior to the traditional particle swarm optimization algorithm in terms of the optimal value, average value and worst value. It is proved that the improved particle swarm algorithm has better global convergence.
2.2 Application of improved particle swarm optimization algorithm in energy saving optimization of central air conditioning.

In this paper, the central air conditioning system energy consumption as the objective function, and its mathematical expression is:

\[
\text{min} P_{\text{total}} = \min(P_{\text{chiller}} + P_{\text{CHWpump}} + P_{\text{fan}} + P_{\text{chiller}} + P_{\text{CHWpump}})
\]

Where \( P_{\text{chiller}} \) is the energy consumption of the chiller, \( P_{\text{CHWpump}} \) is the energy consumption of chilled water pump, \( P_{\text{fan}} \) is the fan energy consumption, \( P_{\text{chiller}} \) is the energy consumption of cooling tower, \( P_{\text{CHWpump}} \) is the energy consumption of cooling water pump. Under the following working conditions, the improved particle swarm optimization algorithm is used to optimize the central air conditioning system, and the corresponding variable parameters are obtained when the system energy consumption is minimum.

The chiller rated capacity \( Q_{\text{chiller}} \) is 1300 kw, rated efficiency \( COP_{\text{chiller}} \) is 6.5; fan coil outlet wet bulb temperature is \( 13^\circ C \); Chilled water pump rated power \( P_{\text{CHWpump}} \) is 15 kw; Cooling water pump rated power \( P_{\text{CHWpump}} \) is 10 kw, rated flow is \( 0.9 \text{ kg/s} \); The rated power of the cooling tower \( P_{\text{chiller}} \) is 4 kw, the rated air flow \( m_a \) is \( 0.9 \text{ kg/s} \), the constraints are as follows:

\[
15^\circ C \leq T_{\text{chill}} \leq 35^\circ C; \\
5^\circ C \leq T_{\text{chill}} \leq 15^\circ C; \\
0.5 \leq m_{\text{cw}} \leq 0.9; \\
0.1 \leq m_{\text{at}} \leq 0.9
\]

Considering the above conditions, the application of improved particle swarm optimization of the central air conditioning system is simulated and its convergence curve is shown in Figure 1:

![Fig.1 The convergence curve of improved particle swarm optimization](image)

Thus, the optimal parameter for the minimum energy consumption of central air conditioning is set as: Chilled water supply temperature \( T_{\text{cw}} \) is \( 9.01^\circ C \); Cooling water supply temperature \( T_{\text{cw}} \) is \( 28.52^\circ C \); Cooling pump flow \( m_{\text{cw}} \) is \( 0.86 \text{ kg/s} \); Fan coil air volume \( m_{\text{at}} \) is \( 0.785 \text{ kg/s} \).

3. Conclusion

1. In this paper, the global extremum and inertia weight of the traditional PSO are improved, and three benchmark functions are selected to verify the validity of the improved PSO, the experiments show that the improved particle swarm optimization has achieved remarkable results in convergence speed and accuracy.

2. The improved PSO algorithm is used to optimize the central air conditioning system, and the optimal variable setting value is obtained when the system energy consumption is minimum.

Application results show that when the particle swarm optimization algorithm is applied to the nonlinear and uncertain central air-conditioning system, the global optimal solution can be confirmed.
by the explicit objective function rapidly and accurately under the constraints, which is the optimal combination of variables corresponding to the minimum system energy consumption.

References
[1] HaiMing Jiang, Kang Xie, YaFei Wang. Improved Particle Swarm Optimization Algorithm with Probabilistic Kickstalk[J]. Journal of Jilin University (Engineering and Technology edition), 2007, 37（1）: 141-145.
[2] Jian Li, Cheng Wang. A Modified Adaptive Particle Swarm Optimization Algorithm[J]. Journal of Huazhong University of Science and Technology (Science and Technology edition), 2008, 36（1）: 118-121.
[3] ChongPeng Huang, WeiLi Xiong, BaoGuo Xu. Research on Nonlinear Decreasing Strategy of Inertial Weights in PSO Algorithm[C]. 2007 Chinese Control and Decision Academic Annual Proceedings, Wuxi: 2007: 481-484.
[4] Chen M R , Li X , Zhang X , et al. A novel particle swarm optimizer hybridized with extremal optimization [J]. Applied soft computing, 2010, 10（2）: 367-373.
[5] Jun Sun, Wei Fang, XiaoJun Wu, WenBo Xu. Quantum behavior Particle swarm optimization [M]. Tsinghua University Press, 2011-8.
[6] Zheng Fang, GuoFang Tong, XinHe Xu. Particle swarm optimization particle filter method [J]. Control and decision making, 2007, 22（3）: 273-277.