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Drilling path optimization by the particle swarm optimization algorithm with global convergence characteristics

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Drilling path optimization is one of the key problems in holes-machining. This paper presents a new approach to solve the drilling path optimization problem belonging to discrete space, based on the particle swarm optimization (PSO) algorithm. Since the standard PSO algorithm is not guaranteed to be global convergent or local convergent, based on the mathematical model, the algorithm is improved by adopting the method to generate the stop evolution particle once again to obtain the ability of convergence on the global optimization solution. Also, the operators are proposed by establishing the Order Exchange Unit (OEU) and the Order Exchange List (OEL) to satisfy the need of integer coding in drilling path optimization. The experimentations indicate that the improved algorithm has the characteristics of easy realization, fast convergence speed, and better global convergence capability. Hence the new PSO can play a role in solving the problem of drilling path optimization.

Keywords: Particle swarm optimization algorithm; Drilling path optimization; Global convergence; PSO

1. Introduction

Holes-machining is one of the typical operations of a machining centre. Because of the point to point machining characteristics, the movement of the cutting tool takes a lot of time. The investigation of Merchant indicates that the cost in time of the cutting tool moving during the machining is an average 70% of the whole operating time (Zhou and Shao 2003). Therefore, how to plan the sequence of drilling the holes beforehand to shorten the moving distances of the cutting tool and to reduce the time taken by the cutting tool while changing directions is the key problem of the holes-drilling process. There has been some achievement in this area. The Hopfield algorithm was used for drilling path optimization (Zhou and Shao 2003). The evolutionary ant colony system algorithm and artificial immune algorithm were used for the single objective and multi-objective drilling path optimization problems (Xiao and Tao 2005). The greedy-opt2 algorithm was used in leather punch path optimization (Tong *et al*. 2005). The genetic algorithm was used for the process route optimization (Zhang *et al*. 2006). The tabu search algorithm was used for holes-drilling path optimization (Kolahan and Liang 2000). The simulated annealing

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algorithm was used to obtain the economical machining process (Khan *et al*. 1999). The adaptive particle swarm optimization (adaptive PSO) was used by Onwubolu and Clerc (2004) to solve the problem of path optimization in automated drilling operation. Although these optimization algorithms are used to solve drilling path optimization, there are still some problems, these are: (i) the global convergence characteristic of the optimization algorithms are not considered in the research and each algorithm has its own limitation and is easy to converge on the local optimization solution, so the global optimization solution cannot be obtained; and (ii) several of the algorithms are difficult to use.

The problem of drilling path optimization for minimum production costs can be expressed as a single objective travelling salesman problem (TSP). The routing of production through a manufacturing facility has often been identified as a TSP (Khan *et al*. 1999). Tong *et al*. (2005) indicated that during leather machining, when punching holes in the surface of the leather, the machining sequence optimization of the holes is similar to TSP. In the literature of Onwubolu and Clerc (2004), the operation path is first defined as a travelling salesman problem.

The TSP is one of the most famous and well-studied NP-problems and was proven to be NP-hard already by Karp in 1972. Since an efficient algorithm for TSP is highly unlikely, it is interesting to investigate algorithms that compute approximate solutions (Palbom 2004). Over the past few years, several researchers have demonstrated the applicability of some methods to TSP. The TSP has been solved by using simulated annealing (Schneider 2002), genetic algorithms (Ponnambalam *et al*. 2004), tabu search (Kolahan and Liang 2000) and particle swarm optimization (Wang *et al*. 2003, Lopes and Coelho 2005, Clerc 2006).

PSO was proposed by Kennedy and Eberhart (1995) and used for optimization of continuous nonlinear functions. Thereafter, PSO has received more and more attention in different research areas. Most of the research focuses on two aspects: (i) the performance improvement of PSO by modifying parameters, increasing population diversity and hybrids with other optimizing approaches; and (ii) the applications of PSO in different areas, such as multi-objective optimization, electronics, training neural network, security and mute selection of network, medicine and emergent system identification, etc. (Song and Gu 2004).

On the basis of the existing research achievements (Wang *et al*. 2003, Lopes and Coelho 2005, Clerc 2006) of PSO applied in TSP and the mathematical model of PSO, a new global convergence PSO fit for drilling path optimization is developed in this paper. The contributions of this paper are in two parts: (i) the capability of convergence on the global optimization solution is obtained by adopting the method of generating the stop evolution particle over again; and (ii) the operators are improved according to the integer coding format in drilling path optimization. Different from the four operators adopted in the literature of Onwubolu and Clerc (2004) and Clerc (2006), the Order Exchange Unit (OEU) and Order Exchange List (OEL) are established and the corresponding handle manners are used to implement the operator operation. Based on the above improvements the new PSO can converge on the global optimization solution and is fit for the problem of drilling path optimization in drilling holes within discrete space. The experiments indicate that the improved algorithm has the characteristics of easy realization, fast convergence speed, and better global convergence capability.

2. Global convergence PSO for drilling path optimization

2.1 *Algorithm description*

The goal of drilling path optimization during a holes-drilling process is to find the optimal path between the start node and the end node. The discrete PSO established for this kind of problem is given as:

1. The particle position $X = \{x_i\}$ is expressed by discrete state points in the search space S;
2. An order C of X can be described with $C(c_i, c_j)$, here $c_i < c_j$ or $c_i \geq c_j$;
3. In the search space S, an objective function f can be defined. The attributive variable is distance d and given as $d = f(X)$, get C' with $\min d$.

In the discrete space, the position X of one particle can be expressed by a finite states list, the change of the particle position, namely the movement of the particle can be expressed by the change of the element x_i in the states list. The movement of the particle is affected by the best previous positions of the particle itself and the swarm. The movement of all particles is implemented by the OEU and OEL. The basic PSO used in drilling path optimization can be described as:

$$v_i(t+1) = (\omega \otimes v_i(t)) \oplus [c_1 \otimes (p_i(t) - x_i(t))] \oplus [c_2 \otimes (p_g(t) - x_i(t))] \tag{1}$$

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

where: $v_i(t)$, $v_i(t+1)$ are the OELs of particle i at time steps t and $t+1$; $x_i(t)$, $x_i(t+1)$ are the positions of particle i at time steps t and $t+1$; $p_i(t)$ is the best previous position of particle i at time step t; and $p_g(t)$ is the best previous position of the swarm at time step t. The parameter ω is the inertia weight and c_1,c_2 are influence factors. The symbols $\otimes$, $\oplus$, $-$ and $+$ are four operators of the algorithm, the realizing method of these operators is expressed in section 2.4.

Each particle generated in the search space S is moving according to equations (1) and (2) from time step t to time step $t+1$, the evolution process of particle P_i is expressed in figure 1. Known from figure 1 is that particle P_i moves toward its own best previous position $p_i(t)$ and toward the best previous position $p_g(t)$ of the swarm. So the moving positions of particle P_i have the capability to converge on the optimization solution.

2.2 *Improvement of algorithm convergence*

When solving problems without a global mathematical expression model such as a drilling path optimization problem, the convergence characteristic of the algorithm is more important than the speed and easy realization characteristics. Van den Bergh (2001) studied the convergence characteristic of the standard PSO and guaranteed convergence PSO (GCPSO) according to the conditions represented by Solis and Wets (1981). These conditions must be satisfied when the stochastic optimization algorithm can converge on the global optimization solution. The study indicated that the standard PSO is not even guaranteed to be a local optimization solution and GCPSO can converge on a local optimization solution. A new PSO which can

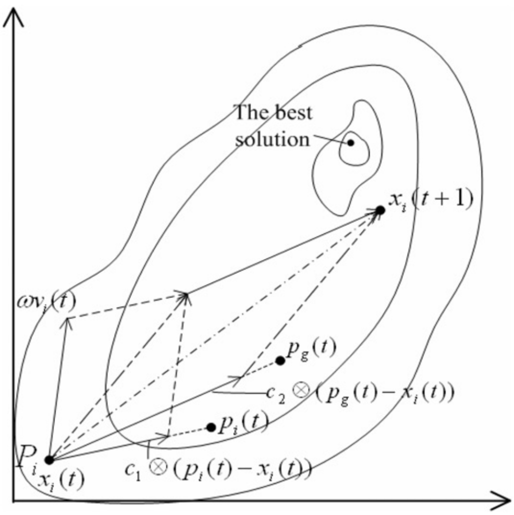

Figure 1. Evolution schematic diagram of particle P_i according to PSO.

converge on the global optimization solution with probability one is represented by Cui *et al.* (2004); this algorithm is named stochastic PSO and is used in the continuous space. Two continuous functions are used to verify the convergence characteristic of the new PSO by the average convergence ratio and average convergence generation number.

In this paper, the PSO algorithm described in section 2.1 is improved to ensure the new PSO converges on the global optimization solution and can be used in discrete space. The difference from the literature of Cui *et al.* (2004) is that the previous speed of the particle is not removed in this paper (namely in equation (1) the item $\omega \otimes v_i(t)$ is kept), the speed memory is kept and the capability of convergence on the global solution of the algorithm is not cut down. The other improvement for the convergence of the algorithm is when the swarm evolves to certain generation, there is at least one particle located in the best previous position of the swarm and this particle will stop evolving, then the particle is improved by the following method to reinforce the global convergence of the algorithm.

For the jth particle at time step t, when the three positions of the particle $x_j(t)$, $p_j(t)$, $p_g(t)$ are superposing, the jth particle will stop evolving. In order to improve the convergence of the algorithm, $p_g(t)$ is kept as the best previous position of the particle swarm, the jth particle position $x_j(t+1)$ is generated randomly again in the search space S, then update $p_j(t+1)$, positions of other particles i can be obtained by using equations (1) and (2) at time step $t+1$, then update $p_g(t+1)$. There are three situations after generating the new particle randomly:

1. If positions $p_j(t+1)$ and $p_g(t+1)$ are superposing, it means that the randomly obtained particle j is in the best position and cannot keep on evolving according to equations (1) and (2), then generate the jth particle position $x_j(t+1)$ randomly again in the search space S, after updating $p_j(t+1)$, other

particles can evolve according to equation (1) and (2), then update $p_i(t+1)$ and $p_g(t+1)$ finally;
2. If positions $p_j(t+1)$ and $p_g(t+1)$ are not superposing and $p_g(t+1)$ is not updated, all particles evolve according to equation (1) and (2);
3. If positions $p_j(t+1)$ and $p_g(t+1)$ are not superposing and $p_g(t+1)$ is already updated, it means that there is a particle k, $k \neq j$, that causes the positions $x_k(t+1)$, $p_k(t+1)$ and $p_g(t+1)$ to superpose, so particle k stops evolving. Then generate particle k randomly again in the search space S, after updating $p_k(t+1)$, other particles can evolve according to equation (1) and (2), then finally update $p_i(t+1)$ and $p_g(t+1)$.

Using this method, there is at least one particle j whose positions $x_j(t)$, $p_j(t)$ and $p_g(t)$ are superposing in certain evolutional generations. Thus at least one particle needs to be generated randomly again in the search space S, so the global convergence capability of the new algorithm is reinforced as a consequence.

2.3 *Evaluation function of algorithm*

During the holes-machining process, the worktable of the numerical control machine tool moves in the x and y axes and when the worktable reaches an exact drilling position, the drilling bit moves in the negative z direction to carry out the drilling operation on the work-piece.

The total operation time of the process will vary for different drilling paths selected, so the operation time is selected as the evaluation function of the PSO for the drilling path optimization algorithm. The evaluation function is given as:

$$t = t_{\mathrm{move}} + n \times t_{\mathrm{drill}} \tag{3}$$

where: n is the number of holes needed to be machined; t_{drill} is the time used for the drilling operation, the parameter is decided by the relative parameters in the numerical control (NC) program and has nothing to do with the selected drilling path; and t_{move} is the time used when the worktable is moving, this parameter is affected by the selected drilling path.

The worktable moves in the x and y directions driven by the motor in the x and y axes. Suppose there are two holes i and j of the work-piece, the coordinates are (x_i, y_i), (x_j, y_j), then the rectilinear distances between two holes is:

$$d_{ij}^R = |x_i - x_j| + |y_i - y_j| \tag{4}$$

During the machining operation, the total distance moved by the worktable is the sum of the absolute values of the distances that the worktable moved in the x and y directions respectively. Suppose the worktable moves with a uniform velocity, the time used by the worktable while moving in the x and y directions is given as:

$$t_{\mathrm{move}} = \sum \frac{|x_i - x_j|}{v_x} + \sum \frac{|y_i - y_j|}{v_y} \tag{5}$$

where: v_x, v_y are the linear velocities of the worktable in x and y axes respectively. Under common situations, set $v = v_x = v_y$ in the NC program to simplify equation (5), then substituting simplified equation (5) into equation (3) the evaluation function becomes:

$$t = \frac{1}{v}\left(\sum |x_i - x_j| + \sum |y_i - y_j|\right) + n \times t_{\text{drill}}. \tag{6}$$

2.4 *Order exchange unit and order exchange list*

The operators in adaptive PSO used for drilling path optimization and in the discrete PSO used for TSP have been introduced (Onwubolu and Clerc 2004, Clerc 2006). In this paper, according to the character of integer coding in drilling path optimization, new operators namely the order exchange unit (OEU) and order exchange list (OEL), are adopted in constructing the global convergence PSO. Because the drilling path optimization problem is a discrete optimization problem, the time is discrete. The time step selected in this paper is 1.

Definition 1: Suppose the random position of a particle with n nodes is $X = \{x_i\}$, $i = 1,2,\ldots,n$. The OEU(j_1, j_2) is defined as exchanging the positions of nodes x_{j_1} and x_{j_2} in position X. The new position of the particle in position X after being handled by the operator will be:

$$X' = X + \mathrm{OEU}(j_1, j_2). \tag{7}$$

The operator is expressed by symbol '+'.

Example 1: Suppose there is a particle with five nodes, the position in certain time is $X = $(b d c e a), the order exchange unit is OEU(2, 4), then:

$$X' = X + \mathrm{OEU}(2,4) = (\mathrm{b} \quad \mathrm{d} \quad \mathrm{c} \quad \mathrm{e} \quad \mathrm{a}) + \mathrm{OEU}(2,4) = (\mathrm{b} \quad \mathrm{e} \quad \mathrm{c} \quad \mathrm{d} \quad \mathrm{a}),$$

where a, b, c, d and e are labels of these five nodes.

Definition 2: The order exchange list (OEL) is defined as an ordered queue constituted by one or more OEUs:

$$\mathrm{OEL} = (\mathrm{OEU}_1, \mathrm{OEU}_2, \ldots, \mathrm{OEU}_n), \tag{8}$$

where: OEU_1,$\mathrm{OEU}_2, \ldots, \mathrm{OEU}_n$ are order exchange units, the order of the units has unique order.

Using the OEL on the position X of a certain particle can be considered as each OEU in the OEL used in turn on list X, namely:

$$\begin{aligned} X' &= X + \mathrm{OEL} = X + (\mathrm{OEU}_1, \mathrm{OEU}_2, \ldots, \mathrm{OEU}_n) \\ &= [(X + \mathrm{OEU}_1) + \mathrm{OEU}_2] + \cdots + \mathrm{OEU}_n. \end{aligned} \tag{9}$$

Definition 3: Several OELs can be united to form a new OEL, the operator is expressed by symbol '$\oplus$'.

Example 2: Suppose $\mathrm{OEL}_1 = (\mathrm{OEU}_3, \mathrm{OEU}_2)$, $\mathrm{OEL}_2 = (\mathrm{OEU}_5, \mathrm{OEU}_4)$, then $\mathrm{OEL}_1 \oplus \mathrm{OEL}_2 = (\mathrm{OEU}_3, \mathrm{OEU}_2, \mathrm{OEU}_5, \mathrm{OEU}_4)$.

Definition 4: Identical new positions will probably be obtained when using different OEL to the same position X, then all the OELs with same effect are called the equivalent assembly of the OEL. The OEL with least OEU in the equivalent assembly is called the basic OEL and defined as $\mathrm{OEL_b}$.

The $\mathrm{OEL_b}$ is constructed by the following methods. Suppose, there are two positions $X=$(b d c e a) and $Y=$(a c d e b), then the $\mathrm{OEL_b}$ is constructed to make $X+\mathrm{OEL_b}=Y$. Known by observing positions X and Y, it shows $Y(1)=X(5)=$a. The first order exchange unit OEU(1, 5) can be obtained. By applying OEU(1, 5) on the position X, the new position X_1 can be created as $X_1=X+\mathrm{OEU}(1,5)=$(a d c e b). As mentioned above $Y(2)=X_1(3)=$c, the second order exchange unit OEU(2, 3) can be obtained. Then the position X_2 can be illustrated as $X_2=X_1+\mathrm{OEU}(2,3)=$ (a c d e b) and is equal to Y. Then the $\mathrm{OEL_b}$ is constructed through the above mentioned process:

$$\mathrm{OEL_b} = Y - X = (\mathrm{OEU}(1,5),\ \mathrm{OEU}(2,3)).$$

The operator is expressed by symbol '–'.

Definition 5: Multiplying the OEL with one real number $\beta(\beta \in [0,1])$ means the OEUs in the OEL are kept with probability β. The operator is expressed by symbol '⊗'. The operator is realized according to the following rules:

$$\text{If } \beta' \le \beta, \text{ then OEU}(j_1, j_2) \text{ cannot be changed.}$$

$$\text{If } \beta' > \beta, \text{ then OEU}(j_1, j_2) \text{ will be changed to OEU}(j_1, j_1).$$

Where β' is a random number adopted in operation, $\beta'=\mathrm{random}(0,1)$.

3. Procedures of the global convergence PSO algorithm for the drilling path optimization

The procedures of the global convergence PSO algorithm for drilling path optimization are expressed as follows:

Step 1: Set an initial position $x_i(1)$ and velocity $v_i(1)$ randomly for each particle in the swarm to initialize the particle swarm and form a stochastic OEL. The fitness value of each particle is calculated according to the evaluation function (equation (6)). Let $p_i(1)$ be the initial position of each particle and $p_g(1)$ be the position with the best fitness value in the swarm.

Step 2: If the finished condition is satisfied, go to Step 7.

Step 3: Determine whether the positions $x_i(t)$ and $p_i(t)$ of particle i and the position $p_g(t)$ are superposing or not. If they are superposing, then generate $x_i(t)$ randomly and check $x_i(t)$ according to the three situations of the method described in section 2.2 until the generated $x_i(t)$ is not superposing with positions $p_i(t)$ and $p_g(t)$.

Step 4: Calculate the next position $x_i(t+1)$, namely the new solution obtained by the current position $x_i(t)$ of the particle. The following illustrates the calculating process:

- Keep the OEU in $v_i(t)$ with the probability ω by using the operator '⊗', namely calculating $\omega \otimes v_i(t)$;

- Use the operator '−' to calculate the differences between position $p_i(t)$ and position $x_i(t)$, namely $p_i(t) - x_i(t)$, to obtain one OEL. Then keep the OEU in OEL with the probability c_1, namely calculating $c_1 \otimes (p_i(t) - x_i(t))$;
- Use the operator '−' to calculate the differences between position $p_g(t)$ and position $x_i(t)$, namely $p_g(t) - x_i(t)$, to obtain one OEL. Then keep the OEU in OEL with the probability c_2, namely calculating $c_2 \otimes (p_g(t) - x_i(t))$;
- Use the operator '$\oplus$' to compute the OEL according to equation (1), then $v_i(t+1)$ can be obtained;
- Use the operator '+' to search the new position (new solution) of the particle according to equation (2).

Step 5: Calculate the fitness value of each particle with the evaluation function (equation (6)) and compare the fitness value of each particle with the fitness value of the best previous position $p_i(t)$ of the particle. If the new fitness value is better, then the current best position $p_i(t)$ of the particle is replaced by the new position.

Step 6: Compare the fitness values of each particle with the fitness value of the best previous position $p_g(t)$ of the swarm. If the new fitness value is better, then the current best position $p_g(t)$ of the swarm is replaced by the new position. Go to Step 2.

Step 7: Output the solution $p_g(t)$.

4. Verifications

The aim of the verifications is to test the validity of the improved global convergence PSO algorithm. In the verifications the improved global convergence PSO algorithm and the basic PSO algorithm are both used to solve the drilling path optimization problem while drilling holes in two work-pieces. In order to simplify the process of verification: equation (4) is used as the evaluation function of the algorithm; parameters c_1 and c_2 are generated randomly in the range of [0, 1]; set ω to 0, 0.5 and 1.0 in each test; set the largest evolution generation number to 10 000; set the swarm population to 100 in verification 1 and to 150 in verification 2; compute 50 generations for each setting of ω.

4.1 *Verification of work-piece 1*

In this verification the improved global convergence PSO algorithm and the basic PSO algorithm are used to solve the drilling path optimization problem while drilling holes in the work-piece shown in figure 2 (the holes are labelled in the figure). The verification result is shown in table 1.

From table 1, the known global optimization solution, 322.5 mm, can be obtained by using both the global convergence PSO algorithm and the basic PSO algorithm, but the convergence ratio of the global convergence PSO is more than three times that of the basic PSO algorithm.

There are a total of $(9-1)!/2 = 20\,160$ solutions in the solution space of this verification. From the minimum generation number in convergence in table 1,

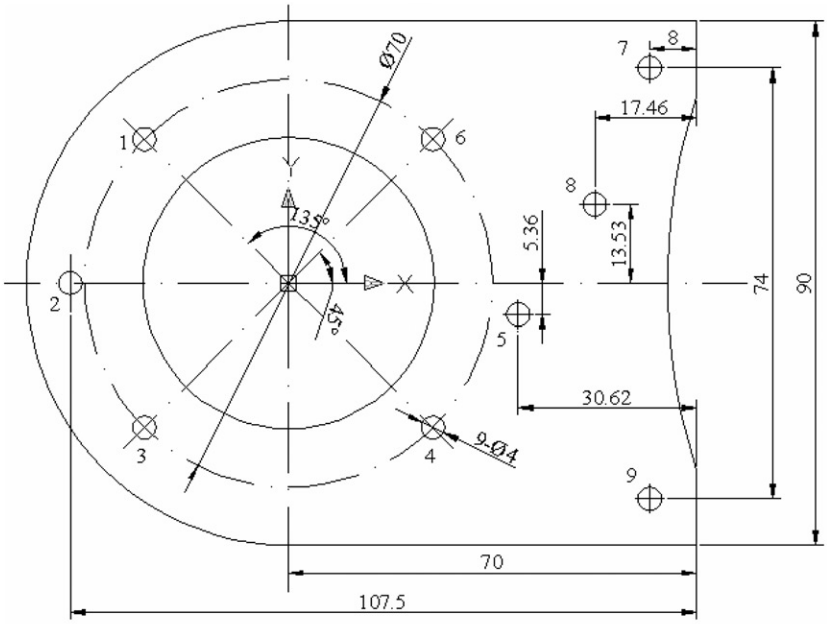

Figure 2. Work-piece 1.

Table 1. Data of verification of work-piece 1.

	Global convergence PSO			Basic PSO		
	$\omega=0.0$	$\omega=0.5$	$\omega=1.0$	$\omega=0.0$	$\omega=0.5$	$\omega=1.0$
Global convergence ratio	0.32	0.34	0.62	0.04	0.16	0.2
The minimum generation number in global convergence	1	5	4	7	3	9
The average generation number in global convergence	1251	646	1620	7	7	20
Length of the optimization path (mm)	322.5	322.5	322.5	322.5	322.5	322.5
Average fitness value after computing 50 generations (mm)	332.25	331.62	327.57	348.07	344.89	338.05

the minimum generation number is between 1 and 5 when the known global optimization solution is obtained. The search ratio equation is described as:

$$\frac{\text{Total of search generation numbers}}{\text{the solution space}} = \text{search ratio} \tag{10}$$

According to equation (10): when the minimum generation is 1, the search ratio is $(1 \times 100)/20160 = 0.5\%$; and when the minimum generation is 5, the search ratio is $(5 \times 100)/20160 = 2.5\%$. This means the known optimization solution is obtained by

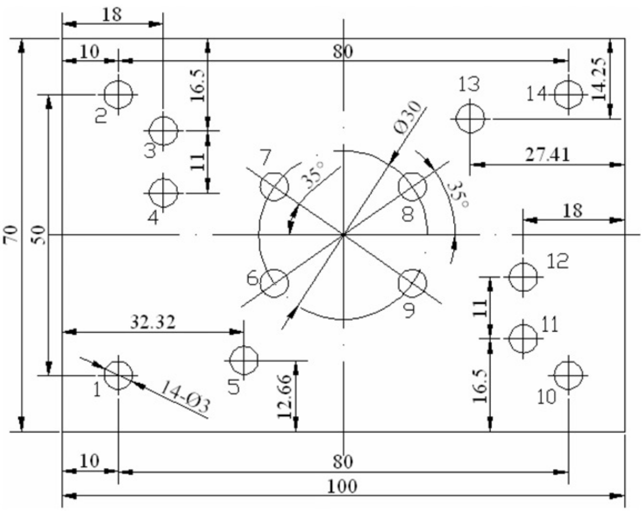

Figure 3. Work-piece 2.

Table 2. Data of verification of work-piece 2.

	Global convergence PSO			Basic PSO		
	$\omega = 0.0$	$\omega = 0.5$	$\omega = 1.0$	$\omega = 0.0$	$\omega = 0.5$	$\omega = 1.0$
Global convergence ratio	0.08	0.08	0.32	0	0	0.12
The minimum generation number in global convergence	815	10	110	–	–	93
The average generation number in global convergence	3806	1620	1764	–	–	847
Length of the optimization path (mm)	280.0	280.0	280.0	–	–	280.0
Average fitness value after computing 50 generations (mm)	304.4	306.4	291	362.3	344	299.2

the global convergence algorithm when only a 0.5–2.5% area of the solution space has been searched. Therefore the conclusion can be reached that the global convergence PSO algorithm has fast convergence speed.

Analysing the results of the average fitness values after calculating 50 generations, the local optimization solutions are improved at the same time by the new PSO algorithm and the improved local optimization solutions are much nearer to the global optimization solution.

4.2 *Verification of work-piece 2*

In this verification the improved global convergence PSO algorithm and the basic PSO algorithm are used to solve the drilling path optimization problem while drilling holes in the work-piece shown in figure 3 (the holes are numbered in the figure). The verification results are shown in table 2, figures 4 and 5. Table 2 shows the data

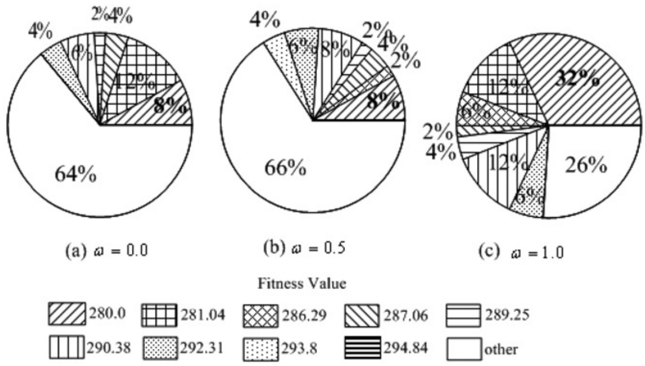

Figure 4. Distribution drawing of the optimization results obtained by the global convergence PSO.

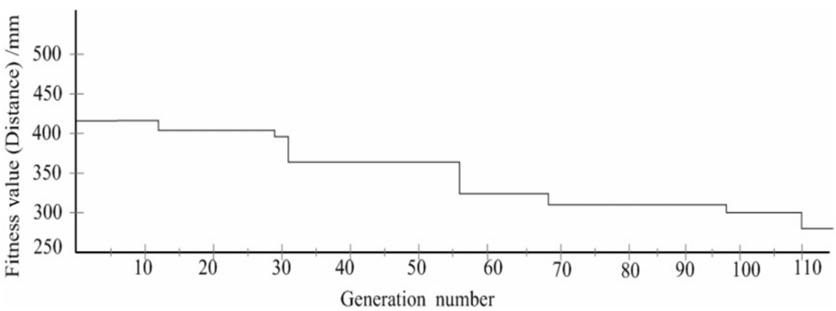

Figure 5. The curve of the fitness value ($\omega = 1.0$).

of verification of work-piece 2, figure 4 illustrates the distribution state of the optimization results and figure 5 shows the curve of the fitness value.

From table 2, the new global convergence PSO algorithm can obtain the known global optimization solution, but the basic PSO algorithm is not guaranteed to be convergent on the global optimization solution. Also the local optimization solutions are improved by the new PSO algorithm in this verification.

When analysing the verification results statistically, there are many local convergence solutions, so only the values with fitness value less than 295 are listed in figure 4. From table 2, the value of ω has great influence on the convergence characteristics of the algorithm when solving this kind of discrete optimization problem. In figure 4, when the values of ω are different, the capability of convergence on the near optimization solution is also different. Figure 4(c) shows that when $\omega = 1.0$, the distribution state of the near optimization solutions are better.

There are a total of $(14-1)!/2 = 3\,113\,510\,400$ solutions in the solution space of this verification. From table 2, when the known global optimization solution of 280.0 is obtained, the minimum generation number is 10 and the maximum generation number is 815. Applying equation (10) as before, when the known optimization solution is obtained by the algorithm, only a 0.000048–0.0039% area of the solution space has been searched. Therefore the conclusion can be reached that the global convergence PSO algorithm has the faster convergence speed.

The curve of the fitness values is shown in figure 5. The curve shows that when the best fitness value is obtained the minimum generation number is 110 in verification 2, when $\omega = 1.0$.

In both verifications, when $\omega = 1.0$, the global convergence algorithm has the highest global convergence ratio and the best average fitness value after calculating 50 generations, so the algorithm is easy to converge on the optimization or near optimization solutions at this time.

5. Conclusions

In this paper, an improved particle swarm optimization algorithm for solving the drilling path optimization problem belonging to discrete space was proposed. The capability of convergence on the global optimization solution of the algorithm was obtained by adopting the method of generating the stop evolution particle once again, and the operators of the algorithm were improved by establishing the OEU and OEL to satisfy the need of integer coding in drilling path optimization. Then the problem of minimizing the discrete space was resolved based on these improvements. The verification results indicate that the improved PSO can obtain the global optimization solution when solving the problem of drilling path optimization and the operation time needed to obtain the global optimization solution can be shortened. This means the satisfied optimization results can be obtained by this new PSO.

Further work will be on how to improve the generating method of the stop evolution particle to obtain better global convergence capability within finite evolution generation numbers. This work will still be the main content of later research.

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