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Research article

Improved fuzzy PID controller design using predictive functional control structure

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ABSTRACT

In conventional PID scheme, the ensemble control performance may be unsatisfactory due to limited degrees of freedom under various kinds of uncertainty. To overcome this disadvantage, a novel PID control method that inherits the advantages of fuzzy PID control and the predictive functional control (PFC) is presented and further verified on the temperature model of a coke furnace. Based on the framework of PFC, the prediction of the future process behavior is first obtained using the current process input signal. Then, the fuzzy PID control based on the multi-step prediction is introduced to acquire the optimal control law. Finally, the case study on a temperature model of a coke furnace shows the effectiveness of the fuzzy PID control scheme when compared with conventional PID control and fuzzy self-adaptive PID control.

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1. Introduction

For industrial production, we must effectively control the key parameters of the process to carry out the production because industrial process variables are important to guarantee safe operation and high quality. However, due to the fact that most processes are with large inertia, serious uncertainty, it is not easy to obtain an ideal process model to yield acceptable process performance [1].

Proportional-integral-derivative (PID) control is one of the popular strategies. Since 1942, researchers have put forward many PID control methods. However, selecting a proper method of adjusting PID parameters is still open nowadays because of the complex industrial processes [2]. For industrial processes, PID tuning methods can be adopted based on the type of process models, for example, first-order plus dead time (FOPDT) models [3,4], integrator plus dead time (IPDT) models [5,6], etc. Some methods can be applied to both FOPDT and IPDT models [7,8]. The following is a brief summary of these classical methods. In [6], the tuning method uses the internal model control (IMC) to adjust PID's parameters. This method has good robustness, but the disturbance rejection for processes with large delay may be poor. In [7], the PID tuning method can improve such situation for IPDT processes, however, for large time-delay processes, control performance will be poor. In [9], robustness and control performance are further discussed. Although traditional PID control is widely applied in various industrial processes, its performance may not always be satisfactory due to time-varying and nonlinear effects.

Since 1970, advanced control such as model predictive control (MPC) has been developed [10–14] and achieved the success in the process industry to show its great potential for complex constrained optimization control issues. However, due to the limitations of cost, hardware and other factors, MPC controllers are not widely used as traditional PID controllers. Therefore, it is important to find a simple method of using MPC controller or to combine the structure of PID controller with MPC algorithms. In [15], fuzzy theory and PID are introduced into the MPC framework to form a multivariable predictive fuzzy PID control strategy. Based on generalized predictive control (GPC), a new type of PID controller is proposed [16]. Wu et al. proposed a new strategy that combines the dynamic matrix control (DMC) with the traditional PID control and tested its control performance on an industrial coke furnace [17]. There are many other research results using advanced algorithms to optimize the PID controller [18,19]. However, MPC and other complex advanced control performance will generally rely on the accuracy of the process model, which will affect the control performance and stability if it is difficult to obtain accurate process models.

In recent years, many intelligent algorithms have been put forward and found various applications [20,21]. Typically, Prof. Zadch firstly put forward the fuzzy set theory [22] to seek a kind of modelling that cannot be accurately described by rigorous mathematical methods. Fuzzy control has the merits of not

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needing precise mathematical models and can just use the information that reflects the prior knowledge of the process characteristics to formulate certain rules of control. Because industrial processes generally show strong nonlinearity, uncertainty and coupling, we need to use fuzzy systems to solve such problems. Conventional PID controllers may not get satisfactory control performance under the nonlinearity and uncertainty, and this paves the way for introducing fuzzy systems [23]. Recently, fuzzy theory based control is extensively studied since fuzzy logic can use people's operation experience to design controllers [24]. For example, a 2-type fuzzy logic controller (FLC) has been studied to resist the impact of uncertain models, such as nonlinear bioreactors [25], non-isothermal continuous stirred tank reactors [26], and binary distillation columns [23]. There are many other research results on fuzzy control [27–30], however, there is still space for fuzzy control to achieve improved control under nonlinearity, uncertainty, etc.

At present, because of the fact that fuzzy control has a strong adaptability and does not need accurate process models and MPC has good prediction ability, the introduction of fuzzy control and MPC to overcome the shortcomings of traditional controllers is a meaningful job. There are many researchers who combine fuzzy control, MPC and PID control to obtain improved control performance. For the automobile suspension system, strengthening evolutionary algorithm of adaptive fuzzy PID controller by using the multi-objective PSO is proposed; however, there is a steady-state error [31]. Savran and Kahraman proposed an adaptive strategy based fuzzy PID controller [32]. By combination of fuzzy theory and MPC, a control method is derived and applied in the medical equipment, which successfully solves the anaesthesia injection quantity control and ensures the injected volume at a safe set-point [33]. A stable fuzzy MPC is proposed to solve the temperature control of a power plant [34]. The principle of MPC and fuzzy control combined for time delayed systems is proposed, which is a new method to control the uncertainty and complexity of the process systems [35]. There are many other research results using fuzzy control and predictive control to optimize PID controllers [36–40].

The purpose of the current study is to propose a new PID control that inherits the merits of fuzzy PID and predictive functional control (PFC). Using prior information, the forecasting model is established as a basic model to predict the process dynamics, and the error between the output measurement and the predicted process output is used as the information to predict the uncertainty. The PID is tuned online by fuzzy inference so that it can meet the requirements under different operating conditions. Results reveal that the proposed controller can achieve good dynamic set-point tracking and disturbance rejection.

This structure of the paper is as follows. In Section 2, the process model is given and described. Then the typical internal model control (IMC) based PID tuning is introduced. In Section 3, the design of conventional fuzzy PID and the proposed predictive fuzzy PID controller (PFPID) are shown. In Section 4, the proposed PFPID is simulated and compared with conventional fuzzy PID controller and IMC based PID controller on a coke furnace. In Section 5, conclusions are drawn.

2. Typical PID tuning methods

For simplicity, we choose the general FOPDT model formulation as an example, which is described as follows:

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

where, K is the process gain, T is the time constant and τ is the time delay.

One typical PID tuning methods is based on internal model control (IMC), which shows acceptable control performance under uncertainty. The method of adjusting the traditional PID control parameters is shown as follows.

$$K_p = \frac{(T + 0.5\tau)}{K(\lambda + 0.5\tau)}, \quad T_i = T + 0.5\tau, \quad T_d = \frac{T\tau}{2T + \tau} \tag{2}$$

where, K_p is the proportional gain, T_i is the integral time, T_d is the derivative time, and λ in Eq. (2) is the IMC filter factor that is usually chosen as $\lambda > 0.8\tau$.

3. Design of FPID and PFPID controllers

For processes with large delay, nonlinearity, etc., it is not easy for conventional PID to achieve the desired performance. The adjustment of fuzzy controller does not depend on the accurate mathematical models and has a great advantage in solving the uncertain problem. However, the control precision of conventional fuzzy control is not good enough and the adjustment speed is slow, which may cause periodic fluctuations in the set-point tracking. In view of this, this paper will proposes a PFC strategy based fuzzy PID (PFPID).

3.1. FPID controller description

Fuzzy control has little requirement on the accuracy of process models and uses linguistic variables rather than numerical variables, i.e., the fuzzy rules to get the control law; however, the control accuracy may not always be ideal. In view of this, fuzzy rules and PID are combined.

A typical two-input three-output fuzzy controller with the error e and the change rate of the error ec as inputs is as follows:

$$\begin{cases} K_p' = K_p + \Delta k_p \\ K_i' = K_i + \Delta k_i \\ K_d' = K_d + \Delta k_d \end{cases} \tag{3}$$

where, K_p, K_i, K_d are nominal control parameters, K_p', K_i', K_d' are the revised parameters, Δk_p, Δk_i, Δk_d are the parameters to be calculated. The control system is depicted in Fig. 1.

3.1.1. The domain and language variable settings

Usually the fuzzy controller input and output variables of the actual range of changes are known as the basic domain. Obviously, the accurate quantity is in the basic domain. In order to carry on the fuzzification processing, we must transform the input variable from

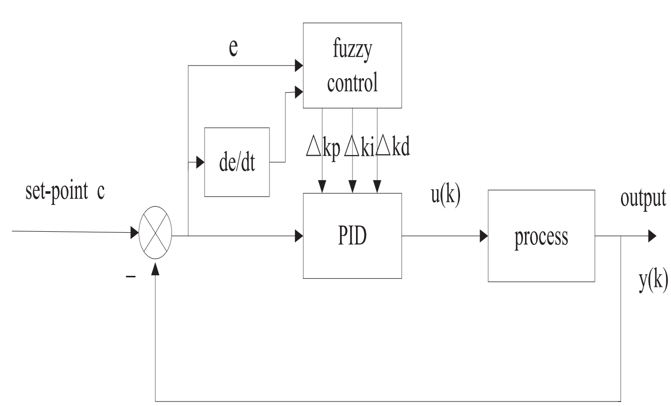

Fig. 1. Fuzzy PID control system.

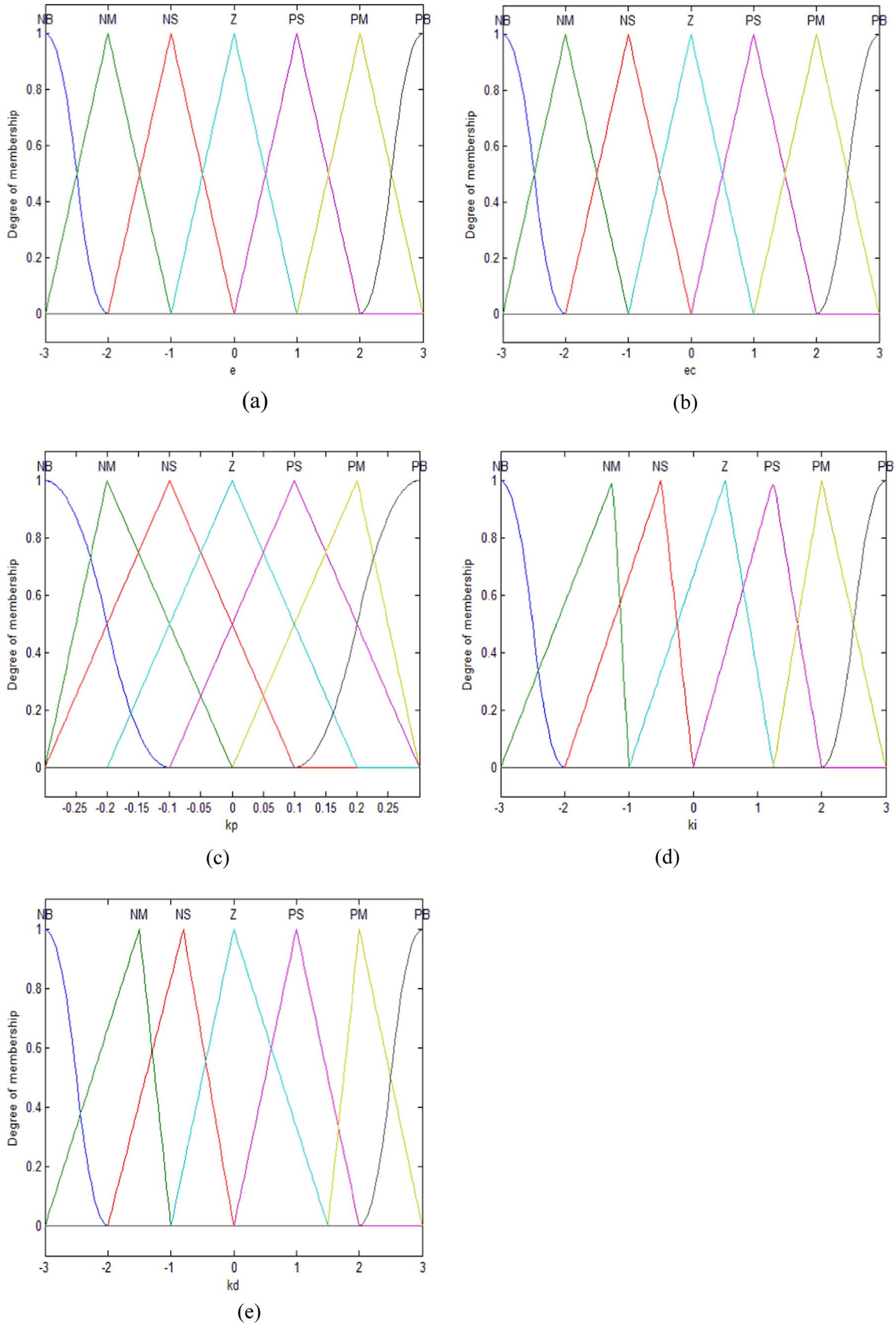

Fig. 2. Membership functions.

the basic domain to the domain of the corresponding fuzzy set, so introduction of quantization factors k_e, k_{ec} is done. The control quantity given by the fuzzy control algorithm cannot be directly controlled at each sampling, and it must be converted into the domain of the controlled object to be accepted, so introduction of proportional factors k_p, k_i, k_d is adopted. Set the basic domain of the error e as $[-x_e, x_e]$, the corresponding domain is the discrete domain $\{-n, -(n-1), \cdots, 0, \cdots, n-1, n\}$,so the quantization factor is $k_e = n/x_e$,Similarly, if we choose the same domain, then $k_{ec} = n/x_{ec}$ and the proportional factor is $k_p = x_p/n,\ k_i = x_i/n,\ k_d = x_d/n$.

The input fuzzy variables e, ec and the output fuzzy variables ΔK_p, ΔK_i, ΔK_d are selected as $[-3\ 3]$, $[-3\ 3]$, $[-0.3\ 0.3]$, $[-3\ 3]$, $[-3\ 3]$, and the fuzzy language set is adopted as [*NB NM NS ZO PS PM PB*].

3.1.2. Membership function settings

Different shapes of the membership functions will cause different influence on the control performance. When choosing a membership function of fuzzy variables, low-resolution membership functions can be adopted for bigger errors and high-resolution membership functions for the errors that are close to zero. Here Triangular membership functions and sigmoid membership functions are adopted in Fig. 2 as follows.

3.1.3. Control rules set

Based on technical knowledge and engineering design, fuzzy control will establish a proper table of fuzzy rules. A general rule set can be seen in [41], which is also adopted in this paper for further PFC use. A brief summary is shown as follows (see Table 1).

3.2. PFPID controller description

In recent years, predictive functional control has been extended to industrial processes, such as reactor, heating furnace and so on. For the dynamic matrix control algorithm, we can find the optimal input of each sampling time, but the input is without clear patterns. The PFC algorithm is different since its input will be the linear combination of a number of basis functions. We reuse the thoughts of predictive control to solve the optimal input at each moment with the calculated linear combination coefficients. Because each time we only needs to determine a small number of linear combination coefficients, the use of PFC algorithm can greatly reduce the online computation.

In this part, the PFC algorithm and fuzzy control algorithm are adopted to optimize the parameters of the proposed PFPID. By doing so, we will get the control performance of the PFC algorithm and also a simple PID controller structure. To design the PFPID, the output prediction is first considered. Then the control part is completed by the FPID to let the predicted output track the target value as close as possible.

See Fig. 3, the PID's output $u(k)$ produces the control commands for the output $y(k)$. In actual industrial production process, various disturbances in the environment make it difficult to exactly match the model between the practical process, which inevitably leads to the deviation between the predicted values and the actual prediction. If we do not correct this deviation, it will have a serious impact on the actual production process. In order to let the output follow the target set-point c, the output value of the k time is predicted by the model and feedback correction is obtained to predict the output $y_p(k+P)$ of the k+P time. The difference between the output $y_p(k+P)$ and the set-point c is the error e. $y_{mav}(k+P)$ is the model output values of the $k+P$ time instant, and $E(k)$ is the revised forecast error.

Table 1
Fuzzy rule table.

(a) Δk_p

e \ ec	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

(b) Δk_i

e \ ec	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

(c) Δk_d

e \ ec	NB	NM	NS	ZO	PS	PM	PB
NB	PS	NS	NB	NB	NB	NM	PS
NM	PS	NS	NB	NM	NM	NS	ZO
NS	ZO	NS	NM	NM	NS	NS	ZO
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	PS	PB

3.2.1. Fuzzy control

Based on the characteristics of adaptive fuzzy control, it is constructed by combining traditional PID control theory, which can realize the automatic tuning of the controller parameters.

The fuzzy self-tuning PID parameters is based on the fuzzy relation between the 3 parameters to find the PID with E and EC. This will be done through continuous detection of E and EC in the operation process. Compared to the previously proposed FPID controller, the controller has greater flexibility because the error and error change rate are adopted to design two input three output fuzzy controller to adjust the PID on an adaptive strategy.

The fuzzy controller with the error e and the change rate ec as inputs is as follows:

$$\begin{cases} K_p'' = K_p + \Delta k_p \\ K_i'' = K_i + \Delta k_i \\ K_d'' = K_d + \Delta k_d \end{cases} \tag{4}$$

where, K_p, K_i, K_d are nominal control parameters, Δk_p, Δk_i, Δk_d are inference parameters, and K_p'', K_i'', K_d'' are the revised PID parameters.

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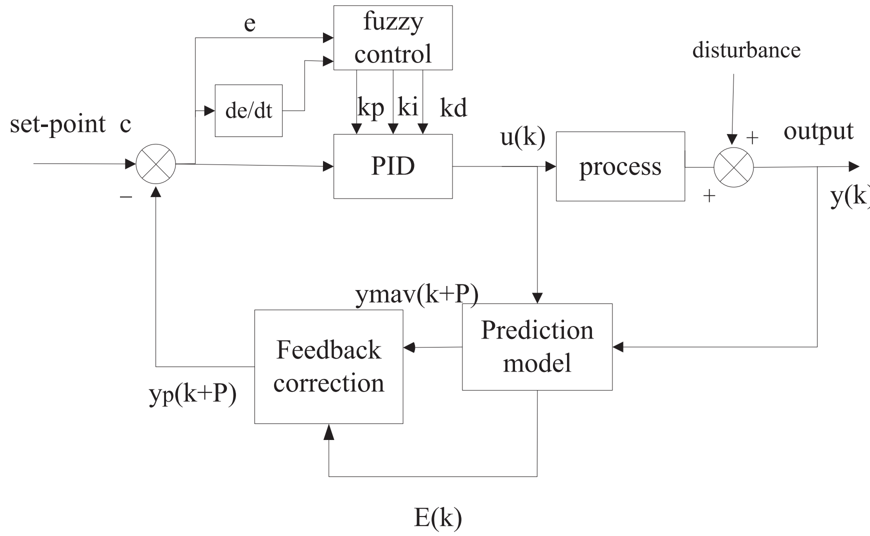

Fig. 3. The structure of PFPID control system.

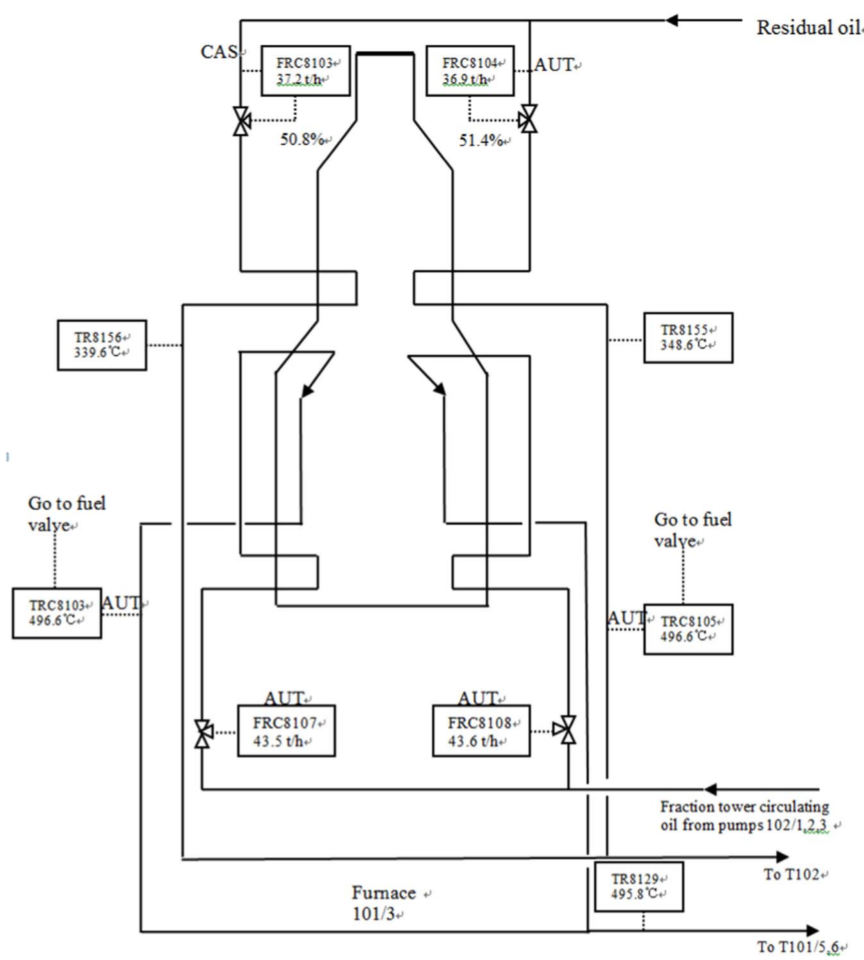

Fig. 4. The coke furnace process (F101/3).

3.2.2. *Prediction model*

In the whole controller design, the PFC idea only plays the role of prediction and does not participate in the system control.

The prediction model of the PFC is a first order model.

$$G(s) = \frac{K_m e^{-\tau_m s}}{T_m s + 1} \tag{5}$$

After discretization using the zero-order holder, the differenced equation model is

$$y_m(k+1) = a_m y_m(k) + K_m(1 - a_m)u(k - L) \tag{6}$$

where, $a_m = e^{(-T_s/T_m)}$, T_s is the sampling time, and L is τ_m/T_s.

Unlike MPC, PFC requires that control performance be related to the structure of the control input. In PFC, the control is expressed as the combination of some basis functions such as step functions, slope functions and so on. Here we select a step function follows

$$u(k+i) = u(k), \quad i = 1, 2, \cdots \tag{7}$$

Based on PFC, the output prediction is obtained according to the current information and the control action in the future. Therefore, let $L = 0$, and we can predict the future P-step output as follows.

$$y_{mav}(k+1) = a_m\, y_{mav}(k) + K_m(1 - a_m)u(k) \tag{8}$$

$$y_{mav}(k+P) = a_m^P\, y_{mav}(k) + K_m(1 - a_m^P)u(k) \tag{9}$$

where, $a_m^P\, y_m(k)$ is the free response and $K_m(1 - a_m^P)u(k)$ is the forced response.

When $L \neq 0$ and based on Smith predictor, PFC still uses the model with $L = 0$, but the system output need to be modified as

$$y_{pav}(k) = y(k) + y_{mav}(k) - y_{mav}(k - L) \tag{10}$$

where, $y(k)$ is the actual process output at time k, $y_{pav}(k)$ is the revised process output value, and the revised forecast error is.

$$E(k) = y_{pav}(k) - y_{mav}(k) \tag{11}$$

To eliminate the effect of disturbance and model/plant mismatch, we can use the feedback correction for the predicted value obtained by Eq. (9) as follows.

$$y_p(k+P) = y_{mav}(k+P) + E(k) \tag{12}$$

$$e = c - y_p(k+P) \tag{13}$$

where, $y_p(k+P)$ is corrected predicted value, $y_{mav}(k+P)$ is the model output values of the $k+P$ time instant, and c is set-point.

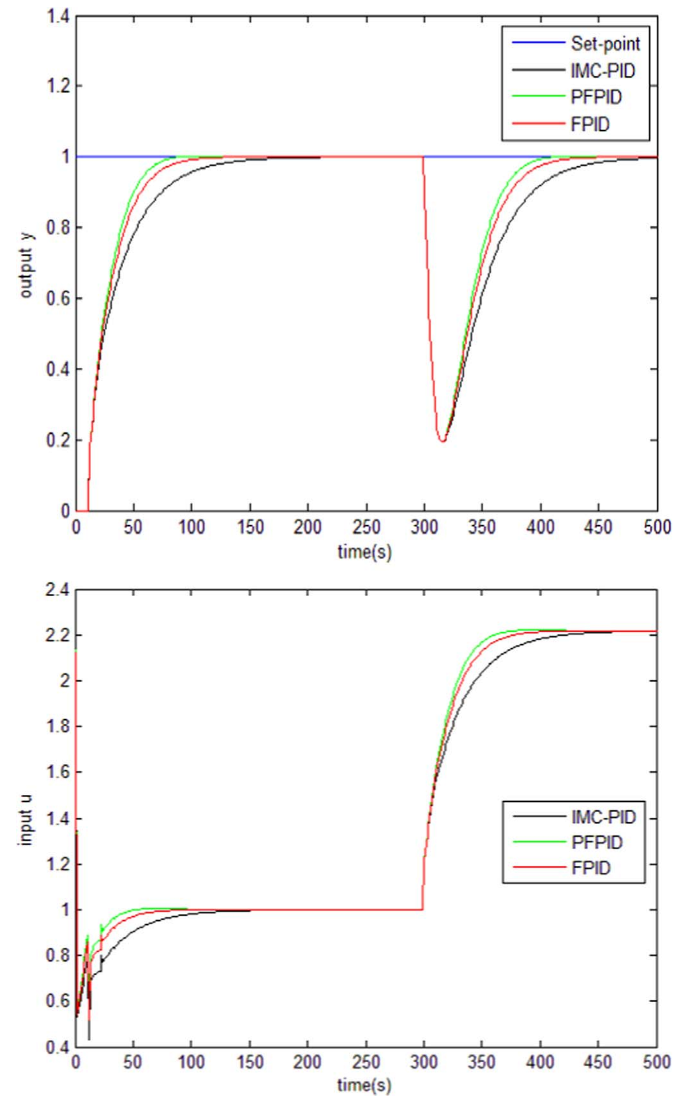

Fig. 5. Closed-loop process responses without model/plant mismatch.

Table 2
Performance requirements.

Coke furnace		Fractionating tower		Coke tower	
Radiation output temperature	495 °C	Top temperature	350 °C	Bottom temperature	415 °C
Convection output temperature	330 °C	Liquid level	70%	Top temperature	300 °C
Oxygen content	5%			Temperature after cooling	85 °C
Circulating oil flow	35t/h			Top pressure	0.25 Mpa

Table 4
Response index of control.

Controller	Response-time	Overshoot	Disturbance rejection time
PID	85	0.8024	117
FPID	59	0.8029	92
PFPID	49	0.8026	79

Table 3
Experimental parameters.

Parameters	Type		
	PID	FPID	PFPID
k_e, k_{ec}, k_p, k_i, k_d		0.001,0.001, 0.1, 0.0008, 2	0.001,0.001,0.1,0.0012,1.5
K_p, K_i, K_d	0.4762,0.00095,50	0.4762,0.00095,50	0.4762,0.00095,50
P			19
disturbance	−0.1	−0.1	−0.1
set-point	1	1	1

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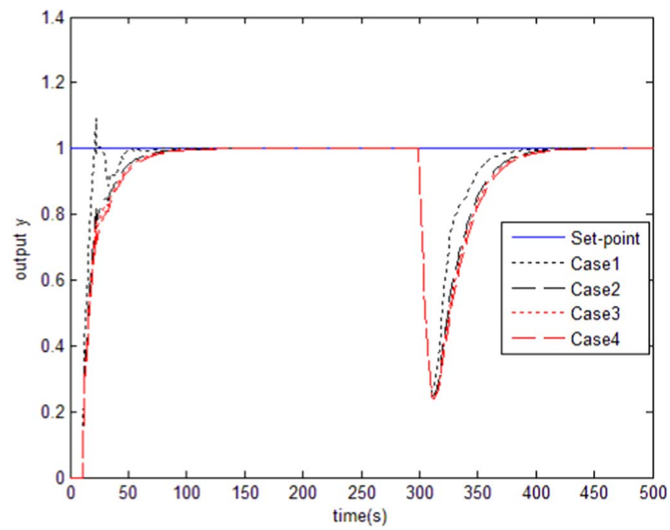

Fig. 6. PID output responses of different λ values.

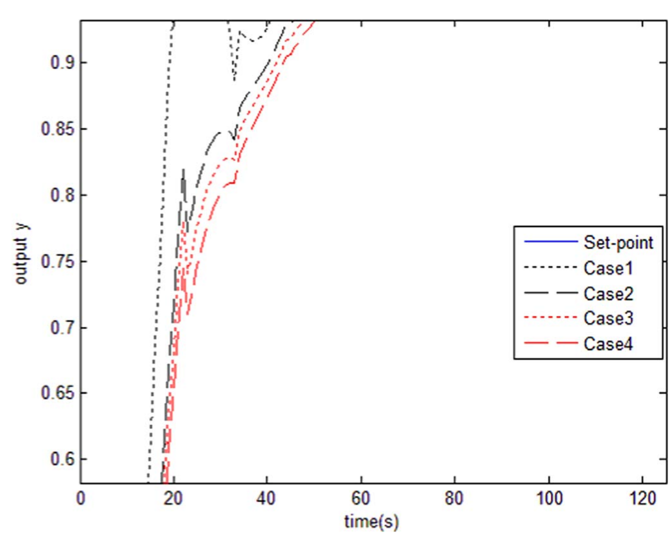

Fig. 7. Zoomed PID output responses.

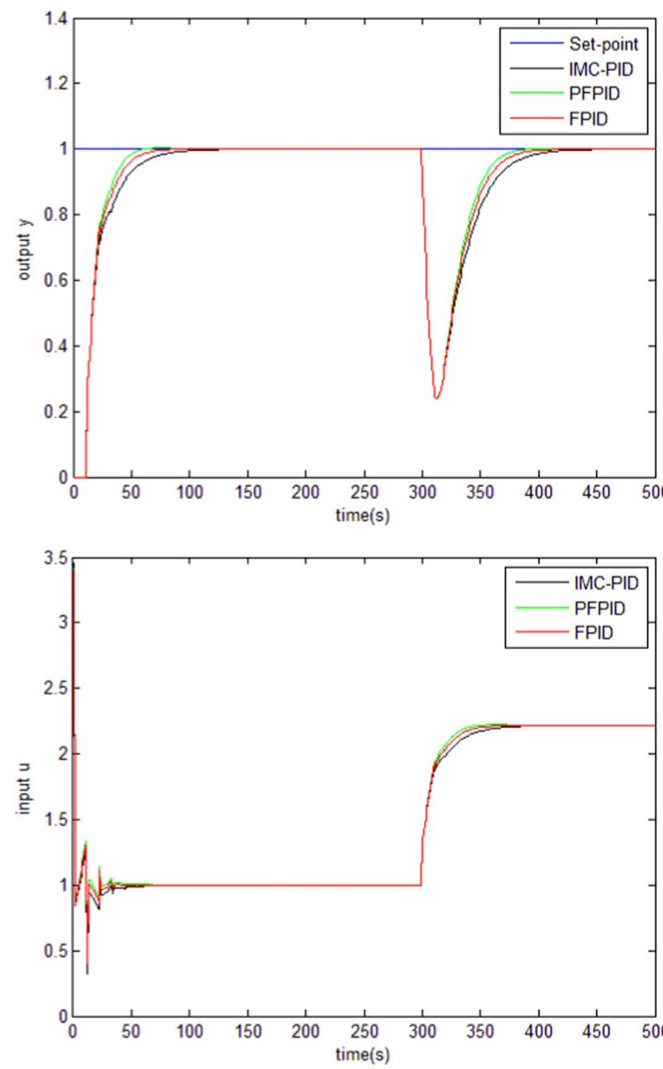

Fig. 8. Closed-loop process responses without model/plant mismatch.

4. Case study

4.1. Process description

In Fig. 4, a schematic diagram of a coke furnace is provided.

The main function of the coke furnace (F101/3) is to refine the oil residue. After entering the coking unit, the residual oil will be divided into two branches (FRC8013, FRC8014) and then sent to the convection room to be heated 330°C. After the heating, the residual oil will be mixed up again and sent to the fractionation tower (T102), where the residual oil will be heated to conduct heat exchange with oil gas from coking tower (T101/5, 6). After the heat exchange is completed, the heavy part of the residual oil will separated into two branches (FRC8107, FRC8108) through the pumps (102/1, 2, 3) to go to the radiation room of furnace (F101/3) to be heated to 495 °C. Finally, the two branches will go to the coke towers (T101/5, 6) to remove coke.

The control requirement of the coking unit is shown in Table 2.

4.2. Control performance of PFPID

Here the loop TRC8105 is taken as an example. Taking into account the actual engineering operation conditions, the coke furnace model is modelled as [18].

$$G(s) = \frac{e^{-300s}}{350s + 1} \tag{14}$$

The sampling time is selected as 30 s and the discrete form of this model can be further obtained. In the FPID control, the fuzzy domains for e, ec, ΔK_p, ΔK_i, ΔK_d were selected as $[-3\ 3]$, $[-3\ 3]$, $[-0.3\ 0.3]$, $[-3\ 3]$, $[-3\ 3]$, respectively. The quantitative factors were selected as $k_e = 0.001$, $k_{ec} = 0.001$, and the proportion factors were selected as $k_p = 0.1, k_i = 0.0008, k_d = 2$. Here the IMC based PID parameters are obtained as $K_p = 0.4762$, $K_i = 0.00095$, $K_d = 50$. The set-point is 1 and a output disturbance with amplitude of 0.1 is added to the process at time. Here we select $\lambda = 3\tau$. In the PFPID control, the prediction horizon is $P = 19$ and the quantitative factors were selected as $k_e' = 0.001$, $k_{ec}' = 0.001$, $k_p' = 0.1$, $k_i' = 0.0012$, $k_d' = 1.5$. The specific parameters are shown in the Table 3.

Here the PID control, FPID and PFPID are compared and simulation results under the three controllers are shown in Fig. 5 and Table 4.

It is seen from Fig. 5 that the response of PFPID control system is the fastest, disturbance can be quickly rejected and the overshoot and oscillation are relatively small. It shows that the overall control performance is improved compared with conventional PID

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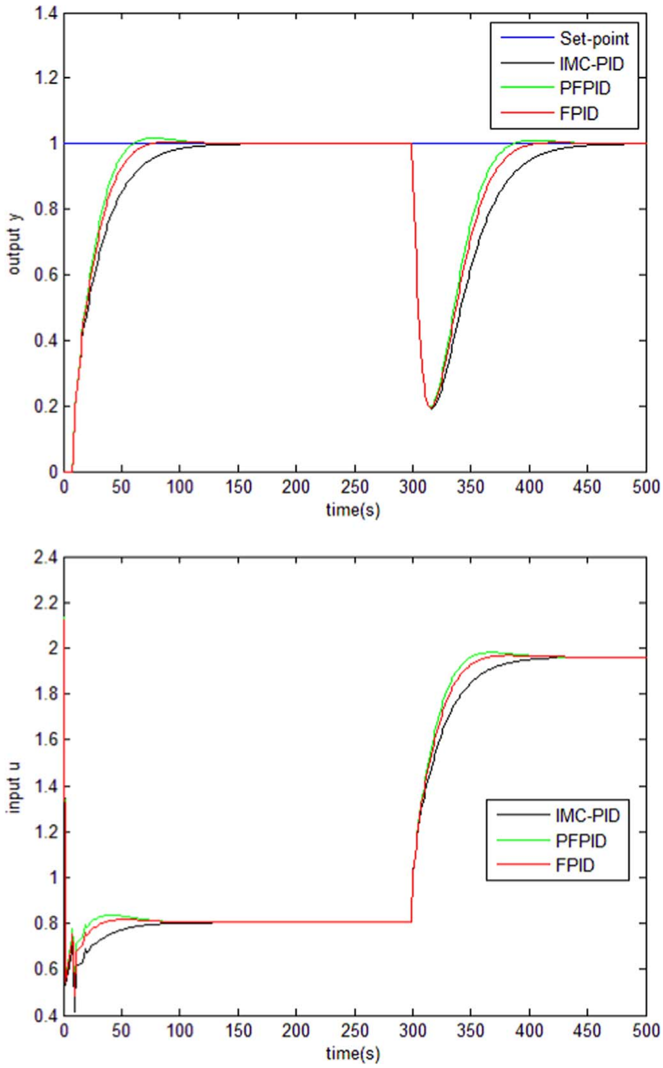

Fig. 9. Closed-loop responses for Case 1.

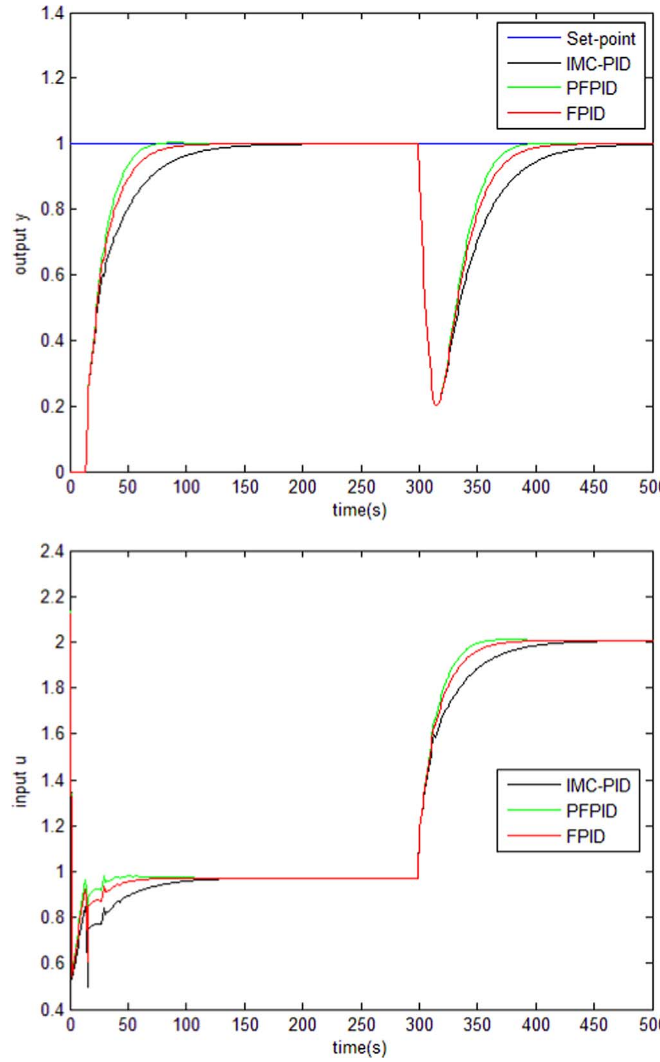

Fig. 10. Closed-loop responses for Case 2.

and fuzzy PID. Table 4 shows the response time of the three controllers and it is seen that the PFPID yields the fastest response.

In IMC, λ will affect the control performance of PID and we further tested different values of λ to verify the IMC-PID performance following its principle that $\lambda > 0.8\tau$. Figs. 6 and 7 show the responses for the following four cases: Case1: $\lambda = 1.0^*\tau$, Case2: $\lambda = 1.5^*\tau$, Case3: $\lambda = 1.6^*\tau$, Case4: $\lambda = 1.7^*\tau$, respectively. It can be seen that when λ increases, the oscillation will be more and more small, so $\lambda = 1.7^*\tau$ may be a better choice for the model/plant match situation.

In Fig. 8, the comparisons of the three methods with $\lambda = 1.7^*\tau$ for the IMC-PID are further done. As can be seen from Fig. 8, the response speed of PFPID is still the best among the three methods.

However, it is known that accurate process models for practical processes cannot be obtained. Therefore, model/plant mismatches are an important issue we must consider. This means that the model in Eq. (14) may not be able to accurately describe the dynamics of the coke furnace, and there is always a difference between the model and the process. In order to mimic such conditions, we use the Monte Carlo method to generate several cases of real industrial processes [42]. Among them, four kinds of model/plant mismatch are randomly generated based on Eq. (14) with the maximum uncertainty as 30%. Here $\lambda = 3\tau$ is selected in order for IMC-PID to yield a more stable response. The transfer functions of the four kinds of practical processes are shown below.

$$\text{Case1: } G(s) = \frac{1.2435}{416.0920s + 1} e^{-232.8576s} \tag{15}$$

$$\text{Case 2: } G(s) = \frac{1.0281}{303.4846s + 1} e^{-384.7067s} \tag{16}$$

$$\text{Case 3: } G(s) = \frac{0.7946}{447.6266s + 1} e^{-382.3512s} \tag{17}$$

$$\text{Case 4: } G(s) = \frac{0.9531}{274.7961s + 1} e^{-374.8324s} \tag{18}$$

The simulation will be done by designing the controllers with the nominal process model Eq. (14) to control the four actual processes described by Eqs. (15–18). Figs. 9–12 show the responses of the four cases and we can easily find that PFPID controller can still obtain satisfactory control performance. In Fig. 9, the PFPID can track the set-point more quickly than the other two methods. On the other hand, there will be a little overshoot. In Figs. 10 and

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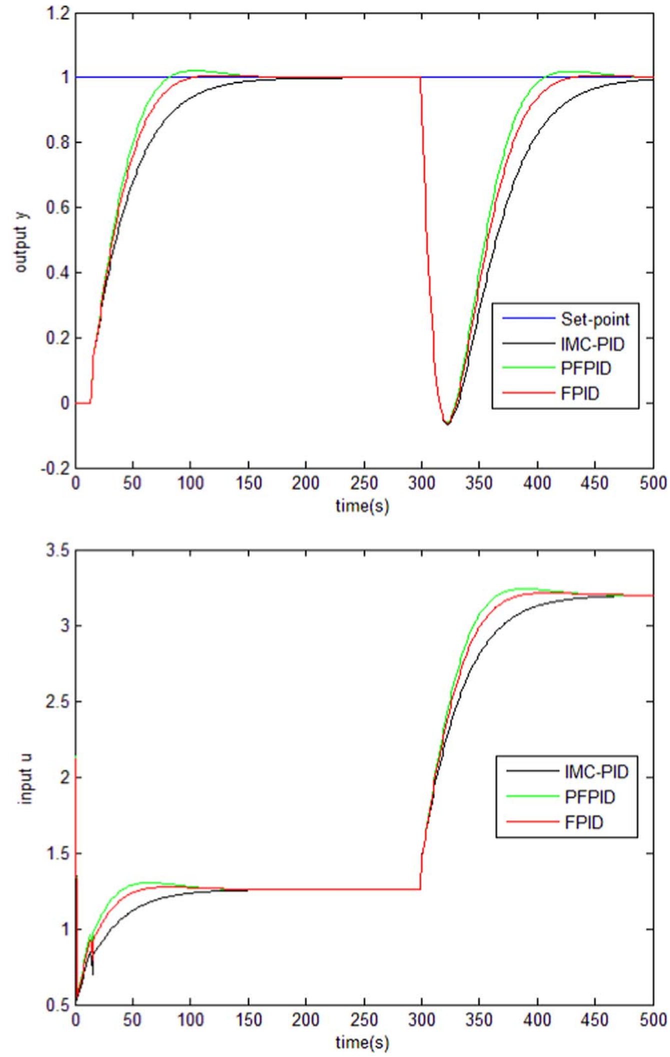

Fig. 11. Closed-loop responses for Case 3.

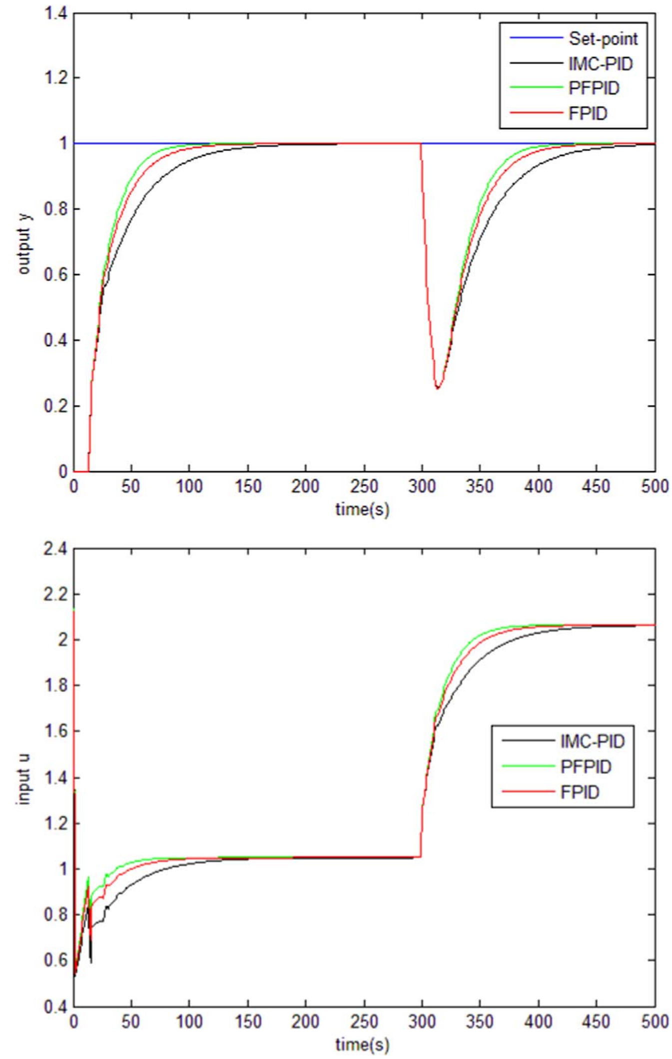

Fig. 12. Closed-loop responses for Case 4.

11, the simulations results are the same as those in Fig. 9, i.e., PFPID has the fastest tracking speed and stronger disturbance rejection ability. In Fig. 12, the IMC based PID controller cannot track the set-point quickly, while PFPID can still track the set-point with the fastest response speed. We can see in these four cases that the PFPID control input signals are stable and smooth with no greater oscillation and fluctuation compared with other methods.

5. Conclusion

A new PID control method is proposed using fuzzy PID and PFC. First, fuzzy rules and appropriate membership functions are formulated. Second, an adaptive mechanism is introduced to tune the PID parameters using PFC strategy to form a fuzzy PID controller. Finally, a coke furnace case study is considered to verify the proposed PFPID algorithm and improved control performance is obtained in comparison with conventional PID and fuzzy PID control. Taking into account the impact of uncertainty, this paper analyzes the model/plant mismatch and the impact of disturbance and simulation results show that the proposed method has the improved control performance.

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References

[1] Zhang R, Tao J, Gao F. A new approach of Takagi-Sugeno fuzzy modeling using improved GA optimization for oxygen content in a coke furnace. Ind Eng Chem Res 2016;55(22):6465–74.
[2] Skogestad S. Simple analytic rules for model reduction and PID controller tuning. J Process Control 2003;13(4):291–309.
[3] Wang QC, Hang CC, Yang XP. Single-loop controller design via IMC principles. Automatica 2001;37(12):2041–8.
[4] Zhang RD, Wu S, Gao FR. Improved PI controller based on predictive functional control for liquid level regulation in a coke fractionation tower. J Process Control 2014;24(3):125–32.
[5] Tyreus BD, Luyben WL, Tuning PI. controllers for integrator/dead time processes. Trans ASME 1992;31(11):2628–31.
[6] Luyben WL. Tunning proportional-integral-derivative controllers for integrator/dead time processes. Ind Eng Chem Res 1996;35(10):3480–3.
[7] Ziegler J, Nichols N. Optimum settings for automatic controllers. Trans ASME 2014;64:759–68.
[8] Astrom KJ, Hagglund T. Revisiting the Ziegler–Nichols step response method for PID control. J Process Control 2004;14(6):635–50.
[9] Normey R, Julio E, Guzman JL, Unified PID. tuning approach for stable, integrative and unstable dead-time processes, In: Proceedings of IFAC conference on advances in PID control, PID 2012, 2, pp. 35–40, (PART 1); 2012.

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[10] Qin SJ, Badgwell TA. A survey of industrial model predictive control technology. Control Eng Pract 2003;11(7):733–64.
[11] Zhang R, Lu R, Xue A, Gao F. New minmax linear quadratic fault-tolerant tracking control for batch processes. IEEE Trans Autom Control 2016;61:3045–51.
[12] Morari M, Barić M. Recent developments in the control of constrained hybrid systems. Comput Chem Eng 2006;30(10–12):1619–31.
[13] Zhang R, Xue A, Gao F. Temperature control of industrial coke furnace using novel state space model predictive control. IEEE Trans Ind Inform 2014;10(4):2084–92.
[14] Zhang R, Xue A, Wang S. Dynamic modeling and nonlinear predictive control based on partitioned model and nonlinear optimization. Ind Eng Chem Res 2011;50(13):8110–21.
[15] Savran A. A multivariable predictive fuzzy PID control system. Appl Soft Comput 2013;13(5):2658–67.
[16] Lee KN, Yeo YK. Predictive PID tuning method based on the simplified GPC control law. J Chem Eng Jpn 2009;42(4):274–80.
[17] Wu S, Zhang R, Lu R, Gao F. Design of dynamic matrix control based PID for residual oil outlet temperature in a coke furnace. Chemom Intell Lab Syst 2014;134:110–7.
[18] Shabani H, Vahidi B, Ebrahimpour M. A robust PID controller based on imperialist competitive algorithm for load-frequency control of power systems. ISA Trans 2013;52(1):88–95.
[19] Zhang R, Xue A, Lu R, Li P, Gao F. Real-time implementation of improved state space MPC for air-supply in a coke furnace. IEEE Trans Ind Electron 2014;61(7):3532–9.
[20] Kariminia S, Motamedi S, Shamshirband S, Piri J, Mohammadi K, Hashim R, Roy C, Petkovic D, Bonakdari H. Modelling thermal comfort of visitors at urban squares in hot and arid climate using NN-ARX soft computing method. Theor Appl Climatol 2016;124(3):991–1004.
[21] Cao J, Hao J, Lai X, Vong CM, Luo M. Ensemble extreme learning machine and sparse representation classification algorithm. J Frankl Inst 2016;353:4526–41.
[22] Zedch LA. Fuzzy sets. Inf Control 1965;8(3):338–53.
[23] Miccio M, Cosenza B. Control of a distillation column by type-2 and type-1 fuzzy logic PID controllers. J Process Control 2014;24(5):475–84.
[24] Hu P, Cao GY, Zhu XJ, Hu M. Coolant circuit modeling and temperature fuzzy control of proton exchange membrane fuel cells. Int J Hydrog Energy 2010;35(17):9110e23.
[25] Galluzzo M, Cosenza B, Matharu A. Control of a nonlinear continuous bioreactor with bifurcation by a type-2 fuzzy logic controller. Comput Chem Eng 2008;32(12):2986–93.
[26] Galluzzo M, Cosenza B. Control of a non-isothermal continuous stirred tank reactor by a feedback-feedforward structure using type-2 fuzzy logic controllers. Inf Sci 2011;181(17):3535–50.
[27] Carmen MC, Noguera JM, Vila MA. Flexible queries on relational databases using fuzzy logic and ontologies. Inform Sci 2016;366:150–64.
[28] Pereira R, Fagundes A, Melício R, Mendes VMF, Figueiredo J, Martins J, Quadrado JC. A fuzzy clustering approach to a demand response model. Electr Power Energy Syst 2016;81:184–92.
[29] Heydari G, Vali MA, Gharaveisi AA. Chaotic time series prediction via artificial neural square fuzzy inference system. Exp Syst Appl 2016;55:461–8.
[30] He YL, Wang XZ, Huang Z. Fuzzy nonlinear regression analysis using a random weight network. Inform Sci 2016;364-365:222–40.
[31] Chiou JS, Tsai SH, Liu MT. A PSO-based adaptive fuzzy PID-controllers. Simul Model Pract Theory 2012;26:49–59.
[32] Savran A, Kahraman G. A fuzzy model based adaptive PID controller design for nonlinear and uncertain processes. ISA Trans 2014;53:280–8.
[33] Méndez JA, Marrero A, Reboso JA, León A. Adaptive fuzzy predictive controller for anesthesia delivery. Control Eng Pract 2016;46:1–9.
[34] Wu X, Shen J, Li YG, Lee KY. Fuzzy modeling and predictive control of superheater steam temperature for power plant. ISA Trans 2015;56:241–51.
[35] Lu JL, Chen GR, Ying H. Predictive fuzzy PID control: theory, design and simulation. Inform Sci 2001;137:157–87.
[36] He M, Cai WJ, Li SY. Multiple fuzzy model-based temperature predictive control for HVAC systems. Inform Sci 2005;169:155–74.
[37] Lepetič M, Škrjanc I, Chiacchiarini HG, Matko D. Predictive functional control based on fuzzy model: magnetic suspension system case study. Eng Appl Artif Intell 2003;16:425–30.
[38] Filip I, Szeidert I. Adaptive fuzzy PI controller with shifted control singletons. Exp Syst Appl 2016;54:1–12.
[39] Moradi H, Setayesh H, Alasty A. PID-Fuzzy control of air handling units in the presence of uncertainty. Int J Therm Sci 2016;109:123–35.
[40] Zhang RD, Cao ZX, Lu RQ, Li P, Gao FR. State-space predictive-P control for liquid level in an industrial coke fractionation tower. IEEE Trans Autom Sci Eng 2015;12(4):1516–24.
[41] Thanana N, Thananchai L. Fuzzy self-tuning PID control of hydrogen-driven pneumatic artificial muscle actuator. J Bionic Eng 2013;10:329–40.
[42] Zou Q, Jin QB, Zhang RD. Design of fractional order predictive functional control for fractional industrial processes. Chemom Intell Lab Syst 2016;152:34–41.

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