

## PID Optimization with Regulation-Based Formulas and Improved Differential Evolution Algorithm

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**Abstract.** Regulation-based formulas and improved Differential Evolution(DE) algorithm is used to optimize PID parameters. In order to improve the global search ability and the convergence rate of the common DE algorithm, self-adaptive method is introduced to obtain DE parameters. On the other hand, initial population quality of DE algorithm has important influence on convergence of the algorithm. So the regulation-based formulas are used to guide the production of initial population, which is good to improve the convergence rate and realize obtaining of PID parameters completely adaptive without any personal experience. The simulation is developed on steam temperature system of cycle fluidized bed boiler with serious parameter uncertainties and many disturbance and long-time delay. The results show that the improved DE algorithm has higher optimal speed, small amount of calculation and effective optimization of parameters. The proposed method has better control quality and system robustness.

### Introduction

These years, with the development of artificial intelligence, some intelligent control algorithms are proved to be better than traditional PID control algorithm. However, in the field of thermal control, PID control is still dominant. PID control effect is mostly influenced by controller parameters. So how to set the parameters is always an important research topic. The traditional methods, as cut-and-try, require experience of field operators and only get a low precision. Nowadays, many researchers introduce intelligent optimizing algorithms into PID parameters selecting, such as PSO(Particle Swarm Optimization), GA(The Genetic Algorithm), ACO(Ant Colony Optimization) which improve the control accuracy, but algorithm itself are relatively complex, easy in local optimum<sup>[1-3]</sup>. DE(Differential Evolution), is an high efficiency intelligent optimizing algorithm which stems from GA, but without encoding and decoding operation. This algorithm is deemed to a potential interdisciplinary optimization algorithm<sup>[4-6]</sup>. Based on the DE algorithm, for improving the search effective and speed, this paper proposes an improved algorithm based on regulation-based formulas and adaptive DE algorithm by introducing regulation-based formulas and self-adaptive operator. Meanwhile, we apply this method into PID control of steam temperature system for cycle fluidized bed boiler. The simulation result shows that this method has much better control effect and robustness than GA algorithm.

### Differential Evolution algorithm

DE algorithm is a kind of real number coding algorithm based on the population evolution. While other evolution algorithm relies mainly on the random distribution function, DE algorithm relies on the difference of a pair of objective vector which is chosen randomly<sup>[4]</sup>. And the distribution of objective vector mainly depend on the characteristics of the objective function, what make the searching way of DE algorithm more suitable for target function, and therefore, having much stronger robustness and global search capability. Summarized speaking, DE algorithm mainly include the following several important contents:

**Initialization.** In order to establish the optimization initial points, population must be initialized and its initial scope should cover the whole solution space. In the feasible solution space of issue, initialize randomly the populations  $X^0=[x_{1,1}^0, x_{1,2}^0, \dots, x_{N_p,1}^0]$ ,  $N_p$  is population scale.  $x_i^0=[x_{i,1}^0, x_{i,2}^0, \dots, x_{i,D}^0]$  is evolution individual, and  $D$  is the dimension of the optimization problems. **Variation.** Using Eq. (1), the variation operation is implemented for the each individual  $x_i^G$  of generation  $G$ , and the corresponding variation individual  $v_i^{G+1}$  is obtained as follows:

$$v_i^{G+1}=x_{r3}^G+F(x_{r1}^G-x_{r2}^G) \quad (1)$$

Where,  $r_1, r_2, r_3 \in (1, 2, \dots, N_p)$  and  $r_1 \neq r_2 \neq r_3 \neq 1$ ; Mutation rate  $F$  is a real number which is used to control the amplification and narrowing of the father generation difference vector.

**Crossover.** Get the variation individual  $v_i^{G+1}$  and current individual  $x_i^G$  cross with binomial distribution, generating test individual  $u_i^{G+1}$ , as follows:

$$u_{i,j}^{G+1} = \begin{cases} v_{i,j}^{G+1}, & \text{if } \text{rand}(j) \leq C_R \text{ or } j = k(i) \\ x_{i,j}^G, & \text{others} \end{cases} \quad (2)$$

Where,  $\text{rand}(j) \in [0, 1]$  is a uniformly distributed random numbers;  $C_R \in [0, 1]$  is the crossover probability; and  $k(i)$  is a random value between  $\{1, 2, \dots, D\}$ .

**Choose.** Compare the object function value of the current individual  $x_i^G$  and the testing individual  $u_i^{G+1}$  by Eq. (3), and select the smaller as a new population individual, as follows:

$$x_i^{G+1} = \begin{cases} u_i^{G+1}, & \text{if } f(u_i^{G+1}) < f(x_i^G) \\ x_i^G, & \text{others} \end{cases} \quad (3)$$

Where,  $f$  is the object function.

### Parameter adaptive DE algorithm based on regulation-based formulas

**Regulation-based formulas.** The quality of DE algorithm optimum solution depends on whether the initial population will be enough to contain the values of the solution in the solution space, and will not lost one of the fine character in the course of evolution<sup>[7]</sup>. Initial population should intersperse in all the solution space and improve the search capability in the field which has most hope to obtain the optimize solution. DE algorithm generally get random number in the scope of the value for each control variables to obtain initial solution group. Because the DE algorithm in this paper is used to optimize the parameters of PID, the initial population is actually the range of the parameters of PID. Currently, most researchers confirm the initial range of PID parameters by trial and error, which requires high level of field operators and it is hard to get the best result. By lots of experiments, we get a group of formals from reference<sup>[1]</sup> to obtain PID parameters.

The thermal objects always can be divided into two kinds, self-balancing objects and no self-balancing objects. Their mathematical description form are as follows:

$$G(s) = \frac{K}{(Ts+1)^n} e^{-\tau s} \quad (4)$$

$$G(s) = \frac{K}{s(Ts+1)^n} e^{-\tau s} \quad (5)$$

Where,  $K$  is static gain of objects,  $e^{-\tau s}$  means pure delay link,  $\tau$  is pure delay time,  $T$  is process time,  $n$  is the degree of objects.

The transfer function of PID controller is as follow:

$$G_c(s) = \frac{1}{\delta} \left( 1 + \frac{1}{T_i s} + \frac{T_d s}{T_d s + 1} \right) \quad (6)$$

Where,  $\delta$  is proportional band, equals reciprocal of proportional gain,  $T_i$  is time of integration,  $T_d$  is derivative time. The steam temperature system for cycle fluidized bed boiler in this paper is a self-balancing object. Hence, the paper provides the regulation-based formulas only for self-balancing object.

After simply calculate, we can get PID parameters directly and we use these values to guide the range of optimizing with DE algorithm. In a word, firstly, we use regulation-based formulas to obtain the range of optimizing, then, we use DE algorithm to adjust these parameters, which is benefit for improving optimizing precision and convergence rate.

**Self-adaptive operator.** The performance of DE is not only relate to optimal range, but also to the parameters in itself, which include variation rate  $F$  and hybridization factor  $CR$ [8]. If  $F$  is much bigger, the individual oscillation range is bigger too, which is good to produce diversified variables, but it is easy to lead to low convergence rate. However, if  $F$  is much smaller, it is good for improving the algorithm convergence rate, but it is easy to fall into local optimum. Therefore, at the beginning of calculating, the value of  $F$  should be big, but should be small at the end of calculating. Meanwhile, if  $CR$  is too small, there will be little new individuals after hybrid operation, which will impair the capability of reclaiming new space. However, if  $CR$  is too big, the stability of algorithm will be reduced. Therefore, as  $F$ ,  $CR$  should be big at the beginning but small at the end of calculating. We introduce self-adaptive operator to adjust  $F$  and  $CR$  adaptively, as follows:

$$F = F_{\min} + \frac{(G_{\max} - G)}{G_{\max}} \times (F_{\max} - F_{\min}) \quad (7)$$

$$C_R = C_{\min} + \frac{(G_{\max} - G)}{G_{\max}} \times (C_{\max} - C_{\min}) \quad (8)$$

Where,  $G_{\max}$  means the biggest iterations,  $G$  is present iterations,  $F_{\min}$  and  $F_{\max}$  are the biggest and smallest probability of mutation respectively,  $C_{R\min}$  and  $C_{R\max}$  are the biggest and smallest hybrid probability respectively. So,  $F$  and  $C_R$  are big at the beginning, the global search ability will be strong, and will be weak with the increase of number of iterations. When the algorithm in the back section, local search ability will be strong, which enhance global search ability and convergence rate.

**Steps for optimizing PID parameters using IDE.** In term of common performance index in thermal control process, we use the integral of second order matrix of absolute error as object function.

So, the steps for optimizing PID parameters using IDE as follows:

We calculate  $K_{p0}$ ,  $T_{i0}$  and  $T_{d0}$  in term of the formula above, thereby, we can confirm the initial population and optimizing range.

Initialize IDE parameters.  $N_p=40$ ,  $G_{\max}=500$ ,  $F_{\min}=0.4$ ,  $F_{\max}=0.9$ ,  $C_{R\min}=0.3$ ,  $C_{R\max}=0.9$ ,  $G=1$ .

Evaluate initial population and calculate object function value in term of formula (13).

Judge whether the result meet end condition, if yes, output the optimal PID parameters. The end condition is that evolution algebra equal 100 or fitness value equal  $1 \times 10^{-4}$ .

Do variation and hybridization operation for all of individuals, then we can get temporary population. Evaluate the temporary population and calculate object function value and do choice operation. Finally, we can obtain new population.

Renew evolution algebra,  $G = G + 1$ , turn to step (4).

### PID parameters optimization using IDE algorithm

**Mathematic model of steam temperature system for cycle fluidized bed boiler.** The steam temperature system of cycle fluidized bed boiler uses cascade control, and its control diagram as shown in figure 3, in which both the inner loop and outside loop apply PI controller,  $\theta_2$  and  $\theta_1$  represent steam temperature of leading and inertia sections.

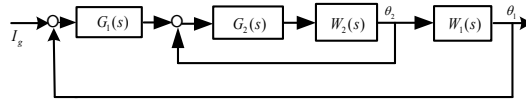


Fig. 1 Main steam temperature control system diagram

$$W_1(s) = \frac{K_1}{(T_1 s + 1)^5} \quad (9)$$

$$W_2(s) = \frac{K_2}{(T_2 s + 1)^2} \quad (10)$$

The formulas above are the transfer function of the system<sup>[9]</sup>, and  $W_1(s)$  is the inertia section transfer function,  $W_2(s)$  is the leading section transfer function, in which  $K_1$  equals to 0.8~0.5,  $T_1$  is 100~80s,  $K_2$  is 2~1,  $T_2$  is 50~35s when Unit load change from 25% to 100%. From this we can see that with the increase of load, the static gain and process time of objects are descend, and shows characteristic of great inertia, pure time-delay, so it uses two-loop cascade control strategies.

#### Controller parameters setting results and performance analysis.

**Experiment of set point is tracked.** The initial PID parameters are calculated through empirical formulas, that is, the secondary controller parameters:  $\delta_{01}=0.9$ ,  $T_{i01}=57.5$ , and the primary controller:  $\delta_{01}=0.9$ ,  $T_{i02}=200$ . Therefore, we can confirm the initial population of DE:  $\delta_1=[0.009,9]$ ,  $T_{i1}=[5.75,575]$ ,  $\delta_2=[0.009,9]$ ,  $T_{i2}=[20,2000]$ . Using the IDE algorithm of this paper get the optimal PID parameters:  $\delta_1=0.9988$ ,  $T_{i1}=228.0577$ ,  $\delta_2=0.0622$ ,  $T_{i2}=359.1242$ . Under 100% load, the system unit step response curve in set point is tracked as shown in figure 2(the dotted line), and its settling time is 762s( $\pm 5\%$ ), overshoot is 1.7473%.

Meanwhile, the figure 2 also shows the control effect of using GA algorithm to optimize PID parameters (Solid line), the optimal PID parameters of which are the secondary controller parameters:  $\delta_{01}=2.1688$ ,  $T_{i01}=114.9876$ , and the primary controller:  $\delta_{02}=0.0918$ ,  $T_{i02}=17.3899$ . Its settling time is 1094s( $\pm 5\%$ ), overshoot is 8.1331%. From this we can see that, at set point unit step disturbance, the control quality of applying IDE algorithm proposed by this paper to optimize PID parameters is better than GA algorithm.

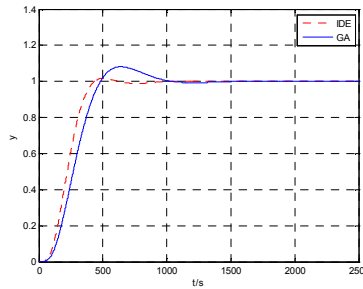


Fig. 2 Output curves of system response when set point is tracked under 100% load

**Robustness experiment.** The static gain and process time of steam temperature system will change a lot when influenced by load and other effects, so assume the inertia section model changed to check the robustness of control system.

(1) Assume the inertia time constant of the object changed, the transfer function of object become into formula (16):

$$W_1(s)' = \frac{0.5}{(100s + 1)^5} \quad (11)$$

The others of this system remain unchanged, and we get the curves of system respond output under setting disturbance as figure 3.

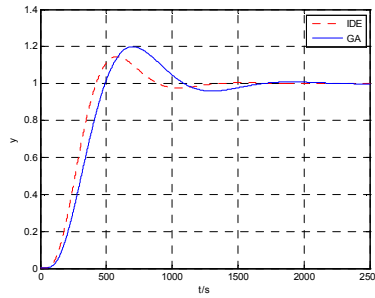


Fig. 3 Curves of system respond output with object model has changed

(2) Assume the gain of the object changed, the transfer function become into formula (16):

$$W_1(s)'' = \frac{0.8}{(80s + 1)^5} \quad (12)$$

The others of this system remain unchanged, and we get the curves of system respond output under setting disturbance as figure 4.

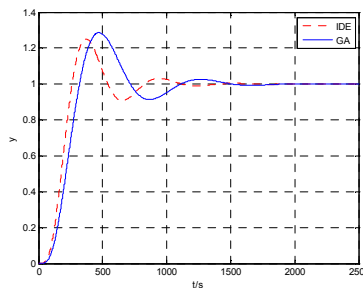


Fig. 4 Curves of system respond output with object model has changed

From figure 3 and figure 4, we can see through, in object properties changing, the parameters selected by the algorithm of this paper, still can obtain better control effect than selected by the GA algorithm, and shows that the algorithm of this paper has stronger robustness and good control quality.

**Upset test.** Because feed water flow makes a big influence on steam temperature, we make step disturbance to feed water under 100% load and we can get the response curve as figure 5.

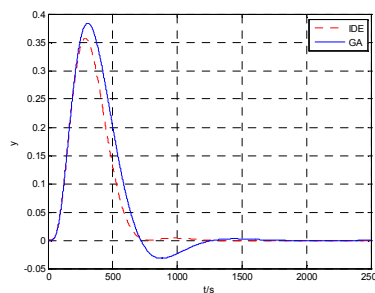


Fig. 5 Curves of system respond output when disturbance happened

From the picture above, we can find that the PID controller has better inhibitory action with the method proposed by this paper than by GA.

## Summary

Aim at PID parameters setting problems, we introduce DE algorithm to optimize PID parameters. Based on the common DE algorithm, we use parameters adaptive differential evolution algorithm, which is good for improving convergence rate and avoiding falling into local convergence.

Meanwhile, we use regulation-based formulas to determine the scope of initial population, which is good for reducing the number of infeasible solution and enhancing convergence rate without any field operators' experience. Through the simulation to practical steam temperature system for recirculating fluidized bed, we can see that accommodation time and overshoot are shortened with the method proposed by this paper. And, the control quality is better than GA. Meanwhile, when object properties and feed water flow are changed, using this method, we can get a better control effect and strong robustness.

## References

- [1] Qian Zhang, Ze Dong, Pu Han, etc, Optimization of Controllers in the Thermal System Using Initial Pheromone Distribution in Ant Colony Optimization, IEEE International Conference on Information Reuse and Integration, Las Vegas, 2008, pp.22-27.
- [2] Li Meng, Shen Jiong, Simulating study of adaptive GA-Based PID parameter optimization for the control of superheated steam temperature, J. Proceedings of the CSEE, 2002, pp.145-149. (in Chinese).
- [3] Li Jian-bo, Wang Dong-feng, Fu Ping, Han Pu, PID controller parameters optimization for the main steam temperature system based on improved particle swarm optimization, J. Journal of North China Electric Power University, 2005, pp.26-30.
- [4] Storn R, Price K, Differential evolution-a simple and efficient heuristic for global optimization over continuous space, J. Global Optimization, 1997 ,pp.341-359.
- [5] Qing A Y, Dynamic differential evolution strategy and applications in electromagnetic inverse scan raring problems, J. IEEE Trans on Geosciences and Remote Sensing, 2006, pp.116-125.
- [6] Lin Lian-lei, Jiang Shou-da, Liu Xiao-dong, Parameter selection for an SVM based on a differential evolution algorithm, J. Journal of Harbin Engineering University, 2009, pp.138-141.
- [7] Zhang Bing-cai, Qin Si-juan, Qiao Shi-jun, Lu Zhi-gang, Reactive power optimization in power system based on modified differential evolution algorithm, J. Power System Protection and Control, 2010, pp. 91-94.
- [8] Jiang Li-qiang, Qiu Ying-feng, Liu Guang-bin, A modified differential evolution algorithm for linear system approximation, J. Electronics Optics & Control, 2008, pp.35-37.