The Distribution Population-based Genetic Algorithm for Parameter Optimization PID Controller[1)]

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Abstract Enlightened by distribution of creatures in natural ecology environment, the distribution population-based genetic algorithm (DPGA) is presented in this paper. The searching capability of the algorithm is improved by competition between distribution populations to reduce the search zone. This method is applied to design of optimal parameters of PID controllers with examples, and the simulation results show that satisfactory performances are obtained.

Key words Distribution population, genetic algorithm, PID controller, parameter optimization

1 Introduction

Proportional-Integral-Derivative (PID) controllers are still used extensively in the process industries because of their robust performance and simplicity. Three parameters of a PID controller must be determined and tuned to obtain a satisfactory closed-loop performance. Thus methods to tune the parameters of PID controllers are very important for the process industries. There are two main classes of methods: traditional methods and intelligent methods. Traditional methods such as Ziegler-Nichols[1], Simplex Method[2], often do not provide good tuning and are easy to produce surge and big overshoot. On the other hand, several intelligent approaches have been suggested to improve PID tuning[3~5], for instance, the fuzzy self-adjusting, artificial neuron network method. As an intelligent algorithm, genetic algorithm (GA) also has been widely used to tune the parameters of PID[6~8]. GA is a stochastic global optimization method inspired by the biological mechanisms of natural selection and natural genetics, which as first developed by Holland in the 1960s[9] and has been widely used for numerical optimization, classifier systems, graph processing and many other engineering problems[10]. But the major problem of GA is that is may be trapped in the local optima of the objective function. In this paper, the distribution population-based genetic algorithm (DPGA) is presented to solve this problem.

At end of this paper, the proposed DPGA is applied to design of optimal parameters of PID controllers for four different plants to demonstrate its effectiveness.

2 Problem description

The control-loop diagram is illustrated in Fig. 1 where r, e, y are respectively the reference, error and controlled variables, $G(s)$ is the plant transfer function and $C(s)$ is the controller transfer function. The Laplace transform of the $C(s)$ is

$$C(s) = K_P + K_I \frac{1}{s} + K_D s \tag{1}$$

where K_P, K_I, K_D are respectively the proportional, integral, derivative parameters of the PID controllers.

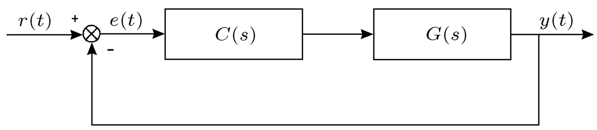

Fig. 1 The diagram of a closed loop system

The three PID parameters must be tuned according to the specific needs. In order to get the good overshoot and short settling time, T_S (settling time) is adopted as the main performance criterion

1) Supported by National Natural Science Foundation of P. R. China (70471052)
Received July 22, 2004; in revised form February 20, 2005

and $ITAE(ITAE = \int_0^\infty t|e|\mathrm{d}t)$ index is adopted as the assistant performance criterion. They together compose the objective function:

$$f_{object} = \min_{\theta}(aTs + (1-a)\int_0^\infty t|e|\mathrm{d}t) \tag{2}$$

where the weighting factor $a \in (0.5, 1]$.

3 Distribution population-based genetic algorithm (DPGA)

3.1 DPGA system

The standard genetic algorithm (SGA) which based on single space is easily trapped into the premature convergence. Furthermore, searching efficiency of the SGA is higher in the first stage but decreases evidently in the later stage.

Consider the multitudinous population distribution of the same kind of biology in the living space. It can be seen that there are different populations distributed in a big living space and various population densities distributed in different areas. And every population evolves gradually with the living condition in a comparatively fixed place, which has natural resources that often are the richest in the space they can reach, or synthetically, configuration for various natural resources is the best, such as abundant water resource, convenient traffic, rich soil and plenteous sunshine. The better the living condition, the more the number of population. For example, it is evident that the number of biology living in the plain area near sea is more than that in the desert frontier, which can be taken as an evidence of further division in the development of population living in the better environment, that is, continuous space subdivision in the subspace.

Follow the principle described previously, the distribution population-based genetic algorithm (DPGA) is proposed. Initially, divide the search space into several subspaces which have a sub-population respectively. Each sub-population operates its own GA to find the best solution of its space. Thus, by comparing the best candidate solution among subspaces, the best subspace will be selected to subdivide again. So the searching capability of the algorithm is improved by competition between distribution populations to reduce the search zone.

The whole space is subdivided to several subspaces which are not intersectant. The expression is

$$K = \cup_1^n K_i, \text{ and } \phi = K_i \cap K_j, \quad \forall i, j (i \neq j) \tag{3}$$

where K is the whole space to be searched, K_i is the i-th subspace.

Each population is distributed separately in every subspace to seek the best solution in its space, and control center is set up to supervise and control each distributed population. The model of communications between sub-population and control central is described in Fig. 2. The control center commu-

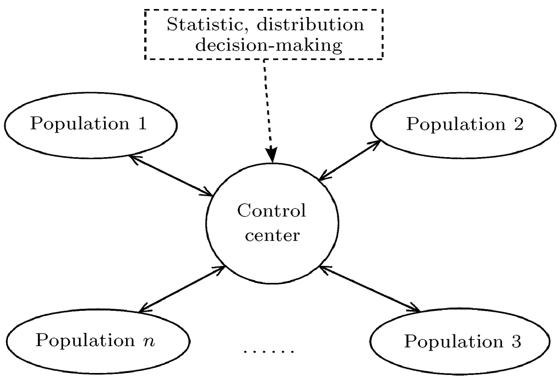

Fig. 2 The model of communications of DPGA

nicates with each sub-population and monitors the evolution character of each sub-population in real time. According to the analysis, the control center dynamically makes decision and timely revision for evolution parameters of each population, such as population size and parameter related to genetic operators. When each population is steady, the control center implements combination and division between them and then further subdivides the excellent subspace to search the best solution.

3.2 Implementation of DPGA

There are many forms to implement the distribution population-based genetic algorithm (DPGA). One of the forms is illustrated in Fig. 3.

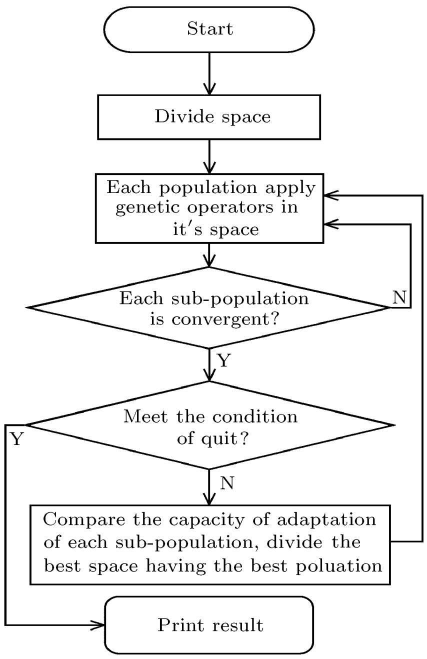

Fig. 3 Flow chart of DPGA

The steps of the DPGA are stated as follows.

1) Set the objective function and the parameters of algorithm such as the maximum number of generation, the size of population, and so on.

2) In every subspace randomly generate the initial population, apply genetic operators, and record average fitting value and the best solution in its space.

Real code is adopted and the three genetic operators are implemented as follows.

a) Selection operation

The normalized geometric ranking (normGeomSelect) method is adopted. This method defines P_i for each individual by

$$P_i = q'(1-q)^{r-1} \tag{4}$$

where q is the probability of selecting the best individual, r is the rank of individual (where 1 is the best), p is the population size, $q' = \dfrac{q}{1-(1-q)^q}$. On this basis, if a parental individual can generate several offspring individuals, we will just copy the parental individual only one time as one of its offspring individuals and let other offspring individuals randomly present at the specific location around the parental individual. The distance between each offspring individual with the parental individual meet the inequality of $|P_x - P_y| < \varepsilon$ where P_x is the offspring individual, P_y is the parental individual, ε is a specified value which is chosen by the size of search space. This operation is good for holding the diversity of population, which can increase opportunity to approach the optimal solution.

b) Crossover operation

Arithmetic crossover is adopted. This method produces two complimentary linear combinations of the parents:

$$\bar{X}' = r\bar{X} + (1-r)\bar{Y}, \qquad \bar{Y}' = (1-r)\bar{X} + r\bar{Y} \tag{5}$$

where $r = U(0,1)$.

c) Mutation operation

Non-uniform mutation is adopted which randomly selects one variable, j and sets it equal to a non-uniform random number:

$$x_i' = \begin{cases} x_i + (b_i - x_i)f(G_t), & \text{if } r_1 < 0.5 \\ x_i - (x_i + a_i)f(G_t), & \text{if } r_1 \geqslant 0.5 \\ x_i, & \text{otherwise} \end{cases} \tag{6}$$

where $f(G_t) = (r_2(1 - \frac{G_t}{G_{\max}}))^b$, r_1, r_2 are uniform random numbers between (0,1), G_t is the current generation, $G_{\max}$ is the maximum number of generations, b is a shape parameter.

3) Each sub-population will be integrally evaluated by some criterion (for example select the space which contains the best solution among all sub-population). Then subdivide the selected space into appropriate number of subspaces again based on the bulk of space.

4) If the specified maximum number of generations is reached or population converges, the algorithm stops. Otherwise, go to step 2) until the termination criterion is met.

3.3 Characteristic of the DPGA

The advantages of the distribution population-based genetic algorithm compared with the standard genetic algorithm include 1) each sub-population searchs its best solution in parallel with others in its own space. 2) each sub-population is not intersectant, and each sub-population can adopt a different seeking method. 3) heep the some excellent solution in first stage from dominating the trend of evolution because of subdividing the entire space into several subspaces. So it can overcome the premature convergence.

4 Simulations

Consider tuning the optimal parameters of PID controllers for the following four plants using DPGA method and Simplex method based ITAE index. The result is given in Table 1.

$$\text{Plant 1}: G_1(s) = \frac{1}{s+1} \tag{7}$$

$$\text{Plant 2}: G_2(s) = \frac{1}{s+1}e^{-0.2s} \tag{8}$$

$$\text{Plant 3}: G_3(s) = \frac{1.6}{s^2+2.584s+1.6} \tag{9}$$

$$\text{Plant 4}: G_4(s) = \frac{1.6}{s^2+2.584s+1.6}e^{-0.1s} \tag{10}$$

Table 1 Comparison in the optimal parameters of PID controllers between Simplex method and DPGA

PLANT	Simplex method					DPGA				
	K_P	K_i	K_d	T_s	**	K_p	K_i	K_d	T_s	**
G_1	8.152	4.3681	0.1101	0.4878	0.0950	4.1984	4.0853	0.3195	0.8895	0
G_2	4.3514	3.3579	0.2438	0.6813	0.1506	2.7811	2.1836	0.0012	0.4500	0
G_3	11.874	4.5275	1.1670	1.0318	0.1850	19.228	9.4888	0.1854	0.2445	0
G_4	6.4282	3.7240	1.1941	1.2818	0.2532	4.9957	3.5826	1.6528	0.6722	0.0511

**: Overshoot

In the simulations, the parameters of DPGA are as follows: the maximum number of generation Ng is 100, the size of population is 100, a is 0.95, the parameter of p in selection operation is 0.08, the parameter b in mutation operation is 3. In addition the entire space is subdivided into several sub-spaces in a grid form. Following this guidance, we get 16 subspaces in the first phase by dividing the parameter of K_P into 4 segments, each parameter of K_I and K_D into 2 segments, respectively.

Table 1 shows the comparisons of performance and the optimal parameters of PID controllers for the four plants using DPGA method and Simplex method, respectively. Figs. 4∼7 show that Simplex method based step response′s curve has larger overshoots and larger settling times as compared with those of DPGA.

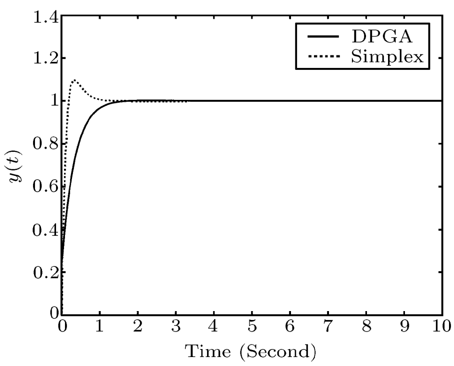

Fig. 4 Step response of $G_1(s)$ with PID

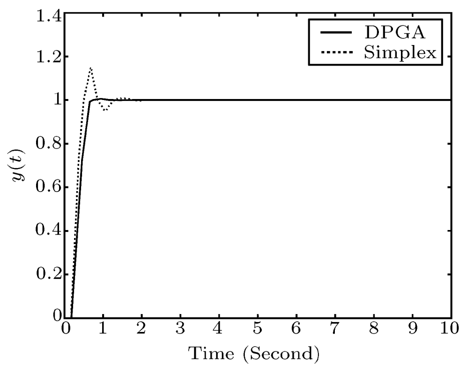

Fig. 5 Step response of $G_2(s)$ with PID

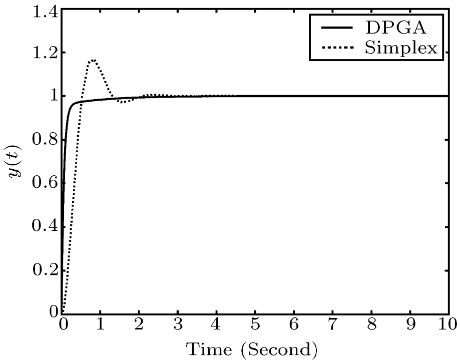

Fig. 6 Step response of $G_3(s)$ with PID

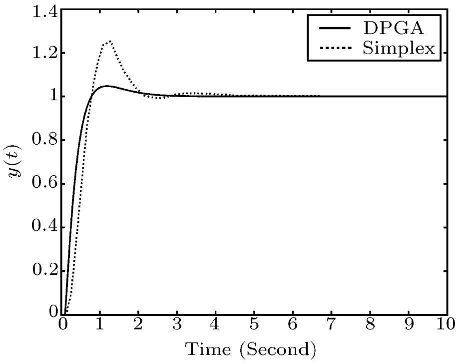

Fig. 7 Step response of $G_4(s)$ with PID

5 Conclusions

In this paper the distribution population-based genetic algorithm (DPGA) is presented and applied to design of optimal parameters of PID controllers. The simulation results show that DPGA based satisfactory performances are much better as compared with those of Ziegler-Nichols, Simplex method.

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