Feed Forward Cascade PID Based Predictive Control of the PH Value of Desulfurization Slurry in Thermal Power Units

Shijie Wang, Li Zhang, Peng Wang, Jie Li, Wenqiang Jiang, Bao Liu

Abstract—**Aiming at the problems of large lag and inertia in the PH control system of gypsum wet desulfurization in thermal power units, this paper proposes a cascade multi-step feed forward predictive control strategy based on proportional integral derivative (PID). Firstly, the paper establishes mechanism model through the transfer function of PH value influence factor to ensure a strong correlation between the control system parameters and the PH value; Secondly, based on the traditional PID control strategy, the paper introduces cascade and multi-step feed forward control mechanisms to solve the strong inertia of the control system; Then, the three-step predictive value of SO_2 content in raw flue gas based on long short term memory network (LSTM) is introduced as the feed forward value, so as to better eliminate system lag characteristics and track the PH setting value; Finally, the simulation experiment is carried out using the desulfurization data of the plant. The simulation results show that, compared with the traditional PID and cascade PID control strategies, the control strategy proposed in this paper achieves more accurate and stable control of the PH value of desulfurization slurry in thermal power units, and improve the desulfurization efficiency.**

Index Terms—**wet desulfurization of gypsum, PID control, multi-step feed forward predictive control, long and short term memory network.**

I. Introduction

WITH the development of the power industry, the content of SO_2 produced by coal-fired power plants in China has been increasing in the proportion of SO_2 emissions nationwide, and has become the main source of SO_2 pollution in China's atmosphere reducing SO_2 emissions from thermal power plants is of great significance for China's environmental protection [1], [2]. However, there are many technological processes for flue gas desulfurization. Among them, the vast majority of thermal power units in China use the limestone gypsum wet desulfurization system. This method uses limestone slurry to react with SO_2 in the inlet flue gas in the absorption tower, and the final gypsum can be used again. The key to affecting the desulfurization efficiency in the desulfurization process is the PH value of slurry in the absorption tower. Therefore, taking the PH value of slurry in the absorption tower as the controlled object to reduce SO_2 emission and improve desulfurization efficiency is the first choice to reduce the sulfur emission of thermal power units [3]-[6].

The limestone gypsum wet desulfurization system is a typical control system with nonlinearity, time-varying, hysteresis, and uncertainty [7]-[9]. In the desulfurization process, the slurry PH control strategy is mainly divided into three categories: traditional manual operation, PID control algorithm, and model predictive control. References [10]-[11] control the model output through manual parameter tuning, but manual operation requires rich experience and knowledge, is time-consuming and laborious, and has large operating errors; References [12]-[17] indicate that traditional PID control has a simple structure, high degree of automation, low cost, and certain robustness. However, for nonlinear, large inertia, and time-varying systems, traditional PID control cannot adjust parameters based on changes in object characteristics, and its adaptive ability is poor, which affects control accuracy. Therefore, references [18]-[21] proposed a cascaded PID control method to solve the nonlinear and large inertia problems of control systems. This method is divided into the main control loop of the main PID control and the auxiliary control loop of the auxiliary PID control. Through the coarse and fine tuning of two circuits, the output of the controlled object is jointly controlled to approach the set value faster, while maintaining system stability and improving process characteristics. However, the cascade PID control method also has its own shortcomings. Cascade PID control cannot solve the lag problem of the control system [22]-[24], and cannot transmit errors to the desulfurization control system in a timely manner, which may lead to overshoot. In reference [25], to improve the control accuracy of the Dynamic Matrix Algorithm (DMC) for desulfurization systems and enable automatic optimization of controller parameters, an adaptive hybrid particle swarm optimization algorithm was proposed to optimize the parameters in DMC.

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Reference [26] proposes a control scheme based on a multivariable model predictive control algorithm, A linear variable parameter model of the desulfurization system is established with boiler load as the scheduling variable. Although DMC and model predictive control have accelerated response speed, there are still shortcomings in overshoot and stable output.

In order to solve the above problems, this paper proposes a cascade PID strategy based on feed forward multi-step prediction to adapt to the multi disturbance control systems. The main contributions are summarized as follows.

(1) By selecting the main influencing factors of PH value, constructing a mechanism model of the control system, and calculating the transfer function between various interference parameters and PH value, the strong correlation between system parameter factors is improved.

(2) In response to the problem of high inertia in control systems, this paper introduces a feed-forward mechanism based on PID cascade, which accelerates the response speed of the system and improves the stability of the output value of the control model through the joint action of the outer and inner loops.

(3) Introducing a third step SO_2 content feed-forward prediction model based on LSTM to solve the lag difficulty of the system, transmitting future predicted values to the control system in advance, and controlling in a timely manner when disturbances occur, rather than waiting for deviations to occur before controlling, effectively eliminating the influence of lag disturbances on controlled parameters.

The rest of this paper is organized as follows. The Section II introduces the relevant knowledge of wet desulfurization; The Section III section introduces the modeling process of the control system mechanism model; The Section IV provides a detailed introduction to the feed forward cascade multi-step prediction system; The Section V conducts simulation verification and result analysis; The Section VI provides the conclusion.

II. Wet Desulfurization System

A. System Process Flow

A typical limestone gypsum wet desulfurization system is shown in Fig. 1, which is composed of a flue gas system, an SO_2 absorption system, an absorbent preparation system, a gypsum dehydration system, an evacuation system, a process water system, and a desulfurization wastewater treatment system. The key to achieving high desulfurization efficiency lies in the SO_2 absorption system, where the absorption tower serves as the main equipment for all absorption reaction processes. Therefore, it plays a crucial role in the overall desulfurization system.

B. System Principle

Before the reaction occurs in the absorption tower, the limestone stored in the bin is first ground into powder using a ball mill. The limestone slurry is then adjusted by a vortex pump. Subsequently, the raw flue gas, which contains a significant amount of pollutants, enters the absorption tower through the inlet of the equipment. In the tower, the $CaCO_3$ in the limestone slurry reacts with the SO_2 in the flue gas, facilitated by sufficient air, resulting in the production of reusable gypsum. The remaining flue gas undergoes further treatment before being discharged into the atmosphere.

To ensure a more thorough reaction, the flue gas, containing a high concentration of pollutants, enters the absorption tower from below through the oxidation fan. It is then mixed with the limestone slurry in a countercurrent manner, promoting a more comprehensive reaction.

The chemical reaction formulas for the absorption and oxidation processes are shown in equations (1) and (2), respectively.

$$2CaCO_3 + H_2O + 2SO_2 \rightarrow 2CaSO_3 \bullet \frac{1}{2} H_2O + 2CO_2 \tag{1}$$

$$2CaSO_3 \bullet \frac{1}{2} H_2O + O_2 + 3H_2O \rightarrow 2CaSO_4 \bullet 2H_2O \tag{2}$$

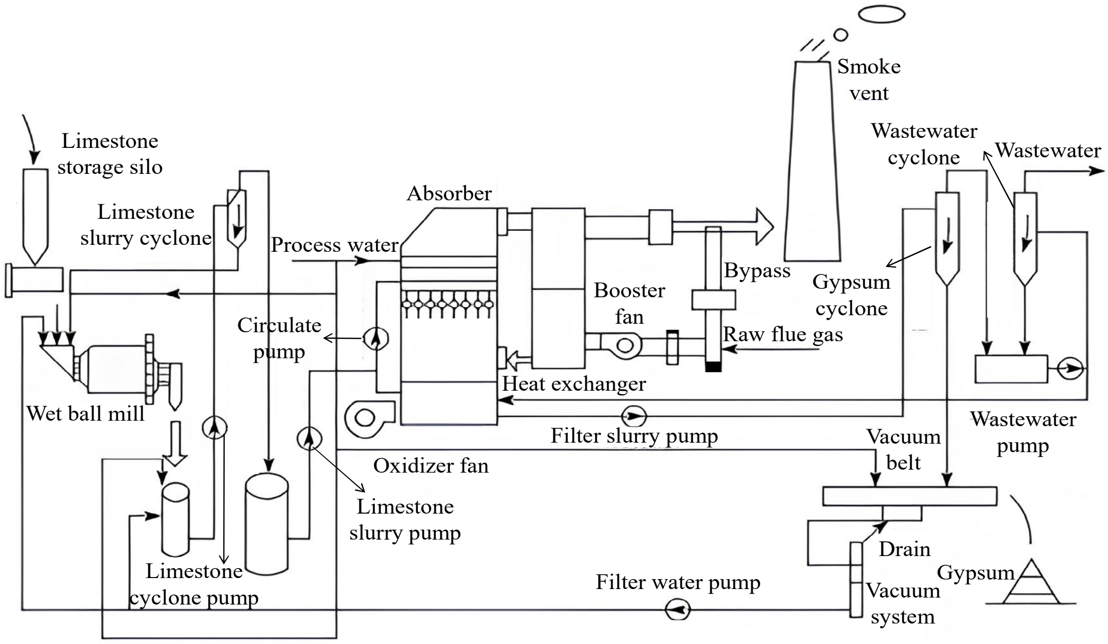


Fig. 1. Limestone-gypsum wet desulfurization system

III. Mechanism Model

By analyzing the actual desulfurization data of a 1000MW thermal power plant, this article studies the correlation between PH value and other characteristics. Through the analysis, paper find that there are four main factors that affect the PH value, namely slurry flow rate, slurry density, flue gas flow rate, and flue gas concentration. These factors are considered as perturbations of PH measurement values, which are then used to calculate the transfer function and construct a mechanistic model.

A. Building Mechanism Model

The constructed mechanism model is shown in Fig. 2, where PID is a PH controller that can adjust the valve opening angle based on the PH set value and the feedback PH measurement value; Fn is the function relationship between slurry flow rate and valve opening, and the amount of slurry flow rate is controlled by valve opening; The four influencing factors are expressed as disturbance quantities in the form of transfer functions to represent the relationship between PH measurement values, where $G1_{(s)}$ is the transfer function of slurry flow rate to PH value; $G_{2(s)}$ is the transfer function of slurry density to PH value; $G3_{(s)}$ is the transfer function of flue gas flow rate to PH value; $G4_{(s)}$ is the transfer function of SO_2 concentration to PH value.

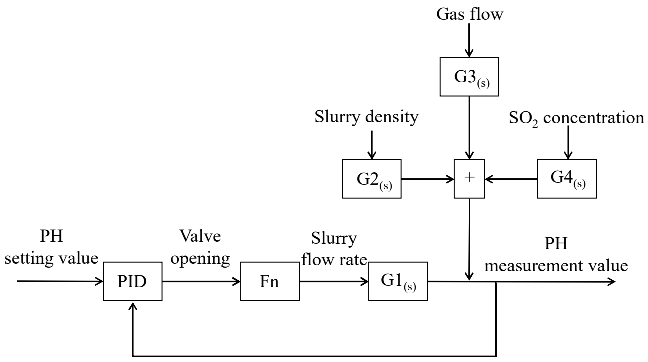


Fig. 2. Mechanistic model based on the transfer function

Due to the real-time measurement of the four parameters of slurry flow rate, slurry density, flue gas flow rate, and flue gas SO_2 concentration, so as long as the four transfer functions $G1_{(s)}$, $G2_{(s)}$, $G3_{(s)}$, and $G4_{(s)}$ can be accurately obtained, the mechanism model of the PH value of the absorption tower slurry can be obtained.

B. Determine Transfer Function

The transfer function with delay elements can be mainly divided into three types, namely: first-order inertia link, second-order inertia link, and n-order inertia link. The parameters of the transfer function mainly include: time constant T, delay time τ, and gain k. Fig. 3 shows the calculation process of the transfer function.

The equations (3) - (6) display the results of each transfer function derived from the actual data and the parameter calculation process.

The transfer function of slurry flow rate to slurry PH value is:

$$G1_{(s)}=\frac{k_1 e^{-\tau_1 s}}{T_1 s+1}=\frac{0.03147}{49.81s+1}e^{-10.8s} \tag{3}$$

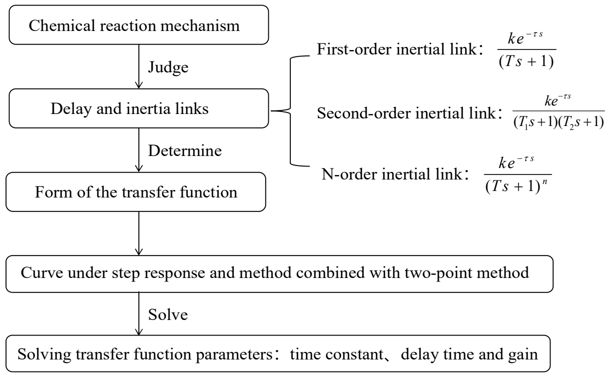


Fig. 3. Flow chart of the transfer function calculation

The transfer function of slurry density to slurry PH value is:

$$G2_{(s)}=\frac{k_2 e^{-\tau_2 s}}{T_2 s+1}=\frac{0.00026225}{49.81s+1}e^{-10.8s} \tag{4}$$

The transfer function of flue gas flow rate to slurry PH value is:

$$G3_{(s)}=\frac{k_3 e^{-\tau_3 s}}{\left(T_3 s+1\right)^3}=\frac{0.005}{\left(15.12s+1\right)^3}e^{-4s} \tag{5}$$

The transfer function of the concentration of SO_2 in the flue gas to the PH value of the slurry is:

$$G4_{(s)}=\frac{k_4 e^{-\tau_4 s}}{\left(T_4 s+1\right)^3}=\frac{0.00031}{\left(38.27s+1\right)^3}e^{-4s} \tag{6}$$

where s is a complex variable that represents the frequency in the laplace transform domain, T represents the time constant of the transfer function, τ represents the delay time parameter, and k represents the gain value of the function.

IV. Feed Forward Cascade PID Control Strategy

A. Introduction to LSTM

The LSTM model was proposed by Hochreiter et al. in 1997, and its main principle is to continuously change the weight through three gating units: forget gate, input gate, and output gate. (Fig. 4, c_{t-1} and h_{t-1} represent the cell state and final output at t-1 time, respectively; x_t, c_t, and h_t represent the input at t time, the output of the cell state, and the final output of LSTM; i_t, f_t, and o_t represent the input gate output, forget gate output, and output gate output, respectively; σ is the sigmoid function; tanh is the tanh function; multiple sign represents multiplication by elements; plus representing summation), it achieves long-term memory of time series in traditional Recurrent Neural Network (RNN).

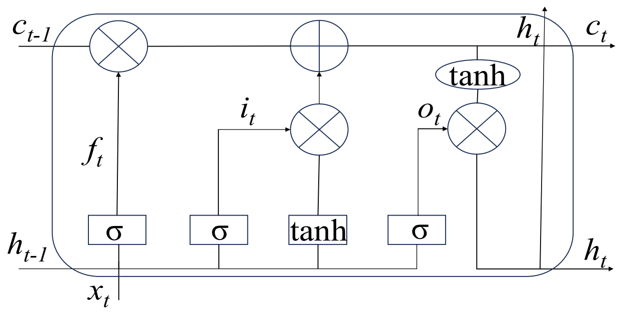
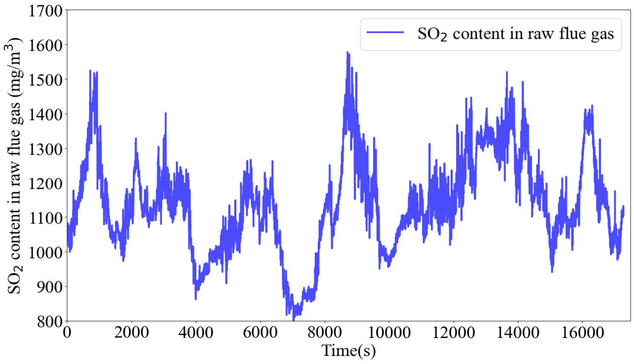


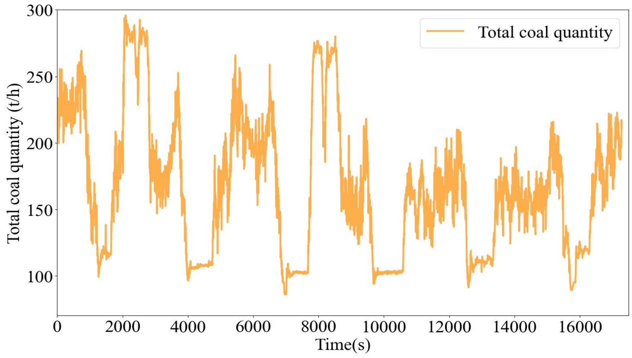
Fig. 4. LSTM schematic

B. Feed Forward Prediction Process and Analysis

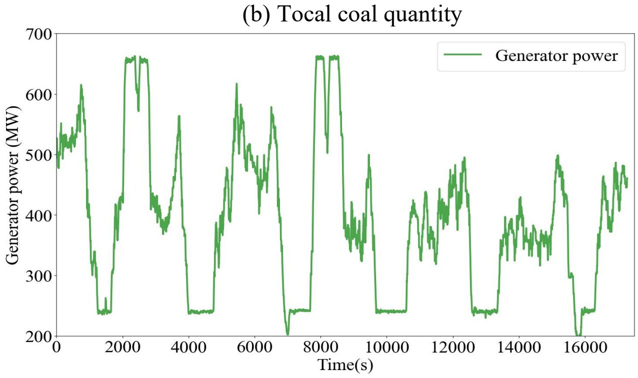
Based on the LSTM model, predict the third step content of SO_2 in the raw flue gas, and use its predicted value as a feed forward to control the PH value. Among them, the input of the prediction model LSTM is the “raw flue gas SO_2 content (mg/m^3)”, “total coal amount (t/h)”, “generator power (MW)”, “raw flue gas temperature (℃)”, and “raw flue gas flow rate (km^3/h)” in the actual desulfurization data; The output is based on the three-step prediction of the original flue gas SO_2 content (mg/m^3). The actual data of the input quantity is represented by a curve graph, as shown in Fig. 5.



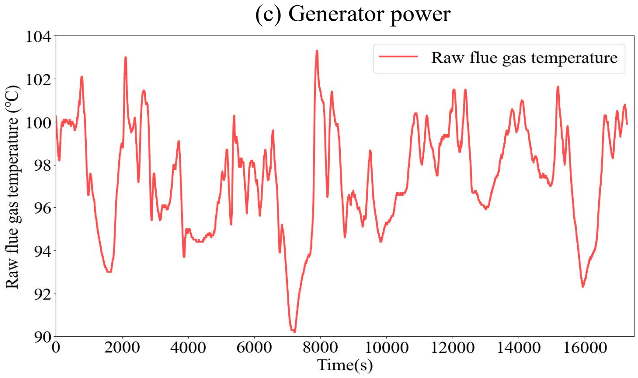
(a) SO_2 content in raw flue gas



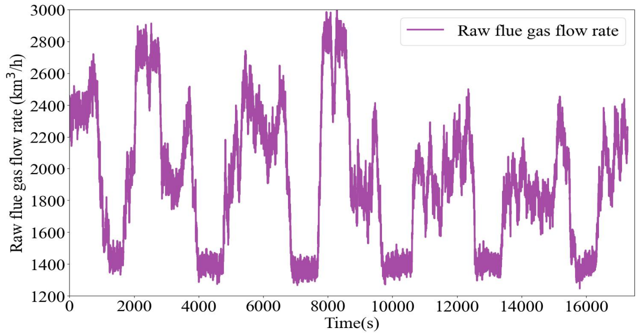
(b) Tocal coal quantity



(c) Generator power



(d) Raw flue gas temperature



(e) Raw flue gas flow rate

Fig. 5. LSTM model input amount

The third step prediction principle of SO_2 content in raw flue gas based on LSTM is shown in Fig. 6. In this prediction model, the five model inputs at time t are fed into the LSTM three-step model for prediction, and the predicted SO_2 content in the original flue gas at time t+3 is output. This feed-forward prediction system consists of an input quantity, a prediction model, and an output quantity.

Through the learning and memory capabilities of the LSTM model, this prediction model is able to capture the time series characteristics of the input quantity and use these features to predict the SO_2 content in the original flue gas. By transmitting the input at time t to the LSTM model, the model can automatically learn the correlation and trend of the input, thereby predicting the original SO_2 content in the flue gas at time t+3. This LSTM based feed-forward prediction system can provide prediction of the future SO_2 content in the original flue gas, providing important reference for the control and optimization of desulfurization systems in thermal power units.

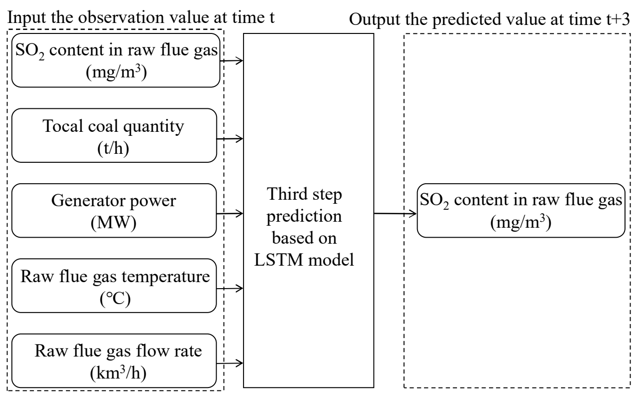


Fig. 6. There-step prediction input-output diagram

C. Prediction Results and Evaluation

The paper selects 3456 samples from actual data and uses the LSTM model based on the third step prediction to predict the SO_2 content in the original flue gas. At the same time, compare the predicted values with the third step prediction values of the neural network (BP) model [27] and support vector machine (SVM) model [28]. The comparison results of different prediction models are shown in Fig. 7.

From Fig. 7, it can be observed that the predicted values based on the LSTM model exhibit a roughly consistent trend with the actual values, with data points that almost overlap. However, the predicted values based on the SVM model lag slightly behind the actual value data, and the predicted values based on the BP model differ significantly from the actual

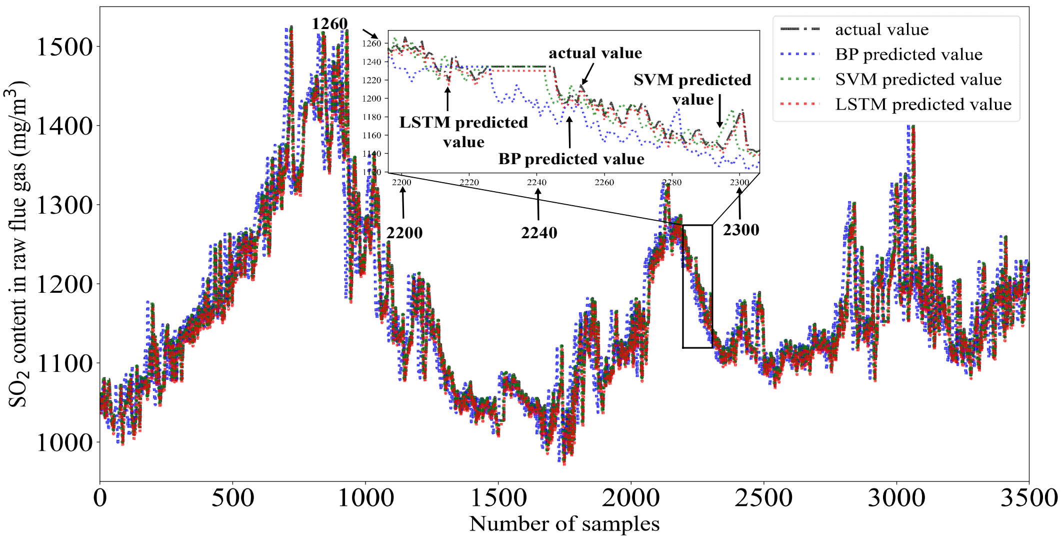


Fig. 7. Comparison of three-step prediction value of raw flue gas SO_2 content with the actual value of different predict model

value data points. Additionally, in order to provide a more intuitive comparison between different prediction models and actual values, the original flue gas SO_2 content of samples 2200-2400 was enlarged in the interval. From the enlarged sub graph, it can be seen that the predicted values based on the LSTM model follow the same pattern as the actual value data, with a small difference between the peak and valley data of the curve. Therefore, compared with the BP model and SVM model, the third step prediction of SO_2 content in raw flue gas based on LSTM has a better effect.

To better quantify the accuracy of the model, the average absolute percentage error (MAPE), root mean square error (RMSE), mean absolute error (MAE), and coefficient of determination (R^2) of the model are selected as measurement indicators. The calculation formulas for these four indicators are obtained from equations (7) - (10), and the evaluation index results of different prediction models are shown in Table I.

$$RMSE=\sqrt{\frac{\sum_{i=1}^{N}\left(y_{i}-y_{r}\right)^{2}}{N}} \tag{7}$$

$$MAPE=\frac{1}{N}\sum_{i=1}^{N}\left|\frac{y_{i}-y_{r}}{y_{i}}\right| \tag{8}$$

$$MAE=\frac{1}{N}\sum_{i=1}^{N}\left|y_{r}-y_{i}\right| \tag{9}$$

$$R^{2}=1-\sum_{i=1}^{N}\frac{\left(y_{i}-y_{r}\right)^{2}}{\left(y_{i}-y_{0}\right)^{2}} \tag{10}$$

where N represents the number of samples; y_i is the true value of the i-th sample; y_r is the predicted value of the i-th sample; y_0 is the average of the true values.

TABLE I
PERFORMANCE COMPARISON OF PREDICTION MODELS

Index	*RMSE*/%	*MAE*/%	*MAPE*/%	R^2
BP	32.476	25.029	2.708	0.854
SVM	31.884	23.177	2.582	0.895
LSTM	**31.297**	**22.972**	**2.194**	**0.924**

From the above evaluation indicators, it can be seen that the LSTM prediction model shows lower error values in RMSE, MAE, and MAPE compared to the BP prediction model and SVM prediction model. This means that the LSTM prediction values are closer to the actual data and have a smaller error range. Meanwhile, compared with the other two prediction models, the R^2 of the LSTM model is relatively large, indicating that the LSTM model has good effectiveness and applicability. Based on the analysis results of these evaluation indicators, we choose LSTM as the predictive model for the feed-forward module.

This selection is based on a comprehensive evaluation of different prediction models, taking into account the prediction accuracy and reliability of the models. The LSTM model has advantages in processing time series data, as it can capture long-term dependencies and make better predictions of future trends. Therefore, selecting LSTM as the prediction model for the feed-forward module can improve the accuracy and stability of the system's prediction.

D. Design of Feed Forward Cascade PID Control

Based on traditional PID control, a cascade PID control system can be constructed through series combination to improve process characteristics and maintain stability. However, the cascade PID control system has a time delay problem, and the entire system and the opening of the slurry valve also have significant time delay. To solve this problem, a feed-forward control system can be introduced and the LSTM model can be used to predict the original SO_2 content in the third step of the flue gas. The purpose of the feed-forward control system is to adjust the output of the controller in advance by predicting the future process variables to reduce the delay of the system. In this case, the LSTM model can convert the predicted raw flue gas SO_2 as a feed-forward quantity.

According to the calculation process of the transfer function mentioned above, the transfer function of the feed forward output quantity to the slurry flow rate is obtained as follows.

$$G_5(s)=\frac{k_5 s+1}{T_5 s+1}=\frac{5s+1}{50s+1} \tag{11}$$

By combining the feed forward predictive control with the cascade PID control part, a feed forward cascade PID control strategy is designed, and its principle is shown in Fig. 8.

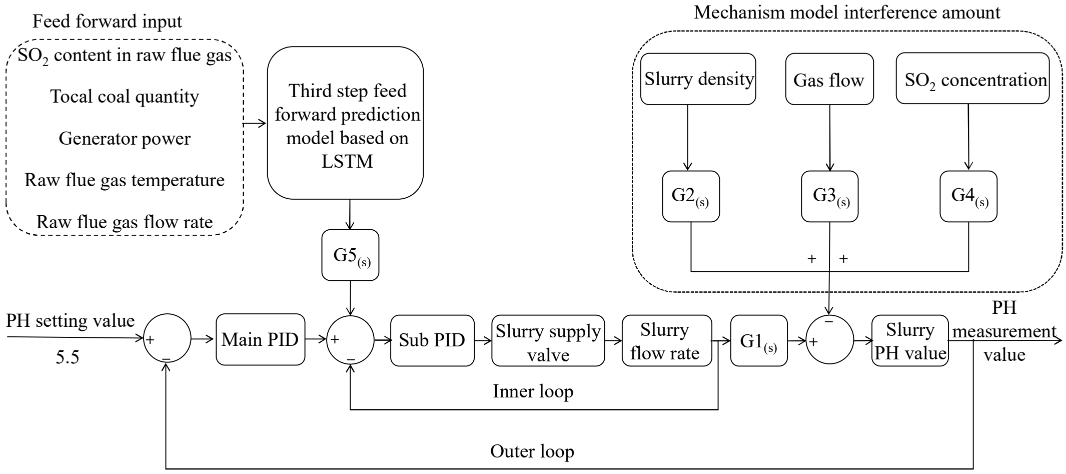


Fig. 8. Schematic diagram of the feed forward-cascade PID

According to the feed-forward cascade PID control strategy shown in Figure 8, this control strategy aims to control the PH value of the absorption tower slurry tank at around 5.5 to achieve the best desulfurization effect.

The control system is divided into an outer loop and an inner loop, corresponding to the main control circuit and the secondary control circuit, respectively. The main control circuit includes a main PID controller, which is used to calculate the error between the set PH value and the actual PH value, and the output result is used as the given value of the limestone slurry flow rate.

The inner loop part includes a sub PID controller, which is used to calculate the error between the given value of limestone slurry flow rate and the actual limestone slurry flow rate, and the output result is used as a control command for the speed of the slurry pump to adjust the increase or decrease of limestone slurry flow rate. The variation of limestone slurry flow rate directly affects the PH value in the slurry tank. During the entire adjustment process, the sub controller plays a coarse adjustment role, while the main controller plays a fine adjustment role, and the two cooperate with each other.

This feed-forward control strategy can respond to disturbances in a timely manner, rather than waiting for errors to occur before controlling, thus more effectively eliminating the influence of disturbances on the controlled parameters. By predicting the SO_2 content of the original flue gas in the third step and converting it into the ideal value of slurry flow as the feed-forward quantity, the parameter changes required by the control system can be adjusted in advance, thus improving the accuracy and efficiency of the control system.

V. Simulation Analysis and Verification

A. Simulation Model Establishment

According to the principle of this model, Simulink software can be used to build simulation diagrams. In the transfer function, the delay values can be achieved by using the Transport Delay module in Simulink [29]. The simulation model building diagram is shown in Fig. 9. In Figure 9, by adjusting the parameters K_p, K_i, and K_d in the main PID and sub PID controllers to achieve more stable control system output. The adjustment of these parameters has a significant impact on the performance of the control system.

Among them, K_p, as a proportional coefficient, has a rapid adjustment effect. When there is a deviation in the system, the regulator will immediately amplify the deviation and output a control signal. A larger K_p value can accelerate the response speed of the system, but an excessively large K_p value may lead to overshoot in the system.

The impact of input bias on system output is adjusted using the integration coefficient K_i. A larger K_i value can shorten the time to eliminate static errors, but an excessively large K_i value may lead to overshoot in the system, especially in systems with inertia.

K_d serves as a differential coefficient to adjust the degree of influence of deviation variation on system output. A larger K_d value can make the system more sensitive to deviation changes, respond in advance, and suppress overshoot, but an excessively large K_d value may lead to system oscillations.

The parameter tuning of the PID controller can be optimized in engineering based on the PID adjustment law, and the optimal value can be obtained by updating the controller parameters. The optimal parameter results of the feed-forward cascade PID controller are shown in Table II.

TABLE II
Simulate Optimal Parameters

Parameter	K_p	K_i	K_d
Main PID	650	0.6	0
Sub PID	0.3	0.000025	0

B. Simulation Results and Analysis

Taking the PH value of the control system slurry as the research and comparison object, qualitative analysis of the mechanism model with and without interference was conducted under the premise of the same PID controller parameters. The comparison of experimental results is shown in Fig. 10. At the same time, the effectiveness of the third step feed-forward prediction model proposed in this article is verified, and the positive effect of feed-forward prediction on the entire control model is analyzed. As shown in Fig. 11, a comparison chart of the PH trend of the slurry with and without the effect of a feed-forward prediction model is presented. The PH value setting value is selected as 5.5, and the actual thermal power unit data of the factory is transmitted to the established simulation model. The optimal tuning parameters in Table II are selected to set the main PID and sub PID. The simulation time for the three control

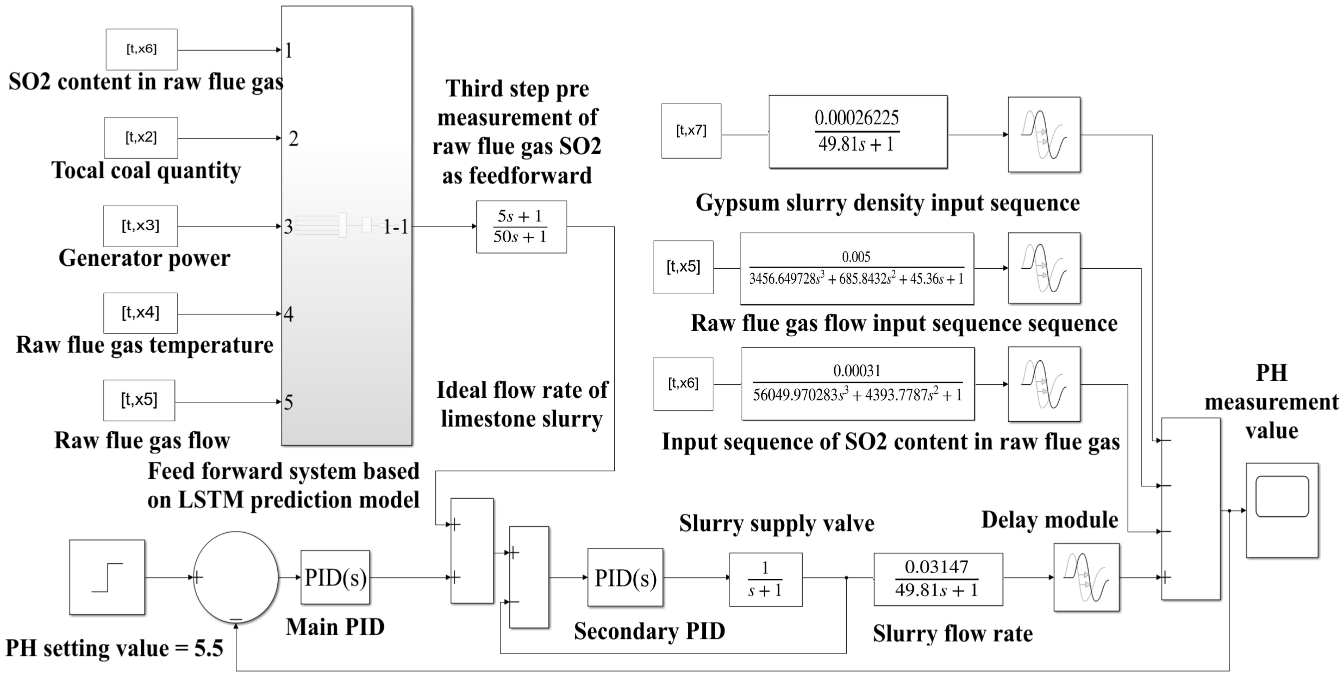


Fig. 9. Feed forward-cascade PID control simulation model diagram

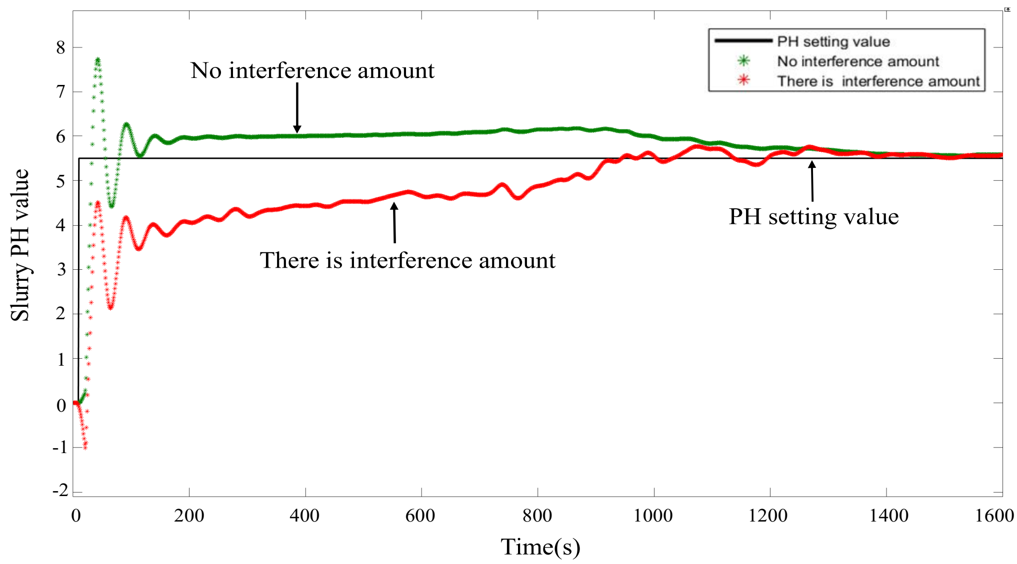


Fig. 10. Comparison chart of the PH value of the slurry with and without interference

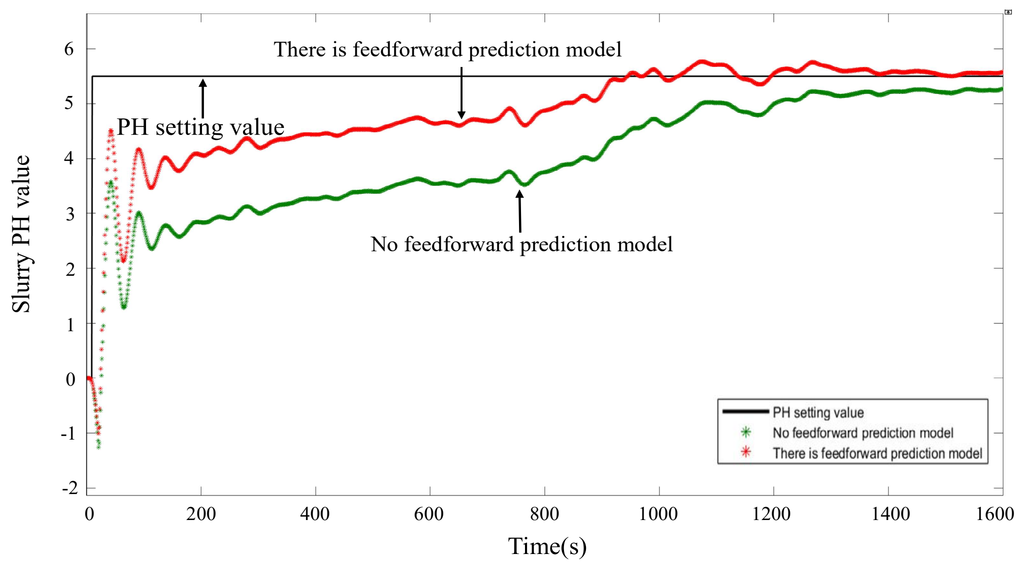


Fig. 11. Comparison chart of slurry PH value with and without feed-forward prediction model

TABLE III
COMPARISON OF EVALUATION INDICATORS FOR ABLATION EXPERIMENTS

Interference amount	Cascade PID	Step 3 feed-forward quantity	Response speed/s	Overshoot/%	Adjust time/s	Stable PH value
			23.4	1.547	2750.6	5.385(-0.115)
√			20.5	1.908	2747.7	5.390(-0.110)
√	√		17.4	5.425	2749.5	5.431(-0.069)
	√	√	16.7	2.251	2747.0	5.551(+0.051)
√		√	16.5	**1.232**	2746.5	5.548(+0.048)
√	√	√	**13.7**	1.244	**2746.2**	**5.544(0.044)**

strategies is set to 1600 seconds.

From Fig. 10, it can be seen that the slurry density, flue gas flow rate, and SO_2 content in the mechanism model have a positive effect on the tracking of the set PH value in the control model. Compared with without interference, when there is interference, on the one hand, it can effectively avoid overshoot phenomenon, and on the other hand, it can better track the set PH value and maintain stable transition. The reason for this phenomenon is that the desulfurization system of thermal power units has a large inertia, and the addition of interference can enhance the model's anti-interference ability to the outside world, better adapt to the inertia in the model, and avoid unstable output. As shown in Fig. 11. When integrating multi-step feed-forward prediction models, it has better response speed and faster arrival at a stable state. Due to the large lag characteristic of the desulfurization system, the model needs to predict the content value of future steps in advance. If the predictive multi-step values cannot be provided as feed-forward for the mischievous model, the response speed of the model will slow down, and the feedback link will also experience lag and delay, resulting in a longer time required to reach the set PH value. Therefore, the multi-step feed-forward prediction model proposed in this article is effective and feasible.

The comparison of indicators for different ablation experiments is shown in Table III. The advantages and disadvantages of the model were comprehensively compared from four evaluation indicators: response speed, overshoot rate, adjustment time, and PH stability value. From Table III, it can be seen that introducing interference in the control strategy can enhance the anti-interference performance of the model. Compared with no interference, it can have faster response speed and adjustment time, and the stable value of PH is also closer to the set value; When designing a single-stage PID control as a cascade PID, although there is some overshoot phenomenon in the middle period, it has better effects in response speed, adjustment time, and PH stability value. The introduction of the third step SO_2 feed-forward in response to the time delay of the model can provide the model with accurate values at this time in advance, accelerate the response time, prevent overshoot, and perform best in ablation experiments, demonstrating good superiority.

In order to further verify the superiority of the control strategy proposed in this article, it is compared with other advanced control methods in the desulfurization system of thermal power units. Figures 12, 13, and 14 show the comparison curves of slurry PH value, slurry flow rate, and desulfurization amount for different control methods, respectively. The comparison of evaluation indicators for different methods is shown in Table IV.

Fig. 12 shows that MPC, DMC, and IMC-PID perform poorly in control systems with high inertia and hysteresis. Unable to track the set value of slurry PH well, in addition, MPC and IMC-PID exhibit significant overshoot, and the DMC model has a slow response speed, which cannot meet the basic response requirements.

The slurry flow rate consumed by different control methods is shown in Fig. 13. Compared with other methods, traditional PID and MPC consume more slurry flow and perform poorly in desulfurization efficiency. The desulfurization amount is shown in Fig. 14, and the desulfurization efficiency of traditional PID and MPC shows a significant decrease trend. Compared with other control methods, feed-forward cascade PID achieves the best desulfurization effect by consuming less slurry flow and significantly higher desulfurization amount.

Table IV shows that MPC has the fastest response speed among different control methods, but this method exhibits serious overshoot, and the performance of adjustment time and PH stability value is also poor. Fuzzy PID control, control have significant advantages over traditional PID control, IMC-PID, MPC, and DMC, with faster response speed and the ability to reach set values more quickly;

TABLE IV
COMPARISON OF INDICATORS OF DIFFERENT CONTROL STRATEGIES

Index		Response speed/s	Overshoot/%	Adjust time/s	Stable PH value
Traditional PID		23.4	1.547	1216.6	5.385(-0.155)
Fuzzy PID		17.2	7.693	1208.2	5.422(-0.080)
Cascade PID		17.4	5.425	1192.5	5.431(-0.069)
IMC-PID		20.8	8.049	1255.0	6.481(+0.981)
MPC		**11.4**	9.872	1236.5	5.697(+0.197)
DMC		27.8	4.201	1233.9	5.702(+0.202)
Feed forward cascade PID	Step 1	14.3	1.539	1189.7	5.563(+0.063)
	Step 2	14.1	1.313	1185.1	5.557(+0.057)
	Step 3	13.7	**1.244**	**1178.2**	**5.544(+0.044)**

However, cascade PID control and fuzzy PID control still cannot avoid overshoot, and there are still their own limitations in the presence of disturbances, which cannot effectively overcome the impact of disturbances; Compared with other strategies, feed-forward cascade PID control has almost no overshoot phenomenon and quickly tends to a constant value within the control error range. The effect is close to the ideal simulation without interference. At the same time, compared with the first and second steps, the third step feed-forward control can more accurately correspond to the time delay problem of the model. During the control cycle, it outputs the current value to the model in advance, with a shorter adjustment time and a stable PH value of 5.544, there is a difference of 0.044 from the PH set value. This facilitates the control of the desulfurization tower as the reaction vessel of the desulfurization system, and the accurate control of flue gas SO_2 emissions and PH values will also be achieved.

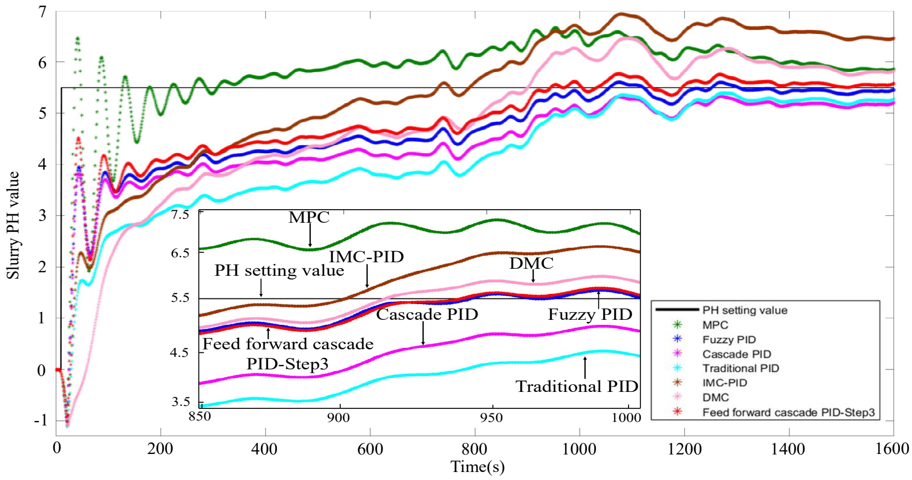


Fig. 12. Comparison chart of slurry PH values using different control methods

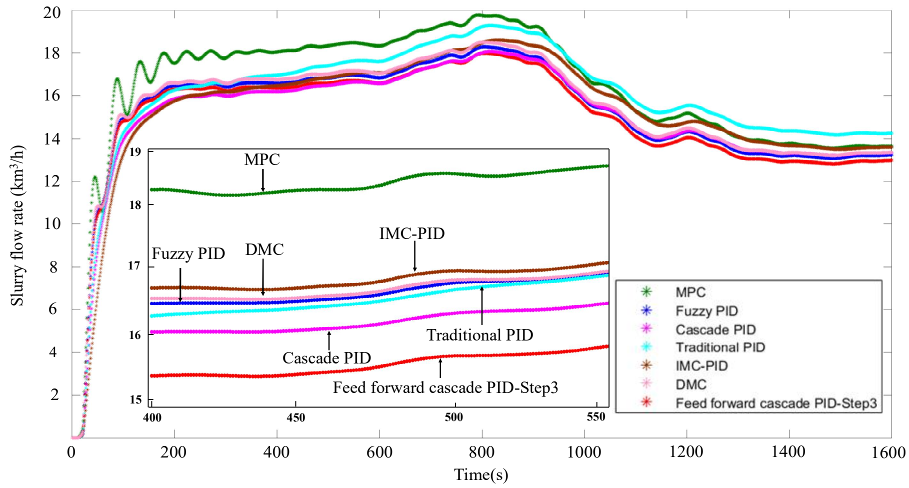


Fig. 13. Comparison chart of slurry flow rate using different control methods

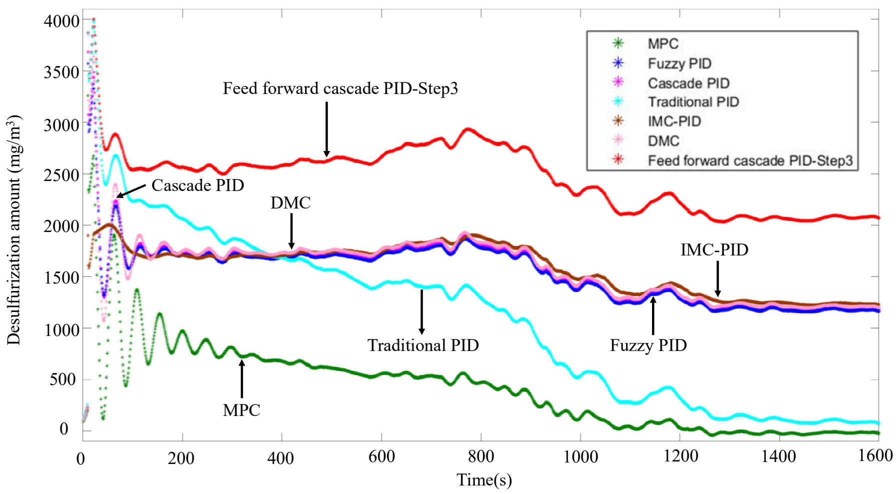


Fig. 14. Comparison chart of desulfurization amount using different control methods

VI. CONCLUSION

In response to the problems of large lag and large inertia in existing wet flue gas desulfurization control systems, this paper designs a feed forward-cascade dual closed-loop PID predictive control scheme with the PH value in the absorption tower as the control object. Firstly, analyze the influencing factors of PH value to obtain the transfer function and establish a mechanism model; Then, establish a control strategy based on feed forward prediction, using LSTM based three-step prediction values as feed forward variables; Finally, establish a simulation model and compare it with traditional PID and cascade PID control strategies to verify the effectiveness and superiority of the feed forward cascade PID predictive control method. This not only enables the PH value to track the set value well, but also better solves the overshoot phenomenon. This article only takes the PH value as the control object, and the control effect is limited. In the future, multiple aspects such as SO_2 concentration, liquid gas ratio, and desulfurization efficiency can be considered to achieve efficient desulfurization of thermal power units.

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