IOP Conference Series: Earth and Environmental Science

Model identification of combined desulfurization system based on improved PSO algorithm

Model identification of combined desulfurization system based on improved PSO algorithm

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Abstract. With the comprehensive promotion of the ultra-low emission and energy-saving renovation plans for coal-fired power plants, for the complexity of the combined SO_2 removal system inside and outside the furnace of CFB units, the traditional identification method has the problems of slow convergence and low identification accuracy. Taking the combined desulfurization system inside and outside the furnace of a 300MW CFB unit of a meteorite power plant as the research object, using the actual operating data of the production system, the particle swarm optimization(PSO) algorithm based on adaptive weight is designed to establish the mathematical model of the desulfurization system inside and outside the furnace, which has reference value for energy saving and optimization of automatic control strategy in the combined desulfurization system

1. Introduction

In recent years, the problem of environmental pollution has become more and more serious. Coal as an important industrial raw material for China's main energy and power generation industry. SO_2 produced by coal combustion is one of the main sources of atmospheric pollutants. The total emissions account for about 55% of total industrial emissions. Although the CFB boiler has high desulfurization efficiency, the single desulfurization in the furnace can not meet the current ultra-low emission requirements[1-3]. Therefore, it is necessary to install a secondary desulfurization device outside the furnace to achieve the ultra-low emission of SO_2, and the subsequent increase in operating costs of the combined desulfurization system and the complexity of the control system have become an urgent engineering problem to be solved. During the “Thirteenth Five-Year Plan” period, the state will continue to increase the implementation of ultra-low emission policies, and on the other hand, it will encourage technical research on reducing pollution control costs and energy consumption[4-6].

So far, many experts and scholars at home and abroad have conducted extensive research on the removal of SO_2: Qiao Z L has established a two-stage ultra-high temperature gas desulfurization purification process. The sulfur content was rapidly reduced after the catalyst was added to the fuel gas of the first stage of the fluidized bed reactor. The second stage removed the remaining hydrogen sulfide from the fuel in a fixed-bed reactor[7]; Zhu J, et al., taking a coal gangue power plant in the northeast as an example, by analyzing the two-stage desulfurization mode of the plant, demonstrated that the CFB boiler adopted the combination of desulfurization in furnace and flue gas desulfurization to realize the rationality and feasibility of ultra-low emission of SO_2[8]; Tan Q Y et al., by analyzing the factors affecting the desulfurization efficiency, the best matching relationship between desulfurization in CFB furnace and outside the furnace was obtained[9]. However, the emission control of SO_2 at home and abroad is mainly concentrated on the removal mechanism and process experiment, less research on the modeling of CFB unit combined desulfurization system.

In this paper, a 300MW CFB unit in Shanxi is used in the dry sulfur-fixing and extra-furnace limestone-gypsum wet desulfurization system as the research object. The typical operating conditions are selected to conduct the disturbance test on the test unit, and the data is collected from the engineering station, and mathematical model of desulfurization system inside and outside the furnace using particle swarm optimization algorithm with adaptive weight are established. It has certain reference value for the identification of the object model of the combined desulfurization system and the optimization of the automatic control strategy.

2. Model identification of particle swarm optimization algorithm based on adaptive weights

2.1. Principle of particle swarm optimization based on adaptive weight

The particle swarm optimization algorithm was first proposed by Kennedy and Eberhart in 1995. The idea stems from the study of predation behavior of birds. It is an optimization method based on Swarm Intelligence[10,11]. The optimal solution for the PSO algorithm is described as follows:

There are N particles in the D-dimensional space, the position of the particle i: xi=(xi1, xi2, ..., xiD), and xi is substituted into the adaptive function f(xi) to obtain the fitness value; the particle i speed: vi=(vi1, vi2, ..., viD); the best position that the particle i has experienced: pbesti = (pi1, pi2, ..., piD); the best position the population has experienced: gbest = (g1, g2, ..., gD). Usually the range of position change in d(1≤d≤D) dimension is limited to [Xmin,d Xmax,d], and the range of speed variation is limited to [-Vmin,d Vmax,d], that is, if the xid or vid exceeds the boundary value during the iteration, the position or speed of the dimension is limited to the dimension boundary position or the maximum speed. The update formulae for the d-dimensional velocity and position of particle i are as follows:

$$v_{id}^{k} = \mathrm{w} v_{id}^{k-1} + c_1 r_1 (pbest_{id} - x_{id}^{k-1}) + c_2 r_2 (gbest_d - x_{id}^{k-1}) \tag{1}$$

$$x_{id}^{k} = x_{id}^{k-1} + v_{id}^{k-1} \tag{2}$$

We call v_{id}^{k} is the d-dimensional component of the particle velocity vector of the k-th iteration; x_{id}^{k} is the d-dimensional component of the particle i position vector of the kth iteration; c_1 and c_2 are acceleration constants; r_1 and r_2 are two random constants, and the range of values are [0, 1] ,to increase the random search property; ω is the inertia weight, and adjust the search scope of the solution space.

The inertia weight ω is introduced to balance the local search and the global search. For the value of ω, the inertia weight decrement strategy is generally adopted, that is, a large inertia weight value is taken in the initial stage of the particle search in order to achieve an effective search for the entire space. In the later stage, taking a smaller inertia weight value is beneficial to the convergence of the algorithm[12,13]. The decreasing formula of inertia weight can be expressed as:

$$\mathrm{w} = \mathrm{w}_{\max} - \frac{\mathrm{w}_{\max} - \mathrm{w}_{\min}}{\mathrm{T}_{\max}} \times t \tag{3}$$

Where: ω_{max} and ω_{min} are the maximum and minimum values of ω, ω is usually in the range of [0.8 1.2]; T_{max} and t are the maximum number of iterations and current iterations.

The inertia weight ω in the PSO algorithm determines the influence of the velocity on the last moment on the velocity of the current moment. The commonly used linearly decreasing inertia weight method has certain defects. It needs to continuously test to determine the minimum and maximum of inertia weight, and the number of iterations, and it is difficult to find the best value that can be applied to the general problem, the linear decrement of the inertia weight has better optimization effect for some problems.

In order to balance the global and local search effects of the particle swarm optimization algorithm, the inertia weight ω calculation method is improved. By changing the linearly decreasing inertia weight value to the adaptively varying inertia weight value, it makes the inertia weight value change with the change of the particle fitness value, that is, the adaptive weight[14]. When the fitness value of the particles tends to be consistent or locally optimal, the inertia weight is increased to increase the global search ability; when the particle fitness value is dispersed, the inertia weight is reduced to increase the local search ability; When the current fitness value is better than the average fitness value, the corresponding inertia weight is important to take a smaller value to protect the particle. For a particle whose fitness value is worse than the average fitness value, the corresponding inertia weight is important to take a larger value to move closer to the better search area[15-16].

The improved inertia weight value calculation expression is as follows:

$$w = \begin{cases} w_{min} - \dfrac{(w_{max} - w_{min}) \times (f - f_{min})}{f_{avg} - f_{min}}, & (f \le f_{avg}) \\ w_{min}, & (f > f_{avg}) \end{cases} \tag{4}$$

Where: f represents the current fitness value of the particle; f_{min} and f_{avg} respectively represent the minimum fitness value and the average fitness value of all particles.

2.2. Parameter identification process of object model using adaptive weight particle swarm optimization algorithm

Using the adaptive weight PSO algorithm to solve the control system model identification problem, the steps can be summarized as follows, Table 1 shows the identification parameter settings.

Step1:Initialize the particle swarm;

Step2:Assign particles sequentially to the model parameters that need to be identified(K, T_1, T_2, τ);

Step3: Step-disturbing the object model after the assignment of the current parameter to obtain a step response curve;

Step4: Convert the step response curve to a discrete point consistent with the field test data sampling period;

Step5: Calculate the deviation e between the value after the step response curve is converted into a discrete point and the field test data, and calculate the value of the ITAE performance index function of the deviation..

Step6: Determine whether the termination condition is satisfied. If the exit iteration loop is satisfied, the optimal particle value is output; if not, update the particle swarm and the corresponding inertia weight, and return to Step 2 to continue to optimize until the termination condition is met or the maximum number of iterations is reached.

Table 1. Identification parameter settings.

PSO algorithm parameter setting	
Particle swarm size	S=200
Number of iterations	MaxGen=30
Population dimension	D=4
Inertia weight	$\omega_{max} = 0.9$ $\omega_{min} = 0.1$
Acceleration weight	c1=2.2 c2=2
Upper and lower particle velocity	Vmax=[10, 20, 15, 5] Vmin=[-10, -20, -15, -5]
Parameter optimization interval	K ∈[-60, -100] $T_1 \in [100, 200]$ $T_2 \in [200,300]$ $\tau \in [80, 150]$
ITEA performance function	$J_{min} = \sum_{n=1}^{N} \lvert e(nT) \rvert \times T$

2.3. Parameter identification and result of object model under typical working conditions of test unit

Combined with the determined object model structure of the desulfurization system inside and outside the furnace, the parameter optimization algorithm of particle swarm model based on adaptive weight was programmed by MATLAB software to identify the model parameters under typical working conditions of the test unit:

2.3.1. Initial parameter setting in the furnace

2.3.2. Identification result. Figure 1 shows the model parameter identification curve of the desulfurization system in the furnace under the 260MW load condition. Results in Table 2 imply that the identification results.

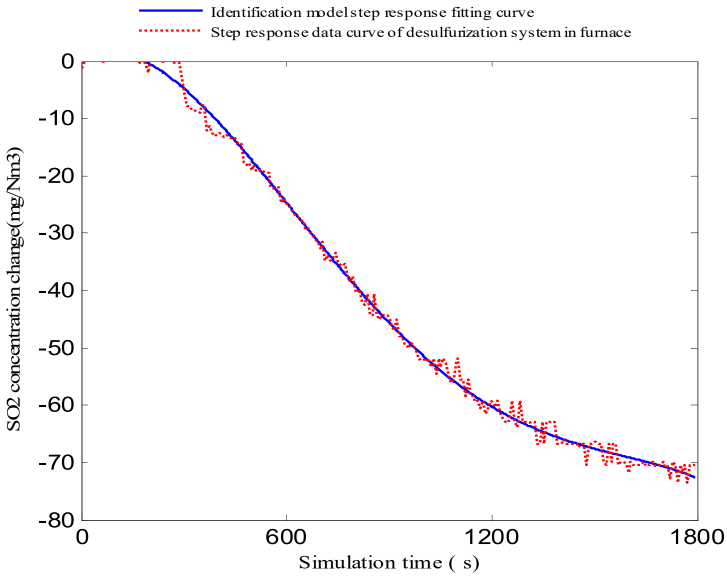

Figure 1. Step response curve of furnace desulfurization system identification model.

Table 2. Model identification results of desulfurization system in furnace under 260MW condition.

Typical working condition	Identification result	System model
260MW	Jmin=3.749×103 K=-66.8, T_1=103.2, T_2=226.7, τ =89.5	$G(s)=\dfrac{-66.8}{(103.2s+1)(226.7s+1)}e^{-89.5s}$

2.3.3. Initial parameter setting outside the furnace

2.3.4. Identification result. Figure 2 shows the model parameter identification curve of the desulfurization system of the limestone slurry replenishment flow step disturbance of the wet desulfurization system under the 260MW load condition.Results in Table 2 imply that the identification results.

It can be seen from the figure that the step response fitting curve of the model to be identified has a good coincidence with the step response data curve of the wet desulfurization system outside the furnace, and the fitting curve is substantially evenly distributed on or coincides with the actual data curve. Therefore, the first-order inertia time-delay model of wet desulfurization system based on adaptive particle swarm optimization algorithm has high accuracy and high reliability, which can be used in control system design and simulation research.

Table 3. Identification parameter settings.

PSO algorithm parameter setting	
Particle swarm size	S=400
Number of iterations	MaxGen=30
Population dimension	D=3
Inertia weight	$\omega_{max} = 0.9 \quad \omega_{min} = 0.5$
Acceleration weight	c1=2 c2=2
Upper and lower particle velocity	Vmax=[1, 1, 1] Vmin=[-1, -1, -1]
Parameter optimization interval	K ∈[-26, 0] T ∈ [0, 200] τ ∈ [10, 60]
ITEA performance function	$J_{min} = \sum_{n=1}^{N} \lvert e(nT) \rvert \times T$

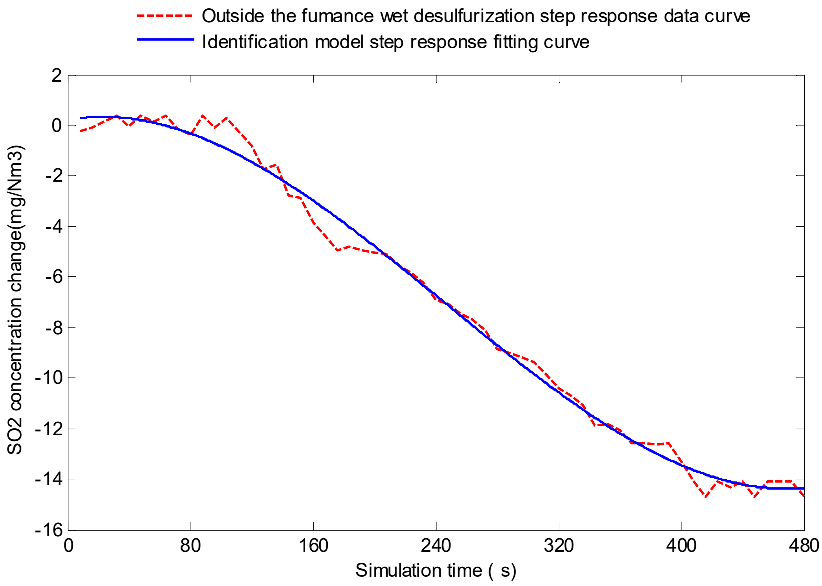

Figure 2. Step response curve of identification model for the wetdesulfurization system outside the furnace.

Table 4. Model identification results of the wet desulfurization system outside the furnace under 260MW condition.

Typical working condition	Identification result	System model
260MW	Jmin=16.2930 K=-18.87, T=107.98, τ =39.19	$G(s) = \frac{-18.87}{107.98s+1} e^{-39.19s}$

3. Conclusions

According to the object characteristics of the combined desulfurization system inside and outside the circulating fluidized bed boiler, using the production site operation data, the particle swarm optimization algorithm based on adaptive weight is used to establish the mathematical model of the combined desulfurization system object inside and outside the furnace. The results show that the improved PSO algorithm can achieve good identification results in system model parameter identification, and provides method guidance for the establishment of complex control object model in thermal process, which has certain reference significance.

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