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Study on Nonlinear pH Control Strategy Based on External Recurrent Neural Network

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Abstract

In the limestone/gypsum wet flue gas desulfurization technology, the control process of the absorber slurry pH value is a significantly non-linear, time-varying process. This paper proposed a combined control strategy for dealing with nonlinear pH control, which composed of a neural predictive controller (by controlling the flow of limestone slurry to control the pH value) and feedback controller (by controlling the loop slurry flow to control the outlet SO2 concentration). This paper introducing the design and implement steps of the combined control strategy and the results show that the control system has good dynamic performance and robustness.

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Key words: Combined control strategy; pH control; neural network predictive controller; feedback controller

As we all know, the emission of Sulfur dioxide has adversely affected on human health and the environment. In recent years, there have been many methods used to remove sulfur dioxide in coal-fired power plant flue gas. In these methods, WFGD (wet flue gas desulfurization) is the most popular technique, and the control of pH value is one of the key factors that affect the desulfurization rate and the quality of gypsum [1], thus, the control model of pH value established is very important. However, because of the complexity, nonlinear and multi-variable of the pH control, it is difficult or even impossible to establish the mathematical model. Traditional methods always take decentralized feedback control or multi-variable predictive control [2] and other linear control strategies. But when the pH has significant

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non-linearity, the linear control techniques may not meet the control requirement. This paper presents a CCS (combined control strategy), which including the pH NNPC (neural network predictive controller) and SO_2 feedback controller.

1. Nonlinear identification of pH value for predictive control

Rated operating points of the identification experiment are: Inlet flue gas SO_2 concentration: 4400mg/Nm^3; L/G ratio: 10; pH value: 5.0-6.0; Desulfurization rate: 95%; Outlet flue gas SO_2 concentration: 220 mg/Nm^3; Reagent ratio (Ca/S): 1.03.

The steps of dynamic system identification are general divided into the following sections [3-5]:

1.1. Input and output selection of dynamic model

NNPC using neural network model to control pH value which by controlling the flow of limestone slurry (Q). Therefore, dynamic model between pH value and Q must be established, because if take multi-variables as input to the system will make the identification process very difficult. Therefore, we use the pH value as output, Q as input of neural network model.

1.2. Identification experiment design

Identification experimental design including the choices of input signals, sampling time and other contents, to make the collected data sequence contains characteristics of the system including the inherent information as much as possible, experiment input signals should meet the following requirements:

- (1)Spectrum requirements, the input signal spectrum required to cover the spectrum of the process.
- (2)Margin requirements, in the entire scope of work, maintaining the input signal amplitude within a certain range. Random amplitude signal meets this requirement.

1.3. Neural network model structure selection

This paper establishes system dynamic model based on ERNN (external recurrent neural network) [6], and selects MLP (multilayer perceptron) neural network with one hidden layer of sigmoid neurons and output layer of linear neurons. The input of ERNN is the regression vector $\varphi(t)$, the number of hidden neurons were designed to 8 with heuristic rules. Therefore, this paper uses a simple three-layer neural network as the prediction model, the structure is shown in Figure 1.

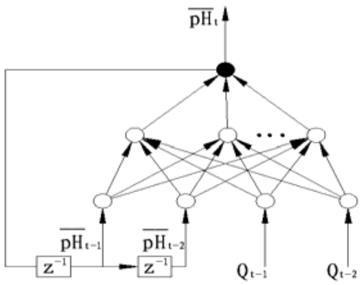

Fig. 1. ERNN network structure of pH predictive control system

The shadow neurons represent the diagonal regression neural element, z^{-1} means the delay of a time step. We can prove that when the network trained by weight decay method, if the learning rate satisfies certain value, then it can be ensuring the training will be convergence with quadratic function.

1.4. Model parameters optimization

The neural network was trained using weight decay method, the training objective function optimization includes two aspects: inhibition of prediction error (LF) and inhibition of neural network parameters for the fitting, as is shown in eq. (1).

$$W = \frac{1}{2N}\sum_{t=1}^{N}\varepsilon^2(t) + \frac{1}{2N}\boldsymbol{\Lambda}^{\mathrm{T}}\boldsymbol{A}\boldsymbol{\Lambda},\ LF = \frac{1}{2N}\sum_{t=1}^{N}\varepsilon^2(t) \tag{1}$$

In eq. (1), N is the number of samples, ε is the predictive error, $\boldsymbol{\Lambda}$ is the neural network parameter vector, and A is a diagonal matrix, which is usually $A = \alpha I$, α is the weight decay, I is the unit matrix. Use the AFPE (Akaike's final prediction error) which bases on LF (Loss Function) criterion [7] to test the results of the identification model. The training objective is to find a weight decay to smallest neural network's AFPE, analyze the sensitivity of the model when $10^{-3} < \alpha < 1$, in order to avoid local minima in the training objective function, for each value of α ,the neural network was trained 3 times with different initial parameters. The minimum AFPE was achieved for $\alpha = 10^{-2}$, as is shown in table 1. Using the optimal ERNN, the neural network can track the pH value dynamic ideally.

Table1. Mean square prediction error (LF) and Akaike's final prediction error (AFPE) Comparison Table

	$\alpha = 10^{-3}$	$\alpha = 10^{-2}$	$\alpha = 10^{-1}$	$\alpha = 10^{0}$
Training 1: AFPE	3.1	2.6	3.0	40
LF	3.7	3.13	3.3	48
Training 2: AFPE	3.2	2.7	3.05	44
LF	3.75	3.1	3.3	52
Training 3: AFPE	3.25	2.75	3.1	68
LF	3.8	3.3	3.6	76

1.5. Model test

This article using a nonlinear model predictive controller based on ERNN to establish pH value control dynamic model, we do experiments to test the NNPC performance for a step change in pH value set point. And the result shows that the control performance is quite good, the closed-loop response is fast, with neither overshoot nor offset at steady state.

2. Combined control strategy

2.1. Neural predictive control of pH

The structure of the neural network predictive control is shown in Figure 2.

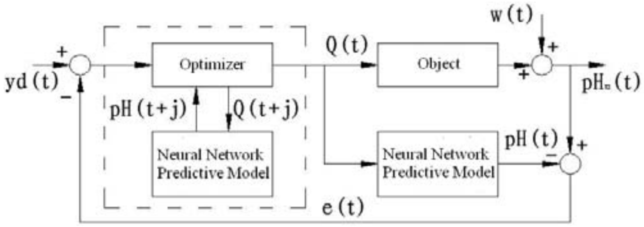

Fig.2. Neural network predictive control structure diagram

The purpose of optimizer is to find optimal control increment sequence $\{\Delta\boldsymbol{Q}^{*}(t+j-1),\ j=1,2,...,m\}$ to smallest the objective function. The objective function is shown in eq. (2).

$$J=\sum_{j=1}^{P}\left[y_d(t+j)-pH(t+j\mid t)\right]^2+\rho\sum_{j=1}^{m}\left[\Delta Q(t+j-1)\right]^2 \tag{2}$$

The optimizer uses the neural network model to predict the future behavior of pH value for changes in limestone slurry flow rate. The neural network also takes into account modeling errors and unmeasured disturbances correction to prevent deviation from the steady state. The most common method in nonlinear predictive control is add a prediction bias correction based on the prediction error, that is, the difference between the current pH value $(pH_{(m)})$ and current predictive current pH value (pH), as eq. (3) show.

$$\begin{aligned} &pH(t+j\mid t)=\overline{pH}(t+j)+e(t)\\ &e(t)=pH_m(t)-pH(t)\end{aligned} \tag{3}$$

The predicted pH value is determined by the equivalent linear model of ERNN, the linear model is shown in eq. (4). (Sampling time: 120s, pH=5.2, Q=44m3/h).

$$\begin{aligned}\overline{pH}(t)&=f(\varphi(t))\\ &=f(pH(t-1),\overline{pH}(t-2),Q(t-1),Q(t-2))\\ &=0.2558pH(t-1)+0.5334pH(t-2)+0.1302Q(t-1)+0.1282Q(t-2)\end{aligned} \tag{4}$$

$\varphi(t)$ is the regression vector.

Constrained optimization problem is as eq. (5).

$$\begin{aligned}&\min_{\Delta\boldsymbol{Q}(t+1)\cdots,\Delta\boldsymbol{Q}(t+m)} J\\ &\Delta\boldsymbol{Q}(t+j-1)\le\Delta\boldsymbol{Q}_{\max}\qquad j=1,\dots,m\\ &\Delta\boldsymbol{Q}(t+j)=0\qquad\qquad j=m,\dots p\end{aligned} \tag{5}$$

2.2. Combined control strategy adjustment

When adjust the CCS, we fist adjust NNPC and feedback controller alone, then fine-tuning the CCS. It needs to set the input and output when adjusting the NNPC, the value of incremental weight coefficient varies between 0 and 1, we limit the $\Delta \boldsymbol{Q}_{\max}$ to 4m^3/h and the desired control effect was achieved when the incremental weight coefficient ρ = 0.05, the initial values were set as: Sampling time(s):120s; Prediction domain (P) :5; Control domain (m) :2; Incremental weight coefficient (ρ) :0.05, and these values will be used to adjust the CCS. SO_2 feedback controller is designed based on the IMC-PID adjustment rules [8] of linear dynamic model identification, specific design process can reference [8]. Using the previous initial set but set the control domain to 4 minutes (two intervals) to adjust the CCS, the result shows good anti-jamming performance.

3. Performance of the combined control strategy

The performance of CCS can only assessed for rejecting changes in the inlet SO_2 load, because this is the most important control objective in wet FGD plants. In order to study the robustness of the control strategy, the control experiments were carried out at different pH values, and each value using inlet SO_2 load with different magnitude changes. To assess the CCS the largest anti-jamming capability by itself, the control system did not add feed-forward action. The principle is to make the pH and the concentration of outlet SO_2 control error less than 0.15 and 145 mg/Nm^3, respectively. Assumed that the concentration of inlet SO_2 is constant (4400 mg/Nm^3), and the expected biggest change in the inlet SO_2 emissions is 300Kg / h. The results are shown in Figure 3 (a) and (b), they are the performance of CCS for 75% and 85% of maximum expected step change in the inlet SO_2 load when set points are: pH =5.2, SO_2=220 and 200 mg/Nm^3. It can seem that using a NNPC instead of a feedback controller in a decentralized control strategy greatly improves the performance of pH control, but cannot get better SO_2 control. Therefore, it should be added feed-forward control to the SO_2 control loop to achieve the desired control effect. This was test by carrying out simulations of the CCS with and without feed-forward action for SO_2, as shown in Figure 3 (c): Simulations of disturbance rejection with and without SO_2 feed-forward action (dashed and solid line, respectively) when the maximum step change in the inlet SO_2 load is 85%.

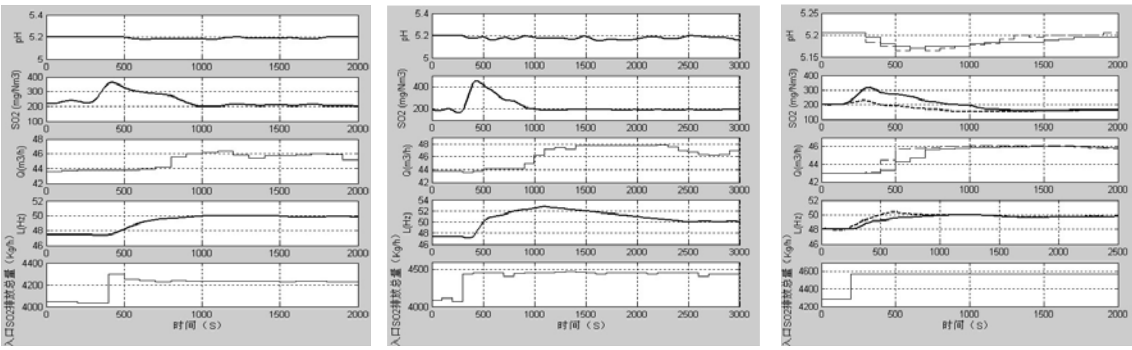

Fig. 3. (a) (b) (c)

It can see from the figure, the SO_2 feedback controller significantly improves the control performance of SO_2, while the control effect of pH by the NNPC is still very good. Meanwhile, in the pH study range, the robustness of NNPC is very good, and it works well with changes in slurry recycle flow rate and inlet SO_2 load which are unmeasured disturbances. It can also concluded that the choice of DMC correction was correct, this is because when the DMC correction was used with a predictive controller based on ERNN, it can effectively control the model error, such as the reference [9] said.

4. Conclusions

This paper proposed and assessed the CCS of nonlinear pH value in the WFGD, and described the design and implementation steps of the CCS. When do experiments without feedback controller, the performance of CCS relatively poor. However, after adding the feedback to the SO_2 loop, the CCS performance has greatly improved. So when the pH value of the non-linearity is very high, the combination of pH nonlinear predictive controller and a SO_2 feedback controller with feedback action can achieve good control objectives. Then, there is no need to use more complex control strategies, such as nonlinear multivariable predictive controllers.

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References

[1] Zheng, Y.J., Kiil, S., Johnson, J.E.: Experimental Investigation of a Pilot-ScaleJet Bubbling Reactor for Wet Flue Gas Desulphurization. J. Chemical Engineering Science58(2003) 4695–4703.

[2] Shi Wuxi.Adaptive fuzzy generalized predictive control for unknown parameters multivariable linear systems [J]. Control and decision. 2009,24(2),313-316.

[3] Fang Congzhi,Xiao Deyun. Process Identification [M]. Beijing: Tsinghua University Press.1998

[4] Xu Nanrong. System Identification[M].Nanjing:Southeast University Press,1991

[5] Doherty SK, Gomm JB, Williams D. Experiment design considerations for non-linear system identification using neural networks. Computers & chemical engineering. 1997, 21(3):327-346.

[6] KuCC, L ee KY. Diagonal recurrent neural networks for dynamic systems control [J]. IEEE Transactions on Neural Networks . 1995, 6 (1) : 144-155.

[7] Rivera, D. E.; Jun, S. K. An integrated identification and control design methodology for multivariable process system application[J]. IEEE Control System Magazine 2000, 25–37.

[8] Pan Xiao, Zhong Yiqing. Design and Realization of PID Control Based on IMC[J]. Computer Simulation,2005,22(8):80-82.

[9] Chu, J.-Z.; et al. Multistep Model Predictive Control Based on Artificial Neural Networks. Ind. Eng. Chem. Res. 2003, 42, 5215–5228.