Constraint genetic algorithm and its application in sintering proportioning

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Abstract. This paper puts forward a method for constrained optimization problems based on self-adaptive penalty function and improved genetic algorithm. In order to improve the speed of convergence and avoid premature convergence, a method based on good-point set theory has been proposed. By using good point set method for generating initial population, the initial population is uniformly distributed in the solution space. This paper Designs an elite reverse learning strategy, and proposes a mechanism to automatically adjust the crossover probability according to the individual advantages and disadvantages. The tests indicate that the proposed constrained genetic algorithm is efficient and feasible.

1 Introduction

Constraint optimization is a kind of optimization problems in numerous fields including industrial process, financial field and aerospace. Generally, equality and inequality constraints, discrete and continuous variables as well as linear and nonlinear objective functions or constraint functions co-exist. This causes that globally optimal solution is difficult to be solved by using traditional optimization methods such as nonlinear programming and criterion optimization. Intelligent algorithms have been increasingly widely used due to advantages including no requirement for differentiable objective function and capable of solving multiple maximum and high-dimensional optimization problems. After constraint problems were transformed into multi-objective optimization problems of two objectives, the solution can be solved by using improved genetic algorithm (IGA) and validity of the method is verified by applying standard test function [1]. In reference [2], a multi-population and independently searching particle swarm optimization (PSO) was proposed and the associated particles in a spherical distribution were introduced to improve diversity of populations. Subsequently, constraint optimization problems are solved based on penalty function method to get a favourable effect. In reference [3], a combined multi-objective with differential evolution (CMODE) algorithm was proposed in which population is divided into elite and common groups based on packet selection method with adaptation sequence. Next, by using different evolutionary strategies, the optimization capacity of the algorithm is verified through simulation. In reference [4], a penalty function method and a bat algorithm were put forward to solve constraint optimization problems.

As a widely used intelligent algorithm, genetic algorithm (GA) has the drawback of prematurity, so it is improved by using good-point set method to produce initial populations. Moreover, elitist reversion learning strategy is introduced and crossover probability is automatically adjusted. The
validity of the method proposed in the study is verified by using standard test function and an engineering application example of proportioning during steel sintering.

2 Improved Genetic Algorithm

Being the same as other intelligent algorithms, GA has the drawback of prematurity. Therefore, GA is improved to strengthen the optimization capacity.

2.1 Population initialization based on good-point set

Initial populations play an important role in improving optimization efficiency of intelligent algorithms. In the study, initial populations are produced by using good-point set method which leads initial individuals to uniformly distribute in feasible regions to improve the optimization efficiency of GA.

2.2 New elite reversion learning strategy

All individuals in populations approach to the optimal individuals in GA in the later evolution, which causes local optimum of the algorithm, so a new elite reversion learning strategy is proposed so as to effectively explore new search regions. In the study, new elite reversion learning strategy is conducted on 10% of optimal individuals.

Definition 1: New elite reversion point; the part of favorable individuals of GA in D-dimensional space are set as $X_j=(X^1_j, X^2_j, \ldots, X^D_j)$ whose corresponding elite reversion points are $\bar{X}_j=(\bar{X}^1_j, \bar{X}^2_j, \ldots, \bar{X}^D_j)$. Where, $\bar{X}^d_j=\gamma \times (0.5 - \text{rand}(1)) \times (l^d - u^d) + \bar{X}^d_j$, and $d=1,2,\ldots,D$ refers to the dimension of variables while $l^d$ and $u^d$ represent $d$-dimensional upper and lower boundaries, respectively. Moreover, $\gamma$ refers to a self-adaptive value, which can be adaptively adjusted according to diversity of populations.

$$
\gamma = \begin{cases} 
1.0 & \text{if } \theta \geq 0.98 \\
2.5 \times \theta - 1.8 & \text{if } 0.8 < \theta < 0.96 \\
0.2 & \text{if } \theta \leq 0.8 
\end{cases} \quad (1)
$$

Where, $\theta$ can be expressed as follows:

$$
\theta = \frac{f_{\text{best}}}{f_{\text{avg}}} \quad (2)
$$

Where, $f_{\text{avg}}$ refers to the average value of individual objective function while $f_{\text{best}}$ represents corresponding objective function value of global optimum of the current generation being optimized. It is supposed that the lower the objective function values, the better the corresponding individuals are. Obviously, the larger the $\theta$ is, the worse the diversity of the population, so the larger the value of $\gamma$. Therefore, search range is extended to improve the globally searching capacity of the algorithm. However, when $\theta$ has a low value, namely, the population exhibits a favorable diversity, $\gamma$ is little to conduct global search so as to accelerate the convergence rate of the algorithm.

2.3 A new adaptive crossover operator

Crossover operators are basic operators of GA. However, conducting high-probability crossover to superior operators with low objective function values probably damages some favorable individuals. Therefore, a new adaptive crossover operator is proposed so that not all individuals have random crossover with other individuals but construct an excellent individual library containing $\frac{M}{5}$ individuals. Where, $M$ refers to the population size and the initial value is equal to the number $\frac{M}{5}$ of excellent individuals in the initial population. After a generation evolves, the optimal individual of the generation is migrated into the excellent individual library while the individual staying the longest
time in the library is taken out. Subsequently, an individual in the excellent individual library is randomly chosen to conduct crossover operation at a crossover probability which is positively correlated with the objective function value. The lower the objective function value, the lower the crossover probability is, which can be expressed as follows:

\[ p_c = a + b \times \frac{f_{\text{sort}}}{M} \]  

(3)

Where, \( f_{\text{sort}} \) refers to the rank of corresponding objective function values of individuals in an ascending order. To be specific, the individual corresponding to the minimal objective function value ranks the first while that corresponding to the maximal objective function value ranks \( M \) (the population size). Moreover, \( a \) and \( b \) refer to coefficients \( (a + b = 1) \) and are set as \( a = 0.3 \) and \( b = 0.7 \) in the study.

3 Numerical experiment
In order to verify the performance of the constrained genetic algorithm (COGA) proposed in the paper. In order to validate this paper, 8 standard test functions (g01, g02, g04, g06, g08, g09, g11 and g12) are selected in the literature [6]. And compared with other improved genetic algorithms, population size \( M=200 \), the probability of mutation is 0.1, each function of the independent test 10 times, the maximum evolutionary algebra for the 2000 times. Record the best result, average result, worst result and standard deviation. Compared with other improved genetic algorithms CRGA, GFCOGA, APMGA and COMOGA. The results are shown in Table 1. (The results of the first four algorithms are directly based on the results of literature [1]). From table 1, The COGA proposed in this paper is better than (or equal to) other improved genetic algorithms.

4 Application of constraint GA in steel sintering proportioning
Lean iron ore or iron concentrate fines cannot be smelted in a blast furnace before being sintered. As a key process before sintering, proportioning determines chemical compositions of sintering [5]. Due to the length limit of the paper, various constraints of components of raw materials, prices and proportioning are displayed in reference [5] in detail. By using penalty function method, the constraints are processed and then the optimization problem is solved by employing IGA. Moreover, the IGA is compared with linear programming method, Standard PSO, PSO-conjugate gradient (CG) algorithm and standard GA. The results are shown in Tables 2 and 3.

| Function | Known optimal value | Statistical results | Method |
|----------|---------------------|---------------------|--------|
| g01      | -15.0000            | The best result     | CRGA   |
|          |                     | -14.9977            | -14.9999 | -14.9998 | -15.0000 | -15.0000 |
|          |                     | Average result      | GFCOGA |
|          |                     | -14.9850            | -14.9977 | -14.9988 | -15.0000 | -15.0000 |
|          |                     | Worst result        | APMGA  |
|          |                     | -14.9467            | -11.9999 | -14.9940 | -15.0000 | -15.0000 |
|          |                     | Standard deviation  | COMOGA |
|          |                     | 1.4E-02             | 8.51E-01 | NA       | 1.20E-12 | 8.50E-13  |
| g02      | -0.803619           | The best result     | COGA   |
|          |                     | -0.802959           | -0.803190 | -0.792523 | -0.803602 | -0.803619 |
|          |                     | Average result      |        |
|          |                     | -0.764494           | -0.755332 | -0.725551 | -0.797372 | -0.798799 |
|          |                     | Worst result        |        |
|          |                     | -0.722109           | -0.672169 | -0.624484 | -0.786114 | -0.787878 |
|          |                     | Standard deviation  |        |
|          |                     | 2.6E-02             | 3.27E-02 | NA       | 5.94E-03 | 8.97E-04  |
| g04      | 30665.53867         | The best result     | CRGA   |
|          | 7                    | -30665.520          | -30665.5312 | -30665.31655 | -30665.53687 | -30665.53687 |
|          |                      | Average result      | GFCOGA |
|          |                      | -30664.398          | -30663.3642 | -30591.65898 | -30665.53687 | -30665.53687 |
|          |                      | Worst result        | APMGA  |
|          |                      | -30660.313          | -30651.9595 | 30458.62922 | -30665.53687 | -30665.53687 |
|          |                      | Standard deviation  | COMOGA |
|          |                      | 1.6E+00             | 3.31E+00 | NA       | 5.56E-12 | 4.39E-12  |
| g06      | -6961.8138          | The best result     | COGA   |
|          |                      | -6956.251           | -6961.1785 | -6961.4475 | -6961.8138 | -6961.8138 |
|          |                      | Average result      |        |
|          |                      | -6740.288           | -6959.5638 | -6913.0708 | -6961.1906 | -6961.6957 |
|          |                      | Worst result        |        |
|          |                      | -6077.123           | -6954.3186 | -6868.6591 | -6959.7659 | -6960.7687 |
|          |                      | Standard deviation  |        |
|          |                      | 2.7E+02             | 1.27E+00 | NA       | 9.68E-01 | 1.23E-02  |
The similar total iron contents, the ratio of harmful elements in the raw material can be significantly decreased using COGA and PSO-CG algorithm in reference [5]. Thus, costs significantly decline. Assuming that annual raw material is 1×10^6 tons, COGA algorithm saves 8.202×10^6, 4.562×10^6 and 3.512×10^6 yuan more costs annually compared to linear programming, standard PSO and standard GA algorithms. As a result, great economic benefits can be achieved. For the ratio result obtained through COGA algorithm, except for impurity lead content, other indices are slightly superior to those obtained by using PSO-CG algorithm in reference [5].

| Ore types and product costs | The best ore ratios obtained by using different algorithms |
|---------------------------|----------------------------------------------------------|
|                           | Linear programming algorithm | Standard PSO algorithm | PSO-CG algorithm | Standard GA | COGA |
| Raw ore                   | 0.00%                      | 0.00%                  | 0.00%           | 0.00%       | 0.00% |
| Blended ore fines         | 75.200%                    | 31.200%                | 21.900%         | 27.500%     | 21.909% |
| Blended concentrate       | 0.00%                      | 0.00%                  | 0.400%          | 3.600%      | 0.391% |
| Brown concentrate         | 0.00%                      | 6.500%                 | 0.000%          | 3.400%      | 0.000% |
| Schreyerite               | 10.000%                    | 50.000%                | 66.000%         | 55.300%     | 65.995% |
| Zinifex                   | 14.800%                    | 12.300%                | 11.700%         | 10.200%     | 11.750% |
| Product costs (yuan/ton)  | 326                        | 322.36                 | 317.8           | 321.31      | 317.798 |

It can be seen from Tables 2 and 3 that under the similar total iron contents, the ratio of harmful elements in the proportioning can be significantly decreased using COGA and PSO-CG algorithm in reference [5]. Thus, costs significantly decline. Assuming that annual raw material is 1×10^6 tons, COGA algorithm saves 8.202×10^6, 4.562×10^6 and 3.512×10^6 yuan more costs annually compared to linear programming, standard PSO and standard GA algorithms. As a result, great economic benefits can be achieved. For the ratio result obtained through COGA algorithm, except for impurity lead content, other indices are slightly superior to those obtained by using PSO-CG algorithm in reference [5].
5 Conclusions
Constraints are processed by using the improved penalty function method in reference [4] and the proportioning problems during steel sintering is solved by using the IGA proposed in the study. The simulation result shows that the method proposed in the study is superior to standard GA, standard PSO and PSO-CG algorithms.

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