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Improvement and Application of Particle Swarm Optimization Algorithm based on the Parameters and the Strategy of Co-Evolution

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Abstract: PSO algorithm is an intelligent optimization algorithm based on swarm intelligence. Particle swarm optimization algorithm is simple, easy to implement, and it has a wide application prospect in scientific research and engineering applications. In real life, most of the optimization problem is the optimization problem of some nonlinear discrete with the existence of local. PSO algorithm also has some defects in treating optimization problem. The optimal performance of the PSO algorithm is efficiency; the attribute weights are optimized, which is the same as to improve the accuracy of case retrieval. The application of case is based reasoning in the optimization of pressure vessel model design. Through the experiment results, the optimization of the performance of PSO algorithm is better; the result of prediction is more approximate to the actual value, which can meet the needs of practical applications in engineering. The evolution strategy algorithm and the control parameters of the algorithm on the algorithm performance are affected. The control parameter adaptive particle swarm optimizer algorithm and evolution strategy of adaptive scheduling particle swarm algorithm, particle swarm optimization algorithm form a parameter and the strategy of co evolution, the co-evolution PSO algorithm and DBPSO algorithm and ASPSO algorithm are compared. The results show that, co-evolution PSO algorithm in the optimization performance improved to a certain extent than DBPSO algorithm and ASPSO algorithm, which achieved good results.

Keywords: Particle swarm optimization, Matrix, Adaptive strategies, Co evolution

1 Introduction

The optimization problem has been accompanied with the development of human existence; it is a very old problem, and the main idea is that from a practical point of view. Some specific problems from a set of candidate solutions to choose a most suitable are to achieve the optimal solution of the objective [1]. Optimization problem permeates all aspects of human life, and it widely exists in various fields of production, management, business, military, decision [2]. In some engineering design parameters, how to choose the most suitable to the production or cost minimum to meet the demand in production planning is very important. There are some problems, namely, how to choose a reasonable plan to make the output maximization, the maximum output and profits. In resource allocation, distribution is to make the economic benefit obtained the best, which can meet different requirements of different aspects [3].

In recent years, inspired by biology, sociology, physics and other disciplines, some intelligent optimization algorithms have been proposed such as evolutionary computation, artificial neural network, swarm intelligence optimization algorithm including genetic algorithm belongs to the evolutionary computation, and these intelligent optimization algorithms obtained the rapid development and application [4]. The intelligent optimization algorithms are novel search algorithms. Their common essence is to simulate and reveal some natural phenomena and processes developed according to the system initializing a set of initial solution, the operation iterative rules specific for a group of solutions combined with the search mechanism itself are iterative, and finally get the optimal solution [5,6].

As the human understand of the world vision and reconstruct the world, it requires in-depth, especially the rapid development of computer technology, which causes

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people put forward higher expectations and demands for science and technology [7]. Optimization problems raised in engineering practice and theoretical research gradually developed to the large-scale, multi-level, strong constraints, which greatly increased the difficulty of solving. The traditional optimization methods are difficult to deal with the increased complex problems and convergences which cannot meet all the requirements [8, 9, 10]. Therefore, optimization techniques and algorithms efficiency have become an urgent needed to optimize technology. Thus the rapid development of optimization theory and algorithm accelerated the pace of the progress of human society.

Study on the convergence of PSO algorithm and the particle trajectory can help us deeply understand its operation mechanism, which is very important to perfect the theoretical foundation. Because of the random quantity of PSO algorithm, a lot of conventional mathematical methods on the invalid make the theoretical analysis become the difficulties of the study. Bergh [11] thought the analysis of the PSO particle trajectories will eventually converge to a stable point. Ceng Jianchao [12] based on the analysis of PSO algorithm proposed that PSO algorithm can guarantee the convergence with probability to the optimal solution. Based on the single particle trajectory simulation and analysis, summarizing the existing problems and their causes in the PSO algorithm, the analysis and optimal position of special populations are discussed, and put forward the corresponding improved algorithm (RDPSO algorithm). The convergence analysis showed that it can guarantee the global convergence, and its effectiveness is verified by simulation despite there are some limitations. The attribute weight in CBR is optimized by the optimization of a strong performance. The improved PSO algorithms used based reasoning optimized implementations are applied to optimize the model design of pressure vessel, and its superiority is verified through simulation, which can satisfy the needs of engineering practice.

2 Related theory of Particle swarm optimization algorithm

2.1 The basic principle of particle swarm algorithm

Particle swarm optimization algorithm is a swarm intelligence optimization algorithm. It is a novel and effective optimization method based on iteration and groups; and it is to find the optimal solution through successive iterations [13]. The system initialized with a random particle, the particle is equivalent to a search space for the optimization problem of a set of potential solutions, which don't take up any space without any quality and volume, but has the memory function. To what degree each particle is made accords to the objective function of the optimization algorithm of calculating fitness value to evaluate the decision. For example, if the optimization objective function is the minimum of the objective function obtained; the fitness values of the particle properties of smaller conversely, such as object function. If the calculated the fitness value is greater; the particle is more superior performance [14].

$$\begin{cases} v_i^j = v_{\min} & if \;\; v_i^j \geq v_{\min} \\ v_i^j = -v_{\min} & if \;\; v_i^j < v_{\min} \end{cases} \tag{1}$$

Every particle in the population accords to the following formula on its location update:

$$x_i^j(t+1) = x_i^j(t) + v_i^j(t+1) \tag{2}$$

2.2 Particle swarm optimization process

Step (1): Random initialization, a group of particle velocity and position are initialized, respectively: $V_i = (V_i^1, V_i^2, V_i^3, \ldots, V_i^d)$; $X_i = (X_i^1, X_i^2, \ldots, X_i^d)$, $i = 1, 2, \ldots, n$, n was the population number of particles, and set when the cut individual best positio $n = X_i$, and select the best position of the swarm., from sand, making it equal to step.

Step (2): On the basis of the objective function and function of each particle corresponds to the value of all the particles, into the objective function for the fitness value calculation, and compared with the best location of pbesti of individual particles own experience, if the X_i is better than pbesfi, then X_i replace the pbesti;

Step (3): The optimal position of the optimal position of each individual has experienced with the entire group comparison, if the pbesti is better than gbest, it will replace gbest;

Step (4): The use of type (1) and type (3) on the particle position and velocity updating, the updated time on particle velocity needs to use the type (2) limit;

Step (5): Judging whether a termination condition is satisfied, if it is satisfied, the search is over, if it is not satisfied, then jump to the step to continue (as is usually the case, the termination condition is set to the maximum number of iterations or certain convergence accuracy). The PSO algorithm flow chart was shown in Figure 1.

2.3 Discrete PSO algorithm

The discrete PSO algorithm is mainly used to make up the basic PSO algorithm which can not be used to solve the problem of combinatorial optimization problems. And this is mainly because the PSO algorithm proposed in the early basically is used to solve continuous optimization problems. The binary version of the PSO algorithm is the first to proposed this idea, the position of the particle can be value 0 or 1, updating formula particles are as follows [15]:

$$v_i^j(t+1) = v_i^j(t) + rand_1^j(pbest_i^j - x_i^j(t))$$

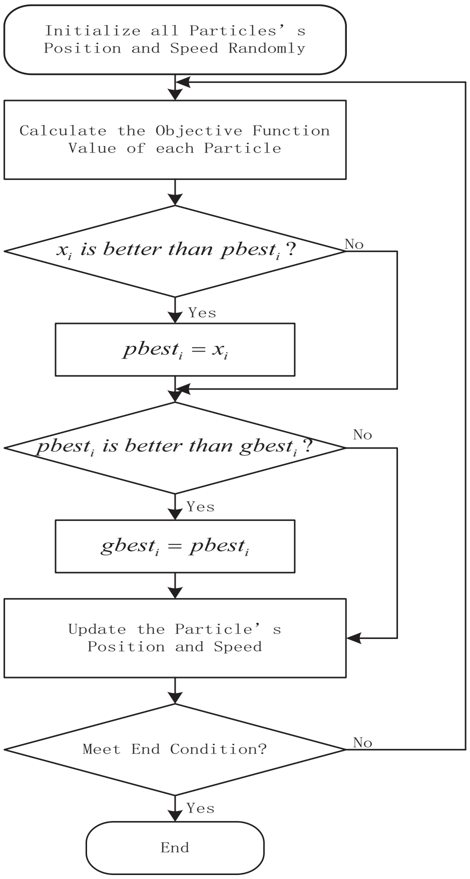


Fig. 1: The PSO algorithm flow chart.

$$+rand_2^j(gbest_i^j - x_i^j(t)) \tag{3}$$

$$x_i^j(t+1) = \begin{cases} 1, & if \;\; rand() < sig(v_i^j(t+1)) \\ 0, & if \;\; rand() \geq sig(v_i^j(t+1)) \end{cases} \tag{4}$$

At present, most of the improved PSO algorithms with adaptive strategy are improved based on adaptive linear; proposed by Shi and Eberhart the decreasing inertia weight strategy can be stated as follows:

$$\omega = \omega_{\max} - (\omega_{\max} - \omega_{\min})\frac{g}{G} \tag{5}$$

The value of inertia weight accords to the type of change:

$$\omega(t) = \left\{\frac{(T-t)^n}{t^n}\right\}(\omega_{\max} - \omega_{\min}) + \omega_{\min} \tag{6}$$

2.4 Characteristics of the Algorithm

Particle swarm optimization algorithm has the following characteristics:
1) Algorithm is simple in concept. It need to tune the parameters of not much good performance and rely on probabilistic search without derivation. Thus, it does not require the optimization function differentiable with invisible; the parallel search can be searched in the global scope, and the convergence was speeded.
2) Communication between the particles is one-way. Learned from the optimal particle population to the same information, the species that is best particle behavior affects the whole particle swarm behavior. Thus, in fact particle exchanged through the optimal particle population impacts on population indirectly.
3) Particles are randomly generated, which can through mutual cooperation and competition consciousness through evolution. However, because of its randomness, the complex and uncertain problems has better search ability.
4) PSO algorithm is based on particle velocity to determine the search path, and along the gradient direction search, iterative to another set of solutions from a set of solutions in many cases, the particle can converge to the optimal solution.

2.5 Stability analysis and parameter selection of particle motion

For optimization algorithm, parameter selection directly influences the performance and efficiency of the proposed algorithm. How to determine the optimal parameters of the algorithm that can optimize the performance is a very complex problem. There are some adjustable parameters affect the performance of the algorithm in PSO algorithm. There is a lack of demonstration and theory of mature parameter selection. Now the most commonly used parameters selection strategy is based on the experience and experiment which is because the PSO algorithm theory foundation is weak.

2.5.1 Stability analysis

Due to the random selection in the search process in the particle is the subscript *i*, the analysis is simplified to one dimension and a particle. If in a short time of individual particle and the global best value pi solid C constant.

$$v(k+1) = w \cdot v(k) - \varphi \cdot x(k) + \varphi \cdot p \tag{7}$$
$$x(k+1) = x(k) + v(k+1) \tag{8}$$

In it:

$$\begin{aligned} \varphi_1 &= c_1 r_1, \\ \varphi_2 &= c_2 r_2, \\ \varphi &= \varphi_1 + \varphi_2 \\ p &= \frac{\varphi_1 p_i + \varphi_2 p_g}{\varphi_1 + \varphi_2} \end{aligned} \tag{9}$$

$$v(k+2) = (w+1-\varphi)v(k+1) - wv(k) \tag{10}$$
$$x(k+2) = (w+1-\varphi)x(k+1) - wx(k+1) + \varphi \cdot p \tag{11}$$

By type (9), velocity change process of particle is a two order homogeneous differential equation. When p_i, and p_j is constant, velocity changes unrelated. By type (11), position change process of particle is a two order non homogeneous differential equation.

Characteristic polynomial:

$$\lambda^2 - \lambda(1 + w - \varphi) + w = 0 \tag{12}$$

According to that eigenvalue for the solution of the equation:

$$\lambda_1 = \frac{1 + w - \varphi + \sqrt{\Delta}}{2} \tag{13}$$

$$\lambda_2 = \frac{1 + w - \varphi - \sqrt{\Delta}}{2} \tag{14}$$

The differential equation (15) and (16) can be expressed as

$$x(k) = a_0 + a_1\lambda_1^k + a_2\lambda_2^k \tag{15}$$

$$v(k) = b_1\lambda_1^k + b_2\lambda_2^k \tag{16}$$

$$a_0 = p$$

$$a_1 = \frac{\lambda_2(x_1 - x_0) + x_1 - x_2}{(\lambda_2 - \lambda_1)(\lambda_1 - 1)}$$

$$a_1 = \frac{\lambda_1(x_1 - x_0) - x_2 + x_1}{(\lambda_1 - \lambda_2)(\lambda_2 - 1)} \tag{17}$$

If the position of the particles tends to infinity, the motion trajectory is divergent; while the motion trajectory divergence can cause the whole particle swarm divergence. That is to say, the stability of single particles impacts the entire particle behavior. Therefore, the stability of particle position and velocity variation need to be analyzed.

2.5.2 The method of selecting parameters

The parameters in PSO algorithm mainly includes: the population size N, the maximum speed threshold $V_{\max}$, threshold $X_{\max}$ maximum position, the inertia weight w, cognitive coefficient C_1 and social factor C_2. Methods of the first three parameters are used to determine the range of numerical experiments. The latter three parameters directly affect the trajectory of particles. Therefore it has a more directly impacts on the performance of algorithm. This paper mainly studies on the three parameters.

In order to understand the effects of various parameters on particle trajectory in the search process, and to verify the convergence condition of a section, parameters is selected based on several classical values for particle optimization trajectory simulation. The simulation conditions were: $X(0) = 10$, $V(0) = 8$, $P = 0$, the iteration number is 50. The results are shown in figure 2. In Figure 2 (a) $w = 0.1$, $P = 0.3$ results, the corresponding eigenvalue is real, non oscillatory convergence; Figure 2 (b) $w = 0.7$, $P = 0.5$ results, the corresponding eigenvalues with positive real part of the complex.

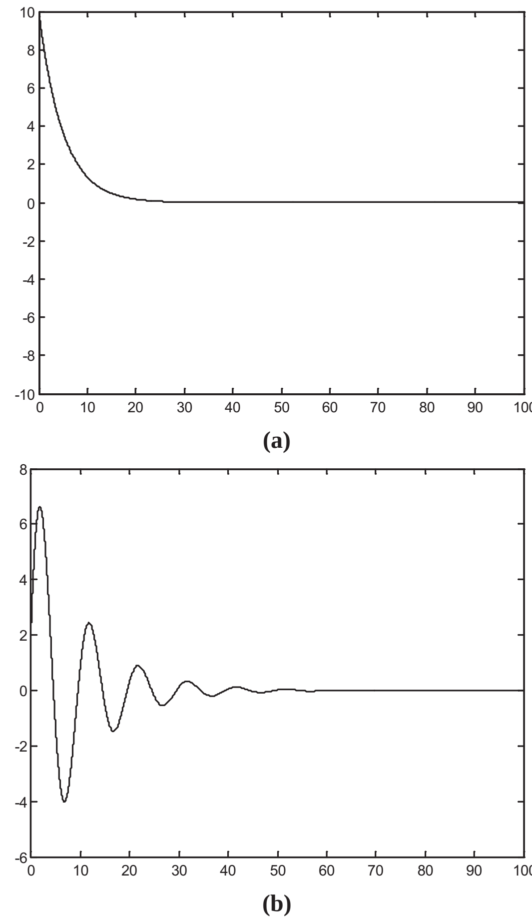


Fig. 2: The results of several classical values for particle optimization.

According to the formula (15-17) showed in the PSO algorithm, particle trajectory is based on Max $(\lambda 1, \lambda 2)$ of the exponential form of convergence or divergence, and the parameter form decides the convergence model of particle trajectories. The different parameters have different optimization results; in fact, even for the same parameter and the random algorithm may also get different results.

3 Analysis and improvement of particle trajectories and algorithm

3.1 Analysis of the neighborhood structure

PSO algorithm is swarm intelligence, cooperative behavior of main power source in groups. The neighborhood structure used to describe group among particles is in the neighbor relationship and interaction. The neighborhood structure not only determines the flow of information, but also decides the speed and strength of the information transmission.

There are several common topological structures, such as the Von Neumann structure, three kinds of Pyramid structure and all kinds structures were shown in Figure 3.

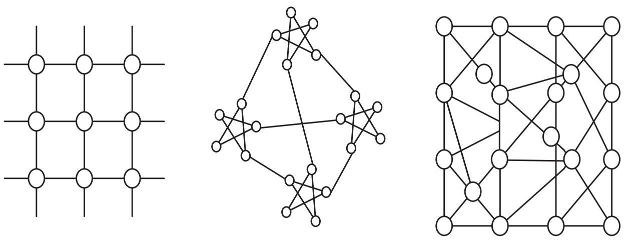


Fig. 3: Three kinds of Pyramid structure.

The topological structure of PSO algorithm refers to the mutual connection between all the groups in the particle, which means communication. The neighborhood structure is a single particle and particles of other communication connection. Topology is the nature of the whole, and the neighborhood structure is local properties. The neighborhood structure determines the topological structure. PSO algorithm is different from neighborhood structures, the performance will be a big difference.

3.2 State space analysis of particles

The optimal neighborhood location hypotheses particle is fixed in a period of time, and each particle has its own local optimal location alone. Because the population based on the optimal neighborhood position is sorted, it is static.

PSO algorithm for stochastic neighborhood structure is based on the velocity updating formula:

$$v_i(k) = wv_i(k-1) + \varphi_1(p_i - x_i(k-1)) + \varphi_2(p_i - x_i(k-1)) \quad (18)$$

The choice is your neighborhood optimal particle, the location update formula:

$$x_i(k) = x_i(k-1) + wv_i(k-1) + \varphi_1(p_i - x_i(k-1)) \quad (19)$$

The state space model was shown in Figure 4.

$(l-(1-p)^{i-1})$ This one shows that the socialization of particle i. With the increasing of i, particle exchanges also increased. More communication occurs between particles, detection ability is strong. Therefore the optimal particle is no longer with the other particles interact, and other particles need to constantly communicate with their surrounding the particle to search for the optimal position of neighborhood.

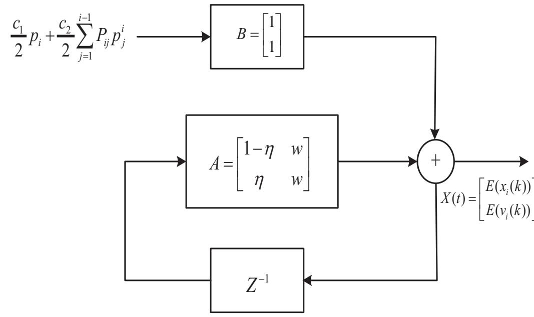


Fig. 4: The state space model.

3.3 Analysis of particle trajectory

In the search process of the PSO algorithm, the particle velocity is limited, so each iteration particle is only in a limited area. It does not cover the whole solution space, and the trajectory of the particle directly affects the search ability of the algorithm.

The search space of [−30, 30], the population size is 10. A random particle, analyze it in the late PSO algorithm optimization of trajectory. Due to the arbitrary selection, its flight path, it can represent the population of all the particles.

Figure 5 shows the advantages of the population from the 0–99 iteration of the trajectory. According to the statistical results, the optimal particle population after first iterations is at positions 1, fourth iterations is at positions 2, sixth iterations is at positions 3, eighth iterations is at positions 4, twelfth iterations is at positions 5, eighteenth iterations is at position 6. It can be seen in figure 5 the optimal particle population in the early iterations of the optimal position of the region to rapidly by pulling, the few times you can reach near optimal position.

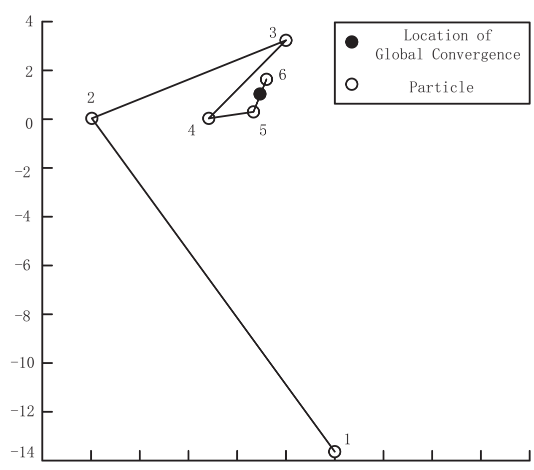


Fig. 5: The advantages of the population from the 0–99 iteration of the trajectory.

Figure 6 shows a particle from the 100–109 iteration of the trajectory. It can be seen that the particles in the global optimal position *P* (coordinate (3,1)) swing around. This is because the PSO algorithm is a random search algorithm, every time of flight direction and step size are random. In the iterative process of a total of 10 times, the particles in the 104th step of the location away from the optimal location of *P* recently. But at its current rate, its historical experience and population of outstanding individual experience the role of the three, 105th step is directly across from the advantages of *P* instead. Therefore, particles in the near the advantages at the same time, the track has great randomness, so the particle is often the line crosses or at a certain offset bypass the most advantages, but can not converge to the optimal position.

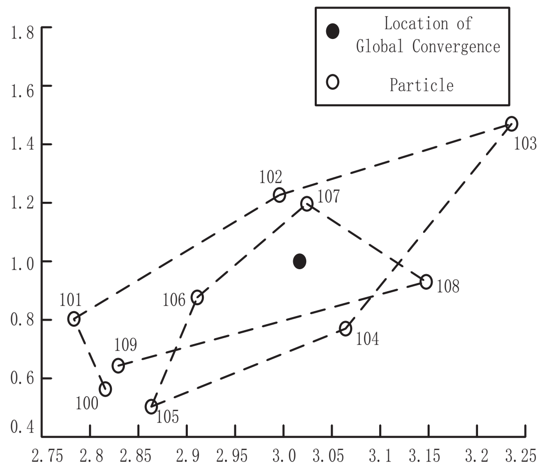
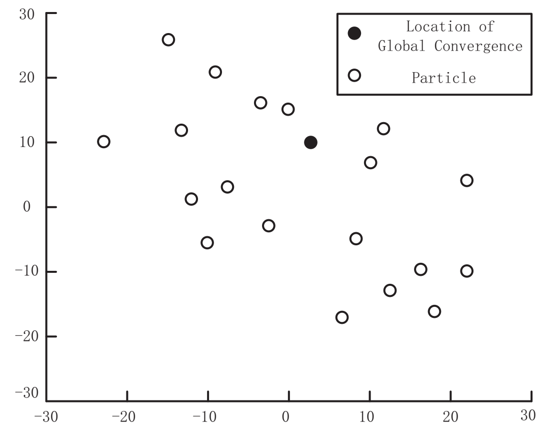


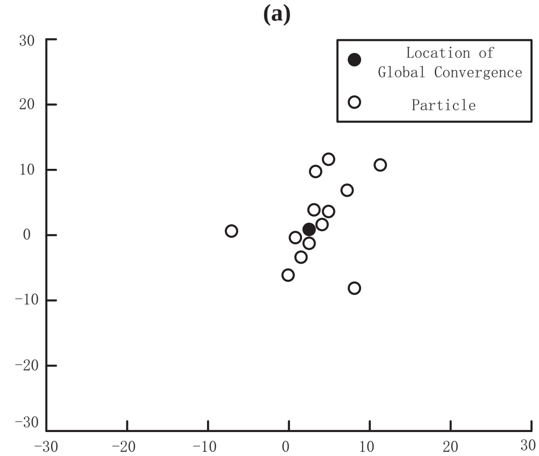
Fig. 6: A particle from the 100–109 iteration of the trajectory.

3.4 Aggregation of particle swarm optimization

Update formula from the speed and location algorithm, all particles are based on own and all the particles search experience. Therefore the information of particle swarm is mainly from the individual optimal position of each particle which extracts the global best position. From the analysis of the convergence of the algorithm, the weighted center particle converges to the optimal position of population and individual best position, and eventually converges to the optimal position of population. When a particle in the current optimal position, other particles would rapidly toward its close, appear close together. Thus, the search space becomes small, and it caused serious lack of population diversity. Figure 7 shows the particle aggregation process group which showed the best position location population. As shown in the picture, in the iterative process, particle continuously near the position of A, and finally gathered around. In fact, in the position of the entire process of A has some appeal in attracting the whole particle swarm optimization, which is the reason for maintaining the aggregation of the population. Population aggregation causes particles to the exchange information quickly, which will rapidly reduce the diversity of population.



(a)



(b)

Fig. 7: The particle aggregation process group.

In conclusion, optimization of PSO algorithm can be divided into 3 stages: initial stage to better region close to the middle stage; in search of better regional long time comprehensive; and optimal position final stage of convergence.

4 Experimental Results

4.1 The simulation and performance study

In PSO, the search interval of each dimension is separately between the value of [0.2, 0.6], [0.8, 1.6] and [2.8, 3.45]. At the same time, the outer layer of the particle inertia weight and learning factor value for 0.75, 1.375, 1.375. In this paper, all the simulation mean value is 10, the evolution is 150000 times. In order to evaluate the DBPSO optimization performance, 5 benchmark function simulation of DBPSO algorithm was used which were shown in Table 1. The test function dimension unified value is 30, and compare the optimization performance with the standard PSO algorithm and NMPSO algorithm DBPSO.

Table 1: 5 Benchmark functions used to test and their parameters

Function Name	Dimension	Search Space
$f_1(x)=\sum_{i=1}^{n} x_i^2$	30	$[-100, 100]$
$f_2(x)=\sum_{i=1}^{n}\left(\sum_{j=1}^{i} x_j\right)^2$	30	$[-100, 100]$
$f_3(x)=\sum_{i=1}^{n} \lvert x_i\rvert+\prod_{i=1}^{n}\lvert x_i\rvert$	30	$[-10, 10]$
$f_4(x)=-20*\exp\left(-0.2*\sqrt{\frac{1}{n}\sum_{i=1}^{n} x_i^2}\right) - \exp\left(\frac{1}{n}\sum_{i=1}^{n}\cos(2\pi x_i)\right)+20+e$	30	$[-32, 32]$
$f_5(x)=\sum_{i=1}^{n}(x_i^2-10\cos(2\pi x_i)+10)$	30	$[-5.12,5.12]$

Figure 8 is modal functions and multi peak function evolution curve of DBPSO algorithm and PSO algorithm (longitudinal axis based on optimal adaptation to natural logarithm value).

As you can see from Figure 8(b), the DBPSO showed a modal function, convergence precision converges faster and better than the basic PSO algorithm. The multi peak function, DBPSO algorithm can avoid the premature convergence, the final convergence solution is better than that of PSO algorithm.

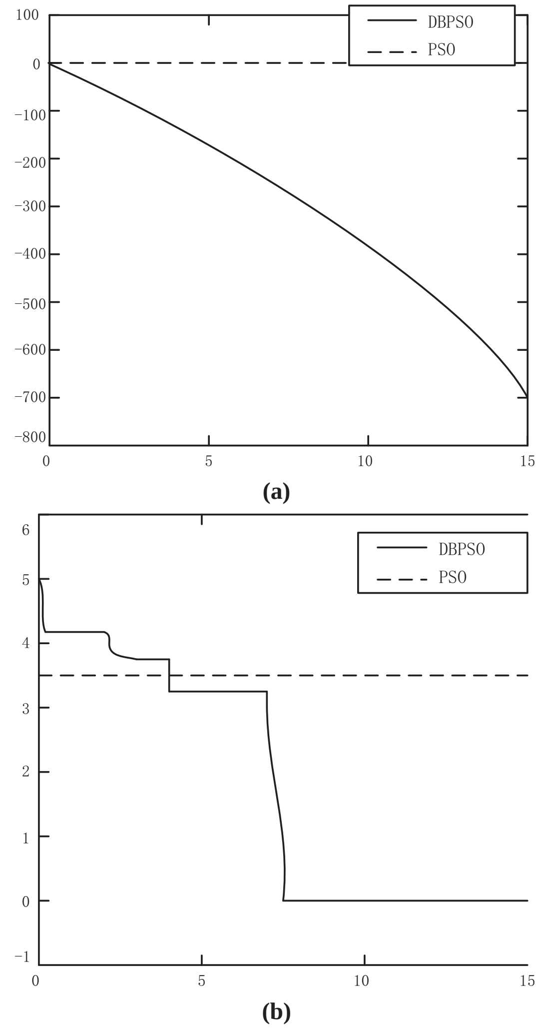


Fig. 8: Modal functions and multi peak function evolution curve of DBPSO algorithm and PSO algorithm.

4.2 Simulation results and analysis

Model design of pressure vessel is a constrained optimization problem. And the optimal target is to design a round container cost minimum. The models have four variables: the thickness of the shell spherical head x1, thickness x2, radius of cylindrical shell length x3, x4. x1 is integer times 0.0625 inch, x3 and x4 are continuous variables, where $40 < x3 < 280$ inch, inch. The pressure vessel model can be described as follows:

$$g_1(x) = 0.00193x_3 - x_1 \leq 0 \quad (20)$$

$$g_2(x) = 0.00954x_3 - x_2 \leq 0 \quad (21)$$

$$g_3(x) = 1296000 - \frac{4}{3}\pi x_3^3 - \pi x_3^2 x_4 \leq 0 \quad (22)$$

$$g_4(x) = x_4 - 240 \leq 0 \quad (23)$$

$$g_5(x) = 1.1 - x_1 \leq 0 \quad (24)$$

$$g_6(x) = 0.6 - x_2 \leq 0 \quad (25)$$

Minimum of DBPSO runs ten times as DBPSO optimization of pressure vessel model is the best model value. The maximum value of evolutionary times each run is 2500, the population number value is 20. Table 2 listed harmony search algorithm of the pressure vessel model. Comparison of these optimization results, it can be seen that the optimization results of the DBPSO algorithm is better than other algorithms.

The proposed DBPSO algorithm and ASPSO algorithm are applied to optimize the parameters of the model of pressure vessel design. DBPSO algorithm and ASPSO algorithm optimization of pressure vessel model results are better than some other algorithms. The pressure vessel model was optimized by using Co-evolution PSO algorithm, and the optimization results was shown in the following Table 3:

It is seen from Table 3, the optimization results of the pressure vessel model parameters in the Co-evolution.

Table 2: Optimization result for pressure vessel design problem

N	Sand gren	Wink Cho	Harmcony Search	CODEQ	AIWPSO	DBPSO
x_1	1.125	1.125	1.125	1.125	1.125	1.125
x_2	0.625	0.625	0.625	0.625	0.625	0.625
x_3	48.97	58.19	58.2789	58.29015	58.29015	58.29023
x_4	106.7	44.29	43.7549	43.69256	43.69265	43.69220
$f(x)$	7980	7207	7198.43	7197.728	7197.728	7197.726

Table 3: Optimization results for pressure vessel design problem

	DBPSO	ASPSO	Co-evolution PSO
x_1	1.125	1.125	1.125
x_2	0.625	0.625	0.625
x_3	58.2902376380	58.26396932521	58.25039720452
x_4	43.6922042233	43.67607978819	43.64409625761
$f(x)$	7197.726	7197.726	7197.725

PSO algorithm is better than those in DBPSO algorithm and ASPSO algorithm.

4.3 The limitation analysis

The global best position disturbance can avoid the algorithm into a local optimum. At the same time, there are some limitations: as shown in Figure 9, the global optimal position to point 0. In an iterative process, the optimal particle population is disturbed, from the position A to position B, the next step is to position the C; or directly from the position A across the global minima of 0 to C. Although fitness is improved, it is far from the global optimum, which is caused by the blindness and random disturbances. This phenomenon often appears in function which has many local minima in the solution. But if the optimal particle population is at position B, several local searches immediately find the global optimal solution.

4.4 Improvement and analysis

The PSO algorithm, particle velocity and position are based on the relevant information. The optimal particle population owns information to complete the update, which is a positive feedback process. The update formula can be learned from speed, no matter how far away from the global best particle, to learn all the same information. In fact, particle exchanges through the optimal particle population have impact on the populations of indirect. It is precisely because of this one-way sharing mechanism which is because the search direction of all particles in

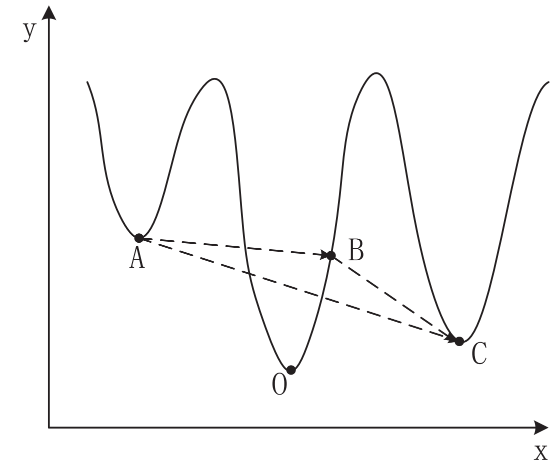


Fig. 9: The global optimal position to point zero.

the population are controlled by the optimal particle population and follow the trajectory of the global attractor, extreme acts as the role.

The optimal position of population in the local has many advantages. Because it has strong appeal, and the particle swarm are clustered in this point which means that the particle swarm into the local optimum and the optimal value can not obviously improve population. At this point, only to get rid of attracting local extremum position can once again find extreme value. As shown in Figure 10, when in a local optimal location A, due to its attractive, particle swarm aggregation in the region near the moving position of A, the optimal position of population basically no change. Only particles from position A to attract and arrive at the position B can produce excellent extreme points of the new B, which will it be possible to achieve the global optimal position C.

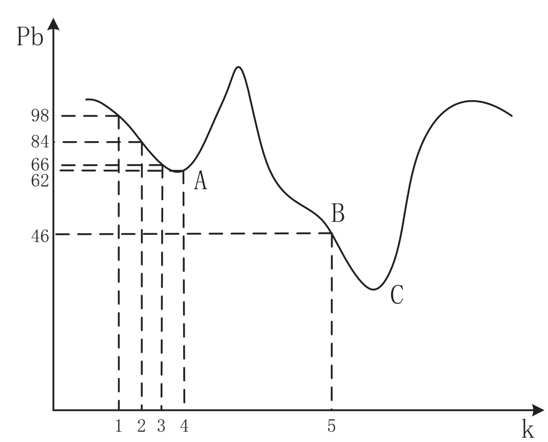


Fig. 10: Particle swarm aggregation in the region near the moving position.

5 Conclusions

Based on the evolution strategy of particle swarm optimization algorithm, performance analysis was obtained and it has found that the different evolutionary strategies have different effect on the particle swarm optimization performance. Therefore the different evolution strategies were discussed together to form a strategy of queue. Thought choice evolution strategy is also based on a dynamic in the process of operating system thread scheduling, which namely particle swarm optimization evolutionary strategy. Particle swarm algorithm can be chosen whether to continue to use the current evolutionary strategy or to use an evolutionary strategy based on the current situation of evolution. The strategy of adaptive scheduling particle swarm optimization algorithm is more conducive to optimization by testing the improved particle swarm optimization algorithm using three standard test functions. Compared with the CPSO algorithm, ASPSO algorithm optimization performance is more excellent than the CPSO algorithm. And the ASPSO algorithm is used to optimize the parameters of the pressure vessel model which also have achieved good performance.

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