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Integration of Genetic Algorithm and Cultural Particle Swarm Algorithms for Constrained Optimization of Industrial Organization and Diffusion Efficiency Analysis in Equipment Manufacturing Industry

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Abstract: Aiming at industrial organization multi-objective optimization problem in Equipment Manufacturing Industry, The paper proposes a new type of double layer evolutionary cultural particle swarm optimization algorithm. The algorithm combines the advantages of the particle swarm optimization algorithm and cultural algorithm. It not only revises the problem that the particles are easy to “premature”, but also overcomes the drawback of penalty function method. Firstly, improved topology structure of Particle swarm optimization algorithm. Secondly, using crossover strategy and niche competition mechanism. Verified by the test functions, the proposed algorithm has good performance. Through the analysis of the manufacturing performance based on the algorithm, the paper proposes some optimization strategies such as improving the manufacturing industry market concentration, improving the manufacturing level of industry product differentiation and so on. *Copyright © 2013 IFSA.*

Keywords: Particle swarm optimization algorithm, Cultural algorithm, Diffusion efficiency analysis, Industrial organization optimization, Crossover strategy, Niche competition mechanism, Genetic algorithm.

1. Introduction

There are a lot of multi-objective optimization problem among optimization problems. The objectives of such issues are interacted on each other. The optimization of one objective must be at the expense of other objectives, so it is difficult to evaluate the advantages and disadvantages of multi-objective problem solution. Currently there are many multi-objective optimization algorithm based on evolutionary and swarm intelligence [1], for example: NSGA [1], SPEA [2], SMES [3], MOPSO [4], etc. These algorithms which are highly parallel mechanism can optimize multi-objectives simultaneously. It promotes the development of solving method which experiences from target combinations gradually to vector optimization method based on Pareto. Since the development time

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is not too long, the method is still in the stage of exploration and research.

With the development of Particle swarm optimization (PSO) algorithm in the ten years, some scholars have used it to solve multi-objective optimization problem [5-7]. Inspired by the improvement strategies of fusion algorithm, this paper proposes Dual-level cultural evolution particle swarm algorithm to solve multi-objective optimization problem. There are highly complementary in the sides of cultural algorithm and particle swarm algorithm: cultural algorithm has a strong capability of global search, but the algorithm itself is complex and converges slowly; PSO algorithm has a poor ability of global search, it is easy to "premature", but the algorithm itself is simple and converges quickly.

Firstly, I improved the topology of PSO algorithm to enhance the information exchanging and sharing between particles. Secondly, I used crossover operation and niche competitive strategy to ensure that optimal solution set can be distributed uniformly in the forefront of Pareto solution and used Pareto solution pool to maintain optimality of solution. The algorithm used a direct comparison method to handle the constraint condition, so that it can overcome the disadvantage of function method [8].

2. Improvement Strategies

The improvement strategies include five parts:

2.1. Selection Strategy

Using the roulette method, the probability of the individual of i being selected is:

$$P_5 = f_i(x) / \sum_{i=1}^{M} f_i(x) \quad (1)$$

2.2. Crossover Strategy

In order to maintain the diversity of particle in the space, I used crossover operation to enhance the information exchanging and sharing between particles. To improve the performance of the algorithm, the crossover operation of particle evolution is performed by those formulas:

$$X_i' = \alpha \cdot X_i + (1-\alpha) \cdot X_j, \quad (2)$$

$$X_j' = (1-\alpha) \cdot X_i + \alpha \cdot X_j, \quad (3)$$

where a is the random number between 0 and 1. X_i and X_j are the parent particles, however X_i' and X_j' are offspring produced by crossover operation. Doing the comparison operation between the new generation of X_i' and X_j' and the parent generation of X_i and X_j. If X_i' and X_j' are Non-dominated set, then use them to replace X_i and X_j, or they will be discarded and retain use X_i and X_j.

2.3. Mutation Strategy

Using the method of sliding window based on the interval in the culture algorithm. It produces new generation individuals by formula (4):

$$X_i''' = \begin{cases} moveTo(choose(Cell[l])) & if\ X_i'' \in \{infeasible\ cells\} \\ X_i'' + \gamma \cdot (u_j - l_j) \cdot N_{i,j}(0,\ 1) & if\ X_i'' \in \{otherwise\} \end{cases}, \quad (4)$$

where, l_j and u_j indicate the upper bound and lower bound about X_i in the j-dimensional respectively. γ is a positive number. $Cell[l]$ is a template of r-dimensional, called regional schemata. It is maintained by the belief space and used to record constraint characteristics of each specific region in search space. For a given cell-i, $Cell[l]$ is a small area space in the corresponding optimization problem domain. According to the different types of cell-i, and assigning the different unit weight by the following formula:

$$W_i = \begin{cases} w_1 & if\ Cell[i] \in \{unknown\ cells\} \\ w_2 & if\ Cell[i] \in \{feasible\ cells\} \\ w_3 & if\ Cell[i] \in \{semi-feasible\ cells\} \\ w_4 & if\ Cell[i] \in \{infeasible\ cells\} \end{cases}, \quad (5)$$

The function choose (cell[*l*]) in the equation (4) is used to select a target unit from all the cells for the function moveTo (C_k). The function chooses (cell[*l*]) select the cell by roulette method according to the weight determined by the equation (5). Suppose C_k is selected by roulette, and then the function moveTo (C_k) will produce a new generation by the equation (6):

$$X_i''' = Left_k + \text{uniform}(0,1) \cdot Csize_k, \quad (6)$$

where $Left_k$ is an array about 1*r and it represents the extreme left position of C_k; $Csize_k$ is an array about 1*r and it represents the size of each dimension space. The function uniform (0, 1) is an array about 1*r and it is produced uniformly.

The mutation operation is guided by constraint knowledge of belief space in the process. Individuals adjust their position constantly to enter the feasible space and semi- feasible space. The intelligent evolutionary strategy based on cultural evolution and it improved search capabilities of cultural genetic algorithm.

2.4. Select Excellent Particle Strategy

The niche competition mechanism is employed here.

I select two candidate particles randomly and compare them with a comparison set which contains a certain quantity of particles. Comparing the candidate particle and the comparison set respectively. There are two possible scenarios and corresponding countermeasures:

1) If one candidate particle is dominated by the comparison set, and the other is not, then the non-dominated solutions will be selected for copying operation.

2) If the two candidate particles are dominated by the comparison set or they dominate the comparison set, then the smaller niche particles are selected for copying. The number of niche particles can be calculated by the sum of the sharing function of the population:

$$m_i = \sum_{i=1}^{swarm\_size} sh(d_{i,j}) \quad (7)$$

where $sh(\cdot)$ is the sharing function, a is the constant, $d_{i,j}$ means that the distance between the particle i and the particle j in the decision space.

The algorithm ensures that the final solution set can converge to the frontier of Pareto and avoid algorithm prematurely.

2.5. Constraint Processing Strategy

Direct comparison method is employed.

The paper references the method of in the literature [10-12] and use the direct comparison method about processing constraint problem.

The method provides a new way to solve constrained optimization problems. It transforms the traditional function method of processing constraint into that determine which individual is selected through comparing the degree of self-constraint violations or fitness, so that it can avoid the problem of penalty factor selection.

3. The Specific Implementation Steps to Improve the Algorithm

Cultural particle swarm optimization (CPSO) is a kind of dual evolutionary mechanism, The various sub-groups of population space as well as the elite swarm of the belief space can be synchronized evolution. The basic steps of CPSO's single thread are shown in Fig. 1.

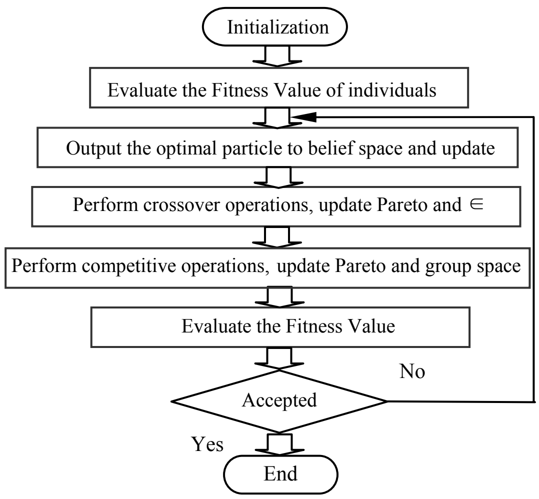

Fig. 1. The specific implementation steps to improve the algorithm.

4. The Verification of the Multi-Objective Test Function About the Improved Algorithm

4.1. The Multivariable and Double Objective Optimization Test Function

Select a constrained multi-objective optimization problem:

$$\begin{aligned} &\min\ f_1(x) = 4x_1^2 + 4x_2^2, \\ &\min\ f_2(x) = (x_1-5)^2 + (x_2-5)^2, \\ &\text{s. t. } C_1(x) = (x_1-5)^2 + (x_2-5)^2 \le 25, \\ &C_2(x) = (x_1-8)^2 + (x^2+3)^2 \ge 7.7, \\ &0 \le x_1 \le 5,\ 0 \le x_2 \le 3, \end{aligned} \quad (8)$$

where w =1, ε =0.001, p =0.1, 20 % individuals of population space consist of the elite swarm of the belief space. From Fig. 2, it shows that the optimal solution is basic evenly distributed along the Pareto front, and it proves the effectiveness of the algorithm.

3.2. Comparison of the Results before and after the Improvement

For example, in reference [10], the single objective nonlinear constrained optimization problem.

$$\begin{aligned} &\min f(x,y) = -12x - 7y + y^2, \\ &\text{s. t.: } 0 \le x \le 2, \\ &0 \le y \le 3, \\ &y \le -2x^4 + 2, \end{aligned} \quad (9)$$

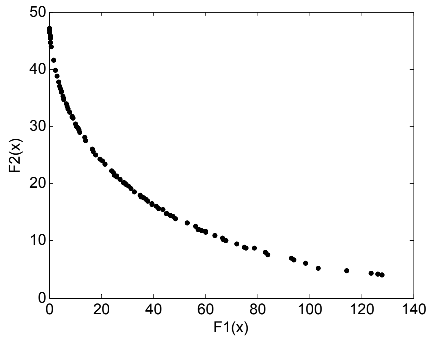

Fig. 2. The optimization results of dual objective function.

Specific parameters are set as follows: set the GA population size as 60, P_c=0.3, γ=0.3, $w_1 = w_2 = 2$, w_3=3, $w_4 = 1$. Compared the CA algorithm, such as the Standard real-valued GA and JIN, the running results show as Table 1 and Table 2.

Table 1. The comparison of iteration and runtime between different algorithms.

No.	Iteration		Runtime(s)	
	Mean value	**Standard deviation**	**Mean value**	**Standard deviation**
1.	4.4	1.2409	1.7024	0.4522
2.	591.6	196.4302	2.7772	0.8151
3.	7.75	2.4264	2.6577	0.9470

1 is the improved algorithm in paper, 2 is the real-coded genetic algorithm and 3 is cultural algorithm.

Table 2. The comparison of optimum value between different algorithms.

No.	Optimized points		Optimized points
	X	Y	
1.	0.7179	1.468	-16.7363
2.	0.7189	1.4643	-16.7331
3.	0.7325	1.4224	-16.7232

1 is the improved algorithm in paper, 2 is the real-coded genetic algorithm and 3 is cultural algorithm.

From Table 1, it shows that the real-coded genetic algorithm requires a lot of iterations in order to get the optimal solution because of the blindness to search the solution space. However, as the algorithm is relatively simple, it doesn't cost too much running time.

Meanwhile, the cultural algorithm requires less iteration and time, because the evolution of its population space is run under the guidance of belief space, the individuals can better adjust their search direction to find the optimal solution quickly.

From Table 2, it shows that the proposed algorithm combines the advantages of genetic algorithm and cultural algorithm, and its stability, running time and iterations has further improved. As a result, it has more excellent performance.

5. The Analysis and Optimization of Manufacture Industrial Organization Performance Based on the Algorithm

The specific parameter settings of algorithm in this paper are written as follows:

The value of individual number of population space is 2, the size of the sub-group in population space is 90, the size of the group in population space is 35, particle dimension is 3, iteration is 120, the learning factor C_1, C_2 and C_3 is 2, inertia weight w is 0.9, degree of comparison set is 28, predetermined constant p is 0.1, controls parameter ε is 0.05.

Making industrial organization multi-objective optimization problem in equipment manufacturing industry parameterized, setting variables and setting the ranges of the scale of the enterprise, manufacturing differentiation level of industry product, product type number and so on. Link found between variables, optimization objective is maximum efficiency, relation between efficiency and output-input is:

$$\begin{aligned} &\theta_j = \max \sum_{r=1}^{s} u_r y_{rj} / \sum_{i=1}^{m} x_{ij}, \\ &s.t \sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} x_{ij} \le 0 \quad j=1,2,\cdots,n, \\ &\sum_{d=1}^{D} \delta_d z_{dj} - \sum_{i=1}^{m} v_i x_{ij} \le 0 \quad j=1,2,\cdots,n, \\ &\sum_{r=1}^{s} u_r y_{rj} - \sum_{d=1}^{D} \delta_d z_{dj} \le 0 \quad j=1,2,\cdots,\text{n}, \\ &u_r \ge \varepsilon, v_i \ge \varepsilon, \delta_d \ge \varepsilon \end{aligned} \tag{10}$$

where, θ_j is the total efficiency of evaluation policy decision unit "j", θ_j^1 and θ_j^2 denote efficiency of sub-processes 1 and sub-processes 2, $x_i (i=1,2,\cdots,\text{m})$ is input, $z_d (d=1,2,\cdots,\text{D})$ is output, final output is $y_r (r=1,2,\cdots,\text{S})$.

The results of input-output analysis and evaluation in policy decision units are showed in Table 3 and Table 4, Table 3 is policy decision units, input-output analysis and evaluation of policy decision units is shown in Table 4.

Calculations result indicate that in seven sub-industries of the equipment manufacturing industry, there are six industries' efficiency values are 1, the six industries includes manufacture of metal products, manufacture of special purpose machinery, manufacture of electrical machinery and equipment, manufacture of communication, computer, other electronic equipment, and manufacture of measuring instrument, machinery for cultural and office work. The efficiency of knowledge chain of manufacture of transport equipment is 0.7808, ranking the 13th among the manufacturing industry; the efficiency of manufacture of general purpose machinery is the lowest. Generally, there are 11 industries with efficiency value is 1 among the 29 manufacturing industry, accounting for more than 37.93 %; the percentage of industries with 1 efficiency value in the equipment manufacturing industries reaches 71.43 %, and 33.50 % higher than the manufacturing industry.

Here optimization strategies are proposed: improving the manufacturing industry market concentration, improving the manufacturing level of industry product differentiation and so on.

Table 3. Policy decision units.

No.	Policy decision units
1.	Processing of Food from Agricultural Products
2.	Manufacture of Foods
3.	Manufacture of Beverage
4.	Manufacture of Tobacco
5.	Manufacture of Textile
6.	Manufacture of Textile Wearing Apparel, Foot ware and Caps
7.	Manufacture of Leather, Fur, Feather and Its Products
8.	Processing of Timbers, Manufacture of Wood, Bamboo, Rattan, Palm, Straw
9.	Manufacture of Furniture
10.	Manufacture of Paper and Paper Products
11.	Printing, Reproduction of Recording Media
12.	Processing of Petroleum, Coking, Processing of Nucleus Fuel
13.	Manufacture of Chemical Raw Material and Chemical Products
14.	Manufacture of Medicines
15.	Manufacture of Chemical Fiber
16.	Manufacture of Rubber
17.	Manufacture of Plastic
18.	Manufacture of Non-metallic Mineral Products
19.	Manufacture and Processing of Ferrous Metals
20.	Manufacture and Processing of Non-ferrous Metals
21.	Manufacture of Metal Products
22.	Manufacture of General Purpose Machinery
23.	Manufacture of Special Purpose Machinery
24.	Manufacture of Transport Equipment
25.	Manufacture of Electrical Machinery and Equipment
26.	Manufacture of Communication, Computer, Other Electronic Equipment
27.	Manufacture of Measuring Instrument, Machinery for Cultural and Office Work
28.	Manufacture of Artwork, Other Manufacture
29.	Manufacture of Artwork, Other Manufacture

Table 4. Efficiency evaluation results of policy decision units.

No.	The total efficiency	
	The first stage	The second stage
1.	0.491	0.159
2.	0.414	0.010
3.	0.481	0.351
4.	0.305	0.032
5.	0.433	0.062
6.	0.992	0.299
7.	0.725	0.008
8.	0.471	0.735
9.	1	0.970
10.	0.368	0.083
11.	1	0.008
12.	1	0.911
13.	0.121	0.143
14.	0.43	0.258
15.	1	0.022
16.	0.376	0.022
17.	0.649	0.341
18.	0.749	0.934
19.	0.761	0.106
20.	0.313	0.108
21.	0.624	0.031
22.	1	0.827
23.	0.601	0.030
24.	0.846	1
25.	0.291	0.711
26.	1	0.120
27.	0.508	1
28.	1	0.232
29.	1	0.017

6. Conclusions

The paper has proposed a new type of double layer evolutionary cultural particle swarm optimization algorithm. The algorithm combines the advantages of the particle swarm optimization algorithm and cultural algorithm. It not only revises the problem that the particles are easy to “premature”, but also overcomes the drawback of penalty function method. Verified by the test functions, the proposed algorithm has good performance.

Through the analysis of the manufacturing performance based on the algorithm, the paper proposes some optimization strategies such as: improving the manufacturing industry market concentration, improving the manufacturing level of industry product differentiation and so on.

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