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Study on an Improved Quantum PSO Algorithm for Solving Complex Optimization Problem

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Abstract

Particle swarm optimization (PSO) algorithm is a population-based search algorithm by simulating the social behavior of birds within a flock. It is a simple and efficient optimization algorithm. But it exists the low computational speed and easy falling into local optimal solution in solving the complex problem. So the quantum theory, adaptive inertia weight, disturbance factor and diversity mutation strategy are introduced into the PSO algorithm in order to propose an improved PSO(IWDMDQPSO) algorithm in this paper. In the IWDMDQPSO algorithm, the quantum theory is used to change the updating mode of the particles for guaranteeing the simplification and effectiveness of the algorithm. The adaptive inertia weight is used to improve the premature convergence of the algorithm. The disturbance factor is used to avoid the premature of the algorithm. The diversity mutation strategy is used to improve the global searching ability and computation speed. Finally, the famous benchmark functions are selected to prove the performance and effectiveness of the proposed IWDMDQPSO algorithm. The experiment results show that the proposed IWDMDQPSO algorithm takes on better solving accuracy and higher computation speed in solving the complex function. So it has a remarkable optimization performance.

Keywords*: Particle swarm optimization algorithm, quantum theory, adaptive inertia weight, disturbance factor, diversity mutation strategy, optimization performance*

1. Introduction

Particle swarm optimization (PSO) algorithm has been concerned by a lot of scholars. All kinds of research results about PSO algorithm are proposed in recent years[1]. The PSO algorithm is a kind of swarm intelligence evolutionary optimization algorithm by inspiring birds foraging behavior. It has its unique advantages, such as the less adjusted parameters, easy achieving, fast convergence speed and so on. So the PSO algorithm has achieved some results in the field of function optimization, neural network training, fuzzy control and power system [2-5].

However, the PSO algorithm is the same as the existing evolutionary algorithms, and it also has some disadvantages, such as long computation time, easy falling into local optimum and premature convergence and so on. Many researchers focused on improving PSO algorithm, such as improving the inertia weight, population diversity, and combining with other algorithms and so on. Da and Ge[6] proposed a modified particle swarm optimization (PSO) with simulated annealing (SA) technique for training the artificial neural network. Hayashi *et al*. [7] proposed an improved PSO algorithm based on different characteristic to behavior of each agent for improving and enhancing the ability of searching global minimum. Luo *et al*.[8] proposed an improved particle swarm optimization (PSO) algorithm based on the discrete variables for solving non-convex NLP/MINLP problem with equality and/or inequality constraints. Yu *et al*.[9] proposed

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an improved particle swarm optimization(PSO) and discrete PSO (DPSO) with an enhancement operation by using a self-adaptive evolution strategies (ES) for joint optimization of three-layer feedforward artificial neural network (ANN) structure and parameters (weights and bias), which is named ESPNet. Li *et al*.[10] proposed an improved hybrid particle swarm optimization(IPSO) to solve complex optimization problems more efficiently, accurately and reliably. It provides a new way of producing new individuals through organically merges the harmony search(HS) method into particle swarm optimization(PSO). Hota *et al*.[11] proposed a new approach based on improved particle swarm optimization(IPSO) technique to the solution of optimal power generation to short-term hydrothermal scheduling problem. Zheng and Liu[12] proposed an collaborative optimization(CO) based on improved particle swarm optimizer(MLPSO) to handle the multidisciplinary design optimization(MDO) methods. Mandad *et al*.[13] proposed an improved parallel particle swarm optimization approach(IPPSO) based decomposed network for economic power dispatch with discontinuous fuel cost functions. Chen and Zhang [14] proposed a new admissible efficient portfolio selection model and design an improved particle swarm optimization (PSO) algorithm because traditional optimization algorithms fail to work efficiently for our proposed problem. Niu and Guo[15] proposed an improved particle swarm optimization(PSO) based on simulated annealing algorithm (SA) to enhance the global searching capacity for optimizing the parameters of SVR and selecting the input features simultaneously. Hu *et al*.[16] proposed a two-stage guide multi-objective particle swarm optimization(TSGMOPSO) algorithm to solve this optimization problem, which can accelerate the convergence and guarantee the diversity of pareto-optimal front set as well. Sun *et al*.[17] proposed the modified particle swarm optimization(MPSO) with feasibility-based rules optimize the structure of main beam in order to find the optimal parameters so as to make minimize the deadweight of main beam. Ding *et al*.[18] proposed a new cooperative extended attribute reduction algorithm named Co-PSAR based on improved PSO, in which the cooperative evolutionary strategy with suitable fitness functions is involved to learn a good hypothesis for accelerating the optimization of searching minimal attribute reduction. Wang *et al*. [19] proposed an improved self-adaptive particle swarm optimization algorithm (ISAPSO) to solve hydrothermal scheduling (HS) problem. Ishaque *et al*.[20] proposed an improved maximum power point tracking (MPPT) method for the photovoltaic (PV) system using a modified particle swarm optimization (PSO) algorithm. Zhao *et al*.[21] proposed an improved discrete immune optimization algorithm based on particle swarm optimization (IDIPSO) for Quality of Service(QoS)-driven web service composition with global QoS constraints. Cavuslu *et al*.[22] proposed an improved particle swarm optimization (PSO) algorithm by modifying the velocity update function for training the ANN. Zhao *et al*.[23] proposed an improved PSO algorithm for constructing the secondary flow calculation model. Hsieh and Chu[24] proposed the optimization of tool path planning in 5-axis flank milling of ruled surfaces using advanced Particle Swarm Optimization (PSO) methods with machining error as an objective. Zeng *et al*.[25] proposed a novel solution algorithm for multi-objective optimization problem based on grey relational degree(termed GRD-MOP). Behrooz *et al*.[26] proposed an improved territorial particle swarm optimization(TPSO) algorithm to tackle the premature convergence to local minima. The diversity is actively preserved by avoiding overcrowded clusters of particles and encouraging broader exploration. Li *et al*.[27] proposed an improved PSO in order to overcome the premature convergence defect of the basic particle swarm optimization(PSO) algorithm and provide an effective method for shape and sizing optimization of truss structure. Li and Yang [28] proposed an improved particle swarm optimization(PSO) based approach is proposed for a team of mobile robots to cooperatively search for targets in complex unknown environments. The improved cooperation rules for a multi-robot system are applied in the potential field function, which acts as the fitness function of the PSO. Li *et al*.[29] proposed an improved particle swarm optimization (PSO) algorithm with a neighborhood-redispatch(NR) technique to design an ultrawideband(UWB) antenna. Ji *et al*.[30] proposed an improved PSO based on update strategy of double extreme value by analyzing the updating ways of double extreme to solve various and complex optimization problems. Tang *et al*.[31] proposed a novel algorithm(MACPSO) based on combining particle swarm optimization(PSO) algorithm with chaos and multi-agent to reactive power optimization of power system. Tan *et al*.[32] proposed an improved particle swarm optimization I-PSOC) routing algorithm for cluster head selection randomness of clustering algorithm. Elloumi *et al*.[33] proposed a novel approach(PSO-ACO) by introducing a PSO, which is modified by the ACO algorithm to improve the performance. The new hybrid method (PSO-ACO) is validated using the TSP benchmarks. Chen *et al*.[34] proposed a novel method to improve the global performance of particle swarm optimization(PSO), which extends the exploring domain of the optimal position in the current generation and the optimal position thus achieved by every particle. Li and Wei [35] proposed an improved natural selection-based particle swarm optimization algorithm (selPSO) to optimize the trajectories. Zhang *et al*. [36] proposed an improved multi-objective PSO algorithm for the feature selection of unreliable data. Two state-of-the-art multi-objective optimization algorithms are also applied to this kind of problem.

Although these improved PSO algorithms have improved the convergence rate, but it has not solved the problem of falling into local optimum and premature convergence. So an improved PSO (IWDMDQPSO) algorithm based on the quantum theory, adaptive inertia weight, disturbance factor and diversity mutation strategy is proposed in this paper in order to improve the premature convergence, the global searching ability and computation speed of the basic PSO algorithm. And the famous benchmark functions are selected to prove the performance and effectiveness of the proposed IWDMDQPSO algorithm.

The rest of this paper is organized as follows. Section 2 briefly introduces particle swarm optimization (PSO) algorithm. Section 3 briefly introduces the quantum PSO algorithm. Section 4 briefly introduces the description of multi strategies, including adaptive inertia weight, disturbance factor and diversity mutation strategy. Section 5 introduces an improved QPSO (IWDMDQPSO) algorithm based on the multi strategies. Section 6 gives experiment for famous benchmark functions and results analysis. Finally, the conclusions are discussed in Section 7.

2. Particle Swarm Optimization (PSO) Algorithm

The PSO algorithm [37] is a population-based search algorithm by simulating the social behavior of birds within a flock. In PSO algorithm, individuals referred to as particles, are “flown” through hyper dimensional search space. The positions of particles within the search space are changed based on the social-psychological tendency of individuals in order to delete the success of other individuals. The changing of one particle within the swarm is influenced by the experience, or knowledge. The consequence of modeling for this social behavior is that the search is processed in order to return toward previously successful regions in the search space. Namely, the velocity(v) and position(x) of each particle will be changed by the particle best value (pB) and global best value (gB). The velocity and position updating of the particle is described as follow:

$$v_{ij}(t+1) = wv_{ij}(t) + c_1 r_1 \left(pB_{ij}(t) - x_{ij}(t) \right) + c_2 r_2 \left(gB_{ij}(t) - x_{ij}(t) \right) \quad (1)$$

$$x_{ij}(t+1) = x_{ij}(t) + v_{ij}(t+1) \quad (2)$$

where $v_{ij}(t+1)$ is the velocity of the i^{th} particle at iterations j^{th}, $x_{ij}(t+1)$ is the position of particle i^{th} at iterations j^{th}. w is inertia weight to be employed to control the impact of the previous history of velocity. Accordingly, the parameter w regulates the trade-off between the global exploration ability and local exploration ability of the population. A large inertia weight facilitates the global exploration, while a small one tends to facilitate the local exploration. A suitable value of the inertia weight w usually provides the balance between the global exploration ability and local exploration ability, and consequently results in a reduction of the number of iterations required to locate the optimum solution. t is the number of iteration, c_1 is the cognition learning factor, c_2 is the social learning factor, r_1 and r_2 are random numbers uniformly distributed in [0, 1], which denote the remembrance ability for the research. So the particle flies through the potential solutions towards pB and gB in one navigated way, while still explore new areas by the stochastic mechanism to escape from the local optimal value . Generally, the value of each component in the V can be clamped to the range $[-V_{\max}, V_{\max}]$ for controlling the excessive roaming of particles outside the search space. The PSO algorithm is terminated with the maximal number of iteration or the best particle position in the population can not be further improved after a sufficiently large number of iteration are executed. The PSO has shown the robustness and effectiveness in solving optimization function problems.

The basic flow chart of the PSO algorithm is shown in Figure 1.

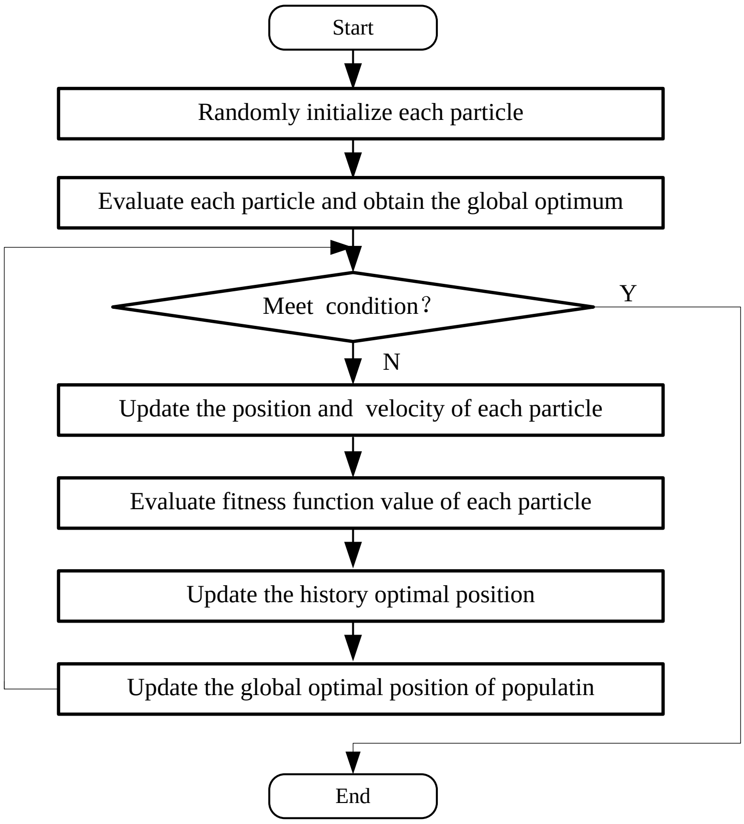

Figure1. The Basic Flow Chart of PSO Algorithm

3. The Quantum PSO Algorithm

In the basic PSO algorithm, the convergence of the particle is realized by using the track method. Because the velocity of the particle is always limited, the search space in the search process is a limited area. It does not include the whole feasible solution space. And the basic PSO algorithm can not ensure that the value of probability is one for searching the global optimal solution. But the particle can meet the aggregation state in the quantum space, and it can realize the search in the whole feasible solution space. Sun proposed a quantum particle swarm optimization (QPSO) algorithm. The QPSO algorithm has better than the basic PSO algorithm. In the QPSO algorithm, the velocity and position of the particles are attributed to one parameter. Each particle must converge to the respective point p in order to ensure the convergence of the QPSO algorithm, and $p=(p_1, p_2, \cdots, p_D)$.

$$p_D = \frac{\varphi_1 \times p_{iD} + \varphi_2 \times p_{gD}}{\varphi_1 + \varphi_2} \tag{3}$$

where φ_1 and φ_2 are random number on [0,1].

In order to calculate the next iteration variable of the particle, a middle optimal position is proposed in this paper. The value of the middle optimal position is described as the average value of the local extremum for all particles. The calculation expression is described as follow:

$$m_{best} = \frac{1}{M}\sum_{i=1}^{M} p_i = \left(\frac{1}{M}\sum_{i=1}^{M} p_{i1}, \frac{1}{M}\sum_{i=1}^{M} p_{i2}, \cdots, \frac{1}{M}\sum_{i=1}^{M} p_{iD},\right) \tag{4}$$

where p_i is the global extremum of the i^{th} particle for controlling the convergence speed, M is the number of particles. So the evolution expression of the particle is described as follow:

$$x(t+1) = p \pm \beta \times | m_{best} - x(t) | \times \ln(1/u) \tag{5}$$

where $u = rand(0,1)$, β is the coefficient creativity. In general, the QPSO algorithm can get the better solving result by using linear decreasing value of β.

$$\beta = (1-0.5) \times (Iter_{\max} - t) / Iteration_{\max} + 0.5 \tag{6}$$

4. The Description of Multi Strategies

4.1. Adaptive Inertia Weight

The inertia weight w in the QPSO algorithm plays an important role for determining the convergence. It can use the particle to keep the motion inertia. The larger value of the inertia weight w is beneficial to improving the fast convergence speed, and it is not easy o obtain the accurate solution. However, the smaller value of the inertia weight w is beneficial to obtaining more accurate solution, but it has the slow convergence speed. So there proposed some improved methods for controlling the inertia weight w, such as the linear reducing inertia weight, dynamical adjusting inertia weight, and so on. But these improved methods can not be widely applied for solving the complex problem because of the complex implementation process. Therefore, an adaptive inertia weight strategy is used to improve the performance of the QPSO algorithm. This strategy is described as follow:

$$w = 1.5 - \frac{1}{1 + k_1 \times \exp(-k_2 \times | f_g - f_{avg}^{'} |)} \tag{7}$$

where k_1 and k_2 are the control parameters, f_g is the optimal fitness value of the population, f_{avg} is the average fitness value of all particles, f'_{avg} is the average fitness value of all particles with superior f_{avg}. $| f_g - f'_{avg} |$ is used to evaluate the premature convergence of the population. If the value is smaller, then the particle is more premature convergence.

4.2 The Disturbance Factor

Like other evolutionary algorithms, the main problem of the QPSO algorithm is how to enhance the searching ability of the particles. With the increasing of the size of the optimization problem, the algorithm must take on the good performance in order to prevent the particles to fall into the local optimal solution and reduce the searching ability.

In order to prevent the occurrence of premature convergence, the disturbance factor is introduced into the search process of the QPSO algorithm. When the two following conditions occur, the premature phenomenon will generate. A part of the particles converge to the current global optimum, or the distance between adjacent particles is smaller. For one random search process, it is inevitable for a part of the particles converge to the current global optimum. Because there will certainly produce the current global optimum by comparing the particles. But it can avoid the premature phenomenon for the smaller distance between adjacent particles. The disturbance factor is introduced to update the position of particle in order to avoid the smaller distance between adjacent particles. The disturbance factor uses the normal distribution vector to change the position and direction of the current search particle, so that the particles are far from the neighboring particle for improving the diversity of the particle. The disturbance factor is described as follow.

$$x(i) = x(i) + \lambda * rand() \tag{8}$$

where $x(i)$ is the current position of the i^{th} individual, λ is a control parameter, $rand()$ is a random function of the normal distribution value. When the distance between adjacent particles is smaller, the disturbance factor can avoid the premature phenomenon. But how to determine the algorithm to occur premature phenomenon, the determining criteria is used in the search process. The premature factor is f_m, the number of repeated iteration is f_g. When the number of repeated iteration is greater than the premature factor($f_g > f_m$), then the disturbance factor is used.

4.3. The Diversity Mutation Strategy

In the random initialization stage of QPSO algorithm, the diversity of the population is higher. But with the advance of evolution, the difference of particles is reduced and the diversity of the population is decreased, which fall into the local optimum and occur the premature phenomenon for QPSO algorithm. So the diversity mutation strategy is used to improve the QPSO algorithm. The advantages of the evolutionary algorithm and QPSO algorithm are combined in order to improve the search performance.

The diversity formula of the QPSO algorithm is described as follow.

$$d^t = \frac{1}{n\delta} \sum_{i=1}^{n} \sqrt{\sum_{j=1}^{n} (x_{ij}^t - \overline{x_j^t})^2} \tag{9}$$

where δ is the length of the longest diagonal line in the search space.

In order to keep the diversity of the population, when $d^t < d_{low}$, the following mutation operation is performed in order to make the population for jumping away the local extreme point.

$$\begin{cases} p_j^t = p_j^t + \rho \times \delta \times \zeta \\ p_{g,j}^t = p_{g,j}^t + \rho \times \delta \times \zeta \end{cases} \tag{10}$$

where $\zeta \sim N(0,1)$, ρ is a specified parameter. $\rho \geq 10 d_{low}$ is proposed in order to meet the requirement of $d^t < d_{low}$ after the mutation is executed.

In the process of the mutation operation, the value of $| p_j^t - p_{ij}^t |$ is increasing with the global best position of particle migration. At the same time, the average best position of the population is also updated to broke the particle aggregation state for increasing the diversity of particles and avoiding the premature phenomenon.

5. An Improved QPSO (IWDMDQPSO) Algorithm Based on the Multi Strategies

Because the PSO algorithm takes on the advantages of the simple concept and easy operation and so on, it obtains the wide research and rapid development in recent years. But the PSO algorithm has the low computation speed, easy falling into local optimal solution, and tendency towards stagnation in solving complex function, and so on. The quantum theory can change the updating mode of the particles to ensure the simplification and effectiveness. The adaptive inertia weight is used to improve the premature convergence of the algorithm. The disturbance factor can avoid the premature phenomenon. The diversity mutation strategy can avoid declining the population diversity in the search process. So the quantum theory, disturbance factor and diversity mutation strategy are introduced into the basic PSO algorithm in order to propose an improved ACO(IWDMDQPSO) algorithm in this paper. In the proposed IWDMDQPSO algorithm, the quantum theory is used to change updating strategy of the particle, improve the global convergence ability and obtain the search method of the particle with the simplification and effectiveness. The disturbance factor is used to prevent the occurrence of premature convergence. The diversity mutation strategy can avoid declining the population diversity in the search process, improve the global searching ability and computation speed. Therefore, the proposed IWDMDQPSO algorithm takes on better solving accuracy , higher computation speed and a remarkable optimization performance in solving the complex function problems.

6. Experiment and Results

6.1. Test Function and Test Environment

In order to test the effectiveness of the proposed IWDMDQPSO algorithm, five benchmark functions and the basic PSO algorithm, QPSO algorithm and APSO algorithm are selected in this paper. The parameters' values of four algorithms are the complicated problems, the parameters' changes could affect the optimum value. So the selected parameters' values are those that gave the best computation results concerning both the quality of the solution and the run time needed to achieve this solution. The obtained initial parameters' values of four algorithms are shown in Table 1.

Table 1. The Obtained Initial Parameters' Values of Four Algorithms

Parameters	PSO	QPSO	APSO	IWDMDQPSO
Population size(M)	100	100	100	100
Iteration ($T_{\max}$)	500	500	500	500
Initial inertia weight(w)	0.80	0.80	0.80	0.80
Max velocity(V)	80	80	80	80
Learn factor	$c_1 = c_2$ =2	$c_1 = c_2$ =2	$c_1 = c_2$ =2	$c_1 = c_2$ =2
Mutation probability(P_m)	N/A	N/A	N/A	0.1

Five benchmark functions from the famous benchmarks are shown in Table 2.

Table 2. Benchmark Functions

Fun.	Function Expression	Opt.	Range
f_1	$f(x) = \sum_{i=1}^{n} x_i^2$		[-100,100]
f_2	$f(x) = \sum_{i=1}^{n} (\sum_{j=1}^{i} x_j)^2$		[-100,100]
f_3	$f(x) = \sum_{i=1}^{n} i x_i^4 + random[0,1)$	0	[-1.28,1.28]
f_4	$f(x) = \frac{1}{4000} \sum_{i=n}^{n} x_i^2 - \prod_{i=1}^{n} \cos(\frac{x_i}{\sqrt{i}}) + 1$		[-600,600]
f_5	$f(x) = \max_i \{\lvert x_i \rvert, 1 \le i \le n\}$		[-100,100]

6.2. Test Results and Analysis

In the experiment process of four algorithms, the optimization result of the proposed IWDMDQPSO algorithm is compared with the optimization results of the PSO algorithm, the QPSO algorithm and APSO algorithm. Each continuous function with 30 dimensions are is independently run 20 times in order to represent the performance of the proposed IWDMDQPSO algorithm. The best value and the average value are selected to describe the performance of four algorithms. The experiment results are shown in Table 3.

Table 3. The Experimental Tested Results

Fun.	Algorithms	Optimal value	Best value	Average value
f_1	**PSO**	0	6.2306E-006	2.4528E-004
	QPSO	0	6.0741E-046	5.5076E-044
	APSO	0	**4.6417E-047**	2.6414E-044
	IWDMDQPSO	0	2.9403E-049	7.3603E-046
f_2	**PSO**	0	3.8651E-003	9.3528E-002
	QPSO	0	4.9034E-012	2.1682E-009
	APSO	0	1.3627E-020	4.5672E-016
	IWDMDQPSO	0	5.4692E-035	6.7063E-032
f_3	**PSO**	0	4.6732E-002	1.3562E-001
	QPSO	0	7.5379E-010	5.8328E-008
	APSO	0	5.4793E-013	3.5938E-010
	IWDMDQPSO	0	2.3627E-020	7.4503E-017
f_4	**PSO**	0	3.4721E-003	2.4610E-002
	QPSO	0	5.5362E-008	2.4529E-006
	APSO	0	4.5631E-020	1.9547E-017
	IWDMDQPSO	0	**0.0000E-000**	2.4526E-040
f_5	**PSO**	0	2.3572E+001	8.4713E+001
	QPSO	0	5.6403E-012	1.4623E-010
	APSO	0	6.5218E-018	4.6046E-015
	IWDMDQPSO	0	**3.0452E-030**	7.4452E-026

As can be seen from Table 3, the IWDMDQPSO algorithm can find the best solution for the five benchmark functions by observing and analyzing the experiment results. For the functions f_4, the best optimal solution (0) is been found by using the IWDMDQPSO algorithm in the experiment. The experiment results show that the IWDMDQPSO algorithm has the better searching ability than the PSO algorithm, QPSO algorithm and APSO algorithm. The proposed IWDMDQPSO algorithm takes on better optimization performance for five functions. So the IWDMDQPSO algorithm can better search for the global optimization solution, and it can improve the computation speed and avoid to fall into local optimal solution and the premature phenomenon in solving the complex problem.

7. Conclusion

The PSO algorithm is a population-based search algorithm inspiring birds foraging behavior. It has the less adjusted parameters, easy achieving, fast convergence speed and so on. But it exists the long computation time, easy falling into local optimum and premature convergence and so on. So an improved PSO(IWDMDQPSO) algorithm based on the quantum theory, adaptive inertia weight, disturbance factor and diversity mutation strategy is proposed to improve the premature convergence, the global searching ability and computation speed of the basic PSO algorithm. The quantum theory is used to change the updating mode of the particles for guaranteeing the simplification and effectiveness of the algorithm. The adaptive inertia weight is used to improve the premature convergence of the algorithm. The disturbance factor is used to avoid the premature of the algorithm. The diversity mutation strategy is used to improve the global searching ability and computation speed. And five benchmark functions, the basic PSO algorithm, QPSO algorithm and APSO algorithm are selected to test the effectiveness of the proposed IWDMDQPSO algorithm. The experiment results show that the proposed IWDMDQPSO algorithm has the better searching ability than the PSO algorithm, QPSO algorithm and APSO algorithm. It can better search for the global optimization solution, improve the computation speed and avoid to fall into local optimal solution and the premature phenomenon in solving the complex problem.

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