Modeling of SNCR denitration system based on adaptive weight particle swarm optimization

Jianyun Bai, Xiujun Lei\(^1\) and Qi Wang

Department of Automation, Shanxi University, Taiyuan 030013, China

\(^1\) Email: 18334793845@163.com

Abstract. In view of the improvement of NO\(_X\) emission control requirements for coal-fired units, traditional PID controllers have been unable to effectively control large delay, large inertia, nonlinear, time-varying SNCR denitration systems, and most advanced control algorithms are often object-based models. Therefore, a model of SNCR denitration system based on adaptive weight particle swarm optimization algorithm is established. A 2×200MW heating steam turbine generator set equipped with a 2×705t/h circulating fluidized bed boiler was used as the test unit, and the selective non-catalytic reduction technology denitration system was analysed. The particle swarm optimization algorithm with adaptive weights was used to model the relationship between the urea flow rate and the NOX concentration at the chimney outlet of the SNCR denitration system under working conditions of 140 MW, 170 MW and 200 MW, respectively, to provide a process for the automatic control of the SNCR denitration system model. Apply the actual data from the field to verify the model. The results show that the error between the output of the model and the actual operational data is within the allowable range, which verifies the validity of the model. This result opens up a new path for the particle swarm optimization algorithm to model the SNCR denitration process, and promotes the application of intelligent algorithms in other industrial processes.

1. Introduction

In recent years, as China's environmental requirements have become more stringent, there are more stringent requirements for SO\(_X\), NO\(_X\) and soot in thermal power plants. However, the circulated fluidized bed boiler (CFB) produces relatively less NO\(_X\) during combustion than other boilers, which is very advantageous for denitration work. CFB boilers generally use selective non-catalytic reduction (SNCR) flue gas denitration technology to make flue gas emissions meet national standards.

Other In the SNCR denitration process, selecting a relatively accurate model is beneficial to effectively control the outlet NO\(_X\) concentration while saving urea usage and reducing ammonia slip. Zhong Wei et al \([1]\) established a high-precision minimal control model by analyzing the dynamic characteristics of the SNCR denitration control system. Bai Jianyun et al \([2]\) used BP neural network to establish a NO\(_X\) production quality concentration prediction model, which realized the soft measurement of NO\(_X\) production quality concentration and applied to the actual power generation process system. Zhu Zhujun et al \([3]\) designed an automatic control strategy based on expert fuzzy SNCR denitration system, which solved the problem that SNCR denitration system could not achieve 100% automatic NO\(_X\) control for a long time. Qin Tianmu et al \([4]\) used a multi-scale kernel partial least squares (MKPLS) method to establish a selective catalytic reduction (SCR) system model. Fang Xian et al \([5]\) used the particle swarm optimization algorithm to optimize the nuclear parameters and penalty factors of TWSVM, and established the SCR denitration efficiency prediction PSO-TWSVM.
All of the above are predictions and soft measurements of generated NOx, or the simplest modeling of SCR denitration systems, but little research has been done on the modeling of SNCR denitration systems.

System modeling methods are two methods, namely mechanism modeling and experimental modeling. Among them: experimental modeling can establish the system model based on the input and output data of the system without knowing the internal structure of the system [6]. The circulating fluidized bed SNCR denitration system is a large inertia, large delay, non-linear object, and its internal structure is usually not available. Therefore, this paper uses particle swarm optimization to model the SNCR denitration system. The method can identify the delay of the SNCR denitration system at the same time. The model is verified by the actual operation data, and the results prove the validity of the model.

2. Model selection of SNCR denitration system

2.1. Introduction to SNCR denitration system

A power plant uses urea as a reducing agent, and uses a urea pump to transfer 40% of the urea solution in the storage tank to the system piping, and then controls the flow of urea injected into the flue before the cyclone through a flow regulating valve to control the concentration of NOx. A total of 21 spray guns were installed. The circulating fluidized bed SNCR denitration process is shown in Figure 1.

![Figure 1](image_url)

**Figure 1.** Process flowchart of SNCR denitration in circulating fluidized bed.

The reactor of the SNCR denitration system of the circulating fluidized bed boiler is a cyclone separator. The cyclone separator temperature is 800-1100 °C, which is just the optimum temperature at which a chemical reaction takes place, so no catalyst is required. The reducing agent passes through the spray gun and the pipeline and enters the front flue of the separator to react with NOx, and is pyrolyzed into NH3 in the reactor to react with NOx in the flue gas to form N2. A power plant uses urea solution as a reducing agent to reduce the reaction with NOx under acidic conditions. The final products are N2, CO2, and H20, which will not cause secondary pollution. The main chemical reactions for removing NOx with urea as a reducing agent are as follows:

\[
\begin{align*}
6NO_2 + ACC(NH_2)_2 & \rightarrow 7N_2 \uparrow +4CO_2 \uparrow +8H_2O \\
6NO + 2CO(NH_2)_2 & \rightarrow 5N_2 \uparrow +2CO_2 \uparrow +4H_2O \\
NO + N_2O_2 & \rightarrow N_2O_3 \\
N_2O_3 + H_2O & \rightarrow 2HNO_2 \\
2HNO_2 + CO(NH_2)_2 & \rightarrow 2N_2 \uparrow +CO_2 \uparrow +3H_2O
\end{align*}
\]  

(1)
2.2. Model selection
At present, in the circulating fluidized bed SNCR denitration control system, the amount of catalyst injected is controlled mainly by controlling the urea solution or the ammonia water flow valve, and then denitration is performed in the separator. This process can be divided into two types of models, the first is the model of urea flow valve opening to urea flow, and the second is the model of urea flow to NOx concentration at the chimney outlet. In this paper, a second-class model is established by using particle swarm modeling with adaptive weights [7].

The NOx emission concentration of the SNCR denitration system of the circulating fluidized bed unit is affected by a series of factors such as total coal volume, urea flow rate, and total air volume, temperature of the cyclone inlet, unit load, and dilution water flow. When the unit is in stable load operation, the total coal volume, total air volume and cyclone inlet temperature remain basically the same, and the urea solution concentration is kept at 40%. Therefore, the NOx concentration discharged from the chimney outlet is mainly determined by the urea solution flow rate. The sampling period is selected before data acquisition[8] [9]. The choice of sampling period depends on the highest frequency in the main frequency band of the identified object, but it is very difficult to estimate the highest frequency before identification. This time, using the experience of the predecessors, the sampling period is 12s. By collecting data from the on-site DCS system every 12s, the data collected in the field inevitably carries errors for various reasons, so it is necessary to eliminate the outliers and perform effective filtering to select representative data [10] [11] [12]. The expression of the transfer function model is a function expression between the increment of the output and the increment of the input when any system is at a certain equilibrium point, that is, when the system is in equilibrium, the input and output of the system and their derivatives are also zero. Therefore, zero initial value processing is required for the original open loop data. The input and output of the original data are \( u(k) \) and \( y(k) \), respectively. The data after the zero initial value is:

\[
\begin{cases}
    u^*(k) = u(k) - \frac{1}{N} \sum_{i=1}^{N} u(i) \\
    y^*(k) = y(k) - \frac{1}{N} \sum_{i=1}^{N} y(i)
\end{cases}
\]

(2)

Where: \( N \) is the number of initial point data.

After the data was collected and the data was pretreated, a model with a flow rate of 40% urea solution as input was generated to generate a NOx concentration as an output. Taking the test unit as an example, three typical working conditions of 140MW, 170MW and 200MW were selected to carry out model identification between urea solution flow rate and NOx emission concentration.

In the actual application process, the characteristics of the controlled process can be described by a first-order inertia time-delay system or a second-order inertia time-delay system. However, after analyzing the process flow of the SNCR denitration system of the circulating fluidized bed, and referring to the model established by Zhang Zhichao et al. on the SCR denitration system, it is concluded that the SNCR denitration system of the circulating fluidized bed has large delay, large inertia and strong nonlinearity [6]. The model of the urea solution flow rate to the NOx concentration generation adopts the fourth-order inertia link with pure delay as the transfer function of the system to be determined model. The specific form is:

\[ G(s) = \frac{K}{(Ts + 1)^p} e^{-\tau s} \]

(3)

Where: \( K \) is the system open-loop gain; \( T \) is the inertia time; \( \tau \) is the pure delay time; \( p \) is the system order

In this paper, the adaptive weight particle swarm optimization algorithm is used to identify the four parameters of the transfer function, and the SNCR denitration system model is obtained.
3. Model identification based on adaptive weight PSO algorithm

The Particle Swarm Optimization (PSO) algorithm is a bionic optimization algorithm that simulates birds to optimize foraging through information sharing during the foraging process [8].

The mathematical process of particle swarm optimization is described as follows. Assume that there is a D-dimensional query space, the population corresponding to n particles is \( X = (X_1, X_2, \cdots, X_n) \), and the position of the \( i \) particle is \( X_i = (x_{i1}, x_{i2}, \cdots, x_{id})^T \), which is the implicit solution to be solved by the problem, and it is substituted into the target function, you can get the fitness value of each particle at this position, set the individual extremum to \( P_i = (P_{i1}, P_{i2}, \cdots, P_{id})^T \), the population extremum is \( P_g = (P_{g1}, P_{g2}, \cdots, P_{gd})^T \), the \( i \) particle movement speed is \( V_i = (V_{i1}, V_{i2}, \cdots, V_{id})^T \), and finally, in the process of the \( k \) cycle calculation, use the current group The extremum and individual extremum determine the next updated particle velocity and position. The corresponding formula for the update is:

\[
X_{id}^{k+1} = X_{id}^k + V_{id}^{k+1} \\
V_{id}^{k+1} = \omega V_{id}^k + c_1 r_1 (P_{id}^k - X_{id}^k) + c_2 r_2 (P_{gd}^k - X_{id}^k) \tag{4}
\]

Where: \( \omega \) is the inertia weight; \( c_1, c_2 \) is the acceleration factor; \( r_1, r_2 \) is the random number distributed in \([0,1]\), which prevents the blind search by limiting the velocity and position of the particle [9].

The above algorithm is based on ordinary particle swarm calculation. Since the ordinary particle swarm algorithm is relatively weak in the global search ability, only the local optimal solution can be found, which is far from enough for the actual demand. Therefore, the inertia weight needs to be updated, and the inertia weight is updated according to the current particle fitness value and the average fitness value [10]. The inertia weight update formula is as follows.

\[
\omega = \begin{cases} 
\omega_{\min} - (\omega_{\max} - \omega_{\min})(f - f_{\min})/(f_{\max} - f_{\min}) & (f \leq f_{\max}) \\
\omega_{\max} & (f > f_{\max})
\end{cases} \tag{6}
\]

Where: \( \omega_{\min} \) and \( \omega_{\max} \) are the maximum and minimum values of inertia weight \( \omega \) respectively; \( f \) is the fitness function value of the particle at this time; \( f_{\max} \) and \( f_{\min} \) are the average fitness function value and the minimum fitness function value of all current particles, respectively.

The steps of the parameter identification method with the adaptive weight particle swarm algorithm are as follows. ①Initial parameter setting. Including the number of variables, population size, range of parameters to be identified, range of inertia factor, range of particle velocity, number of iterations, acceleration factor, etc.;②Population initialization. The performance index value of each moment is calculated by the randomly generated population, and then the individual optimal value and the global optimal value are obtained. ③Population updates. According to the parameter setting and weight update formula, the inertia factor value and the individual movement speed of the population are calculated, the population is updated, and the calculated performance index is compared with the historical optimal value of the individual and the population, and the history of the two is optimally updated. ④If the termination condition is met, stop searching; otherwise, return to step ② to continue searching. ⑤If the number of cycles is reached, stop searching; otherwise, return to step ① to search again. Achieve multiple iterations to obtain the global optimal value. The parameter identification flow chart is shown in Figure 2.
4. Modeling and verification of SNCR denitration system

Using Matlab to write the particle swarm optimization algorithm to identify the main program and the calculation and identification optimization function subroutine, taking 200MW load case as an example, select 150 sets of open loop test data. Identify the mathematical model parameters of the object. First, the zero-initial value processing is performed on the historical open-loop data under the condition of 200 MW, and the result of zero initial value of the urea solution flow data and the outlet NOX concentration data is obtained as shown in Figure 3-4.

Figure 3. Process flow chart of SNCR denitration in circulating fluidized bed.

Figure 4. Comparison chart of NOx concentration data before and after processing.
It is seen from Figure 4 that the NOx concentration data after the initial value processing becomes a negative number, but this does not affect the establishment of the model. The model is identified by the particle swarm optimization algorithm with adaptive weights. The simulation parameters are set as follows.

Parameter optimization interval: $K \in [-10, 10]$, $T \in [20, 400]$, $N \in [2, 5]$, $r \in [20, 200]$.

Number of particles: 200, Evolutionary algebra: 80, Inertia weight: $\omega_{\text{min}} = 0.4$, $\omega_{\text{max}} = 0.9$, Learning factor: [0.6 0.8], Acceleration factor: $c_1 = 2$, $c_2 = 2$, Speed range interval: $V \in \{-1, 1\}$, $[-1, 1]$, $[-1, 1]$, $[-1, 1]$. The corresponding parameter values of the simulation results are: $K = -1.46$, $T = 400$, $N = 4$, $r = -165$.

Similarly, the open-loop model of the SNCR denitration system from 40% urea solution to NOx concentration can be obtained when the load is 140MW and 170M. The transfer function model for the identification of three different working condition models and the corresponding parameters are shown in Table 1.

| Typical working condition | Identification result | Model transfer function |
|---------------------------|----------------------|------------------------|
| 140MW                     | $K = -1.14$, $T = 350$ | $G(s) = -\frac{1.14}{(350s + 1)^r}$ |
|                           | $n = 4$, $r = -196$   |                        |
| 170MW                     | $K = -1.23$, $T = 390$ | $G(s) = -\frac{1.23}{(390s + 1)^r}$ |
|                           | $n = 4$, $r = -185$   |                        |
| 200MW                     | $K = -1.46$, $T = 400$ | $G(s) = -\frac{1.46}{(400s + 1)^r}$ |
|                           | $n = 4$, $r = -165$   |                        |

In this paper, the model identified under the load condition of 200MW is taken as an example to verify. The step disturbance of the urea solution flow rate from 310kg/h to 330kg/h was selected. In order to verify the stability of the established model, the step disturbance was added to the identification model and the actual measured data respectively. Output curves. Figure 5 shows the curve of the 200MW model verification.

It can be seen from Figure 5 to Figure 8 that the output curve of the model identified by the group algorithm with adaptive weight particles under the step disturbance is basically consistent with the output curve of the data collected by the field under the step disturbance. The relative error between the model output and the actual data is around ±0.5. The identified open-loop model from 40% urea solution to NOx concentration can be used for the control of the SNCR denitration system.

![Figure 5](image_url)  
**Figure 5.** Comparison of the recognition results of 200MW model and measured data.

![Figure 6](image_url)  
**Figure 6.** Comparison of the recognition results of 200MW model and measured data.
In the same way, the model under the other two conditions can be verified, the output curve results are roughly the same, and the error is within the acceptable range. The model identified by the above three conditions is basically consistent with the measured data. Through the identified model parameters, the transfer function under three operating conditions is obtained, and a reliable model is established for the SNCR denitration control of the circulating fluidized bed from urea flow to NOx concentration. The model is built to facilitate effective control of the generated NOx concentration and to reduce ammonia slip.

5. Conclusions
In this paper, the historical open-loop data of the SNCR denitrification system of a 200MW circulating fluidized bed unit in a power plant is collected, and the data is removed from the outlier and zero initial value. According to the expert experience and thermal process, the model from the urea solution flow to the outlet NOx concentration in the SNCR denitrification system is determined. The PSO optimization algorithm based on adaptive weight is used to identify the model parameters under three different working conditions. Later, the model was validated under different working conditions. The simulation results show that the adaptive weight based PSO optimization algorithm has a good effect on the model parameter identification in the SNCR denitrification system. The identified model provides an advanced intelligent control algorithm for the application of the SNCR denitrification system in thermal power plants, providing a model basis, which can better control NOx emissions and reduce ammonia slip, and ultimately reduce the use of reducing agents to improve economic efficiency. Promote the application of intelligent algorithms in other industrial processes.

References
[1] W Zhong, Y YSun, Y Li, et al. 2017 [J]Industrial control computer30(06)10-12+14
[2] Bai J Y,Zhu Z J,Zhang P H2016[J]Thermal Power Generation45(12)78-83
[3] Zhu Z J, Bai J Y, et al. 2018 .[J]Automation Instrumentation39(07)34-38
[4] Qin T M,Liu J Z, et al.2016[J]Proceedings of the CSEE36(10)2699-2703
[5] Fang X,Tie Z X,Cui S W,et al. 2018 [J]Thermal Power Generation47(01)53-58
[6] Zhang Y W, Cao S S, et al.2018[J]Automated instrument39(12)13-17
[7] Han P. Modern Engineering Cybernetics2017[M]. Beijing: China Electric Power Press
[8] Huang T A, Sheng J G, et al.2013[J]Computer Simulation30(02)327-330+335
[9] ZHUC X ,YingjiuZheng,Zhou Hao2016[J]Electric Power49(2)164-169
[10] Xie F L2015 [D]South China University of Technology
[11] Olawoyin R2016[J]Chemosphere[0045-6535]161145-150
[12] LiM L,Zhang H L,et al.2018 [J]Clean Coal Technology24(03)96-102