Research on the Control System of Greenhouse Based on Particle Swarm and Neural Network

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Abstract. In terms of problems from the quantification factor and scaling factor for fuzzy controller in networked control systems (NCS), which are hard to tackle with conventional empirical methods, the improved quantum particle swarm optimization (IQPSO) based on adaptive mutation of the artificial bee colony operator is proposed in this paper, which is inspired by the thought of searching for nectar source in artificial bee colony algorithm (ABC algorithm) and the performance test is conducted against three types of typical test functions. Then IQPSO is applied into the parameter optimization of fuzzy controller in NCS with time delays, and one typical case in the industrial process control is used to perform the simulated experiment, of which the results indicate that fuzzy controller designed with the aid of IQPSO algorithm PID controller is of better control effect and higher adaptive capacity than those of the PID controller designed with IQPSO and the fuzzy controller designed with standard QPSO algorithm.

Introduction

In recent years, the traditional point-to-point system structure has had difficulty in meeting the production requirements with the growing demands for industrial production and the increasingly complicated system, and the closed-loop feedback control system, i.e. NCS , which enables information exchange among system units, such as controller, actuator, sensor, etc., with computer networks or field bus as transmission media, has been widely used in industrial production and aerospace field . However, all information in NCS are transmitted through network and during transmission problems like network-induced time delay and data packet loss usually lead to the reduced control performance and system instability . Currently, study on network delay mainly includes time-delay compensation method , predictive control method and method based on fuzzy control . The network delay in NCS is hard to compensate due to its uncertain changes, the predictive control algorithm is usually complex and the fuzzy control algorithm is easy to be realized without compensating the network delay for ease of engineering.

QPSO algorithm based on adaptive mutation of the ABC operator

QPSO algorithm

Jun Sun has delved into the convergence behavior of single particles in PSO algorithm, considering that the individual-best and random numbers are all constants. PSO algorithm is not one

global convergence algorithm, that is to say, it cannot converge to global optimal solution with probability 1 with the iterations tending to be infinite. He also deems that the organisms' searching mechanism is of quantum behavior, thus adopting DELTA potential well to derive the QPSO algorithm with Schrodinger equation, and the equation for the algorithm is:

$$p_j = (\varphi_1 * p_{i,j}(t) + \varphi_2 * p_{g,j}(t)) / (\varphi_1 + \varphi_2) \quad (1)$$

$$mbest(t)_j = \sum_{i=1}^{M} p_{i,j}(t) / M \quad (2)$$

$$x_{i,j}(t+1) = p_j \pm \beta * \left| mbest(t)_j - x_{i,j}(t) \right| * \ln(1/u) \quad (3)$$

Wherein φ_1 and φ_2 are random numbers in (0,1); $p_{i,j}(t)$ and $p_{g,j}(t)$ are individual best position and global best position respectively of the ith particle in jth dimension at tth iteration; $mbest(t)_j$ is the mean of best positions of all single particles in jth dimension; M refers to the population size; $x_{i,j}(t)$ refers to position information of the ith particle in jth dimension; u refers to the random number in (0,1); During the iteration, the "−" is taken when the random number is greater than 0.5, otherwise, the "+" is taken; β refers to the shrinkage and expansion factors.

Introduction of the QPSO algorithm with adaptive mutation of the artificial bee colony operator

Like many other optimization algorithms, primary problems that QPSO is confronted with are overcoming premature convergence, how to enhance the particle's searching capability, and preventing particle from falling into the local optimal solution, which can lead to reduced searching capability. Seen from equation for the standard OPSO algorithm, $p_{ij}(t)$ (i =1,2,…, M) guides the search track of particles. If $p_{i,j}(t)$ traps in local optimum and cannot jump out, the ith particle will be led to the local optimal area, and when most particles are led to the local optimal area, it is easy to result in premature in the algorithm. Therefore, how to improve the searching capability of standard QPSO algorithm to help the algorithm jump out of the local optimum is the crux to increase the algorithm performance.

In 2005, Karaboga weighs in with a new intelligence algorithm to resolve the function optimization problems, i.e. artificial bee colony algorithm (ABC algorithm). ABC algorithm is of better optimization performance in optimizing the complicated function problems owing to the employed bees in ABC algorithm search new nectar source with equation (4) in the neighborhood of each nectar source

$$\hat{x}_{i,j}(t) = x_{i,j}(t) + \phi_{i,j}(x_{i,j}(t) - x_{k,j}(t)) \quad (4)$$

Wherein $x_{i,j}(t)$ refers to the position vector of ith nectar source in jth dimension; $x_{k,j}(t)$ refers to the randomly selected nectar source position unequal to i; $\hat{x}_{i,j}(t)$ refers to the new nectar source position; $\phi_{i,j}$ refers to the random number in [−1, 1]. The introduction of random numbers $x_{k,j}(t)$ and $\phi_{i,j}$ ensures the strong searching capability of the algorithm. searching operators of the ABC operator is of strong searching capability, but of poor development capability. Therefore, Zhu brings in the global best value in searching operators inspired by PSO algorithm and obtains a new searching operator

$$\hat{x}_{i,j}(t) = x_{i,j}(t) + \phi_{i,j}(x_{i,j}(t) - x_{k,j}(t)) + R_{i,j}(P_{g-j} - x_{i,j}(t)) \quad (5)$$

Wherein $R_{i,j}$ refers to the random number in [0, 1.5] with other parameters identical to those in equation (4).

Based on the above analysis, with renewing idea of the nectar source position in ABC algorithm for reference in this paper, the ABC searching operator is used for mutation after the positions of QPSO algorithm evolve and update. With the aid of exploration competence of the ABC searching

operator, guide $p_{i,j}(t)$ (i=1,2,…, M) to rapidly jump out of the local optimum in avoidance of premature.

Besides, seen from the entire optimization process, it is mainly to extend the search space in the early stage of optimization process, which is in want of greater mutation; while in the later stage, it is mainly to conduct a refined search around the optimum, which is in want of smaller mutation. Therefore, according to the iterative time t in the paper, the adaptive mutation is performed in monotonically decreasing sequence of the geometric factor η and the mutation probability is

$$A(t) = \eta^t \quad (0<\eta<1) \tag{6}$$

The evolution equation of improved QPSO algorithm is:

$$x_{i,j}(t+1) = p_j \pm \beta * \left| mbest(t)_j - x_{i,j}(t) \right| * \ln(1/u) + A(t)(\phi_{i,j}(x_{i,j}(t) - x_{k,j}(t)) + R_{i,j}(P_{g,j} - x_{i,j}(t))) \tag{7}$$

The evolution equation (7) of improved QPSO algorithm clearly shows the mutation operator of artificial bee colony being introduced in the early stage of evolutionary computation can search the previous best positions, which can enhance the detection ability of improved QPSO algorithm and make it rapidly jump out of the local best position in avoidance of the algorithm being premature. Besides the global best position of population being introduced to the ABC mutation operator accelerate the convergence speed of algorithm in the later period. Meanwhile, the adaptive mutation in monotonically decreasing sequence of geometric progression of the iterative time is adopted to gradually decrease the influence on convergence speed. The adaptive mutation operator of artificial bee colony being introduced to the improved QPSO algorithm is equivalent to adding one disturbance term to the standard QPSO algorithm and its introduction improves the diversification of population, which contributes to getting rid of the local maximum point in search process.

Simulated analysis

Parameter coding & performance index and parameter setting of the algorithm

Apply QPSO and IQPSO to optimize and tune the controller parameters. Above all, encode the optimized parameters in the controller into the particle's coded string with the forms of traditional PID and fuzzy controller respectively being

$$\begin{cases} [k_p \ \ k_i \ \ k_d] \\ [Ke1 \ \ Kc1 \ \ Ke2 \ \ Kc2 \ \ \text{Gp} \ \ \text{Gi} \ \ \text{Gd}] \end{cases} \tag{8}$$

Then by means of presenting value range of the variables according to the engineering application background, the algorithm can search optimal combination of the above variables over a given range performance index through IQPSO optimization.

As a rule, the performance index functions of control system primarily contain IAE, ISE, ITAE, etc. in which ITAE criteria turns to be one of the most common performance indices in control system design featuring speediness, stationary and low overshoot. Therefore, the ITAE criteria is adopted in this paper as the performance index function of optimization algorithm with the expression being:

$$J = \int_0^\infty t \left| e(t) \right| dt \tag{9}$$

Initial population size $N = 20$; Maximum number of iterations $G_{\max} = 30$; Other parameters are the same with those when the test function is optimized.

Simulated analysis

The object of study in this paper is the first order water-tank control system in the simulated production process in laboratory and through fitting the deliver function of system obtained is $G(s)=2.27e^{-s}/(70s+1)$, the regulation time is $\pm 2\%$ terminal value, and τ^{ca} and τ^{sc} are random time-delay in rand(0,0.2). Respectively adopt QPSO and IQPSO to optimize the obtained relevant parameters of the pure PID controller and the fuzzy PID controller just as shown in Table 1-2 and the system performance is shown in Table 3.

Table 1 Parameters of PID controller

	K_P	K_i	K_d
IQPSO	17.1255	0.2066	2.7678

Table 2 Parameters of fuzzy PID controller

	QPSO	IQPSO
K_{e1}	1.3613	1.3080
K_{c1}	6.6176	6.4043
K_{e2}	4.8391	5.4587
K_{c2}	2.6032	1.9001

Table 3 Performance index

Controller	&%	t_r/s	t_s/s
IQPSO-PID	2.78	1.652	4.451
QPSO-Fuzzy	0.05	1.566	3.773
IQPSO-Fuzzy	0.07	1.352	3.165

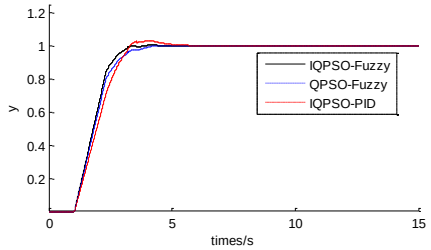

Fig.1 Effect comparison chart without parameter perturbation

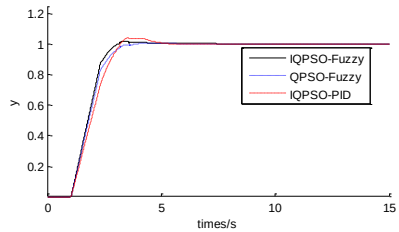

Fig.2 Effect comparison chart with parameter perturbation

In terms of NCS with random network time delays, Table 3 and Fig.1 indicate that fuzzy controller optimized with QPSO and IQPSO is of lower overshoot, rise time and regulation time compared with traditional PID controller optimized with IQPSO. Fuzzy controllers optimized with IQPSO and standard QPSO respectively are of approximate overshoot with the former being of greater rapidity.

Considering the model error of practical system and that the controlled object in actual working conditions can perturb with the changes of environment, the time constant is taken as 68. Simulate in the circumstances when the controller parameters are not changed with the results as shown in Fig.3. It is clear that the fuzzy PID controller is of better adaptability fitted with IQPSO even though perturbation exists in the model.

Conclusion

The paper has proposed an improved QPSO optimization algorithm with adaptive mutation synthesizing influence of the adjacent particles and the global optimal value, which endows the algorithm with stronger search capability in search process in avoidance of the disadvantage that the standard QPSO algorithm can easily fall into the local maximum point; what's more, geometric adaptive probabilistic operator can make the algorithm be of faster convergence speed. Apply the improved algorithm in the design of NCS controller with random time delay. The results show that the fuzzy PID control algorithm is of faster response speed and more steady compared with those of the traditional PID control algorithm, and the fuzzy PID controller optimized with IQPSO is of shorter transit time than that of the fuzzy PID controller system optimized with QPSO and presents better adaptability for the system perturbation in particular, which is of huge significance in actual industrial control.

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