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Improved evolutionary algorithm and its application in PID controller optimization

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Dear editor,
As a common control loop feedback mechanism, the proportional-integral-derivative (PID) controller has been widely applied in industrial control systems [1–3]. The PID control method is simple, stable, and reliable; thus, it has realized considerable economic benefits in the field of industrial process control.

Unfortunately, the parameter tuning of PID controllers remains a sticking point. For example, properly adjusting the gains of PID controllers is difficult, because the transfer functions of many industrial plants often face various problems such as high-order, time-delay, and nonlinearity [4, 5].

In recent decades, with the rapid computational intelligence development, the nature-inspired population-based metaheuristics [6–8] have been applied in PID parameter tuning owing to their superior performance and robustness. To this end, based on a novel evolutionary algorithm (EA) [9], we propose LEEA to improve the accuracy of PID parameters. In LEEA, a nonlinear regressive function is employed to tune the inertia weight ω. The cognitive coefficient C and social coefficient S adopt a linear dynamic adjustment strategy, and an elite strategy is employed in the iterative update process of the entire solution. In addition, to validate the superiority of LEEA, the LEEA-PID controller is compared with artificial bee colony PID and chicken swarm optimization PID controllers.

Contributions. The primary contributions of this study are summarized as follows. (1) A nonlinear regressive function and linear dynamic adjustment ensure that the solution of the parameters of the PID controller does not easily fall into a local optimum. Specifically, the inertia coefficient ω, cognitive coefficient C, and social coefficient S dynamically change in an iterative process. Results indicate that ω attempts to balance the exploration of global and local regions; C and S are applied to promote the global exploration of the early phase and the local exploration of a later phase, respectively. Dynamic adjustment of the three parameters ω, C, and S allows a swarm to quickly identify the promising regions and helps LEEA to increase the solution precision in a limited running time. (2) The search scale of the solution is increased using the elite strategy, which guarantees the accuracy and diversity of solutions. (3) Obtaining an optimal solution using LEEA is faster than other common algorithms, such as artificial bee colony algorithm and chicken swarm optimization algorithm.

Statement. In EAs, the diversity of population particles plays a vital part in the efficiency of evolution, and premature convergence may result from a lack of diversity. To strengthen diversity and avoid being caught in local optimal values, correlation parameters should be adjusted according to the fitness value of particles. In addition, the flight of particles is not a simple linear pro-

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cess. Thus, the nonlinear regressive function and linear dynamic adjustment are employed to adjust inertia weight ω, cognitive coefficient C, and social coefficient S, respectively. In LEEA, we define the diversity as follows:

$$D(t) = f_{\min}(a(t))/f_{\max}(a(t)), \tag{1}$$

and

$$\begin{cases} f_{\min}(a(t)) = \min(f(a_i(t))), \\ f_{\max}(a(t)) = \max(f(a_i(t))), \end{cases} \tag{2}$$

where $f(a_i(t))$ is the fitness value of the ith particle and i ranges between $[1, N]$. $f_{\min}(a(t))$ and $f_{\max}(a(t))$ are the minimum and maximum fitness values of the population at time t, respectively. This diversity $D(t)$ is applied to describe the movement characteristics of the particles. Then, to tune the inertia weight, such that the search ability is balanced, the following nonlinear regressive function is presented:

$$\beta(t) = (\mathrm{B} - D(t))^{-t}, \tag{3}$$

where $\mathrm{B} \geqslant 2$ is a predefined constant.

In addition, to acquire a suitable route, the change ratio between the ith particle and the best particle of the population is given as follows:

$$L_i(t) = f(g(t))/f(a_i(t)), \tag{4}$$

where $f(g(t))$ is the best fitness value of the population.

After comprehensive analysis, we define the inertia weight as follows:

$$\omega_i(t) = \beta(t)(L_i(t) + c), \tag{5}$$

where $\omega_i(t)$ is the inertia weight of the ith particle at time t and $c \geqslant 0$ is a constant to enhance the global search ability of the particles. Moreover, cognitive coefficient C and social coefficient S, which are similar to the self and social learning factors in particle swarm optimization are linearly time-variant. The dynamics of C and S can promote the global exploration of the early phase and local exploration of later phases. Generally, C takes a larger value and a smaller value in the early and late search stages, respectively, but S in contrast. The corresponding updating formulas of cognitive coefficient C and social coefficient S are represented as follows:

$$\begin{cases} C = C_s + \dfrac{C_e - C_s}{t_{\max}} \times t_n, \\ S = S_s + \dfrac{S_e - S_s}{t_{\max}} \times t_n, \end{cases} \tag{6}$$

where t_n is the number of current iterations and $t_{\max}$ is the maximum number of iterations. C_s and S_s are the initial values of the cognitive coefficient and social coefficient, respectively. C_e and S_e are the termination values of the cognitive and social coefficients, respectively. The improved foraging formula is expressed as follows:

$$\begin{aligned} a_{i,j}^{t+1} =& \omega_i(t) a_{i,j}^t + (p_{i,j} - a_{i,j}^t) C \mathrm{rand}(0,1) \\ &+ (g_j - a_{i,j}^t) S \mathrm{rand}(0,1). \end{aligned} \tag{7}$$

In addition, we use elite strategy to ensure the accuracy and diversity of the solutions. Specifically, we divide the solution for each iteration into two parts, i.e., elite and the ordinary solutions. Here, elite solutions coevolve with the offspring in the next iteration. Figure 1(a) shows a flowchart of the LEEA process.

Obviously, the performance of the PID controller depends on parameters K_p, K_i, and K_d. Therefore, the parameters of the PID controller must be optimized, wherein the optimization problem of the PID controller is to find the optimal K_p, K_i, and K_d to minimize the error. In the PID control field, a common indicator is the integrated of time absolute error (ITAE), which is given as

$$\mathrm{ITAE} = \int_0^\infty t\,|e(t)|\mathrm{d}t. \tag{8}$$

Smaller ITAE values indicate better control parameters, and vice versa. In the iterative process, we define the fitness value of ITAE as fitness-value, and the fitness value of the control parameters as 1/fitness-value.

Experiments. Using simulink, a circuit simulation model is designed for some benchmark transfer function models, which are unstable systems, shown as follows.

$$G_1(s) = \frac{1}{s^2 + s}; \tag{9}$$

$$G_2(s) = \frac{10}{0.04s^3 + 0.54s^2 + 1.5s + 1}; \tag{10}$$

$$G_3(s) = \frac{s+2}{s^4 + 8s^3 + 4s^2 - s + 0.4}; \tag{11}$$

$$\begin{aligned} G_4(s) &= \frac{1}{s(s+1) + e^{-s}} \\ &\approx \frac{s^2 + 6s + 12}{s^4 + 7s^3 + 19s^2 + 6s + 12}. \end{aligned} \tag{12}$$

The circuit simulation model is shown in Figure 1(b). The connection between LEEA and the simulink model is each particle (i.e., the PID controller parameters) and the fitness value for each particle (i.e., the ITAE value). The optimization process is described as follows. First, LEEA generates an initial population, which may be an

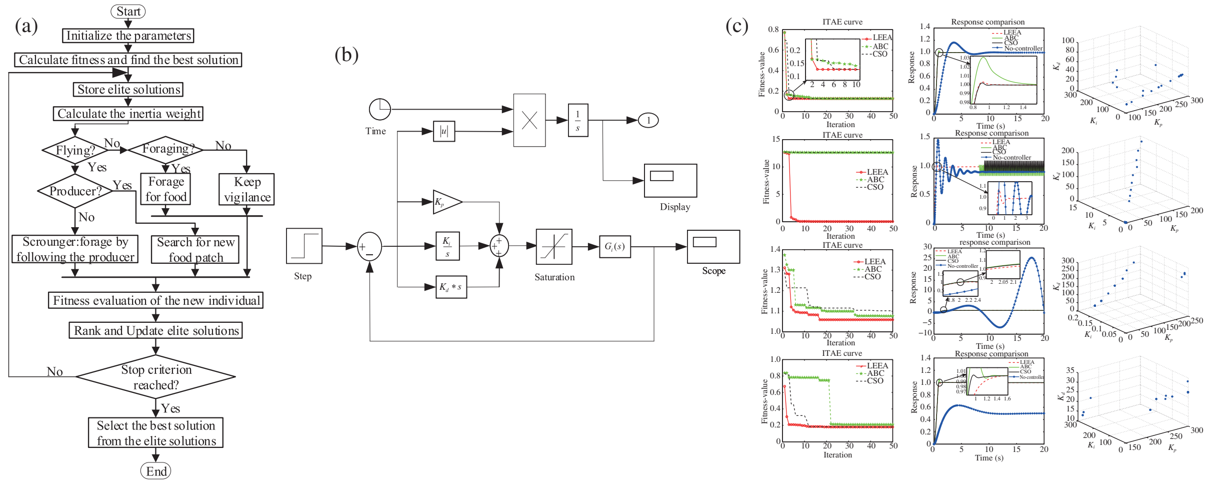

Figure 1 (Color online) (a) Flowchart of LEEA; (b) PID controller simulation model; (c) $G_1(s)$–$G_4(s)$ simulation test diagram.

initial or updated population, and assigns each particle to replace the PID controller parameters K_p, K_i, and K_d. Then, the simulink model of the control system is run to acquire the corresponding performance index for the given parameter set. To verify the superiority of LEEA relative to optimizing the parameters of PID controller, we compare it to representative baseline algorithms. We consider ITAE as the optimization object. The number of iterations is 50. These tests are run on an Intel(R) Core(TM) i5-6500 CPU @ 3.20GHz 64-bit Win7 operating system. The experimental results are presented in Figure 1(c).

As shown in Figure 1(c), among the four tested models, LEEA achieves the minimum ITAE value, which is faster than two algorithms; the convergence speed is also batter than that of two algorithms.

Conclusion and future work. Based on a novel EA [9], an improved approach named LEEA is proposed to optimize PID controllers. The PID controller is simultaneously combined with LEEA, which is defined as an LEEA-PID controller. Our LEEA is also compared with existing algorithms. Finally, the experiments validate that the proposed LEEA is superior than some representative baseline EA in benchmark models.

We have demonstrated the superiority of the LEEA-PID controller; however, a theoretical proof of convergence is lacking. Therefore, addressing this issue will be the focus of the future work. In addition, we plan to apply the LEEA-PID controller to more control cases.

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