Verification of calculation efficiency of a new CS-PSO algorithm and its application

Juan Yang*, Xuesong Han

Cheng De Petroleum College, Chengde, Hebei, 067000, China

Received 1 July 2014, www.cmnt.lv

Abstract

Intelligent algorithm is developing rapidly with the development of computer technology. And it is widely used in scientific research and industrial application. As a kind of intelligent algorithm, particle swarm optimization (PSO) has been used in solving problem for a long time. It is based on the bird group behaviour and uses biological group model to find the optimal solution. Its advantages are fast calculation speed and easy implementation while the disadvantages are easily getting into the local extreme, slow convergence speed in the late evolutionary and poor precision. In order to avoid the disadvantages, some modification has been studied for PSO algorithm and establishes the concentration degree and steady degree based PSO (CS-PSO) algorithm in the paper. Based on the convergence performance of particle swarm depends on the particle exploration ability, search space has been adaptively adjusted to improve the convergence performance of particle swarm optimization with the variation of optimal fitness value. Corresponding adjusted method has been shown in the paper. According to the example verification, the CS-PSO is effective and then the algorithm is used in the bellow structure optimization.

Keywords: intelligent algorithm, particle swarm optimization, space adjusted, experimental test

1 Introduction

Intelligent computing is also known as "soft computing", which is affected by natural rules of enlightenment. According to its principle, imitate the algorithm to solve the problems. Principle of bionics design (including the design algorithm) is intelligent computing thought. Intelligent algorithms [1-5] are more and more widely used in solving different optimization problems. Programming of the intelligent algorithm includes linear programming [6-9], dynamic programming [10-12], etc. The content includes many algorithm, such as artificial neural network [13-15], genetic algorithm [16], simulated annealing algorithm [17], and swarm intelligence technology [18].

As an important kind of intelligent algorithm, the PSO is easy to realize with not too many parameters need to be adjusted. It needs not differentiable derivative and related information. PSO can be used as a permutation and combination optimization method to solve mixed integer nonlinear problems [19].

Particle swarm optimization (PSO) algorithm is a new evolutionary algorithm which is developed by Kennedy and Eberhart in 1995. The basic idea is inspired by results of bird group behaviour, and use and improved the biological group model developed by biologists to provide the particles fly to the optimal results in solution space. It belongs to a class of stochastic global optimization technique and finds optimal regions in complex search spaces through the interaction between particles. Its advantages are fast calculation speed and easy implementation while the disadvantages are easily getting into the local extreme, slow convergence speed in the late evolutionary and poor precision.

In PSO, each solution of the optimization problem is a bird in space, which we call "particle". All the particles have a fitness value, which is determined the optimized function. Each particle has a speed to determine the direction and distance. Then particles follow the current optimal particle to search in the solution space.

PSO is initialized to a group of random particles (stochastic), and then through the iteration to find the optimal solution. In each iteration, particle is updated by following two extreme values. The first is the optimal solution found by particles themselves, and this solution is called. The other extreme is the optimal solution found by all the particles, and this solution is called. It is also just to one part of the particles as neighbour instead of all the particles. In this condition, the optimal solution is the local optimal solution. When particles find the two optimal solutions, they will update the information of themselves.

Iteration termination condition usually select maximum iterative times or current optimal position fit for the minimum adaptive threshold as the terminal conditions. The basic particle swarm optimization will not need the user to determine many parameters, so the method is quite convenient. But it is easy to fall into local optimum, and the search accuracy is not high. Therefore, it is necessary to improve [20-25].

Although there is many improved method for PSO, it still has room to grow. In order to avoid the disadvantages, some modification has been studied for PSO algorithm and establishes the concentration degree and steady degree

* ***Corresponding author*** e-mail: yangjuansky@126.com

based PSO (CS-PSO) algorithm in the paper. Based on the convergence performance of particle swarm depends on the particle exploration capability, search space has been adaptively adjusted to improve the convergence performance of particle swarm optimization with the variation of optimal fitness value. The main contribution of the paper is the proposition of an improved PSO algorithm (CS-PSO). The remainder of the paper is organized as follows: Standard PSO algorithm is described in section 2. CS-PSO method, including some definition and the mathematical model is shown in section 3. Examples verification and engineering application are shown in section 4. Application introduction is shown in section 5. And the conclusion is described in section 6.

2 PSO

2.1 STANDARD PSO algorithm

For arbitrary particle *d* in the space, position and speed updated at *k-th* times iteration can be expressed as the x_d^k and v_d^k. The position and speed of $(k+1)$ times of iteration would be updated by the Equations (1) and (2).

$$x_d^{k+1} = x_d^k + v_d^{k+1}, \tag{1}$$

$$v_d^{k+1} = \omega v_d^k + c_1 r_1 (p_d^k - x_d^k) + c_2 r_2 (p_g^k - x_d^k), \tag{2}$$

where, ω is the inertia coefficient; r_1 and r_2 are the random number between 0 and 1. Generally, $c_1 = c_2 = 2$. Position vector p_d^k is the optimal position in *k-th* times iteration of particle *d*, which is called p_{best}. p_g^k is the optimal position in *k-th* times of iteration found by all the particles, which is called G_{best}.

The inertia coefficient would vary in the search process with the principle of Equation (3).

$$\omega = \omega_{\max} - \frac{\omega_{\max} - \omega_{\min}}{k_{\max}} \times k\,. \tag{3}$$

3 CS-PSO method

How to improve global convergence performance of PSO is always one of the focuses of current research. The convergence performance of particle swarm depends on the particle exploration capability in the solution space. The global convergence performance of PSO algorithm can be improved by improving the particles search ability.

3.1 DEFINITION

In this paper, we will give some definitions and these definitions would be used in the modified PSO method.

Definition 1: Set $p_{best}(i,k)$ as the fitness value for the best position of the particle *i* at time *k*, and set $g_{best}(k)$ as the best position of all particle's fitness value. Then we define the concentration degree $con\_\deg(k)$ as the following:

$$con\_\deg(k) = \begin{cases} \dfrac{|g_{best}(k)|}{\frac{1}{M}\sum_{i-1}^{M}|p_{best}(i,k)|} & \frac{1}{M}\sum_{i-1}^{M}|p_{best}(i,k)| \neq 0 \\ \lim \dfrac{|g_{best}(k)|}{\frac{1}{M}\sum_{i-1}^{M}|p_{best}(i,k)|} & \frac{1}{M}\sum_{i-1}^{M}|p_{best}(i,k)| = 0 \end{cases}. \tag{4}$$

Apparently, $con\_\deg(k)$ is between 0 and 1. After iteration for a certain time, $con\_\deg(k)$ would move close to 1. This means the particles concentrate together. $con\_\deg(k)$ reflects all particle concentration degree at time k.

Definition 2: Set the steady degree $ste\_\deg(k)$ as:

$$ste\_\deg(k) = \begin{cases} \dfrac{|g_{best}(k)|}{\frac{1}{S}\sum_{i-1}^{S}|g_{best}(i,k)|} & \frac{1}{M}\sum_{i-1}^{M}|p_{best}(i,k)| \neq 0 \\ \lim \dfrac{|g_{best}(k)|}{\frac{1}{S}\sum_{i-1}^{S}|p_{best}(i,k)|} & \frac{1}{S}\sum_{i-1}^{S}|p_{best}(i,k)| = 0 \end{cases}. \tag{5}$$

In the definition, S is the smooth order. It usually uses an integer between 10 and 200. $ste\_\deg(k)$ is also between 0 and 1. After iteration for a certain time, the $ste\_\deg(k)$ would move close to 1. Then, the velocity of the particle is approximately to 0. It reflects the steady degree of the particle at the time k.

Obviously, at a certain time in the iteration, all or part of the particles can be modified to jump out of local solutions to obtain the global optimal solutions with the concentration and stable degree of the particle.

3.2 CONCENTRATION AND STEADY DEGREE BASED PSO ALGORITHM (CS-PSO)

Searching in the standard PSO algorithm, particle swarm will move to the local minimum or global minimum convergence. In this case, PSO often has searched the region or close region with global optimal position in it. Then, the searching speed is much slower than earlier period, the search speed is almost zero and the local search ability is extremely low. Therefore, it is necessary to avoid the occurrence of this phenomenon by effective measures to provide finer search for the small range of the global optimal solution to improve the efficiency and accuracy. In this condition, search space should be adaptively adjusted to improve the convergence performance of particle swarm optimization with the variation of optimal fitness value.

Main idea of the CS-PSO.

Set $g_{best}(k)$ as the fitness value of particle swarm optimization at the iteration step K, the corresponding optimal position is $x_g = (x_{g1}, x_{g2}, \ldots, x_{gN})$. The original variation interval of dth dimension variable particle is $region(d) = [s_{left-d}, s_{right-d}]$, $d = 1,2,\ldots,N$. Shrinkage factor of the interval $\alpha \in (0,1)$ and maximum permissible error of the interval is δ. After iteration for K steps, then $g_{best}(k) - g_{best}(k-L) < \varepsilon$, and $K - L > 0$, ε is the permissible error with given fitness. L is a positive integer. Adjustment of particle swarm search space will be given according to the following formula:

$$region(d) = \begin{cases} [x_{gd} - \alpha(1-\alpha)(x_{gd} - s_{left-d}), x_{gd} + \alpha(1-\alpha)(s_{right-d} - x_{gd})] \\ if\ \max\{s_{rght-d} - s_{left-d}\} > \delta \\ [s_{left-d}, s_{right-d}] \\ others \end{cases}, \quad d = 1,2,\ldots,N. \tag{6}$$

So, as the iteration proceeds, convergence speed of particle swarm optimization ability and local exploration would be enhanced according to the contraction of particle swarm search space to improve the convergence accuracy of particle swarm. When it at a certain moment and the solution space contraction to a certain extent, it can be extended particle swarm search space to provide all particles have fully variation in the new space to jump out of local optimum to obtain the global optimum. This method can balance the efficiency and precision of the optimization process"

The CS-PSO algorithm can be divided in to some steps as shown in Figure 1.

4 Verification

4.1 MATHEMATICS MODEL VERIFICATION

Parameters in the PSO will be set as: the inertia weight of the maximum and minimum values is 0.9 and 0.1 respectively. Maximum iteration number is 2000 and independent operation for 50 times.

1) Test function is shown as the following:

$$\min f_1(x) = (x_1 - 10)^3 + (x_2 - 20)^3,$$

$$\text{S.t} \begin{cases} 100 - (x_1 - 5)^2 - (x_2 - 5)^2 \le 0 \\ (x_1 - 6)^2 + (x_2 - 5)^2 - 82.81 \le 0, \\ 13 \le x_1 \le 100, \quad 0 \le x_2 \le 100 \end{cases}$$

The global optimal solution is $x^* = (13.985, 0.8216)$, and then $f(x^*) = -6908.324$.

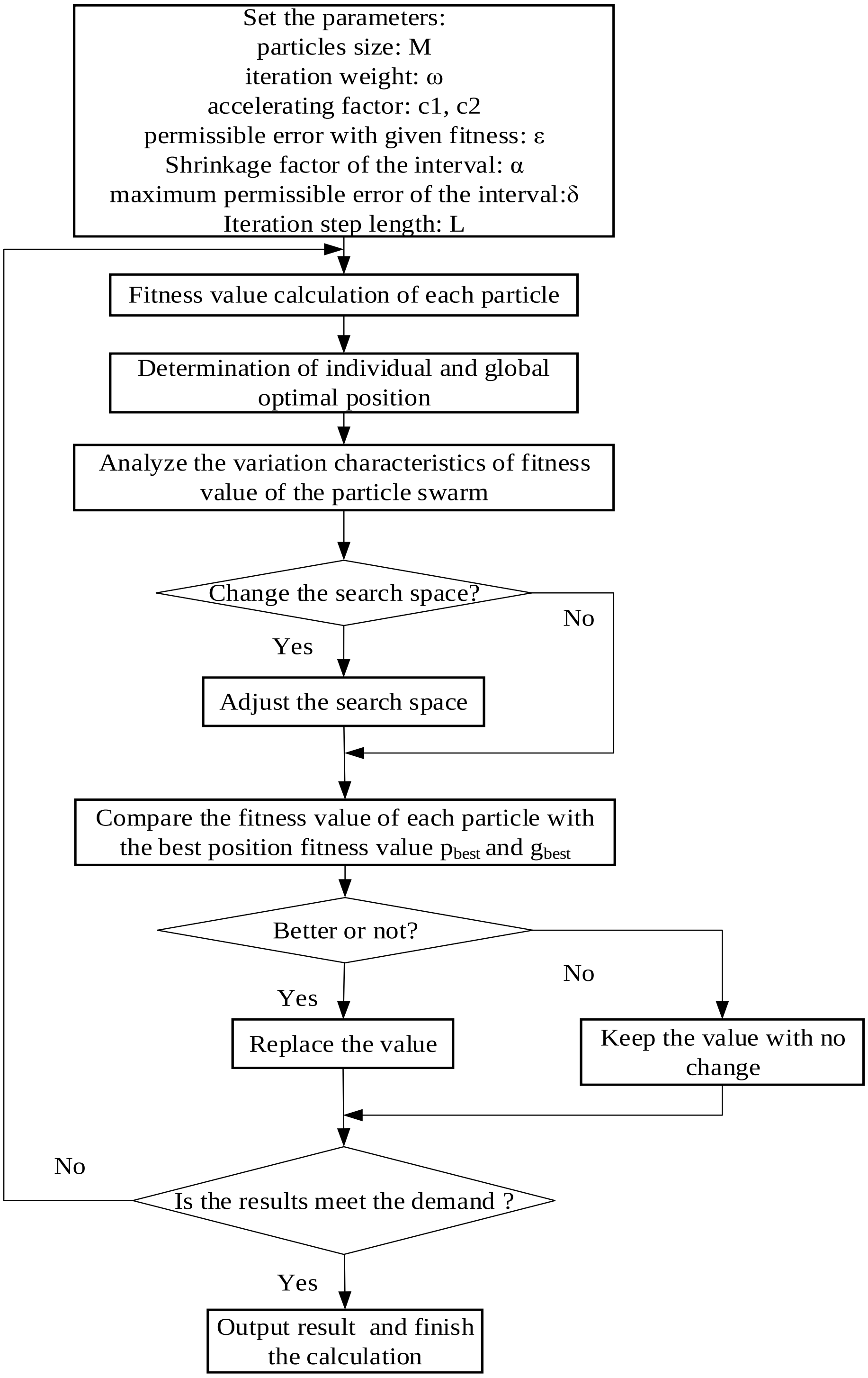

FIGURE 1 Flow chart of CS-PSO

2) Test function is shown as the following:

$$\min\ f_1(x) = (x_1 - 10)^3 + (x_2 - 20)^3 .$$

$$\text{S.t.} \begin{cases} 0 \le 85.125 + 0.005723 x_2 x_5 + 0.000624 x_1 x_4 - 0.002204 x_3 x_5 \le 100 \\ 90 \le 80.5125 + 0.007231 x_2 x_5 + 0.0030032 x_1 x_2 + 0.0021813 x_3^2 \le 110 \\ 25 \le 9.300736 + 0.0047012 x_3 x_5 + 0.0012591 x_1 x_3 - 0.00190021 x_3 x_4 \le 25 \\ 75 \le x_1 \le 103,\ 33 \le x_2 \le 50 \quad 25 \le x_i \le 45,\ i = 3,4,5 \end{cases} .$$

The optimal value is $f(x^*) = 680$.

3) $\min f_3(x) = x_1^2 + (x_2 - 1)^2$.

$$\text{S.t} \begin{cases} x_2 - x_1^2 = 0 \\ -1 \le x_i \le 1, \quad i = 1,2 \end{cases}.$$

The optimal value is $f(x^*) = 0.74$.

4) $\min f_4(x) = x_1^2 + 4x_2^2$.

$$\text{S.t} \begin{cases} x_1 - x_2 - 1 \le 0 \\ x_2 - 1 \le 0 \\ -x_1 - x_2 + 1 \le 0 \end{cases}.$$

The optimal value is $f(x^*) = 0.800001$, while the $x^* = (0.8, 0.2)$.

Table 1 gives the results comparison of algorithm proposed in the paper and other algorithms referred in other paper. In the table, results of algorithm proposed in the paper show better performance than PSO.H and GA algorithms. The optimal value found by the particle size of 20 with the method proposed in the paper has a good performance with the optimal value found by particle size of 20 with the other method. For some functions, algorithm proposed here can get better results.

TABLE 1 Results comparison with other algorithms

Function	TRPSO Particles size M=40; $c_1=c_2=1$	TRPSO M=20; $c_1=c_2=1.8$	**f(x*) M=20; $c_1=c_2=1.8$**	**PSO.H**	**GA**
$f_1(x)$	-6961.813876	-6961.813876	-6961.813876	-6961.7	-6952.1
$f_2(x)$	-30665.538672	-30665.538672	-30665.538672	-30665.5	-30664.5
$f_2(x)$	0.749912	0.749917	0.749990	0.75	0.75

TABLE 2 Results comparison with other algorithms

Function		**Number of experiments**	**Effect number of experiments**	**Mean number of iteration**
$f_3(x)$	TRPSO	50	50	12.1
	MRR	10	6	30
$f_4(x)$	TRPSO	50	50	16.3
	MRR	10	10	25

The algorithm in calculation is compared with the other algorithms by the convergence rate and stability. The results are shown in Table 2. It is shown that the convergence efficiency and velocity of the algorithm in this paper are higher. The experimental results show the effectiveness and rationality of the proposed algorithm, which means certain advantage of the algorithm.

4.2 ENGINEERING EXAMPLES

Bellows expansion joints are widely used in petroleum system, chemical plant and the nuclear system. They are the temperature and stress displacement compensation element. The bellows are the main components, and the structural design parameters are integer and discrete. The design process involves many performance constraints and highly nonlinear for objective function. Bellow optimization design problem belongs to problems with nonlinear constrained discrete design variables.

1) Use this method to optimize the structure parameters for bellow with design pressure of 0.25MPa and diameter of 400 mm. The optimal solution of $x_1, x_2, x_3, x_4(n, N, h, t)$ is found the least unit volume weight.

x_1, x_2, x_3, x_4 are layers number, wave number, wave height and single wall thickness. x_1, x_2, x_3, x_4 are all discrete variables, and x_1, x_2, x_3 are integer multiple while x_4 is the integer multiple of 0.2.

The constraint condition of the self-variable are:

$$\begin{cases} 1 \le x_1 \le 10 \\ 1 \le x_2 \le 10 \\ 30 \le x \le 70 \\ 0.6 \le x_4 \le 1.2 \end{cases}.$$

Corrugated pipe material is 316L and the design temperature is 300℃. The pitch of waves is $q = 41mm$, and fatigue life cycles is 10500 times. Taken steel plate utilization into consideration, the bellows expansion length should be 500 mm with an error less than 5%.

Constraint conditions of calculation method, relevant parameters, strength, stability and fatigue life of the bellows are referred with related papers. For the simplification of calculation, strength factor of $C_m = 3.0$ are adopted. Then, the mathematics model for the bellow can be described as the following:

Find $X(x_1, x_2, x_3, x_4)$ to provide the $\min f(x) = \dfrac{Q}{E}$, $Q = (D_b + x_1 x_3) \times 3.14 x_1 x_3 \rho$, $L = (2x_3 + 0.57lq)x_2 + 2L_l$, where, ρ is the density of bellow material; D_b is the diameter.

$Q = (D_b + x_1 x_3) \times 3.14 x_1 x_3 \rho$, $E = x_2(e - 0.15q\phi)$, where, e is the compensation rate for bellow.

$$e=\max\left\{e_1=e_\theta+e_y-|e_x|, e_2=e_\theta+\frac{0.15q\phi}{c\theta}-|e_x|\right\},$$

$e_{x,y}=\dfrac{[2\sigma_T-0.7(\sigma_T+\sigma_T)]x_3^2}{\dfrac{E_b t_p^2}{2x_3C_f}+\dfrac{5E_b t_p}{3C_d}}$, where, t_p thickness of the bellow; e_x, e_y, e_θ are the displacement of axial, horizontal and angular direction; C_d, C_f, C_θ, ϕ are the coefficients. E_b is the elastic modulus which is subject to $\begin{cases} p-p_{sc}\le 0 \\ p-p_{si}\le 0\end{cases}$, where, p is the design pressure; p_{sc}, p_{si} are column instability and plane instability pressure limit.

$\begin{cases}\sigma_1-\sigma_{sb}^{'}\le 0\\ \sigma_2-\sigma_{sb}^{'}\le 0\\ (\sigma_3+\sigma_4)-3\sigma_{ab}^{'}\le 0\end{cases}$, where, $\sigma_{sb}^{'}$ is the allowable stress for the corrugated pipe with design temperatures; $\sigma_1,\sigma_2,\sigma_3,\sigma_4$ are the film pressure and bending stress due to the stress for corrugated pipe, respectively.

$0.95L_d\le L\le L_d$, $N_C-[N_C]\le 0$, where, L_d is expansion to fixed length or their divisibility times, L is the bellow expansion length, $[N_C]$ is the allowed design life of bellow, N_C is the working life of bellow.

The equations described above represent the variable constraint, stability constraint, strong constraint, expansion length constraint and fatigue life constraints.

2) The optimization calculation and result analysis

To meet the requirement of engineering, the optimal solution should be discrete solution in the feasible domain. Define initial constraint penalty factor is big enough relative to the optimal objective function. With the test results, define $r=100$, discrete penalty factor $s_{d0}=1$ and $c=1.005$. The maximum iterations number $K_{\max}=100$. Particle number $N_d=50$ and $\omega_{\max}=1.2$, $\omega_{\min}=0.4$. Optimization design of discrete variables is processed for the bellow and calculation results and theoretical solution is included in the Table 3 by using the grid method.

TABLE 3 Comparison of results with different calculation methods

Method	x_1	x_2	x_3	x_4	$F(x)$	$s\phi(x)$	$rG(x)$	$\frac{Q}{E}$
Existing parameters	1	3.0000	45	1				0.086
New method	1	4.9893	30	0.58	0.046	0	0	0.0472
Theoretical solution	1	5.0000	32	0.6				0.047

From the result of this method, the optimization target value increases by 66.31%. The difference between the method and the theoretical solution is less than 1%. The optimal solution is $(1,4.9893,30,0.6)$. The discrete degree is very high and satisfies the discrete accuracy requirements.

In the solving process, 10 local optimal solutions have been acquired. It can be seen that when it is at iteration times of 29, the optimal solution is approximately to the global optimal solution (Figure 2).

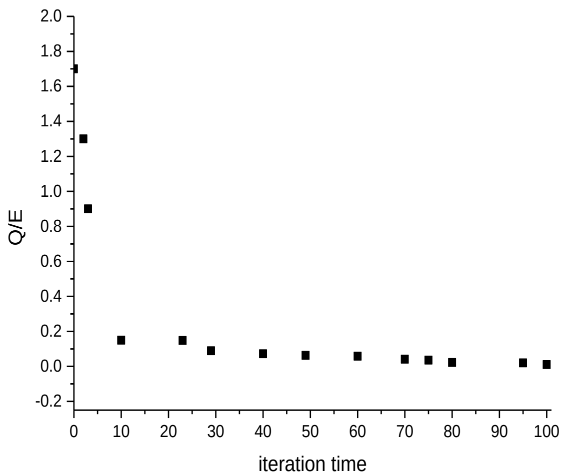

FIGURE 2 Local optimal solution

5 Application introductions

PSO algorithm is widely used in neural network training for function optimization, fuzzy system control and other intelligent algorithm. Here we give some introduction of the applications of the algorithm.

5.1 OPTIMIZATION OF FUNCTION

Study of particle swarm algorithm and convergence is to study and solve the optimization problem much better. Usually, this kind of problem is quite complex for the problem having character of large scale and high dimension. At the same time, in the mathematical nature, the complexity can be reflected as non-linear, non-convex and non-differentiable calculus properties and large number of local extreme values exists in function distribution. Compared to the traditional deterministic optimization algorithm, the PSO algorithm has the characteristics of fast reaction and high sensitivity in solving this kind of problem with the proper choice of initial value. Other global optimization algorithms, such as genetic algorithm, simulated annealing algorithm, evolutionary programming, etc. have different mechanisms and single structure, and it is difficult to achieve efficient optimization in complex functions with high dimension and direction. But the PSO algorithm combines the advantages and disadvantages and it can achieve efficient optimization of this kind of problems.

5.2 NEURAL NETWORK TRAINING

The PSO algorithm is now mainly exist in 3 aspects of training neural network:
1) network topological structure and function transfer;
2) weight settings in connection;
3) intelligent learning. Each particle can completely describe all the related parameters of the neural network. Optimization of these parameters can be obtained with repeated updating to achieve the training effect. Compared with similar types of learning algorithms, such as back propagation algorithm, particle swarm algorithm used in the neural network has advantages of without the help of differentiable derivative and differential properties in transferring information between the functions. PSO also can get better results than the error back-propagation algorithm with higher speed under high probability conditions.

5.3 PARAMETERS OPTIMIZATION

Particle swarm optimization algorithm can be used in parameters optimization in continuous and discrete problems. The problems mainly include signal processing, path planning of robot, the fuzzy controller design, and the pattern recognition problem

5.4 COMBINATORIAL OPTIMIZATION

Particle swarm algorithm with "01" string coding needs a more reasonable solution and measures in many ordered structure problems in combinatorial optimization problem and the expression of constraint handling problems. When the problems are different, correspond particles descriptions are different. It can be solved by redefining a new operator. The optimization scheme has solved a variety of TSP, VRP and scheduling problem in factories.

6 Conclusions

Intelligent algorithms are more and more widely used in solving different optimization problems. As an important kind of intelligent algorithm, the PSO is easy to use for the reason of not too many parameters to be changed. Particle swarm optimization (PSO) algorithm belongs to a class of stochastic global optimization technique and finds optimal regions in complex search spaces through the interaction between particles.

In order to avoid the disadvantages, some modification has been studied for PSO algorithm and establishes the concentration degree and steady degree based PSO (CS-PSO) algorithm in the paper. From the convergence performance of particle swarm depends on the particle exploration capability, search space has been adaptively adjusted to improve the convergence performance of particle swarm optimization with the variation of optimal fitness value. Corresponding adjusted method has been shown in the paper.

The method is applied in some functions to verify the validity, and then bellows structure design has been processed with the CS-PSO algorithm. The design process involves many performance constraints and highly nonlinear for objective function. Bellow optimization design problem belongs to problems with nonlinear constrained discrete design variables. All the application shows the availability of the method.

Although improved algorithm improves the global search ability and convergence performance of PSO algorithm to a certain extent and the significant effect of various control parameters on the performance of the proposed algorithms. How to balance control parameters in the algorithm is still needed to further studied.

References

[1] Zhang Q, Li X, Tran Q 2003 Particle swarm optimization based hybrid intelligent algorithm *International Conference on Machine Learning and Cybernetics* **3** 1648-50
[2] Wan S, Sun L 2009 Hybrid intelligent algorithm for optimization design of annular water supply network *2009 International Workshop on Intelligent Systems and Applications* ISA 2009 1-4
[3] Zhao R, Song K 2003 A hybrid intelligent algorithm for reliability optimization problems IEEE International Conference on Fuzzy Systems **2** 1476-81
[4] Zhao M 1997 Hybrid computational-intelligent algorithm for the nonlinear least-squares global solution *Journal of Software* **8**(7) 555-60
[5] Zhang Y, Chen S, Wan Y 2009 An intelligent algorithm based on grid searching and cross validation and its application in population analysis *Proceedings of the 2009 International Conference on Computational Intelligence and Natural Computing CINC 2009* **2** 96-9
[6] Punekar M, Flanagan M F 2010 Low complexity linear programming decoding of nonbinary linear codes *The 48th Annual Allerton Conference on Communication, Control, and Computing* Allerton 2010 6-13
[7] Zhang X, Siegel P H 2012 Adaptive cut generation algorithm for improved linear programming decoding of binary linear codes *IEEE Transactions on Information Theory* **58**(10) 6581-94
[8] Wan S-P, Dong J-Y 2014 Possibility linear programming with trapezoidal fuzzy numbers *Applied Mathematical Modelling* **38**(5-6) 1660-72
[9] Gordon G J, Hong S A, Dudík M 2009 First-order mixed integer linear programming *Proceedings of the 25th Conference on Uncertainty in Artificial Intelligence UAI 2009* 213-222
[10] Liu F, Sun J, Si J, Guo W, Mei S 2012 A boundedness result for the direct heuristic dynamic programming *Neural Networks* **32** 229-235
[11] Zhou Y, Cao L, Pan Y 2009 The optimal inventory model based on the dynamic programming method. *Proceedings of the 2nd International Conference on Modelling and Simulation ICMS2009* **3** 74-8
[12] Li W, Xu G, Wang Z, Xu Y 2008 Dynamic energy management for hybrid electric vehicle based on approximate dynamic programming *Proceedings of the World Congress on Intelligent Control and Automation (WCICA)* 7859-63

[13] Zhang Z, Gao J, Zhong Q, Li S 1997 Application of artificial neural network on diagnosis of cold brittle fracture *Journal of Materials Engineering* **5** 28-30

[14] Xu W, Wang D, Zhou Z, Chen H 1997 Application of artificial neural network combined by genetic algorithm in fault diagnosis of power transformer *Proceedings of the Chinese Society of Electrical Engineering* **17**(2) 109-12

[15] Sun C, Bao J, Zhang J, Huang J 2003 Study of artificial neural network applied in the active control of diesel vibration *Journal of Shanghai Jiaotong University* **37**(5) 781-4

[16] Vivekanandan P, Rajalakshmi M, Nedunchezhian R 2013 An intelligent genetic algorithm for mining classification rules in large datasets *Computing and Informatics*, **32**(1) 1-22

[17] Han W, Jin X, Ren H 2007 Defect reconstruction from MFL signals using genetic-simulated-annealing algorithm *Journal of Basic Science and Engineering* **15**(2) 257-62

[18] Cao L, Jin Q, Fan T, Su W 2012 On-line identification of process model based on swarm intelligence technology *Advanced Materials Research* **403-408** 3216-9

[19] Eberhart R, Kennedy J A 1995 New Optimizer Using Particle Swarm Theory *Proceedings of the Sixth International Symposium on Micro Machine and Human Science* 39-43

[20] Ding W, Wang J, Guan Z 2012 Cooperative extended rough attribute reduction algorithm based on improved PSO *Journal of Systems Engineering and Electronics* **23**(1) 160-6.

[21] Gu T-Y, Ju S-G, Han Fei 2009 An Improved PSO algorithm encoding a priori information for nonlinear approximation *ICIC'09 Proceedings of the Intelligent computing 5th international conference on Emerging intelligent computing technology and applications* 223-231

[22] Chen Q, Guo W, Li C 2009 An improved PSO algorithm to optimize BP neural network *The 5th International Conference on Natural Computation ICNC 2009* **2** 357-60

[23] Liu Z, Li L 2013 An algorithm of license plate recognition based on improved PSO-BP network *Mechanics and Materials* **427-429** 1714-7

[24] Chen Y, Sun H, Wen J, Cheng S, Huang J 2011 Application of improved PSO algorithm in network reconfiguration of shipboard power system *Electric Power Automation Equipment* **31**(3) 29-34

[25] Thanushkodi K, Deeba K 2012 On performance analysis of hybrid intelligent algorithms (Improved PSO with SA and Improved PSO with AIS) with GA, PSO for multiprocessor job scheduling *WSEAS Transactions on Computers* **11**(5) 131-47

Authors

Juan Yang, born in May, 1979, Shuangyashan, Heilongjiang, China

Current position, grades: lecturer.
University studies: Chengde petroleum college.
Scientific interest: wireless sensor network communication and information fusion.

Xuesong Han, born in July, 1980, Jilin, Jilin, China

Current position, grades: lecturer.
University studies: Chengde petroleum college.
Scientific interest: wireless sensor network communication and information fusion.