Coke Oven Flue Temperature Control Based on Particle Swarm Optimization and Fuzzy-PID with Variable Universe

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Abstract: Coke oven flue temperature is an important factor to ensure coke output, coke quality and energy consumption in coking production process. The heating process of coke oven is an object with multiple control variables, nonlinearity and large delay. The traditional PID control algorithm cannot further improve the control performance of the coke oven system. This paper proposes a controller based on particle swarm optimization and variable universe Fuzzy-PID, and applies it to the control of coke oven flue gas temperature. In order to solve the problem of local self-adjustment optimization of controller parameters, the variable universe is adopted to ensure the global optimal control parameters of the system, which solves the problem that the fuzzy controller cannot guarantee high accuracy under given rules. At the same time, according to the performance index of the control system, the scale factor is adjusted online through particle swarm optimization (PSO) algorithm. The proposed controller combines the advantages of three different methods. Finally, according to the actual operation, the simulation under four working conditions, namely, normal working condition, given temperature change, random disturbance and coke oven parameter change. At the same time, on-site experiments are conducted on the JN-60 coke oven. The simulation and actual experimental results show that the controller is feasible.

Keywords: coke oven, flue temperature, Fuzzy-PID controller, variable universe, scaling factor, particle swarm optimization algorithm.

1. INTRODUCTION

1.1 Research background

Coke oven is an industrial furnace with special structure. It is widely used in the steel industry. The flue temperature is the average value of the vertical flame temperature measured in each combustion chamber of the coke oven (Buczynski and Kim, 2022). It is an important process parameter in the heating process of coke oven. The flue temperature can directly reflect the overall heating state of the coke oven (Ren et al., 2022). Coke oven is a complex system with large inertia, large delay, nonlinear and other characteristics. Coke oven flue temperature is the core parameter of coke oven control system, but there is no accurate mathematical model for coke oven flue temperature. According to relevant research, the stability of flue temperature can improve the quality of coke, reduce costs, and effectively reduce the emission of nitrogen oxides and other pollutants. Therefore, stable and fast flue temperature control of coke oven can play an effective role in environmental protection, energy saving, improving coke quality, and extending the service life of coke oven (Yang et al., 2021). Therefore, the control of coke oven flue temperature is an urgent problem to be solved in the metallurgical industry.

At present, the control means of coke oven flue temperature mainly focus on PID algorithm. The controller designed with PID algorithm can only guarantee the control performance or stability of the controlled object under certain operating conditions. PID algorithm cannot make the controlled object have good control performance in a wide range. Therefore, the flue temperature control of coke oven based on PID algorithm has great limitations. With the wide application of information technology in the industrial field, many scholars have proposed many new control methods to control the flue temperature of coke oven. These control methods contain fuzzy control (Feng et al., 2016; Yin et al., 2019; Lei et al., 2015), Fuzzy-PID control (Li et al., 2015; Xie et al., 2013; Li et al., 2012), intelligent control (Patra et al., 2019; Li et al., 2019; Mozaffari et al., 2016), predictive control (Gao and Weng, 2020; Wu et al., 2020; Tian et al., 2018), expert system (Gangadaran and Mitra, 2016; Liu, 2014) and etc. Compared with the conventional PID algorithm, the control effect of these methods is improved, but there are also some shortcomings. Fuzzy rules and membership functions limit the performance of Fuzzy control and Fuzzy-PID. The intelligent control algorithm is complex and requires a lot of calculation time. Therefore, intelligent control algorithm is difficult to be applied in practical control. Although predictive control has good robustness, it needs a long time to solve the inverse operation of matrix. The expert system has no self-learning and adaptive ability, and needs a lot of rules. Its maintenance and control process is difficult, resulting in the expert system is not particularly suitable for the complex coke oven production process.

The concept of variable universe was put forward in 1999 (Li, 1999). The idea of variable universe is that under the premise of constant rules, the universe will shrink with the reduction of error or expand with the increase of error, thus improving the adjustment range and control accuracy of the control system. Variable universe Fuzzy control can be applied to systems with nonlinearity, parameter uncertainty and large time delay. It has certain adaptability to the time delay, nonlinearity and time-varying of the controlled object. However, there are still some static errors in the system. PID control has simple structure and strong robustness. Considering the advantages of variable universe Fuzzy control and PID control, a variable universe Fuzzy-PID controller is proposed. In the control process, the Fuzzy-PID controller with variable universe can detect and analyze uncertainties, parameters, delays and disturbances. The controller adopts online fuzzy reasoning method to realize the self-adjustment of PID parameters. The controller not only retains the advantages of simple, convenient and robust PID control principle, but also has greater flexibility, adaptability and better control accuracy (Jia et al., 2022; Ding et al., 2021).

The input and output proportional factors of variable domain fuzzy PID controller are important factors affecting the control effect (Jalali et al., 2020). If the scaling factor is adjusted manually, the control effect will not be ideal. In order to achieve the desired control effect, particle swarm optimization (PSO) is introduced to optimize the input and output scaling factors of the variable universe Fuzzy-PID controller. The main innovations of this paper are as follows.

1. A variable universe Fuzzy-PID controller based on PSO algorithm is proposed for coke oven flue temperature control. The constantly changing scale factor can ensure the continuous adjustment of the universe. The parameters of PID controller are adjusted in real time according to the error and error change rate.

2. PSO algorithm is used to optimize the scale factor of variable universe to optimize the fuzzy controller.

3. Combined with the actual situation, various simulations under different working conditions and experiments on actual coke oven equipment are carried out. The results show that the controller has the advantages of strong robustness, strong adaptive ability and high control accuracy.

This paper is organized as follows. In Section 2, it introduces that the preliminaries of a coke oven system. In Section 3, the PSO-based Fuzzy-PID controller with variable universe is designed for coke oven flue temperature control. The simulation results are shown in Section 4, and the effectiveness of the proposed controller is verified. Section 5 presents the results of on-site experiments. The last section gives the conclusion and prospect of this paper.

2. PRELIMINARIES

Coke oven is a unique industrial furnace, its main body is composed of 50-100 heating units. The carbonization chamber, combustion chamber and regenerator constitute each heating unit. The structure of coke oven is shown in Fig. 1.

The heated gas enters the combustion chamber through the gas pipeline. The combustion gases in the combustion chamber produce heat. The required heat is transferred to the coal in the carbonization chamber through the furnace wall. The carbonized coal forms coke in the carbonization chamber. A certain number of flues form all combustion chambers. Two flues form a group, which is composed of a gas channel and connected with the regenerator respectively (Weng and Gao, 2017). As shown in Figure 1, after preheating of the regenerator, gas and air enter the combustion chamber through the chute. A large amount of heat generated by the gas is burned in the combustion chamber to heat the coke oven. The coal in the carbonization chamber absorbs the heat transferred from the furnace wall and forms coke through a long coking process, which is the main process of heat consumption. The coking process releases untreated coke oven gas. The untreated coke oven gas enters the gas collector. At the same time, two adjacent heat accumulators release the exhaust gas generated by combustion.

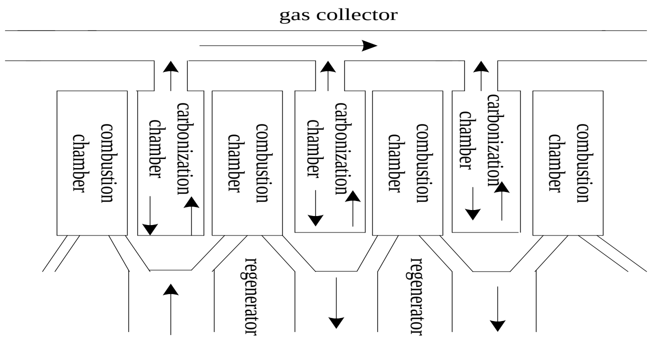

Fig. 1 The structure of coke oven.

Only by solving the following problems in the coke oven heating and combustion process control system can the stability of coke oven flue gas temperature control be guaranteed.

1. The decline of coke quality is due to the wide range fluctuation of flue temperature caused by the change of coke oven operation process and gas calorific value.

2. When the working conditions are changed, the parameters of the controller are adjusted offline. The hysteresis of the parameter adjustment process will have a great impact on the production process.

3. Before adjusting the controller parameters, the system performance must be accurately judged. Otherwise, unnecessary parameter adjustment will reduce the stability of the system.

3. PROPOSED CONTROLLER

3.1 Fuzzy-PID controller with variable univers

On the premise that the rules remain unchanged, the universe changes with the error, which means that the shrinking of the universe is equivalent to increasing the corresponding rules. Dense interpolation nodes are very helpful for improving control accuracy (Xue et al., 2021; Tao and Liu, 2021).

Suppose that $X_e = [-E, E]$ is the universe of input error e, $X_{ec} = [-EC, EC]$ is set as the universe input error change rate ec, $Y = [-U, U]$ is specified as the universe of output y. With the introduction of scale factor, the universe of input and output variables can be expressed as the following.

$$X_e(e) = [-\alpha_1(e)E, \alpha_1(e)E] \tag{1}$$

$$X_{ec}(ec) = [-\alpha_2(ec)E, \alpha_2(ec)E] \tag{2}$$

$$Y(e,ec) = [-\beta(e,ec)U, \beta(e,ec)U] \tag{3}$$

where α_1, α_2 and β is the scaling factor. Fig. 2 shows the process of the universe variation of the input variable error.

The scaling factor based on fuzzy control rules is to choose the rules, and they are easy to express. The different scale factor is chosen in the different response stage of the system. Here is the basic idea. When the input variable is large, its universe should remain unchanged in order not to suppress the normal response of the system without increasing overshoot. When the input variable is small, the universe is shrunk, fuzzy partition is compressed. The available rules of input variable are increased. The variable universe solves the contradiction between the number of fuzzy rules and the control precision. The accuracy of the control precision is also improved.

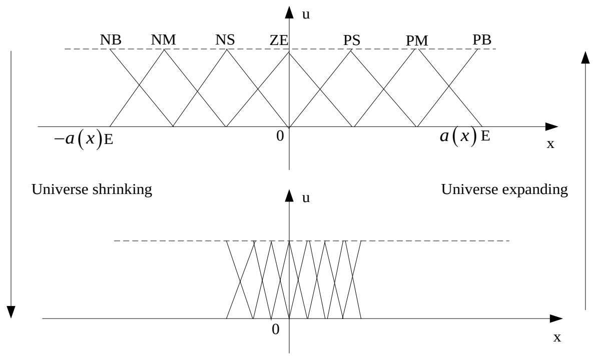

Fig. 2. The process of the universe variation of input.

Taking error e and error change rate ec as the inputs of Fuzzy-PID controller can meet the requirements of parameter self-regulation of e and ec at different times. The parameters of PID algorithm are modified by fuzzy control rules, and a Fuzzy adaptive PID controller is obtained. The Fuzzy-PID controller has two inputs and three outputs. Then select e and ec as the input, and the output is the three adjustment parameters ΔK_P, ΔK_I and ΔK_D of the PID controller. On the basis of identifying these three parameters, the output can be obtained according to fuzzy theory.

The structure of fuzzy PID controller with variable universe is shown in Figure 3. $r(t)$ is the reference temperature, $y(t)$ is the actual output of the main steam temperature, $e(t)$ is the deviation between the reference temperature and the actual temperature, e is the error, ec is the error change rate, and $u(t)$ is the control variable generated by the PID controller. Error e and error change rate ec can adjust the change range of input and output of the fuzzy controller. The system can be divided into three parts: upper layer, middle layer and lower layer. The upper layer is the interpolation unit. Error e and error change rate ec are the inputs of interpolation. The scaling factors α_e, α_{ec}, β_p, β_i and β_d can be obtained by interpolation. These scale factors are the outputs of the fuzzy control unit. The middle layer is a fuzzy control unit. The output after fuzzy reasoning is the increment value of K_P, K_I and K_D. The lower level is a simple PID controller, whose output includes ΔK_P, ΔK_I and ΔK_D fuzzy controller combined by an add operation. Then the parameters of PID controller are obtained and applied to the controlled object.

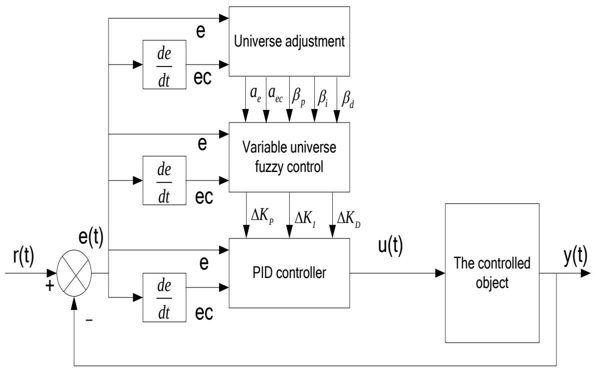

Fig. 3. The structure of the proposed controller.

The parameters of the PID controller are adjusted online as follows.

$$K_x = K_x^{'} + \Delta K_x \tag{5}$$

where x=P, I, D.

The coke oven takes the error e and error change rate ec of flue temperature as the input state variables of the proposed controller, and determines the three parameters of PID as the output of the controller. Therefore, a fuzzy controller with two inputs and three outputs is adopted. The three parameters of PID controller, including K_p, K_i and K_d, are adjusted by detecting e and ec.

3.2 PSO algorithm

PSO algorithm is a search algorithm based on parallel global population, which has the advantages of simple concept, easy implementation and faster convergence speed (Eberhart and Shi, 2002). Many optimization problems have been solved through PSO algorithm (Peng et al., 2022; Dong et al., 2022; Wang et al., 2022). PSO algorithm finds the optimal solution by randomly initializing particles and then iterating. The following two extreme values will update the particles in each iteration. The first is that the particle itself finds the optimal solution, which is called individual extreme value p_{best}, and the other extreme value is the optimal solution found by the whole population, which is called g_{best}.

In the D dimensional target search space, the population is composed of N particles. The D dimension vector represents the ith particle in the population, which can be written as:

$$\boldsymbol{X}_i = (x_{i1}, x_{i2}, ..., x_{iD}), \quad i = 1, 2, \cdots, N \tag{6}$$

The flying speed of the ith particle is also a D-dimensional vector, which can be written as:

$$\boldsymbol{V}_i = (v_{i1}, v_{i2}, ..., v_{iD}), \; i = 1, 2, \cdots, N \tag{7}$$

The ith particle is the best search location so far, called the individual's optimal value, which can be written as:

$$p_{best} = (p_{i1}, p_{i2}, ..., p_{iD}), \; i = 1, 2, \cdots, N \tag{8}$$

So far, the best search location of the whole population is called the global optimal solution, and its expression is as follows.

$$g_{best} = (p_{g1}, p_{g2}, ..., p_{gD}) \tag{9}$$

After finding the two optimal values, update the particle's speed and position according to equation (10) and equation (11).

$$v_{id}^{k+1} = \omega \times v_{id}^{k} + c_1 \times rand_1^k \times (Pbest_{id}^k - x_{id}^k) + c_2 \times rand_2^k \times (Gbest_d^k - x_{id}^k) \tag{10}$$

$$x_{id}^{k+1} = x_{id}^{k} + v_{id}^{k+1} \tag{11}$$

3.3 The design of the Fuzzy-PID controller

Two input and three output fuzzy controller is adopted. Through the error and error change rate, the three parameters of the PID algorithm are continuously adjusted to realize the adaptive adjustment of the system to achieve the purpose of real-time control. Based on the control requirements, the input and output state variables are composed of three levels, and the linguistic variables are NB (negative big), NM (negative middle), NS (negative small), ZO (zero), PS (positive small), PM (positive middle) and PB (positive large). The temperature control error range is assumed to be [− 20 °C, 20 °C]. The interval of error change rate is [− 0. 2°C, + 0. 2°C]. The universe of input error and error change rate quantized as an integer [− 6, + 6]. The quantization factor of error is $K_e = 6/20 = 0.3$, and the quantization factor of error change rate is $K_{ec} = 6/0.2 = 30$. The range of output linguistic variables is [− 1, + 1] and quantified into the integer universe [− 3, + 3]. Therefore, the quantization factor of output is 1/3. The input membership is shown in Figure 4. Similarly, the output membership is shown in Figure 5.

When designing corresponding fuzzy rules, the fuzzy PID controller shall meet the following principles.

1.When the error is large, ΔK_p should take a larger value in order to speed up the response speed of the control system. At the same time, due to the rapid increase of error, the value of ΔK_d should be small in order to prevent large overshoot.

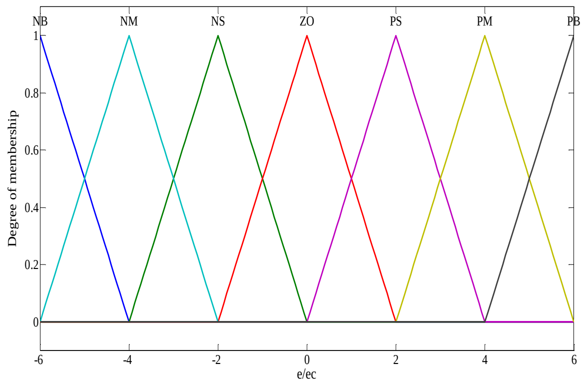

Fig. 4. The membership of input.

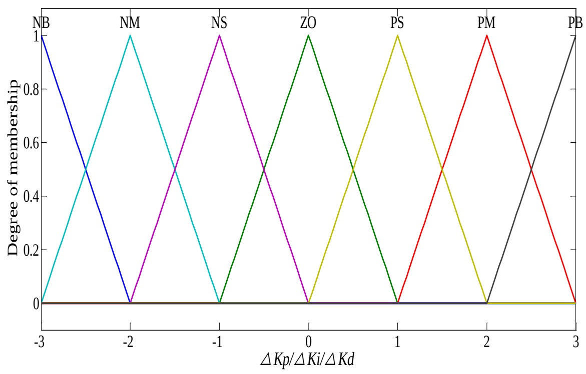

Fig. 5. The membership of output.

2.When the system error is moderate, the values of ΔK_p, ΔK_i and ΔK_d should not be set too large in order to obtain small overshoot. The setting should be as small as possible.

3. When the system error is small and tends to zero, the values of ΔK_p and ΔK_i should be appropriately increased to obtain good steady-state performance. At the same time, considering the possibility of oscillation at the balance point, in order to improve the anti-interference ability of the system, the value of ΔK_d should be moderate.

Based on the above discussion, the fuzzy control rules are set. The fuzzy control rules of ΔK_p are shown in Table 1. The fuzzy control rules of K_i are shown in Table 2. The fuzzy control rules of ΔK_d are shown in Table 3. In these three tables, *E* represents the universe of *e*, and *Ec* represents the universe of *ec*.

After three parameters ΔK_P, ΔK_I and ΔK_D are identified, the output can be obtained according to fuzzy theory. According to the fuzzy controller, the changes in control values are calculated using fuzzy inference rules as follows.

Table 1. Fuzzy control rules of ΔK_p .

E	Ec						
	NB	NM	NS	ZO	PS	PM	PB
NB	PB	PB	PM	PM	PS	ZO	ZO
NM	PB	PB	PM	PM	PS	ZO	ZO
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 control rules of ΔK_i .

E	Ec						
	NB	NM	NS	ZO	PS	PM	PB
NB	NB	NB	NM	NM	NS	ZO	ZO
NM	NB	NM	NS	NS	ZO	PS	PS
NS	NM	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	PS	NB	PB

Table 3 Fuzzy control rules of ΔK_d .

E	Ec						
	NB	NM	NS	ZO	PS	PM	PB
NB	PS	NS	NB	NB	NB	NM	PS
NM	PS	NS	NM	NM	NS	NS	PS
NS	ZO	NS	NM	NM	NS	NS	PS
ZO	ZO	NS	NS	NS	NS	NS	ZO
PS	ZO	ZO	ZO	ZO	ZO	ZO	ZO
PM	PB	NS	PS	PS	PS	PS	PB
PB	PB	PM	PM	PM	PS	PB	PB

$$\mu_{k_x}(K_x) = \vee[\mu_R(e, ec, k_x) \wedge \mu_E(e) \wedge \mu_{EC}(ec)] \tag{12}$$

Then， fuzzy decision will be carried out. In this paper, weighted average method is chosen as fuzzy decision method. For simplicity, the centroid method is usually chosen as the weighting factor, and the results can be expressed as

$$z_0 = \sum_{i=1}^{n} \mu_U(z_i) \cdot z_i \bigg/ \sum_{i=1}^{n} \mu_U(z_i) \tag{13}$$

3.4 The design of the PSO-based Fuzzy-PID controller with variable universe

The scale factor of the variable universe fuzzy PID controller has a great influence on the performance of the controller. If the scale factor is set to a fixed value, it will not adapt to the change of coke oven flue temperature system. Therefore, this paper introduces PSO algorithm to optimize the scale factor to improve the control performance. The structure of the proposed variable domain fuzzy PID controller based on PSO is shown in Figure 6. The input scale factors α_e and α_{ec} are divided by the input variables. The output scale factors β_p, β_i and β_d are multiplied by the output variables and input to the PID controller.

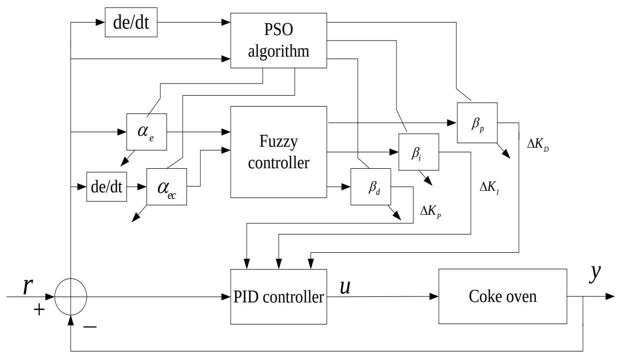

Fig. 6. The structure of PSO-based Fuzzy-PID controller with variable universe.

How to establish an appropriate fitness function before PSO algorithm is used to optimize the scale factor of the variable universe of Fuzzy-PID controller is the key. The fitness function not only meets the overall performance index, but also needs to consider the characteristics of error and error change rate (Wu 2012). In order to ensure the rapidity and accuracy of the system, the fitness function is selected as the integrated time and absolute error (ITAE). The fitness function can be written as equation (14).

$$Fitness = \int_0^{ts} (0.95t^* |e| + 0.05t^* |ec|) dt \tag{14}$$

In Figure 6, the five scale factors of α_e, α_{ec}, β_p, β_i and β_d are optimized by PSO algorithm. Set the population size of particles in PSO to N and the number of iterations to M. The coordinates of each particle in three-dimensional space can be expressed as $\boldsymbol{X}_i = (x_{i1}, x_{i2}, x_{i3}, x_{i4}, x_{i5}),\ \ i = 1, 2, ..., N$, where x_{i1}, x_{i2}, x_{i3}, x_{i4} and x_{i5} correspond to α_e, α_{ec}, β_p, β_i and β_d .

The flying speed of particles can be described as $\boldsymbol{V}_i = (v_{i1}, v_{i2}, v_{i3}, v_{i4}, v_{i5})$, $i = 1, 2, ..., N$. In this paper, the implementation process steps of the proposed controller in each sampling period can be described as follows.

Step 1 Initializes the speed and position of each particle in the particle swarm randomly. The value range of the scale factor is set to (0, 1].

Step 2 Calculate the fitness value of each particle according to the fitness function of formula (14), then calculate the position of each particle, and store the fitness value p_{best} and g_{best} of each particle.

Step 3 Set the maximum number of iterations M and termination conditions. Set the current iteration number k to 1.

Step 4 Update particle velocity and position according to equations (10) and (11) respectively. The fitness value of each particle is recalculated through fitness function.

Step 5 Update p_{best} and g_{best} of the particles. If the particle's current fitness value is better than the historical best value, the particle's current position and fitness value will be updated to the current value. If the fitness of the particle with the best fitness value is better than the global best value, the global best value is updated with the position and fitness value of the particle with the best fitness value.

Step 6 Judge the termination conditions. If the termination conditions are met, go to **Step 7**. Otherwise, k=k+1, then go to **Step 4**.

Step 7. Output global optimal values α_e , α_{ec} , β_p , β_i and β_d . These optimal values are picked out as scaling factors in Fuzzy-PID controller. These optimal values are selected as scale factors of Fuzzy-PID controller. In the Fuzzy-PID controller, e and ec are input, ΔK_P , ΔK_I and ΔK_D are output. Then the control variable u can be obtained and applied to the coke oven temperature control system.

4. SIMULATIONS

Coke oven is an extremely complex controlled object, therefore there is no especially precise mathematical model to describe at present. According to the characteristics of large lag and inertia of coke oven, a carbonization chamber is used as the controlled object, and the first order lag plus inertia model is simplified from the flue temperature system of coke oven (Tian, 2020).

The transfer function of the simplified system can be written as equation (15). Many research results indicate that simplified models can effectively fit actual coke oven systems (He et al., 2018; Liu and Dong, 2017). The model shown in equation (15) can effectively verify the effectiveness of the control algorithm. Meanwhile, this paper utilizes the PSO algorithm to adaptively adjust the scale factor, which can adapt to situations where the controlled object does not match the model.

$$G(s) = Ke^{-\tau s} / (Ts+1) \tag{15}$$

Because of the characteristics of large lag of coke oven, the sampling time cannot be extremely short. The value of this paper is 20s and the value of K is 7.5. The value of τ is 10. The value of T is 100.

All simulations in this paper are implemented in Simulink in Matlab 2018b software. Build corresponding controlled objects, such as Fuzzy logic and other functional modules in Simulink, and implement the PSO algorithm through m file. Add a scope at the output for display and comparison. The parameters of the PSO algorithm, such as maximum number of iterations, population size, etc., are configured in the m file, and the optimization results are assigned to the variable universe Fuzzy module.

To verify the effectiveness of the control algorithm, the proposed control algorithm is compared with fuzzy control (Yin et al., 2019) and improved implicit GPC algorithm (Tian et al. 2018). In the improved control method, which is proposed in this paper, the population size of the particles in PSO algorithm is 20, the number of iterations is 100, c_1 is 1.7, c_2 is 1.5, w is 0.9. The parameters of improved implicit GPC in this paper are designated as $P = 7$, $M = 5$, $\alpha = 0.7$, $\beta = 0.5$. The fuzzy control rules for coke oven which is found in literature (Yin et al. 2019). Considering the possible situations in the actual coke oven heating process, the following three main situations are simulated in the simulation.

4.1 The design of the PSO-based Fuzzy-PID controller with variable universe

In the actual heating process, the maturity of coke needs to reach 950 ~ 1050℃, which can make the quality of coke be guaranteed. If the temperature is in this range, it can greatly reduce energy consumption. Consequently, the reference flue temperature of coke oven here which is set as 1000℃. Fig. 7 gives the simulation results of three control methods. As seen in Fig. 7, compared with the improved implicit GPC and fuzzy control, the proposed PSO-based Fuzzy-PID controller with variable universe has short transition process, small overshoot, and faster adjustment time.

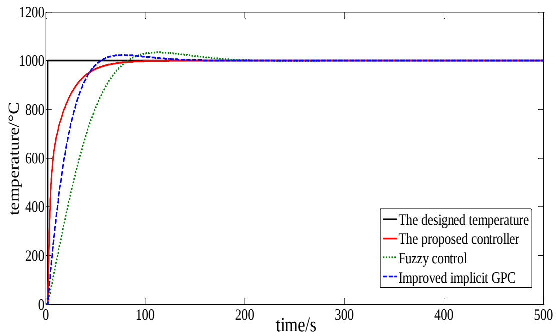

Fig. 7. The control effect curve under normal working condition.

By comparison, stabilizing the system needs more time to improved implicit GPC and fuzzy control. Consequently, the control performance of the whole system is more improved.

4.2 The change of the designed temperature

In simulation, the designed temperature is 1000 ℃ in the first 300 seconds and it is changed to 1200 ℃ in 400th seconds, and then temperature is changed to 800 ℃ in 800th seconds. Fig. 8 shows the control effect curve. It can be seen from Fig. 8, when the setting value is changed, compared with fuzzy control and improved implicit GPC algorithm, the proposed controller can make the system respond rapidly and track the new setting value, and has faster response speed, faster adjustment time and smaller overshoot which is different from fuzzy control and improved implicit GPC algorithm.

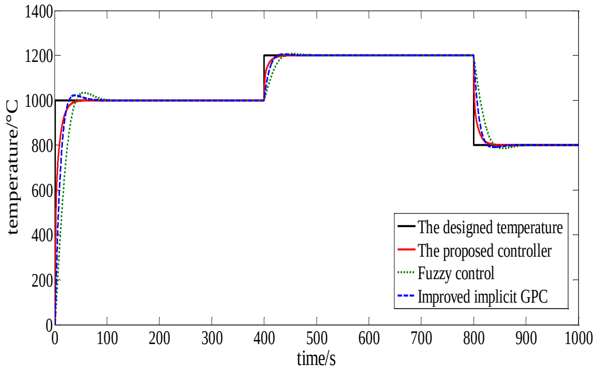

Fig. 8. The control curve under the change of designed temperatura.

4.3 Under random disturbance

Add the random disturbance between -30°C and + 30°C into the simulation system, and Fig. 9 shows that the contrast curve of control effect. It can be seen that when the system is subject to unknown random disturbance, to make the system have better robust performance, the proposed control method can be used. The temperature control in the vicinity of the set value and the deviation is smaller. Compared with the fuzzy control and the reason why the controller has better overshoot performance and only produced a minor fluctuation is improving implicit generalized predictive.

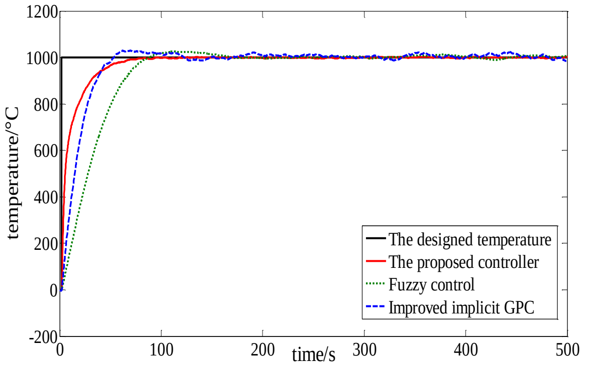

Fig. 9. The control effect curve under random disturbance.

4.4 The change of the parameters of the coke oven

The mathematical model of the coke oven flue gas temperature will change in actual applications. In this paper, the following three parameters include K, τ and T are changed. In the first simulation experiment, the change of K is 7, the change of τ is 15, and the change of T is 150. In the second simulation experiment, the change of K is 8, the change of τ is 5, the change of T is 200. In the third simulation experiment, the change of K is 7, the change of τ is 15, the change of T is 50. Figs. 10 to 12 shows the corresponding simulation results.

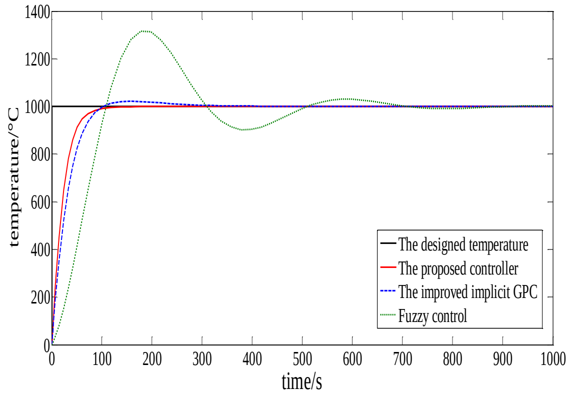

Fig. 10. The first simulation when the model changes.

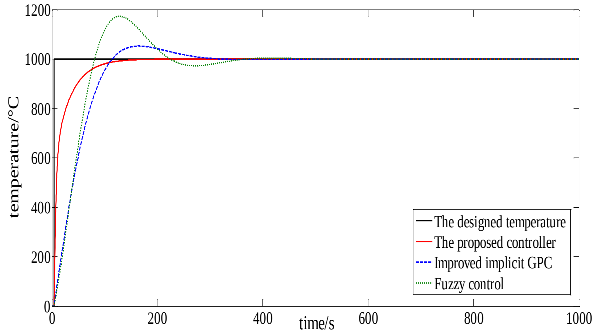

Fig. 11. The second simulation when the model changes.

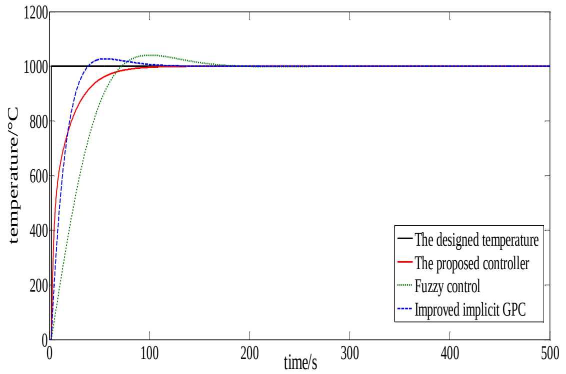

Fig. 12. The third simulation when the model changes.

From Figs. 10 to 12, it can be seen that when the mathematical model of the coke oven flue gas temperature system changes, the system returns to the steady state faster through the proposed controller and the overshoot is small. By contrast, the improved implicit GPC and fuzzy control algorithm will cause a larger overshoot. In a word, with mathematical model changing, the controller in this paper has a relatively small overshoot, a relatively short adjustment time, and achieves a good system control effect.

5. EXPERIMENTS

The effectiveness of the proposed control algorithm is tested by controlling the actual flue temperature of the coke oven in a certain steel enterprise. Based on the existing Honeywell distributed control system configuration platform, real-time production data of coke oven is obtained from distributed control system using object linking and embedding for process control and data communication technology. These data are processed and sent back to the application server for control law calculation. The corresponding control algorithm program was implemented on the application server through Visual C++ and Matlab programs combined with dynamic data exchange technology. Transfer the control law calculated by the controller to distributed control system to control the flue temperature of the coke oven system. The control frame of the coke oven flue temperature system is shown in Fig. 13.

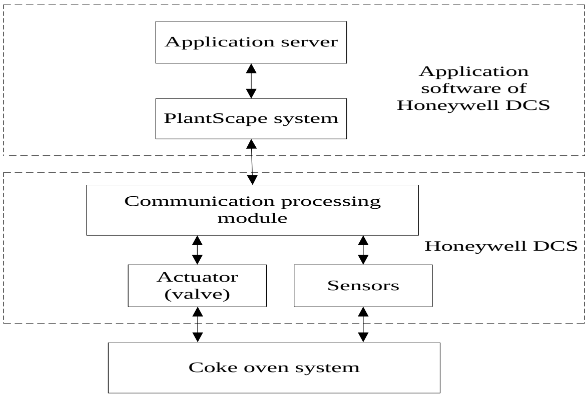

Fig. 13. The control frame of the coke oven flue temperature system.

The model of the coke oven is JN-60, which includes 55 carbonization chambers, 56 combustion chambers, and 57 regenerative chambers. The blast furnace gas flow rate is 26435 m^3/h, the mixed gas flow rate on the propulsion side is 1200 m^3/h, the mixed gas flow rate on the coke side is 1450 m^3/h, the blast furnace gas pressure on the propulsion side is 735 Pa, the blast furnace gas pressure on the coke side is 760 Pa, the flue pipe on the propulsion side is 200 Pa, and the flue pipe on the coke side is 205 Pa. The discharge frequency is 25, and each hole is loaded with 20 tons of coal. The coking time is 19.5h. The performance indicators of a coke oven include coke production, coke oven gas consumption, compressive strength, and wear resistance. Table 4 lists the comparison results between the control algorithm proposed in this paper and traditional PID control. The experimental results of actual coke oven equipment have verified that the proposed control algorithm improves various performance indicators of the coke oven production process compared to common PID control algorithm.

Table 4. Comparison of performance indicators.

Control algorithm	Coke yield (ton/8h)	Coke oven gas consumption (m^3/8h)	Crushing strength (%)	Abrasion strength (%)
PID	253.32	37028	82.52	5.12
Proposed algorithm	277.63	35572	92.64	4.25

6. CONCLUSIONS

The Coke oven heating control system is a complex dynamic process. This process has the characteristics of strong nonlinearity, large time-delay and strong disturbance. The traditional control algorithms are difficult to let the flue gas temperature of coke oven achieve the expected control effect. Consequently, advanced control algorithms of great significance are applied to reduce fuel consumption, improve the quality of coke and prolong coke oven life. According to the analysis of the difficulties of coke oven flue gas temperature control, the main works are as follows:

1. It is because the continuously scale factor can guarantee the continuity of global contraction that the proposed controller can adjust the parameters of PID algorithm in real time according to the error and the rate of error change.

2. PSO algorithm is introduced to optimize input and output scaling factor of Fuzzy-PID controller with variable universe, which is for optimizing the fuzzy controller is achieved.

3. On the basic of the practical applications, various simulations under the different working environments are performed. The simulation results and experiments on actual coke oven equipment verify the effectiveness of the controller.

This study has achieved some desired results, but it has also some issues that need to be further studied in the future. The PSO algorithm directly affects the performance of the controller, so future research will focus on how to improve the PSO algorithm to determine more suitable scaling factors to improve control effectiveness.

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