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Research on a Modified Smith Predictive Control Scheme of Main Steam Temperature of Circulating Fluidized Bed

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Abstract: In order to solve the current difficulties of modeling for designing Intelligent Service Mobile Robot (ISMR), a new modeling method based on metasynthesis is proposed from the macro and micro levels. And the system analysis and design agent-oriented based on POMDP are provided in the same time. Finally, the two case studies are given and the experimental results have shown efficiency and rationality of this modeling method.

Key words: Fuzzy control, gain adaptive, main steam temperature, smith predictor

INTRODUCTION

The circulating fluidized bed is a clean coal combustion technology with many advantages. At present, it is widely used. The main steam temperature is one of the important parameters of the circulating fluidized bed boiler. When the main steam temperature is too high, the security of the unit will be affected. When it is too low, the economy of the unit will be affected. Therefore, the main steam temperature needs to be controlled within a reasonable range.

The main steam temperature object has a large delay, large inertia and nonlinear characteristics. Using the conventional cascade control method cannot generate well controlled results. In recent years, some new control schemes of main steam temperature of CFB is proposed, such as adaptive series-step control system (Niu *et al*., 2004), fuzzy predictive function control scheme (Liu *et al*., 2007) and active disturbance rejection control program (Wang *et al*., 2010). These control scheme can get better effect than traditional control scheme. But it is difficult to be applied to the actual engineering.

The Smith predictor is an effective way to solve the control problem of delay. However, it requires an accurate plant model. When the model is not accurate, the Smith predictor control scheme cannot achieve good control results (Filess *et al*., 2002). In light of this problem, based on fuzzy control and adaptive control, this study will present an improved Smith predictor control scheme. The scheme improves on the traditional Smith predictor control in two ways. On the one hand, it dynamically adjusts the PID parameters in accordance with fuzzy control rules. On the other hand, it introduces the Smith predictor model to an adaptive mechanism.

The main steam temperature of the circulating fluidized bed model is usually in the form of higher order inertia link. But the Smith predictor control needs the controlled object in the form of an inertia link with a pure, definite delay. Therefore, this study presents a model reduction algorithm based on an adaptive chaotic particle swarm optimization algorithm. In this way the main steam temperature model is changed into the form of a one-order lag with a pure delay.

According to the main steam temperature object of circulating fluidized bed, a new cascade control scheme will be designed in this study, The outer ring of a cascade system uses an improved Smith predictor control. The inner ring still uses the traditional PID control. Simulation results show that the main steam temperature control scheme proposed in this study can achieve better control effect and has better robustness.

METHODOLOGY

The model reduced-order algorithm based on adaptivechaotic particle swarm optimization: The model reduced-order problem was first proposed by Davison, (1966). A variety of model reduced-order algorithms was developed over a period of decades.

The traditional reduced-order algorithm is based upon mathematical principles including pade reduced-order algorithm, the Routh reduced-order altgorithm and reduced-order algorithm based on balance realization. Therefore they are very complex.

In recent years, the model reduced-order algorithm based on the optimization algorithm has been proposed by some scholars. Using this method, the structure of the reduced-order model can be determined according to different needs and good results can be obtained. The

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adaptive chaotic particle swarm optimization algorithm is formed on the basis of a particle swarm optimization algorithm. It effectively solves the defect of trapping into the minimum easily of the particle swarm optimization algorithm. A new model reduced-order algorithm is formed when the adaptive chaotic particle swarm optimization algorithm is applied to solve the model reduced-order problem.

The principle of original particle swarm optimization algorithm: The Particle Swarm Optimization (PSO) was proposed by the American scholar Eberhart and Kennedy (1995). It is a new intelligent bionic algorithm. The PSO algorithm mainly simulates the behavior of birds of prey. Its search process is realized by two ideas; one is that individual knowledge comes from the accumulation of its own knowledge and experience. The other idea is that individual knowledge comes from the accumulation of knowledge of the whole group.

PSO firstly initialize a group of rand particles and then finds the optimal solution through two learning iterations. Therefore, the particles, by tracking the two extreme values update themselves in its iteration. One is the optimal solution found by itself, called individual extremum, Pbest. The other is the optimal solution found by the entire population, called global extremum, Gbest. The basic process is as follows:

Suppose there is a community consisting of m particles in a D-dimensional target in the search space. The ith particle is expressed as a D-dimensional vector solution $x_i = (x_{i1}, x_{i2}, \ldots, x_{iD})$(i = 1, 2, ..., m) The location of the ith particle in the D-dimensional search space is x_i. In other words, the position of each particle is a potential solution. A fitness value can be calculated after x_i referred to above is put into an objective function. We measure the pros and cons of x_i depending on the size of the fitness value.

Velocity of the ith particle is a D-dimensional vector, denoted by $v_i = (v_{i1}, v_{i2},\ldots,v_{iD})$. The optimal location searched by the i th particle so far is $p_i = (p_{i1}, p_{i2},\ldots,p_{iD})$, the optimal location searched by the whole particle swarm so far is $p_g = (p_{g1}, p_{g2},\ldots,p_{gD})$. PSO algorithm operates the particle using the following formula:

$$v_{id} = \omega v_{id} + c_1 r_1 \left(p_{id} - x_{id}\right) + c_2 r_2 \left(p_{gd} - x_{gd}\right) \tag{1}$$

$$x_{id} = x_{id} + v_{id} \tag{2}$$

Among them, i = 1, 2, ..., m, d = 1, 2, …, D, learning factor c_1 and c_2 is a nonnegative constant. Usually $c_1 = c_2 = 2$.r_1 and r_2 are a random number between [0, 1]. $v_{id} \in [v_{min}, v_{max}]$, v_{min} and v_{max} are set by the user. ω is a non-negative number, called the inertia factor.

The iteration termination condition is chosen according to specific issues. It is the maximum number of iterations or the best value searched by the particle swarm meeting the minimum adaptation threshold in general.

The adptive chaos PSO algorithm: The PSO algorithm has a wide range of applications, because it is simple and easy to implement. However, the PSO has a problem. When particles encounter local minima in the optimization, this often causes all the particles to fly into the extreme point. Therefore the algorithm is trapped into local minima.

This study studies a adaptive chaotic PSO algorithm. It is proposed by introducing an adaptive adjustment mechanism of the inertia factor and chaos optimization into basic PSO algorithm.

Studies have shown that the larger value of the inertia factor is conductive to jump out of local minima, while the smaller is conductive to the convergence of algorithm. Through the adaptive adjustment of the inertia factor, both search efficiency and search accuracy can be thought of. Therefore the adaptive mechanism is introduced into the original PSO algorithm. With the iteration carried out, it adaptively adjusts to the inertia factor adjustment formula (Zhou *et al*., 2009), as in Eq. (3):

$$w = \begin{cases} \omega = \omega_{\min} + \dfrac{(\omega_{\max} - \omega_{\min})(f_i - f_{\min})}{f_{avg} - f_{\min}} & f_i \le f_{avg} \\ \omega_{\max} & f_i > f_{avg} \end{cases} \tag{3}$$

In the formula (3), ω_{min} is the minimum value of the inertia factor. f_{avg} is the maximum value of the inertia factor. f_{avg} is the average of fitness value of the current whole group. f_{min} is the minimum value of the current whole group. f_i is the current fitness value of the i th particle.

Chaos is a common phenomenon existing in nonlinear systems, with randomness, ergodicity and regularity in a certain range. The chaos optimization algorithm uses the unique ergodicity of the chaotic system. Introducing chaos to optimization variables in a similar way to the carrier has it shown in a chaotic state. Meanwhile, it has the traverse range of the chaotic motion zoom into the range of optimization variable and then search global optimization using the chaotic variables. Chaos optimization is introduced to the adaptive particles swarm optimization, thus forming the adaptive chaotic particle swarm algorithm.

When the adaptive particle swarm converges to a local extreme point, they have the chaotic iteration within the provisions of the solution space in order to replace part of the populations of particles. In this way, it increases the diversity of the population of particles and has the algorithm jump out of the local optima. Therefore the global search performance of the algorithm is improved.

A logistic map is used in this study. The mapping is shown in Eq. (4):

$$z_{i+1} = u z_i (1 - z_i), z_i \in [0,1], u \in [2,4] \tag{4}$$

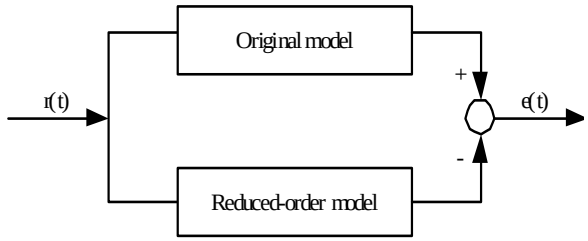

Fig. 1: The error model reduction

In Eq. (4), u are the Control parameters. When u = 4, the logistic map is entirely in the chaotic state (Zhang *et al*., 2009).

Model reduction based on adaptive PSO algorithm: The model reduced-order problem can be equivalent to an optimization problem. In the case of a high order model known, we select the appropriate objective function and get the optimal reduced-order model by parameter optimization. There are a wide variety of indicators and definitions to evaluate the effect of model reduction. The most intuitive form is to define the error of reduced-order model according to the Fig. 1 (Xue, 2007).

The Adaptive chaotic pso algorithm is a good optimization algorithm. The adaptive chaotic pso model reduced-order algorithm is based on a new reduced order model algorithm. It is realized as follows:

- Determine the reduce-order model structure. Determining the reduced-order model structure is to determine the order of molecules and denominator as well as whether to join the pure delay. In order to determine the structure, first we analyze the dynamic characteristics of a high-order system and choose a different reduced-order model structure according to different research needs.
- Determine the objective function. Choosing a different objective function will receive a variety of reduced-order effects. The error of model reduction is usually used to solve the model reduction problem. The ITAE objective function takes into account the factors of time and error. Therefore, this study uses the ITAE objective function. The formula is as follows:

$$J_{ITAE} = \int_0^{\infty} t\left|e(t)\right| dt \tag{5}$$

- When the reduced-order model structure and the objective function are known, the optimal reduced-order model can be got by optimization through the adaptive chaotic PSO algorithm. Before the optimization, various parameters in the adaptive chaotic PSO algorithm need to be set.

Improved smith predictor control scheme: In order to accelerate the regulation process, first we pre-estimate the dynamic characteristics of a process under the basic disturbance and then compensate the delay by the Smith predictor (Smith, 1959).

In this way, overshoot is significantly reduced and adjustment process is accelerated. If the charged object and the model are an exact match and there is no external interference case, the Smith predictor completely compensates the impact of delay and good control effects can be got. However, because the actual production process is very complex, it is very difficult to build an accurate model. Meanwhile, there are various disturbances in the field. Therefore, the Smith control scheme can not get good control effects.

According to the problems of the Smith predictor control, based on the fuzzy control and adaptive control, this paper proposes an improved Smith control scheme. Its control structure is shown in Fig. 2. The new scheme introduces the dynamic adjustment mechanism of PID parameters based on fuzzy rules and the Smith predictor model gain adaptive mechanism into the traditional Smith control scheme.

When the controlled object changes, PID controller parameters can be adjusted in a timely manner based on fuzzy rules and the gain of Smith predictor model can be adaptively compensated.

Dynamic adjustment of PID parameters based on fuzzy rules: In the industrial production process, many of the controlled objects change as the load changes or are affected by interference factors and the objects' characteristics parameters will change (Liu, 2004). When using the traditional PID controllers the change of the controlled object properties will result in poor control effect, so the PID parameters need to be dynamically adjusted.

Dynamic adjustment is based on the experience of the engineer, but because the level of experience of the engineer is not easy to estimate accurately, all kinds of signal quantity and evaluation index it is not easy to say the quantity during the control process, so people use fuzzy mathematics theory and method to represent the rules of the condition and operate with fuzzy set and

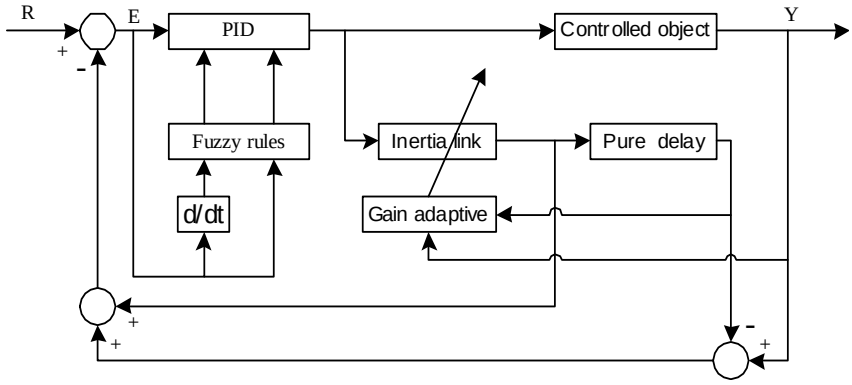

Fig. 2: The control structure of improved smith predictive control

fuzzy rules. The relevant information will be stored in the computer's memory. According to the actual situation of control system and the application of fuzzy reasoning, it can automatically realize the dynamic adjustment of the PID parameters.

The dynamic adjustment of the PID parameters based on fuzzy rules is achieved by computing the current system error and error rate of change using fuzzy rules for fuzzy reasoning and querying fuzzy matrix table for parameter adjustment.

In this study, the input of the fuzzy system is error and the error rate of change, the output is the proportional gain and integral time constant. The error and the change range of the error change rate are defined as a fuzzy subset domain:

$$e, ec = \{-5, -4, -3, -2, -1, 0, 1, 2, 3, 4, 5\} \quad (6)$$

The fuzzy subset is as follows:

$$e, ec = \{NB, NM, NS, O, PS, PM, PB\} \quad (7)$$

A subset of elements represent the negative big, negative middle, negative small, zero, positive small, positive middle, positive big.

The dynamic adjustment formula of PID parameters is shown in Eq. (8) and (9), K_0,T_0 are the initial parameters, ΔK_p,ΔT_i are respectively proportional gain and integral time of fuzzy correction:

$$K_p = K_0 + \Delta K_p \quad (8)$$

$$Ti = T_0 + \Delta T_i \quad (9)$$

In the process of online operation, control system complete the dynamic tuning of PID parameters through queries and forms and operations.

The heart of fuzzy control design is the summary of the engineering technical personnel's knowledge and practical experience and then establishing a suitable rules table. Table 1 is the fuzzy rules table of proportional gain. Table 2 is the fuzzy rules table of integral time table.

Table 1: Fuzzy rules table of proportional gain

	ΔK_p(ec)						
ΔK_p(e)	NB	NM	NS	ZO	PS	PM	PB
NB	PB	PB	PM	PM	PS	ZO	ZO
NM	PB	PB	PM	PS	PS	ZO	NS
NS	PM	PM	PM	PS	ZO	NS	NS
ZO	PM	PM	PS	ZO	NS	NM	NM
PS	PS	PS	ZO	NS	NS	NM	NM
PM	PS	ZO	NS	NM	NM	NM	NB
PB	ZO	ZO	NM	NM	NM	NB	NB

Table 2: Fuzzy rules table of integral time table

	ΔT_i(ec)						
ΔT_i(e)	NB	NM	NS	ZO	PS	PM	PB
NB	NB	NB	NM	NM	NS	ZO	ZO
NM	NB	NB	NM	NS	NS	ZO	ZO
NS	NB	NM	NS	NS	ZO	PS	PS
ZO	NM	NM	NS	ZO	PS	PM	PM
PS	NM	NS	ZO	PS	PS	PM	PB
PM	ZO	ZO	PS	PS	PM	PB	PB
PB	ZO	ZO	PS	PM	PM	PB	PB

Gain adaptive compensation scheme: The gain Adaptive compensation scheme was proposed, in 1977, by Jabbar and Batley on the basis of Smith control (Luo *et al*., 2010). Apart from the Smith model, it has a divider, a leading differentiator and a multiplier. The divider is the value of the output of the process divided by the model of the output values. The leading differentiator is to let the ratio of output values of the process and output values of Smith predictor model enter the multiplier a certain amount of time in advance. Multipliers are to have the Smith predictor output multiplied by the leading differential output and then the output is sent to the regulator. The function of these three links is to automatically correct the gain of the Smith predictor model according to the ratio between the Smith predictor

model and the output signal of process. In reality, the deviation of the prediction model and dynamic characteristics of a real object exist. The gain-Adaptive mechanism plays a good compensation role.

Simulation:

The model of main steam temperature of CFB: The object of main steam temperature of CFB is divided into the leading zone and the inert zone. The model of leading object is with the lower order and less inertia time constant. The form of the transfer function is as follows:

$$W_1(s) = \frac{K_1}{(T_1 s + 1)^2} \tag{10}$$

The inert zone object is with higher order and bigger inertial time which has a great deal of delay characteristics. The transfer function form is as follows:

$$W_2(s) = \frac{K_2}{(T_2 s + 1)^5} \tag{11}$$

When the boiler load is changed from 25 to 100%, K_1 change from 2 to 1,T_1 change from 50 to 35, K_2 change from 0.8 to 0.5,T_2 change from 100 to 80 (Wang *et al*., 2010).

THE RESULTS OF SIMULATION

In the simulation, according to the object in 100% load, a improved smith predictor cascade control scheme is designed. The outer ring of the cascade system uses an improved Smith predictor control. The inner ring of the cascade system still uses the traditional PID control.

First, the main steam temperature object needs to be changed into the form of one lag with a delay with adaptive chaotic PSO model reduction algorithm. In the adaptive chaos PSO algorithm, the number of particles N is 20. Maximum iteration algebra is 30. The search dimension D is 3. The maximum weight ω_{max} is 0.9. The minimum weight ω_{min} is 0.1. Acceleration constant c_1 and c_2 is 2. In the Logistic map, u is 4. The reduced-order model calculated based on MATLAB is shown in Eq. (12):

$$G_m(s) = \frac{0.5}{191.59s + 1} e^{-222.17s} \tag{12}$$

Figure 3 is the comparison chart of a step response of the reduced-order model and the original model. The comparative result shows that the initial error is relatively large and the later error is very small. The reason is that a pure delay is included in the reduced-order model.

The reduced-order model is applied to the improved smith cascade control scheme and a traditional cascade control scheme is designed in order to compare.

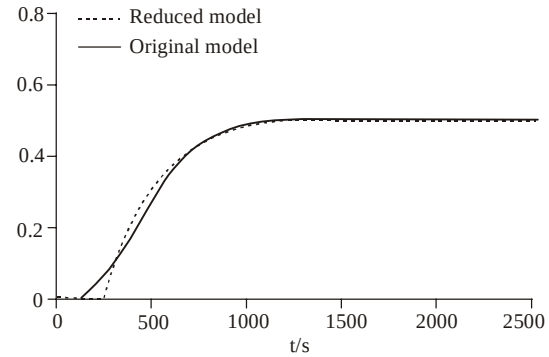

Fig. 3: The comparison chart of step response

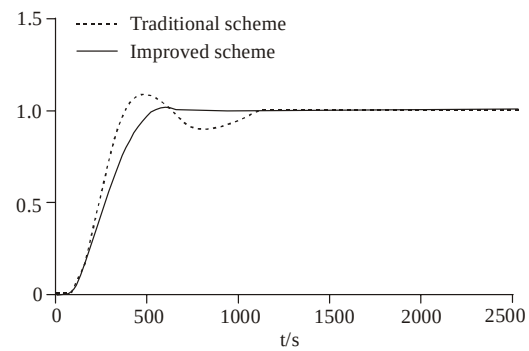

Fig. 4: Control effect when model is exact match

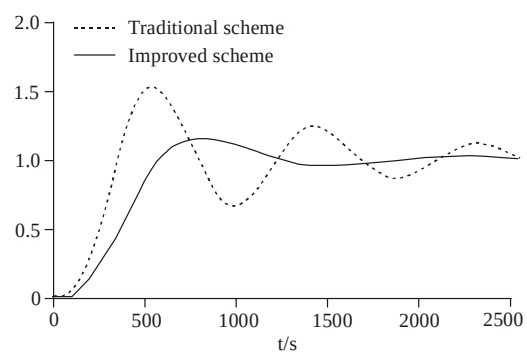

Fig. 5: Control effect when controlled object parameters become smaller

When the Smith predictor model matches the controlled object, the result is shown in Fig. 4. When the inertia time of controlled object becomes 70 and the proportional gain of controlled object becomes 0.3, the result is shown in Fig. 5. When the inertia time of controlled object becomes 100 and the proportional gain of controlled object becomes 0.8, the result is shown in Fig. 6.

The simulation results show that the Smith predictor cascade control scheme proposed in the paper can achieve better control results and has better robustness.

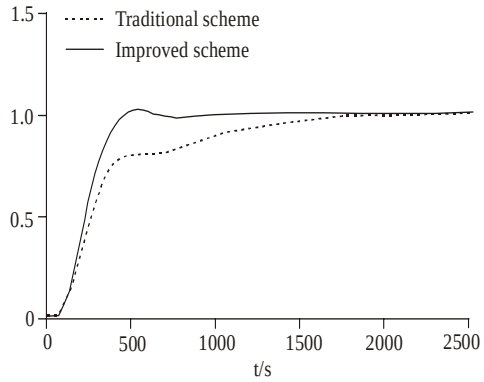

Fig. 6: Control effect when controlled object parameters become bigger

CONCLUSION

In summary this study firstly studied the dynamic characteristics of circulating fluidized bed main steam temperature. Then it studied the principles of the Smith Predictor control and proposed an improved Smith predictive control scheme based on fuzzy control and adaptive control thought. Based on the improved Smith predictive control scheme this paper has designed the improved Smith cascade control scheme of circulating fluidized bed main steam temperature. The inner ring of the improved Smith cascade control scheme still uses PID control, the outer ring uses the improved Smith predictive control. Simulation experiments show that the control scheme that this study proposes can achieve better control results with more robustness.

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