Hindawi
Mathematical Problems in Engineering
Volume 2019, Article ID 6812754, 10 pages
https://doi.org/10.1155/2019/6812754

Research Article

Model Predictive Control of Duplex Inlet and Outlet Ball Mill System Based on Parameter Adaptive Particle Swarm Optimization

Leihua Feng,[1,2] **Feng Yang**,[3] **Wei Zhang**,[1] **and Hong Tian**[1]

[1] *School of Energy and Power Engineering, Changsha University of Science & Technology, Changsha 410114, China*
[2] *Key Laboratory of Renewable Energy Electric-Technology of Hunan Province (Changsha University of Science & Technology), Changsha 410114, China*
[3] *JME (HuNan) Automation Engineering Co., Ltd., Changsha 410013, China*

Correspondence should be addressed to Leihua Feng; fengleihua80@126.com

Received 26 October 2018; Revised 8 December 2018; Accepted 22 January 2019; Published 7 March 2019

Academic Editor: Francesco Conte

The direct-fired system with duplex inlet and outlet ball mill has strong hysteresis and nonlinearity. The original control system is difficult to meet the requirements. Model predictive control (MPC) method is designed for delay problems, but, as the most commonly used rolling optimization method, particle swarm optimization (PSO) has the defects of easy to fall into local minimum and non-adjustable parameters. Firstly, a LS-SVM model of mill output is established and is verified by simulation in this paper. Then, a particle similarity function is proposed, and based on this function a parameter adaptive particle swarm optimization algorithm (HPAPSO) is proposed. In this new method, the weights and acceleration coefficients of PSO are dynamically adjusted. It is verified by two common test functions through Matlab software that its convergence speed is faster and convergence accuracy is higher than standard PSO. Finally, this new optimization algorithm is combined with MPC for solving control problem of mill system. The MPC based on HPAPSO (HPAPSO-MPC) algorithms is compared with MPC based on PAPSO (PAPSO-MPC) and PID control method through simulation experiments. The results show that HPAPSO-MPC method is more accurate and can achieve better regulation performance than PAPSO-MPC and PID method.

1. Introduction

Direct-fired system with duplex inlet and outlet ball mills is widely used in large thermal power plants because of its strong adaptability of coal and wide range of load regulation. But, due to its complex operation mechanism, a mechanism model is difficult to be established, and, because of its strong hysteresis and nonlinear, the control effect is difficult to meet production needs.

Many scholars have done a lot of researches on the control of ball mills. Aiming at the multivariable system of ball mill, Chen et al. [1] developed a control scheme of disturbance observer based on multivariable to solve the interference problem of ball mill. Luo et al. [2] adopted a grid search method based on steady-state gain model to realize direct control and optimization of hierarchical structure. Chai et al. [3] proposed an intelligent decoupling control method for the strong coupling, nonlinear, and time-varying characteristics of ball mills. Liu [4] proposed a multilayer structure direct control and optimization scheme for coal mill in thermal power plant, which can be used to identify the relation between input and output variables and identify the disturbances. Zeng et al. [5] established the mathematical model of duplex inlet and outlet ball mill system by taking the humidity of coal as an important parameter and adopted the extended state space predictive controller to control the multivariable system. However, these control problems have not been able to solve the control problems better of direct-fired system.

Model predictive control (MPC) is designed for the delay system. It does not need the accurate mathematical model of controlled device [6] and is suitable for multivariable control

operation. Since the advent of MPC, its application has been expanding. It covers not only the petrochemicals fields, but also automotive, aerospace, metallurgy, and defense industries [7, 8]. Authors in [9] solved the dynamic ED problem using MPC in both regulated and deregulated systems. Authors in [10] used MPC to solve the optimal operation of power system. Obregón, Quiñones, and Velázquez [11] used MPC approach to control particle moisture content on a lab-scale FBD. Chen et al. [12] applied model predictive control to solve the control problem of the three input and three output strong coupling coal mill system. But the control effect is limited because of adopting the mechanism model and the basic optimization algorithm.

Although MPC has been used in industry for a long time, its optimization algorithm limits its application and has become the subject of many scholars. Genetic algorithm (GA), simulated annealing (SA), and particle swarm optimization (PSO) have been used as optimization algorithms in many applications of MPC [13], and PSO has become one of the most popular methods because of its versatility and simplicity [14]. But the basic PSO algorithm also has some defects, such as easy to fall into the local minimum, the parameters ware not adjustable, etc. Scholars have proposed some improved PSO algorithms.

A variant of PSO algorithm named Comprehensive Learning PSO (CLPSO) was introduced in [15]. The algorithm updated the particle velocity with the best particle experience to avoid premature convergence. Wang et al. [16] proposed a parameter adaptive particle swarm optimization (PAPSO) which automatically adjusted its parameters to achieve better control results. Yi Ye et al. [17] proposed an improved PSO algorithm which was a hybrid based on the standard PSO algorithm and with the addition of selection and crossover operators from genetic algorithm in order to enhance the searching efficiency. Fu et al. [18] proposed a dynamic adaptive particle swarm optimization and was applied for the modified thermal system parameters optimization. W. Dong and M. C. Zhou [19] presented an adaptive particle swarm optimization with supervised learning and control (APSO-SLC) to adaptively choose parameters of PSO while improving its exploration competence. In order to solve the problems of disordered charging about plug-in hybrid electric vehicles, Kang et al. [20] proposed a WA-MOPSO method by incorporating weight aggregation (WA) into multi-objective particle swarm optimization (MOPSO).

In this paper, the LS-SVM model of duplex inlet and outlet ball mill system is established and verified by experiments. Then, a parametric adaptive particle swarm optimization algorithm based on particle similarity function is proposed and is named HPAPSO. In this method, a particle similarity function is put forward firstly, and based on this function the dynamic adjustment algorithm of weights and acceleration coefficients of particle swarm optimization is presented. This version of PSO has the advantages of more effective exploration of the search space, easier to lead to the global optimum, and more effective in avoiding premature convergence. At last, the HPAPSO method is combined with MPC, named HPAPSO-MPC, and is applied to solve the control problem of duplex inlet and outlet ball mill system.

2. Process Description

2.1. Duplex Inlet and Outlet Ball Mill System. The system structure of duplex inlet and outlet ball mill system is shown in Figure 1. The system flow is as follows: the raw coal is dropped into the mixing box from the coal bunker through the coal feeder, is mixed with the high temperature bypass wind in the mixing box, and is pre-dried in the falling coal pipe, then enters the coal mill cylinder body through a hollow shaft, and is grinded. The primary air is divided into two parts through a fan and one part of them is sent directly to the coal mill as cold air. Another part is sent into the air preheater to be heated into hot air. Mixed cold and hot air enters into the cylinder through center pipes in the hollow shaft of mill both ends. The incoming air stream on both sides scours in the middle of the barrel, then returns to return, and carries out coal from the annular channel inside the hollow shaft of the coal mill barrel. The gas powder mixture is mixed with the bypass wind at the outlet of the coal-outlet-pipe to enter the coarse powder separator, and the separated coarse powder is mixed into the raw coal by the return pipe and then is returned to the mill to be grinded again. A guide vane is arranged on the upper part of the coarse powder separator, and the fineness of pulverized coal can be adjusted by changing the inclination angle of the vane. Air powder mixture from the separator, which contains pulverized coal, is blown into the furnace for combustion. The working principle of the duplex inlet and outlet ball mill system shows that the system has many control variables and its operation is very complicated [21].

2.2. Process Model

2.2.1. Model Establishment. It is difficult to establish an accurate mechanism model for duplex inlet and outlet ball mill system because of its characteristics of large lag and strong nonlinearity. Least squares support vector machines (LS-SVM), as an efficient machine learning algorithm, have been used more and more widely in many fields. Its advantages of small sample learning make up for the inferior of unreliable sample information about duplex inlet and outlet ball mill system. Therefore, the LS-SVM model of mill output is adopted as the control model in this paper.

From the front analysis, there are many factors influencing the mill output, mainly as follows: ventilation quantity, hot air door opening, speed of coal feeder, mill current, mill outlet temperature, fineness of pulverized coal, ball load, diameter and proportion of steel ball, coal properties, length of mill, diameter of the cylinder, speed of mill, and so forth. If all the above factors are used as input variables of the model, the learning speed will be seriously affected. Therefore, through the grey relational analysis of the factors, five of them are chosen as input parameters, and they are as follows: hot air door opening, mill current, mill outlet temperature, fineness of pulverized coal, and mill speed [22].

The radial basis kernel function (RBF) with better generalization ability is selected as follows:

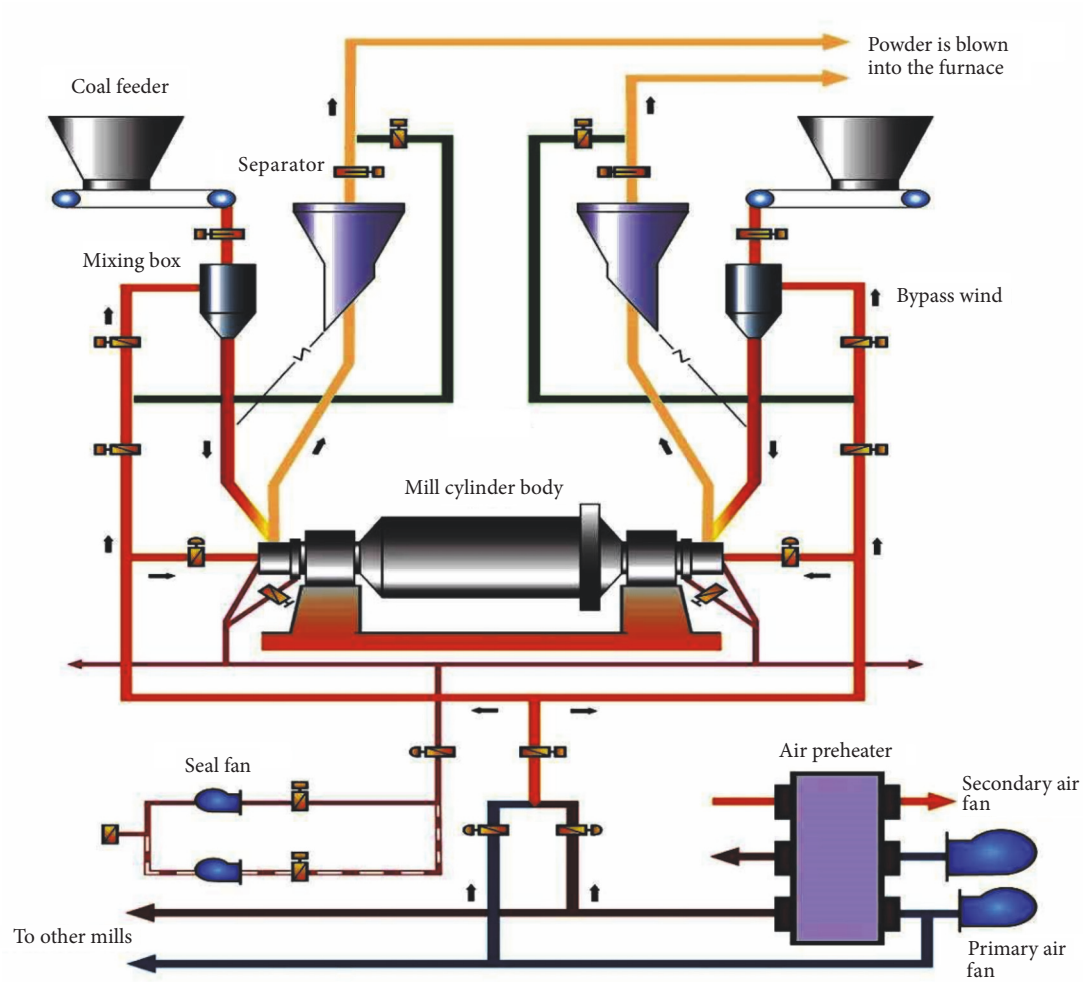

Figure 1: Structure of duplex inlet and outlet ball mill system.

$$K(x_i, x) = \exp\left[-\frac{|x - x_i|}{2\sigma^2}\right] \quad (1)$$

where σ is kernel width.

It is very important to select two parameters in the modeling of LS-SVM for pulverizing system; they are regularization parameter C and kernel width σ. In general, the values of parameters C and σ are related to learning samples and practical problems. Parameter C is a tradeoff between structural risk and sample error. Larger C allows smaller error and smaller C allows larger error. The kernel width σ is related to the range or width of the sample input space. If the value of σ is large, the range of sample input space is also large. On the contrary, the range of sample input space is smaller. The value of σ is generally proportional to the noise level.

Based on the above selection of input parameters, the LS-SVM model of mill output is established and is shown in Figure 2. In this model, various auxiliary variables are as input, and the output is mill output, that is pulverized coal production. This model is a multi-input and single-output model. The nonlinear function relation between model input and output is realized by LS-SVM.

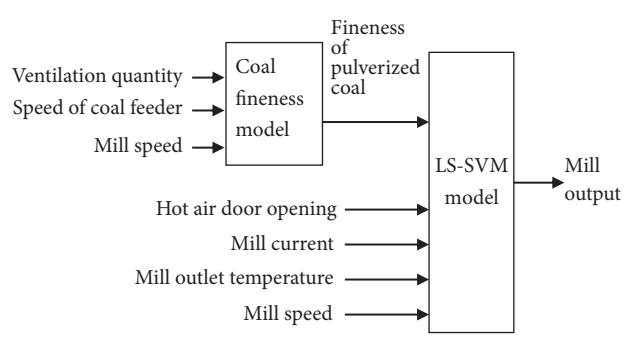

Figure 2: LS-SVM model of mill output in pulverizing system.

In the input layer, mill current is used to represent the coal storage in grinding. There are two measuring points are arranged on both sides of the mill, and the average value of the two points is taken as the level signal. The fineness of pulverized coal is difficult to be measured on-line directly, but it is mainly affected by the quantity of air supply, the amount of coal and the speed of the mill, so it can be represented by these three variables indirectly.

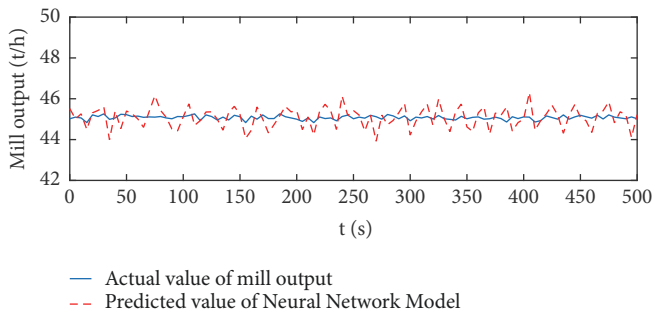

Figure 3: Comparison between actual value and predicted value of neural network model (at 80% rated load).

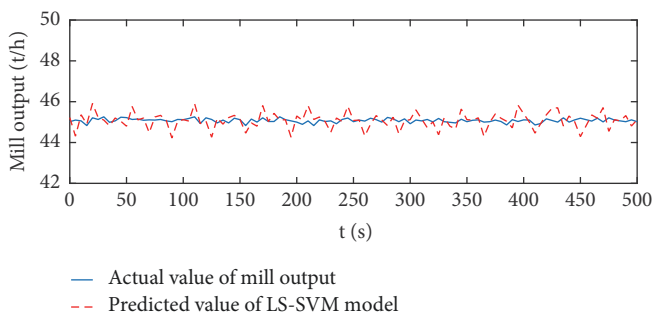

Figure 4: Comparison between actual value and predicted value of LS-SVM model (at 80% rated load).

2.2.2. Model Verification. A coal mill pulverizing system of 300 MW units in a power plant was continuously sampled with a sampling period of 5 s. According to the input and output parameters of LS-SVM model, 200 sets of measured data were obtained. There is no direct on-line measurement value of mill output in power plant, so there is no actual value used to compare with the predicted value. Consider that the mill output of direct-fired system is basically equal to the quantity of coal feed under steady condition, and in the field the quantity of coal feed is often used to express the fuel quantity into furnace, that is the mill output. Therefore, under the steady condition, the quantity of coal feed represents the actual value of mill output and is used to verify the model output. The above data are normalized, and the first 100 groups of data are used as training samples, the latter 100 groups are used as test samples. The two parameters of model are selected as follows: $C = 98$, $\sigma = 1.2$.

The LS-SVM model established in this paper is compared with the usual neural network model by simulation. The comparisons between the predicted value and the measured value of coal feed are shown in Figures 3 and 4, respectively. In Figures 3 and 4, the solid line represents the actual value of mill output, and the dashed line is the predicted value of model. Table 1 shows the results of statistical analysis about errors.

The experimental results show the following: the errors between model output and actual value, such as the maximum absolute error, the mean relative error, and the mean square error are all smaller when the model is established by LS-SVM algorithm than by neural network algorithm. Therefore, the model based on LS-SVM algorithm is more reliable.

3. Improvement of Particle Swarm Optimization Algorithm

3.1. Standard PSO. The basic idea of PSO algorithm is as follows. Each individual is regarded as a particle without volume (or point) in D dimensional search space. These particles are flying at a certain speed in the search space, and each was moved to a good area based on the fitness of the environment. The velocity of the particle's flight is dynamically adjusted according to experience of its own and the companion. The particle i is represented as $X_i = (x_{i1}, x_{i2}, \cdots, x_{iD})$, and the best location it has ever experienced is recorded as $P_i = (p_{i1}, p_{i2}, \cdots, p_{iD})$ and can also be called p_{best}. The best position experienced by all particles is expressed by index number g, that is, p_g or g_{best}. The velocity of particle i is represented as $V_i = (v_{i1}, v_{i2}, \cdots, v_{iD})$. For each generation of particles velocity, its d $(1 \le d \le D)$ dimension varies according to the following equations:

$$v_{id}^k = wv_{id}^{k-1} + c_1 \text{rand}_1 \left(p_{id} - x_{id}^{k-1}\right) + c_2 \text{rand}_2 \left(p_{gd} - x_{id}^{k-1}\right) \quad (2)$$

$$x_{id}^k = x_{id}^{k-1} + v_{id}^{k-1} \quad (3)$$

where w is the inertia weight, c_1 and c_2 are acceleration factors, $rand_1$ and $rand_2$ are two random functions in the range of $[0, 1]$, $i = 1, 2, \cdots, M$, and M is particles total number in a population, x_{id}^k is the d dimension component of position vector about k iteration particle i, v_{id}^k is the d dimension component of velocity vector about k iteration

Table 1: Statistical analysis of predicted value errors using two models (at 80% rated load).

	Maximum absolute error	Mean relative error	Mean square error
Neural network model	1.20	0.0237	0.3509
LS-SVM model	0.87	0.0035	0.2748

particle i, p_{gd} is the d dimension component of g_{best}, and p_{id} is d dimension component of p_{best}.

The inertia weight w affects the search ability and convergence speed of the algorithm and balances these two capabilities. If w is large, the global search ability is enhanced. If w is small, the convergence speed is enhanced. The inertia weight of the standard PSO algorithm is linearly reduced, which makes the algorithm have a stronger ability of global search in early stage and higher convergence rate in late. In fact, the search process is a nonlinear complex process for the coal pulverizing system, and the linear change of the inertia weight cannot reflect the actual search process.

The acceleration factor c_1 affects the individual cognition of particles and c_2 affects the social cognition. They, respectively, dominate the global search ability and local search ability. If the individual cognition is improved, the global search ability of the algorithm can be effectively enhanced. If the social cognition is improved, the local search ability can be enhanced. In the standard PSO algorithm, c_1 and c_2 are constant. While in practice, the two values need to be adjusted.

Through the above analysis, we can see that the standard PSO algorithm will be difficult to meet the needs of the control optimization for duplex inlet and outlet ball mill system. So, a parameter adaptive particle swarm optimization algorithm based on particle similarity function (HPAPSO) is proposed in this paper.

3.2. Improvement of PSO. The parameters adjustment of PSO will directly affect its optimization performance, and the regulation has a certain rule. They are closely related to population distribution and location of individual particles. Particles are more and more similar in iteration. So, the parameters can be adjusted by the degree of particle similarity. A particle similarity function is proposed in this paper as follows:

$$h(i,e) = 1 - \frac{|J_i - J_e|}{J_{max} - J_{gbest}} \tag{4}$$

where $h(i,e)$ is the similarity between particle i and desired particle, J_i is the fitness value of particle i, J_e is the fitness value of desired particle, J_{gbest} is the fitness value of population historical extreme value Y_g, and J_{max} is the maximum value of particle fitness.

In the standard PSO algorithm, the weights of all particles are uniformly adjusted without considering the differences between them. If the optimal location has been found in the early stage but was jumped out of the best position because its weight is too large, then the search efficiency will be reduced. For this reason, an improved PSO algorithm is designed to dynamically adjust the inertia weight according to the similarity degree of each particle and the expected particle position. Formula is as follows:

$$w_i^{t+1} = w_{min} + (w_{max} - w_{min}) \frac{(t_{max} - t)^m}{{t_{max}}^m} \cdot h(i,e) \tag{5}$$

where w_i^{t+1} is the weights of particle i at the moment t+1, t is the current iteration, t_{max} is maximum iteration number in operation, w_{max} is the initialization weight at the start of operation, w_{min} is the last weight, and m is nonlinear adjustment factor. If $m \neq 1$, the change of weights is nonlinear. In this improved algorithm, particles with smaller similarity to expected particles should have larger weights and should be accelerated to explore the entire solution space; otherwise, they should be weighted smaller and should be microexplored within the desired optimal location to enhance its development capability.

For acceleration factors c_1 and c_2, in the initial search of algorithm, c_1 should be larger to increase the diversity of population, and c_2 should be smaller to avoid population falling into local optimal; in the latter, c_1 should be smaller to faster convergence speed, and c_2 should be larger to leading the population tends to global optimal position. According to this adjustment idea, the iterative formulas are presented as follows:

$$c_{1i}^{t+1} = c_{1max} - (c_{1max} - c_{1min}) \cdot h(i,e) \tag{6}$$

$$c_{2i}^{t+1} = c_{2min} + (c_{2max} - c_{2min}) \cdot h(i,e) \tag{7}$$

where c_{1i}^{t+1} and c_{2i}^{t+1} are acceleration factors of particle i at the moment t+1, c_{1max} and c_{2max} are, respectively, the maximum values of c_1 and c_2, and c_{1min} and c_{2min} are, respectively, the minimum of c_1 and c_2.

Through the concept of similarity, the inertia weight and the two acceleration factors are adaptively adjusted. That is HPAPSO algorithm improved from PSO, which can effectively balance the global and local search ability and improve the search accuracy of the algorithm.

3.3. Verification of HPAPSO Algorithm. In order to verify the performance of the improved algorithm, the Matlab software is used, and two common test functions are used to test and verify the algorithm. The convergence rate and average optimal fitness are calculated. The PSO test results are used to compare the superiority of the improved algorithm. The test functions are as follows:

f_1 is Sphere function; its mathematical expression is as follows:

$$f_1(x) = \sum_{i=1}^{n} x_i^2, \quad x \in (-100, 100)^n \tag{8}$$

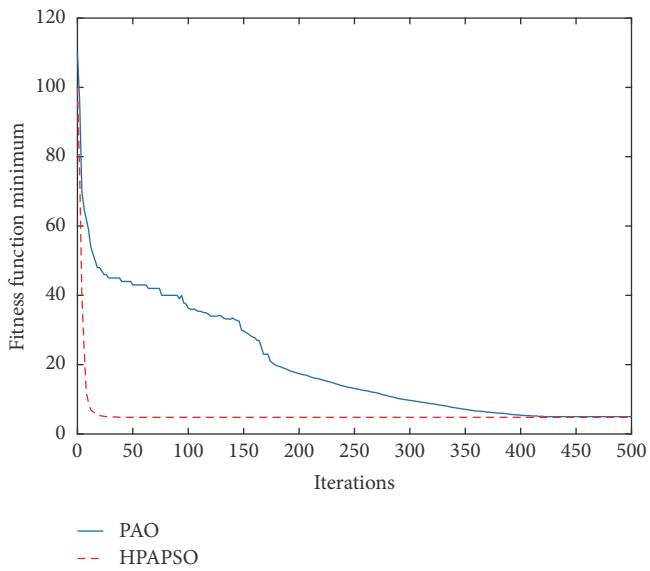

Figure 5: Sphere function optimization results.

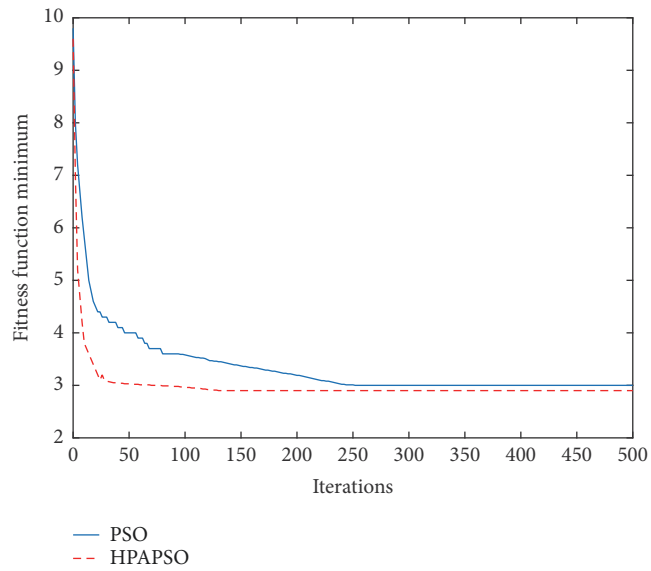

Figure 6: Griewank function optimization results.

f_2 is Griewank function; its mathematical expression is as follows:

$$f_2(x) = \frac{1}{400}\sum_{i=1}^{n} x_i^2 - \prod_{i=1}^{n}\cos\left(\frac{x_i}{\sqrt{i}}\right) + 1, \quad x \in (-600, 600)^n \tag{9}$$

In this case, f_1 is a unimodal function and f_2 is a multi-peak function. Their minimum values are both zero, and they both converge to $(0, 0, \cdots, 0)$. The maximum number of iterations is 500, the population size is 50, and each algorithm runs 100 times. Finally, the average fitness of 100 times is taken as the optimal result, and the convergence rate and convergence algebra are used as the evaluation data.

Figures 5 and 6 show the variation process of the fitness function minimum with two methods in 100 iterations. It can be seen from the figures that the HPAPSO algorithm has good convergence in the early stage of iteration, and the late convergence results are better than the standard PSO algorithm. In the simulation experiments, by changing the variable factors such as convergence algebra, particle dimension, and other variables, the improved algorithm is superior to the unimproved one in many tests under the same conditions. It shows that the HPAPSO algorithm has fast convergence speed and high convergence accuracy.

4. MPC Control Algorithms

4.1. Basic Structure of MPC. For the direct-fired system with duplex inlet and outlet ball mill, HPAPSO optimization algorithm is adopted to realize the predictive control of mill output, which can make it to meet the load demand of the unit at any time. The basic structure of control system is shown in Figure 7, where $y_r(k+i)$ is given value of mill output at the moment $k+i$, $y(k)$ is output of pulverizing system at the moment k, $y^{\wedge}(k)$ is model predictive output value at the moment k, $e(k)$ is error between actual output and predicted output of the model at the moment k, $y^{\wedge}(k+i)$ is model predictive output value at the moment $k+i$, $y_P^{\wedge}(k+i)$ is predictive output after feedback correction, $u_j(k)$ is the control input at current time, $j = 1, \cdots, n$, and n is the number of input variables in mill output prediction model, and $u(k+i)$ is optimal control sequence for future moments, $i = 0, \cdots, M-1$. According to known information and future input $u(k+i)$, future mill output $y^{\wedge}(k+i)$ is predicted.

4.2. Rolling Optimization. In nonlinear model predictive control of pulverizing system, HPAPSO optimization algorithm presented in this paper needs to define a particle as follows:

$$p_{id}^t = [u_1(k), \cdots, u_m(k), u_1(k+1), \cdots, u_1(k+M-1), \cdots, u_m(k+M-1)] \tag{10}$$

where id is sequence number of particles and t represents the current iteration step. The location of particle swarm can be expressed as follows:

$$POS(t) = \left[p_1^t, \cdots, p_{num}^t\right]^T \tag{11}$$

where num represents particle population and $POS(t)$ is a $num \times (m \cdot M)$ dimensional matrix and represents the current position of all particles.

The following objective function (12) is used as the fitness function of HPAPSO algorithm:

$$\begin{aligned} J = &\sum_{i=1}^{M} Q_i \sum_{j=1}^{n}\left(y_{rj}(k+i) - y_j^{\wedge}(k+i)\right)^2 \\ &+ \sum_{i=1}^{M-1} R_i \sum_{j=1}^{n}\left(u_j(k+i) - u_j(k+i-1)\right)^2 \\ &+ R_0 \sum_{j=1}^{n}\left(u_j(k) - u_j(k-1)\right)^2 \end{aligned} \tag{12}$$

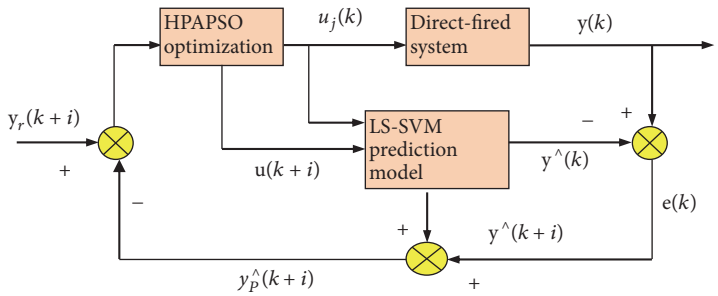

Figure 7: The MPC control structure of direct-fired system.

And it satisfies the constraint conditions of the following:

$$u(t) \in U,$$
$$x(t) \in X, \quad \forall t > 0 \tag{13}$$

In (12), R_0 is constant, both Q_i and R_i are weighted positive definite matrices, which are set by the designer. Equation (12) is the bridge between LS-SVM model and HPAPSO algorithm. So, it contains the input information of future and system output information predicted by the LS-SVM model as follows:

$$u_j(k+i), \quad j = 1, \cdots, n; \; i = 0, \cdots, M-1 \tag{14}$$

$$y_j^{\wedge}(k+i), \quad j = 1, \cdots, n; \; i = 1, \cdots, M \tag{15}$$

HPAPSO gives the particles location at each iteration. After obtaining the future input information in (14), the future prediction information in (15), (12) is used to calculate the fitness value corresponding to each particle and then enters the HPAPSO iteration to find the optimal input.

5. Simulation Study

5.1. Experimental Platform. In order to verify the effect of predictive control system based on HPAPSO algorithm proposed in this paper, the research team set up an experimental platform of direct-fired system with duplex inlet and outlet ball mill. The scene of the experimental platform is shown in Figure 8. The main equipment includes duplex inlet and outlet ball mill, coal feeder, fan, coarse powder separator, burner and some related pipes, valves, and so on.

Taking into account the space of experimental site, the installation of various test instruments, and the consumption of pulverized coal in the experiment, the platform is a model designed according to the proportion of 1:10. According to the principle of similarity, the prototype is reduced according to geometric size. The normal temperature air was selected as the cold primary air. The air after heating was adopted as the hot primary and then determines the relevant physical quantities. The specific parameters are shown in Tables 2 and 3.

Figure 8: Experimental platform of duplex inlet and outlet ball mill system.

Table 2: Design parameters list of platform.

Parameters	Value
Scale k	1/10
Main pipe diameter/mm	90
Branch pipe diameter/mm	70
coarse powder separator diameter/mm	300
Maximum flow velocity/m/s	35
Minimum flow velocity/m/s	18
Maximum air quantity/m^3/s	0.135
Minimum air quantity/m^3/s	0.069
Maximum differential pressure/kp_a	10.9

5.2. Simulations. The historical data used in this part of the simulation experiment are from the above experimental platform. In order to analyze and compare the control effect more comprehensively, PID control method, MPC based on PAPSO (from [16]) (abbreviated as PAPSO-MPC), and MPC based on HPAPSO (abbreviated as HPAPSO-MPC) algorithms are adopted, respectively, to control the mill output in normal rise load operation process for the above experimental equipment of pulverizing system, and the simulation study is carried out. During the process of simulation, the target value of mill output is given by the monitoring computer, and the whole process is stepped up load.

Through the comparison of experience and simulation, a group of PID parameters with better effect are selected as follows: P = 0.8, I = 0.4, D = 1.1; the parameters value of PAPSO are selected as follows: $w_{max} = 1.2$, $w_{min} = 0.2$,

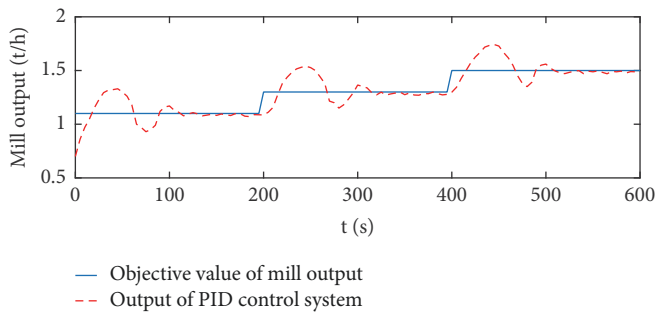

Figure 9: Output of PID control system.

Table 3: Main technical parameters of mill.

Parameters	Value
Mill outlet temperature/°C	60~80
Specifications for steel balls/mm	20/15/10/5
Various steel ball proportion/%	20/30/30/20
Mill speed/(r • min^{-1})	20
Milling capacity/(t • h^{-1})	5
Fineness of pulverized coal R_{90}/%	10
Rated current/A	14.2
Power rating/kW	16

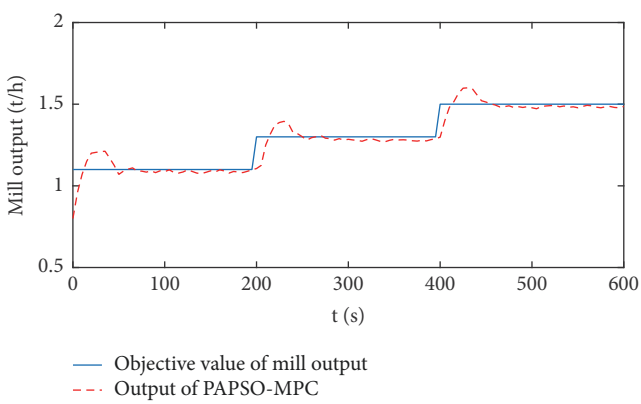

Figure 10: Output of PAPSO-MPC.

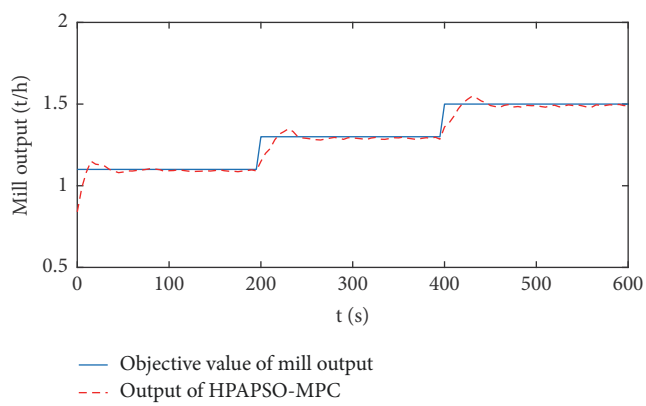

Figure 11: Output of HPAPSO-MPC.

$v_{max} = 3$, acceleration factors $c_1 = c_2 = 1.6$, and maximum iteration number $t_{max} = 40$.

In order to compare the control effect, the same parameters HPAPSO with PAPSO algorithm have the same values. The other parameters of HPAPSO are selected as follows: acceleration factors $c_{1min} = c_{2min} = 0.3$, $c_{1max} = c_{2max} = 3.0$; nonlinear adjustment factor $m = 0.8$.

Figure 9 is the result of PID control system, Figure 10 is the result of PAPSO-MPC, and Figure 11 is the result of HPAPSO-MPC. Among them, the solid line is the objective value of mill output, and the dashed line is actual value.

The comparisons of two control algorithms about mill output are shown in Table 4.

From Figures 9, 10, and 11, it can be seen that the convergence and the optimization effects of the HPAPSO-MPC method in this paper three cases are best, and the fluctuation of the system is smallest when the objective value of mill output is changed. When using conventional PID control method, because of the strong lag of the system, the control effect is not so good. While using PAPSO-MPC method, the control effect is relatively good, but it can be further improved. It is more intuitive to see from Table 4 that the overshoot, adjustment time, and rise time of HPAPSO-MPC are all smallest compared to the values of PAPSO-MPC method and PID control method. In terms of mean relative error and mean square error, it is 0.0156 and 0.0390, respectively, and they are both smallest compared to the values in PAPSO-MPC and PID control method. The steady-state error of HPAPSO-MPC is 0.5%, also smallest compared to that of PAPSO-MPC and PID control. Therefore, the HPAPSO-MPC algorithm proposed in this paper has better

Table 4: Comparisons of dynamic and static performances of three control methods.

Performance parameter	PID	PAPSO-MPC	HPAPSO-MPC
Overshoot %	20.9	10.2	4
Adjustment time/s	85	50	30
Rise time/s	45	20	10
Pure delay time/s	5	5	0
Mean relative error	0.0620	0.0306	0.0156
Mean square error	0.1139	0.0573	0.0390
Steady-state error/%	1.8	1.2	0.5
Per iteration optimization time/s	-	0.849	1.36

regulation performance and can better solve the lag problem of mill system.

At the same time, it can be seen that each iteration time (1.36s) of HPAPSO-MPC is longer than that of PAPSO-MPC (0.849s). It shows that the above results of HPAPSO-MPC are obtained at the expense of calculation amount and computation time, and they will also increase as the input dimension of the system increases. Nevertheless, as for the large time-delay and strongly nonlinear system of mill, as long as the sampling period (5s) is longer than the time required for each iteration (1.36s), it does not affect the control effect.

6. Conclusions

The operation mechanism of duplex inlet and outlet ball mill system is complex, it is difficult to establish a mechanism model, and it has strong hysteresis and nonlinearity, so the control effect is difficult to meet the production needs. Firstly, this paper established the LS-SVM model of mill output, and, based on the dynamic adjustment of weights and acceleration coefficients of PSO, proposed a HPAPSO algorithm. Then the new optimization algorithm is combined with MPC for solving control problem of mill system. Through the simulation experiment, we can see that adopting HPAPSO-MPC method is more accurate and can achieve better regulation performance than PID and PAPSO-MPC method. So it can better meet the needs of industrial production.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

The authors gratefully acknowledge the financial support of the Natural Science Foundation of Hunan Province of China (Grant no. 2018JJ3552), the Key Laboratory of Renewable Energy Electric-Technology of Hunan Province (Changsha University of Science & Technology) (Grant no. 2018ZNDL001), the Key Laboratory of Renewable Energy Electric-Technology of Hunan Province (Grant no. 2016ZNDL005), the Open Fund of Innovation Platform of Hunan Provincial Education Department of China (Grant no. 17K002), the Natural Science Foundation of China (Grant no. 51706022), and the Natural Science Foundation of Hunan Province of China (Grant no. 15JJ4007).

References

[1] X. S. Chen, J. Yang, S. H. Li, and Q. Li, "Disturbance observer based multi-variable control of ball mill grinding circuits," *Journal of Process Control*, vol. 19, no. 7, pp. 1205–1213, 2009.

[2] Y. Luo, L. Jia, W. Cai, and H. Liu, "Set-point optimization and control of coal-pulverizing systems with ball-tube mill," in *Proceedings of the 2009 4th IEEE Conference on Industrial Electronics and Applications, ICIEA 2009*, pp. 1690–1694, China, May 2009.

[3] T. Chai, L. Zhai, and H. Yue, "Multiple models and neural networks based decoupling control of ball mill coal-pulverizing systems," *Journal of Process Control*, vol. 21, no. 3, pp. 351–366, 2011.

[4] L. Liu, "A intelligent slef-tuning control for ball mills pulverizing systems in coal-burning power plants," in *Proceedings of the 31st Chinese Control Conference, CCC 2012*, pp. 379–383, China, July 2012.

[5] D. Zeng, Y. Wang, S. Gao, and J. Liu, "Modeling and control of ball mill system considering coal moisture," *Measurement*, vol. 90, pp. 43–51, 2016.

[6] F. Xu, H. Chen, X. Gong, and Y. Hu, "Engine idle speed control using nonlinear model predictive control," *The International Federation of Automatic Control*, vol. 46, no. 21, pp. 171–176, 2013.

[7] S. S. Kaddah, K. M. Abo-Al-Ez, and T. F. Megahed, "Application of nonlinear model predictive control based on swarm optimization in power systems optimal operation with wind resources," *Electric Power Systems Research*, vol. 143, pp. 415–430, 2017.

[8] A. Parisio and L. Glielmo, "Stochastic model predictive control for economic/environmental operation management of microgrids," *Control Conference*, vol. 415, no. 1, pp. 2014–2019, 2013.

[9] A. M. Elaiw, X. Xia, and A. M. Shehata, "Application of model predictive control to optimal dynamic dispatch of generation with emission limitations," *Electric Power Systems Research*, vol. 84, no. 1, pp. 31–44, 2012.

[10] P. J. Dinesen, *Unit commitment and economic model predictive control for optimal operation of power systems [Masters, thesis]*, Industrial Collaboration, 2015.

[11] L. Obregón, L. Quiñones, and C. Velázquez, "Model predictive control of a fluidized bed dryer with an inline NIR as moisture sensor," *Control Engineering Practice*, vol. 21, no. 4, pp. 509–517, 2013.

[12] X.-S. Chen, Q. Li, and S.-M. Fei, "Constrained model predictive control in ball mill grinding process," *Powder Technology*, vol. 186, no. 1, pp. 31–39, 2008.

[13] H. Izakian and A. Abraham, "Fuzzy C-means and fuzzy swarm for fuzzy clustering problem," *Expert Systems with Applications*, vol. 38, no. 3, pp. 1835–1838, 2011.

[14] S. Alam, G. Dobbie, Y. S. Koh et al., "Research on particle swarm optimization based clustering: a systematic review of literature and techniques," *Swarm and Evolutionary Computation*, vol. 17, pp. 1–13, 2014.

[15] V. Haji Haji and C. A. Monje, "Fractional order fuzzy-PID control of a combined cycle power plant using particle swarm optimization algorithm with an improved dynamic parameters selection," *Applied Soft Computing*, vol. 58, pp. 256–264, 2017.

[16] C. Wang and J. Qiao, "A parameter adaptive particle swarm optimization for optimal design of water supply systems," *CAAI Transactions on Intelligent Systems*, vol. 10, no. 5, pp. 722–728, 2015.

[17] Y. Ye, C.-B. Yin, Y. Gong, and J.-J. Zhou, "Position control of nonlinear hydraulic system using an improved PSO based PID controller," *Mechanical Systems and Signal Processing*, vol. 83, pp. 241–259, 2017.

[18] W. Fu, J. Li, L. Wang, Y. Shi, and Y. Yang, "Optimal design for thermodynamics system of double reheat coal-fired power plants with post-combustion carbon capture based on dynamic adaptive particle swarm optimization," *Proceedings of the Chinese Society for Electrical Engineering*, vol. 37, no. 9, pp. 2652–2659, 2017.

[19] W. Dong and M. Zhou, "A supervised learning and control method to improve particle swarm optimization algorithms," *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, vol. 47, no. 7, pp. 1135–1148, 2017.

[20] Q. Kang, S. Feng, M. Zhou et al., "Optimal load scheduling of plug-in hybrid electric vehicles via weight-aggregation multi-objective evolutionary algorithms," *IEEE Transactions on Intelligent Transportation Systems*, vol. 18, no. 9, pp. 2557–2568, 2017.

[21] L. Feng, *Modeling and Control of Direct-Fired System with Duplex Inlet & Outlet Ball Pulverizer*, Central South University, 2012.

[22] L.-H. Feng, W.-H. Gui, and F. Yang, "Soft sensor modeling for mill output of direct fired system based on improved least squares support vector machines," *Electric Machines and Control*, vol. 15, no. 11, pp. 79–82, 2011.