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Research Article

Intelligent Optimization Control Strategy for Secondary Pollution of Flue Gas in Municipal Solid Waste Incineration

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Aiming at the problem of serious secondary pollution caused by improper control strategy in the waste incineration process, this paper proposes an intelligent optimization control strategy for secondary pollution of flue gas in municipal solid waste incineration. Firstly, the control difficulties of waste incineration and cybernetic characteristics of combustion process in incinerators are analyzed, and the basic algorithm based on human simulated intelligent control is proposed accordingly. Then, genetic algorithm is used to improve particle swarm algorithm and search ability in wide space, which can avoid the premature phenomenon of local optimum. Finally, improved particle swarm algorithm is utilized to optimize the parameters in human simulated intelligent control algorithm to realize intelligent optimization control in the waste incineration process. Based on MATLAB simulation platform, experimental results show that when delay parameters and time constant change significantly, there are large disturbances, and the process response of proposed strategy is fast and stable, which is superior to other comparison strategies.

1. Introduction

With the rapid development of domestic economy and acceleration of urbanization process, the municipal waste disposal problem has become more and more prominent. At present, the main waste disposal methods include landfill, composting, and incineration for power generation (Figure 1). Among them, landfill disposal not only causes serious environmental pollution but also occupies lot of land and wastes lot of resources. Composting treatment is difficult to deal with the current complicated types of domestic waste and high cost [1, 2]. Waste incineration power generation treatment has received great attention from government agencies and scientific researchers because of its advantages of resource utilization, reduction, and harmlessness [3].

However, due to the inadequate level of waste classification and treatment at present, the calorific value of waste is generally low, and dioxins cannot be effectively decomposed. Its direct pollution reaches a range of 5 km, which makes waste incineration environmental protection projects often turn into pollution-intensive emission projects [4]. Dioxins belong to chlorinated ring triaromatic compounds, which are very stable, difficult to decompose, and first-class carcinogens with toxic strength. Once the human body is contaminated by dioxins, it cannot be degraded or discharged in the body. It can cause major damage to the immune and reproductive functions of human body, causing large-scale deformities, cancer, and other diseases. Thus, the ecological pollution hazards of dioxin in developed countries have received considerable attention [5].

In view of the seriousness and universality for waste incineration flue gas pollution, many scientific researchers have explored the waste incineration pollution control from multiple angles. In particular, it is aimed at avoiding the dioxin secondary pollution problem caused by improper control of combustion flue gas temperature. However, there are still some shortcomings in terms of control strategies [6, 7], among which the commonly used forms of waste incinerators are shown in Figure 2. However, the flue gas treatment link, that is, the treatment and control strategy of devices in dashed box in Figure 2 on the harmful gas, needs to be improved.

In order to improve the intelligent control during incineration of domestic waste, it is necessary to develop a set of

FIGURE 1: Municipal solid waste incineration.

simulators. For now, the simulators of large thermal power plants have been widely promoted and applied in major power stations and universities. However, there are few simulators for waste incineration power plants [8]. This is mainly because the domestically operated incinerators and other key equipment still rely on foreign imports. Many of the corresponding supporting control systems have problems with the transfer and use of patented technologies [9, 10]. Therefore, it is of great significance to study the simulation and its control system of waste incineration power plants. Besides, it is necessary to conduct an in-depth study on the secondary pollution control caused by waste incineration from the perspective of control engineering.

Aiming at the secondary pollution problem caused by improper control in the waste incineration process, this paper proposes an intelligent optimization control strategy for secondary pollution of flue gas in municipal solid waste incineration. The main innovations are summarized as follows:

(1) Because the traditional control strategy cannot match the characteristics of incineration rate control theory, a human simulated intelligent control algorithm is proposed to achieve the optimal control of flue gas temperature in the waste incineration

(2) In order to solve the problems of low search accuracy, premature convergence, and low later iteration efficiency of particle swarm algorithm, the proposed strategy adopts genetic algorithm to improve particle swarm algorithm. The genetic crossover operator is used to increase the diversity of particles and improve search ability in a wide range of spaces

2. Materials and Methods

The waste incineration technology originated from abroad and has been quite perfect after more than 100 years of development. It already has some advanced technologies and methods, such as expert system real-time control, fuzzy control, neural network control, and simulation intelligent control [11, 12]. Among them, the conventional Proportional Integral Derivative (PID) controller has been able to meet the requirements of on-site operation, but the control

optimization problem for secondary pollution is less involved [13, 14]. Reference [15] studied the difficult control and disposal problem of residues for fly ash purification from domestic waste incineration, such as vitrified materials, and tested factors affecting the alteration rate. Reference [16] developed a new melting system on the basis of discussing operating conditions of ash slag melting furnace for municipal solid waste incinerator to solve the problem in the ash treatment of municipal solid waste incinerator. However, the dependence on external control factors such as temperature was relatively large. Reference [17] proposed a heat treatment method for solid domestic waste (SDW) to meet the conditions of SDW incineration and flue gas purification. However, the types of domestic garbage were complicated, and their universality was not good. Reference [18] proposed a method for the treatment of domestic garbage on the island, which uses diesel engine flue gas to dry garbage and shells to purify the gas generated by garbage incineration. This method can effectively reduce the energy consumption and pollution degree of waste incineration but did not consider the secondary pollution problem in the flue gas.

At the same time, there are many systematic discussions on waste incineration. Reference [19] focused on the production mechanism and preventive measures of major secondary pollutants such as dioxins, heavy metal elements, and oxidizing oxides produced by incineration of domestic waste. However, the specific implementation methods were not studied and only remain at the theoretical level. Reference [20] combined the characteristics of domestic waste, people's environmental awareness, willingness to pay, and its influencing factors and proposed a differentiated treatment plan for urban and rural domestic waste. Reference [21] analyzed the changes in operating parameters of domestic waste incinerator after cofiring of medical waste and the impact of the system on operating conditions, equipment life, and production costs by comparing operating data before and after the domestic waste incineration power plant. But it lacked the optimization research of corresponding control strategy. Reference [22] deeply studied the generation, treatment, and impact range of municipal solid waste and did not conduct a feasibility analysis of the waste treatment method.

In addition, in order to better grasp the combustion of garbage in incinerator, some scholars use numerical simulation to simulate the movement and combustion of garbage in incinerator to improve theoretical support for control system optimization [23, 24]. But overall, the treatment effect on secondary pollution caused by municipal solid waste incineration is not good. The control strategy needs to be improved.

3. Combustion Stability Control and HSIC Control Algorithm

3.1. Control Difficulties of the Incineration Process. The control difficulty in the incineration process is mainly reflected in the uncertainty for calorific value of waste. The calorific value of waste as a raw material for incineration process will vary depending on specific conditions of the city, as well as with changes in the climate, residents, and waste collection
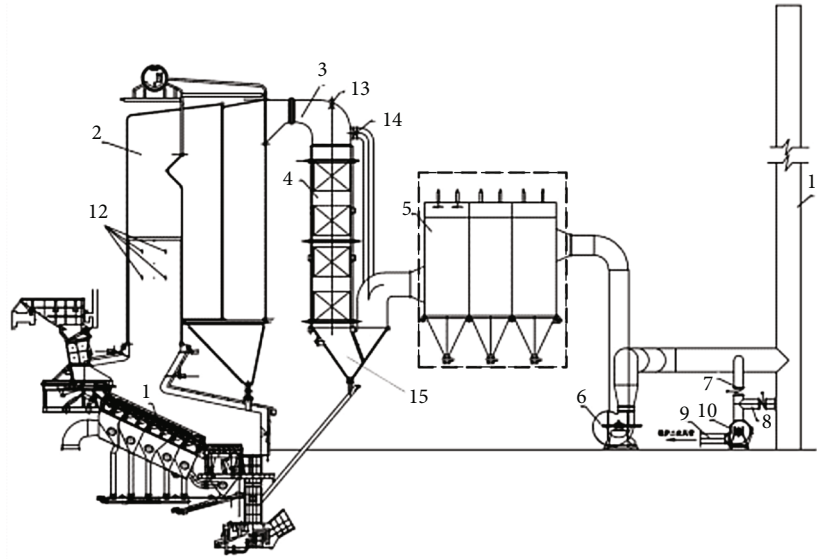
Figure 2: Principle and structure of typical incinerators.

conditions. Thus, the calorific value of municipal solid waste is extremely unstable. At the same time, the waste incinerator will also experience changes in the thermal characteristics of incinerator due to long-term equipment operation, overhaul, and transformation, such as difficulty in ignition, incomplete combustion, slagging in the furnace, corrosion, and increased secondary pollution. The effect of waste incineration, the control of pollutant generation, and economics of treatment are difficult to reach expectations [25].

The traditional control strategy is difficult to accurately grasp the characteristics of incinerator object, because the combustion process in incinerator is a very complex physical and chemical process. The incinerator itself is a strongly coupled multi-input, multioutput, nonlinear system, and it is difficult to establish an accurate mathematical model and implement paradigm quantitative control. Because its safe operation is closely related to the stability of combustion process, once the combustion stability declines, it will lead to increased incomplete combustion, reduced combustion efficiency, increased emissions of incineration pollutants, secondary pollution, and increased high-temperature corrosion. Therefore, it has a serious impact on the safety and economy of incinerator. The abovementioned are the control difficulties in the incineration process.

3.2. Cybernetic Characteristics of the Incineration Process.
The reason why the incineration process is difficult to accurately control is that the selected control strategy does not match the cybernetic characteristics of waste incinerator combustion process. Starting from the analysis of control difficulties, it is not difficult to summarize the cybernetic characteristics of combustion process:

(1) The composition of waste is complex and changeable, and there are many factors that affect combustion. The calorific value of waste as a combustion raw material has great uncertainty. For uncertain processes, it is difficult to implement effective control using mathematical modeling methods

(2) The incinerator is a complex object with a high degree of nonlinearity. Although there are many existing nonlinear control methods, they are not suitable for application in incinerator control engineering due to the excessive complexity of the control methods

(3) The problem of semistructured and unstructured in combustion process control of incinerator is prominent. It is difficult to describe the semistructured and unstructured processes using quantitative mathematical methods. Since traditional control belongs to the category of quantitative control, traditional control cannot do anything about the unknown, time-varying, and randomness of semistructured and unstructured process parameters, as well as the unknown and time-varying process delays

(4) In the complex combustion process, each combustion element restricts each other and is highly coupled. It is impossible for traditional control to decouple and implement control

(5) The external environment of incineration process is harsh, and industrial interference is serious. Traditional control does not have the ability to resist strong industrial interference

In short, the cybernetic characteristics of combustion process are mainly manifested as follows: the uncertainty for calorific value of waste; the randomness, unknown, and time-varying nature of other parameters process; the correlation and nonlinearity between process variables; the thermal inertia and process; the unknown and time-varying nature of time lag; and the unknown, diversity, and randomness of external interference. For the abovementioned cybernetic characteristics, it is impossible to use traditional control strategies to match its cybernetic characteristics. Therefore,

the control strategy and control algorithm that match its process characteristics must be adopted.

3.3. HSIC Control Algorithm. The control process model of Human Simulated Intelligent Controller (HSIC) is shown in Figure 3. In the figure, $r(t)$ and $y(t)$ are the input and output of control process, respectively. $e(t)$ and $G(t)$ are error and controller output, respectively.

$\hat{e}$ is the error rate of change, and the error phase plane is shown in Figure 4, which reflects the law of error change. When $e \cdot \hat{e} > 0$ or $e = 0$ and $\hat{e} \neq 0$, the absolute value function $\text{Abs}(e)$ shows an increasing trend; when $e \cdot \hat{e} < 0$ or $\hat{e} = 0$, $\text{Abs}(e)$ shows a decreasing trend and eventually tends to zero.

The above results show that when $e = 0$ and $\hat{e} \neq 0$ or $e \cdot \hat{e} > 0$, the control should select the "proportional" mode; when $\hat{e} = 0$ or $e \cdot \hat{e} < 0$, the control should select the "hold" mode.

Summarizing the above two basic control modes, the basic control algorithm is as follows:

$$G = \begin{cases} K_p \cdot e + \kappa \cdot K_p \cdot \sum_{i=1}^{n-1} e_{\max}^i, & e \cdot \hat{e} > 0 \cup e = 0, \hat{e} \neq 0, \\ \kappa \cdot K_p \cdot \sum_{i=1}^{n-1} e_{\max}^i, & e \cdot \hat{e} < 0 \cup \hat{e} = 0, e \neq 0, \end{cases}$$

$$(1)$$

where $e_{\max}^i$ and $\hat{e}$, respectively, represent the i peak value of the maximum error and error rate of change; G is the controller output; κ is the suppression coefficient; K_p is the proportional coefficient.

The HSIC algorithm is characterized in that different control modes are adopted for different positions of error characteristic in the error phase plane. The simplest case is to realize the control of controlled process with open and closed loop alternate control [26, 27]. For complex processes, the operator's control skills, skills and wisdom, expert knowledge, and practical experience can be incorporated into the control algorithm. With the help of production rules in artificial intelligence, an HSIC control algorithm that matches the characteristics of process cybernetics is constructed [28]. In the error phase plane, if vertical coordinate $\hat{e}$ is divided into $\hat{E}_1$ and $\hat{E}_2$ according to the characteristic threshold for the error rate of change, $\hat{E}_2 \geq \hat{E}_1$. Divide the abscissa e into E_1, $E_2, E_3, E_2 \geq E_1$, and $E_3 \geq E_2$ according to the error characteristic threshold. Then, the error phase plane can be divided into multiple different control areas, so as to obtain HSIC control algorithm that is more suitable for the error characteristic mode of each area, which is expressed as follows:

$$\begin{cases} g = \text{sgn}\,(e) \cdot G, |e| \geq E_1, \\ g = K_{P1} \cdot e + K_{D1} \cdot \hat{e}, |e| < E_1 \cap |e| \geq E_2, \\ g = K_{P2} \cdot e + K_{D2} \cdot \hat{e}, |e| < E_2 \cap |\hat{e}| \geq \hat{E}_1, \\ g = K_{P3} \cdot e + K_{D3} \cdot \hat{e}, |e| < E_2 \cap |\hat{e}| < \hat{E}_1 \cap |e| > E_3 \cap |\hat{e}| > \hat{E}_2, \\ g = g_{n-1}, |e| \leq E_3 \cap |\hat{e}| < \hat{E}_2, \end{cases}$$
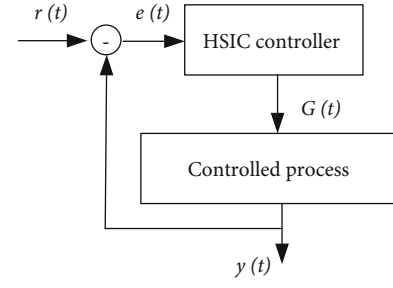
$$(2)$$

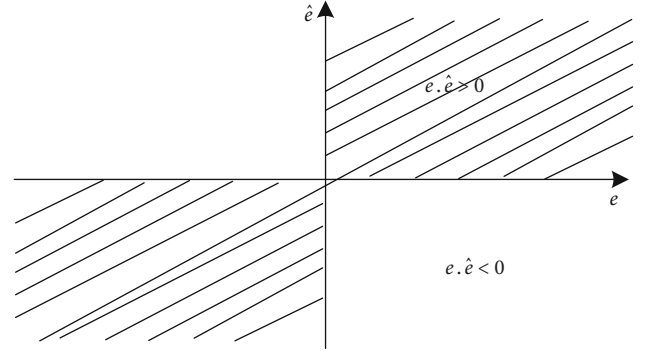FIGURE 3: HSIC control process model.

FIGURE 4: Error phase plane.

where E_1, E_2, E_3, $\hat{E}_1$, and $\hat{E}_2$ are the different characteristic thresholds of process error and its rate of change, respectively. The control parameters to be set are K_{P1}, K_{D1}, K_{P2}, K_{D2}, K_{P3}, and K_{D3}, where g_{n-1} is the output value of the previous control cycle of controller.

4. Intelligent Control Strategy Based on Improved PSO Algorithm

4.1. Standard Particle Swarm Optimization Algorithm. The particle swarm optimization algorithm is an optimization algorithm based on iterative mode. It is a group of m particles flying at a certain speed in the D dimensional search space. When each particle searches, it considers the best historical point it has searched and the historical best point of other particles in the group and changes its position on this basis. The j particle of the particle swarm is composed of 3 H dimensional vectors:

Current position

$$x_j = \left(x_{j1}, x_{j2}, \cdots, x_{jH}\right). \tag{3}$$

Best location in history

$$l_j = \left(l_{j1}, l_{j2}, \cdots, l_{jH}\right). \tag{4}$$

Speed

$$v_j = \left(v_{j1}, v_{j2}, \cdots, v_{jH}\right), \tag{5}$$

where $j = 1, 2, \cdots, m$. Currently, location is regarded as a coordinate describing a point in space. In each iteration of

Parameter meaning:

Initialize the particle swarm, including randomly generating m particles in space R^n; setting: search space dimension n, particle swarm size m, learning factors c_1 and c_2, inertia weight coefficients ω_{max}^0 and ω_{min}^0 and the maximum number of iterations t_{max}. The current number of iterations is 1, the coding method forms a population matrix and a particle velocity change matrix;

Begin
1. For $t=0$, $t=t+1$ Do
2. Update the inertia weight coefficient and calculate the fitness of each particle;
3. Genetic manipulation produces next-generation particles;
4. Update the individual extreme value of particle;
5. Update the global extremum of the population;
6. Generate new populations.
7. End
8. If the set conditions are met, the search will stop and results will be output
End

ALGORITHM 1: Pseudocode of IPSO algorithm.

algorithm, the current position x_j is evaluated as the problem solution. If the current position l_j is better than the historical optimal position, then the current position replaces the vector l_j. In addition, the best position found so far in the entire particle swarm is recorded as the vector $l_b = (l_{b1}, l_{b2}, \cdots, l_{bH})$.

For each particle, the change of its first dimension $(1 \le h \le H)$ is as follows:

$$\begin{cases} v_{jh} = \omega \cdot v_{jh} + c_1 \cdot \text{rand}\,() \cdot (l_{jh} - x_{jh}) + c_2 \cdot \text{rand}\,() \cdot (l_{bh} - x_{jh}), \\ x_{jh} = x_{jh} + v_{jh}, \end{cases}$$

$$\omega = \omega_{max} - \frac{t}{t_{max}}(\omega_{max} - \omega_{min}),$$

(6)

where ω is the inertia weight, ω_{max} and ω_{min} are the maximum and minimum inertia weights, t_{max} is the maximum number of iterations to run, c_1 and c_2 are the learning factors, and rand () is a random function with a value in the range of [0,1]. The particle speed is limited to a range $[V_{max}, V_{min}]$, that is, after the speed update formula is executed, we get the following:

$$\begin{cases} \text{if } v_{jh} < V_{min} \text{ then } v_{jh} = V_{min}, \\ \text{if } v_{jh} > V_{max} \text{ then } v_{jh} = V_{max}. \end{cases}$$

(7)

4.2. Control Parameter Optimization. There are only κ, K_P, K_D, and other control parameters in the above HSIC algorithm. Parameter optimization is relatively simple, and manual tuning can generally be used in engineering based on control experience [29]. However, for multimodal control algorithms, due to the numerous control parameters, it is difficult to tune the optimal control parameters using manual methods. Therefore, it is necessary to study the method of optimization and setting of control parameters [30].

It is due to the fast convergence speed of particle swarm algorithm and the strong generality of algorithm. However, there are also shortcomings such as low search accuracy, premature convergence, and low later iteration efficiency

[31]. To this end, based on genetic ideas, an Improved Particle Swarm Optimization (IPSO) is proposed. The basic idea is as follows: based on genetic algorithm (GA), it is easy to perform cross-mutation operations and improve the search ability in a wide space, so that the global optimal solution can be efficiently searched. In the iterative process, IPSO can increase diversity of particles with the help of genetic crossover operations, thereby speeding up the convergence speed of particles and avoiding the premature phenomenon of local optimum. Moreover, the global and local search capabilities are determined by the inertia weight ω. In order to improve the convergence performance of original algorithm, the inertia weight is realized by a nonlinear decreasing method, and the inertia weight is selected as follows:

$$\omega_i = \left(\omega_{max}^0 - \omega_{min}^0\right) \cdot \left(\frac{t_i}{t_{max}}\right)^2 + \left(\omega_{max}^0 - \omega_{min}^0\right) \cdot \left(\frac{2t_i}{t_{max}}\right) + \omega_{max}^0,$$

(8)

where t_i is the current iteration algebra, respectively; since the inertia weight is changing, ω_{max}^0 and ω_{min}^0, respectively, represent the maximum and minimum values of the initial inertia weight. It can be seen that in the iteration, the inertia weight coefficient appears to be nonlinearly decreasing. Thus, a balanced global and local search capability can be obtained.

In summary, the pseudocode of IPSO algorithm is shown in Algorithm 1.

5. Results

In the experiment, proposed control strategy is researched based on MATLAB simulation platform. The parameter settings of IPSO are as follows: ω_{max}^0 and ω_{min}^0 are 1.4 and 0.5, respectively, the learning factor $c_1 = c_2 = 1.1$, the maximum number of particle swarms is 100, and the maximum number of iterations is 800.

5.1. Parameter Tuning. Compare the two control strategies to determine the optimal strategy parameter settings. The control parameters K_P, K_I, and K_D of control strategy 1
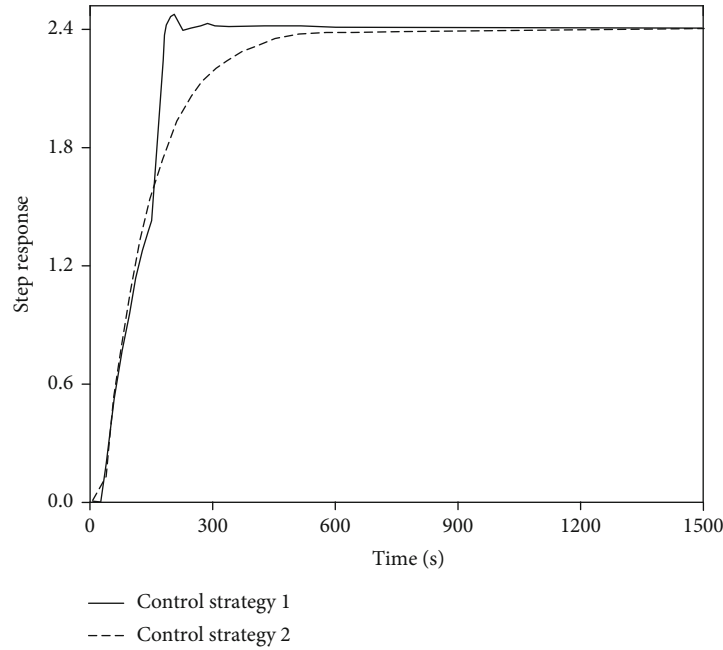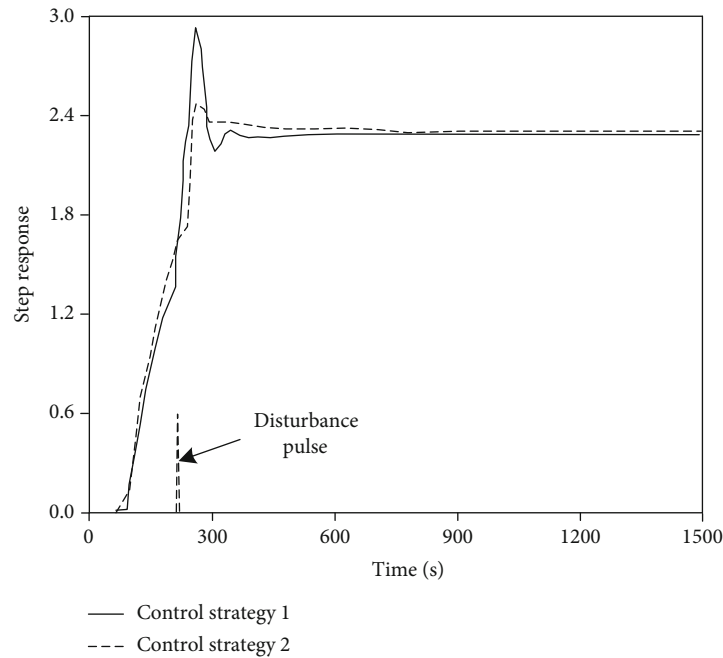
FIGURE 5: Comparison of process response curve.

FIGURE 6: Comparison of response under pulse interfering.

are 0.398, 0.002, and 3.240, respectively; the control parameters K_{P1}, K_{D1}, K_{P2}, K_{D2}, K_{P3}, and K_{D3} of control strategy 2 are 6.340, 8.854, -6.707, 0.148, 26.486, and 3.053, respectively.

The simulation process control uses unit step input. Under the control of the two algorithms, the step response is shown in Figure 5.

It can be seen from Figure 5 that the two control strategies can make the intelligent optimization system of flue gas in municipal solid waste incineration reach a stable state. Among them, control strategy 1 has overshoot and oscilla-

tion, which is not desirable. On the contrary, control strategy 2 does not have overshoot and oscillation, has better control quality, and is obviously more suitable for the application of the treatment process of secondary pollution in the flue gas.

To investigate the influence of external disturbances on the process, we can start from analyzing the anti-interference performance of control strategy. Assuming that the two control strategies both impose a disturbance pulse at $t = 150\,s$, with an amplitude of 0.5 and a width of 10 s, the response curve of process is shown in Figure 6.
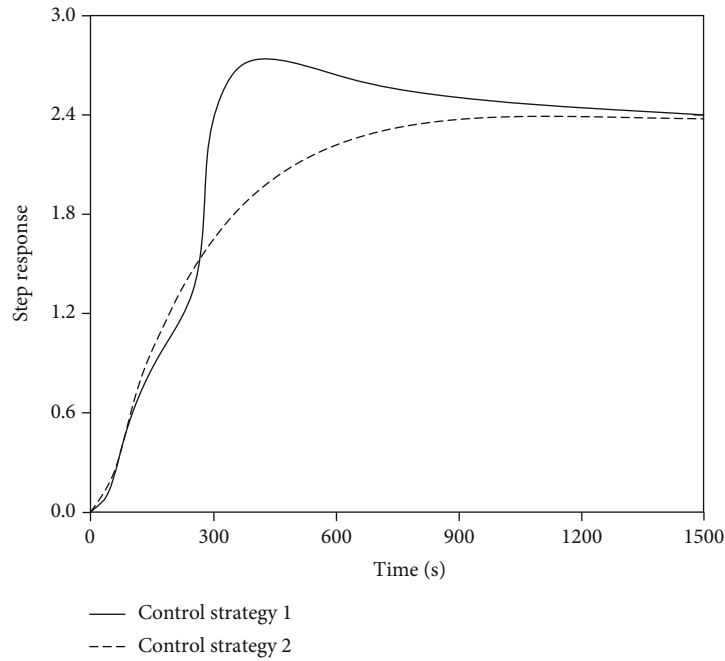
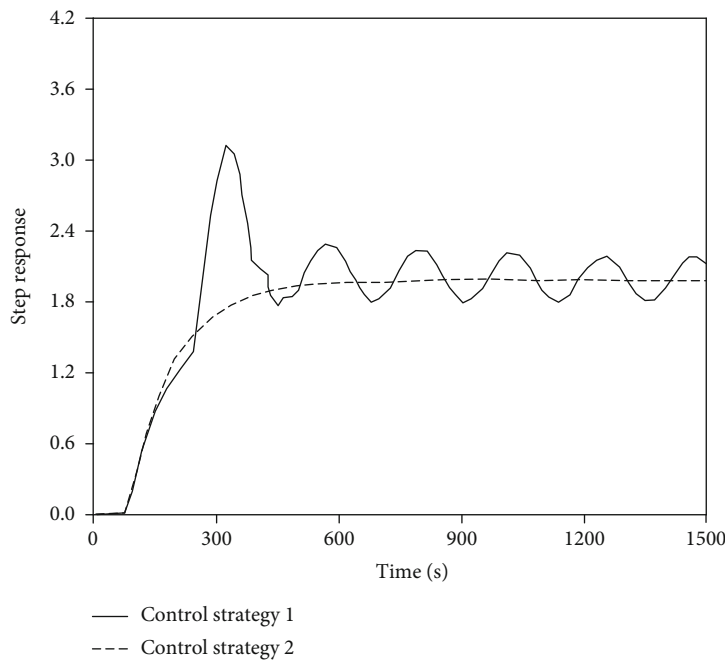FIGURE 7: Comparison of process response at $\tau = 160$ s.

FIGURE 8: Comparison of process response at $\tau = 160$ s.

As can be seen from Figure 6, the simulation response curves of these two control strategies have overshoot. However, the overshoot and oscillation amplitude of control strategy 1 is large, and the oscillation frequency is relatively high. Obviously, the anti-interference performance of control strategy 2 is better. Considering the influence of process internal parameter disturbance on the process, the robustness analysis of control strategy can be carried out. If it is robust, then control strategy 2 is preferable.

When the time constant changes from $T = 75$ s to $T = 160$ s, the step response curve of process is shown in Figure 7.

It can be seen from Figure 7 that the control strategy 1 obviously has a large overshoot, and the adjustment time to reach a steady state is long. Control strategy 2 does not produce overshoot, the process response is very stable, and the control effect on process is obvious. Thus, control strategy 2 exhibits strong robust performance.
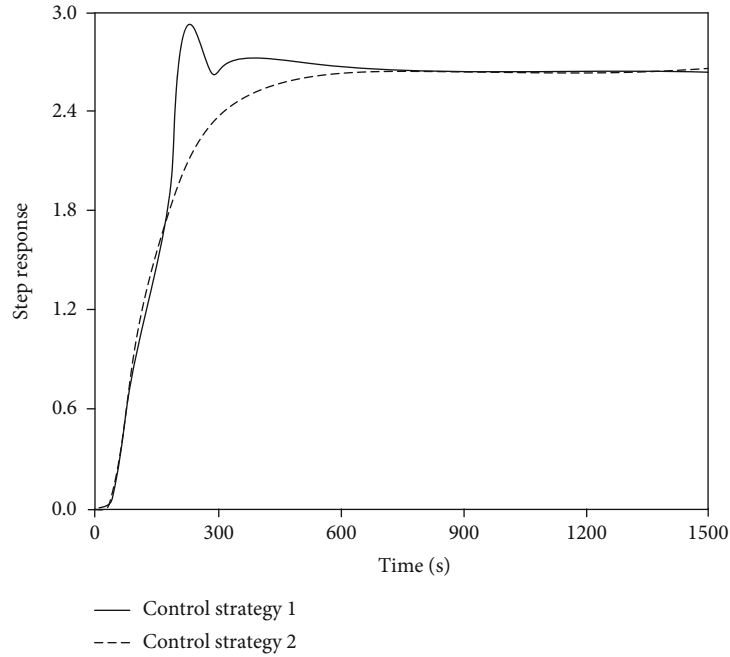
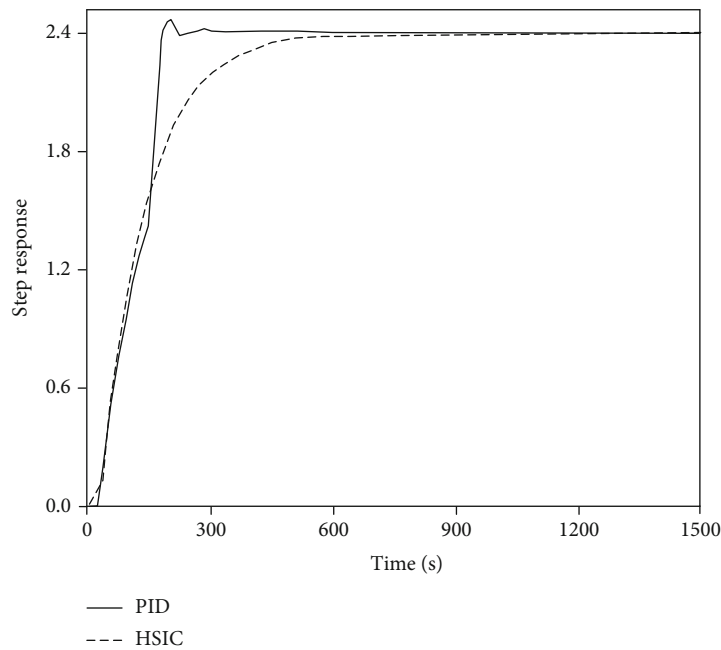FIGURE 9: Comparison of response adding an inertia node.

FIGURE 10: Comparison results of step response curves.

The time delay parameter changes from $\tau = 20$ to $\tau = 60$, and the process response curve is shown in Figure 8.

It can be seen from Figure 8 that the control strategy 1 produces a large overshoot and a strong oscillation. The oscillation frequency is high, and the process cannot reach the desired steady state at all. Therefore, it must not be used for process control in this case. Control strategy 2 has no overshoot, the process response is very stable, and the control effect on the process is obvious. Even when the delay parameter is increased by 3 times, the control strategy 2 still

shows very strong robust performance and excellent control quality. In control engineering, this is very valuable.

When an inertia link is added to the original process model, when the process model becomes $G_1(s) = 7.8125$ $e^{-20s}/(74s + 1)(5s + 1)$, the process response curve is shown in Figure 9.

It can be seen from Figure 9 that the control strategy 2 has better control quality than the control strategy 1, the process response is stable, the response rise time is fast, the adjustment time is short, and the stable state can be reached
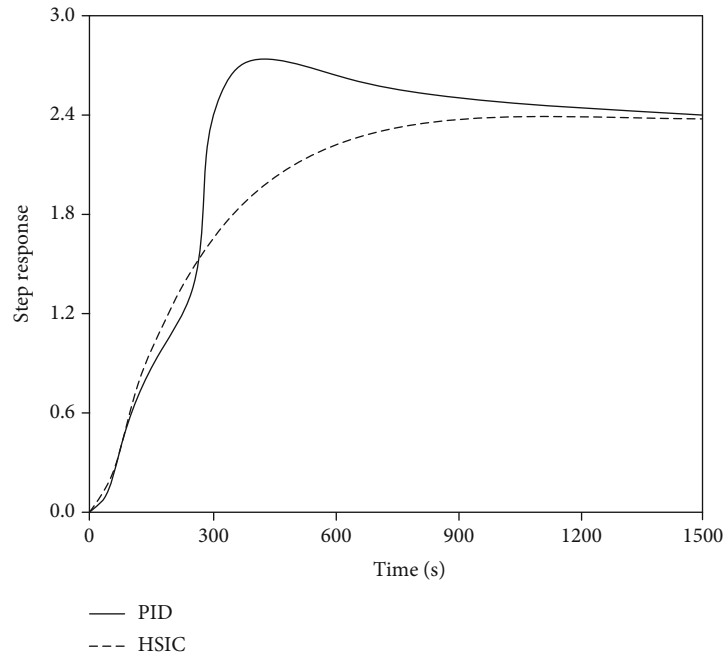
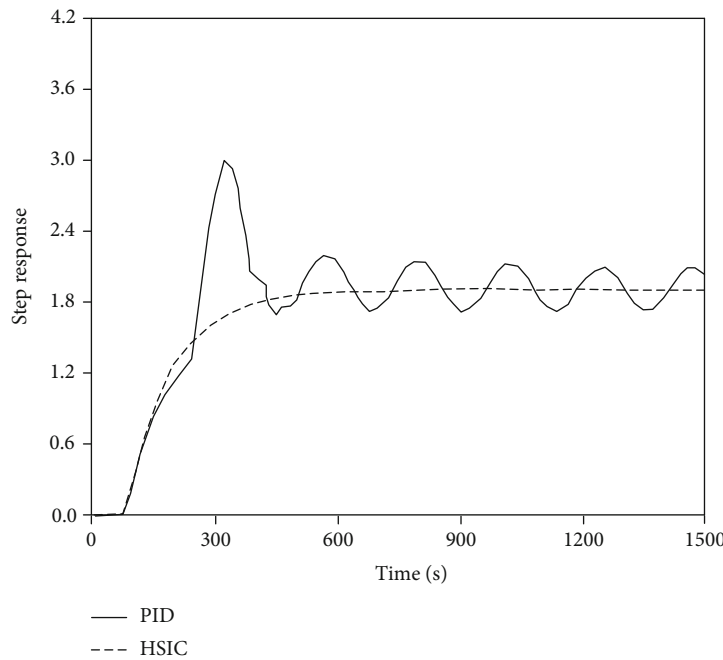FIGURE 11: Comparison results of response with time constant change.

FIGURE 12: Comparison results of process response at $\tau = 50$ s.

relatively quickly. Control strategy 1 produces severe overshoot and oscillation, which is undesirable.

5.2. Comparison with PID Control Algorithm. In order to demonstrate the performance of proposed HSIC control algorithm, it is compared and analyzed with PID control algorithm. It can be determined that the three parameters of PID control algorithm are $K_P = 0.398, K_I = 0.002$, and $K_D = 3.240$; the six parameters of HSIC control algorithm are $K_{P1} = 6.340$, $K_{D1} = 8.854$, $K_{P2} = -6.707$, $K_{D2} = 0.148$, $K_{P3} = 26.486$, and $K_{D3} = 3.053$. In the process, the step response of these two algorithms is shown in Figure 10 under the action of a step excitation with an input amplitude of 3.

It can be seen from Figure 10 that PID control algorithm has overshoot and oscillation. However, the proposed HSIC algorithm does not have oscillation and overshoot. Obviously, HSIC is better than PID control.

Considering the perturbation of internal parameters process, if the time constant changes from $T = 75\,s$ to $T = 160\,s$ and the input amplitude is 3 step response in the process, the process step response curves of these two algorithms are shown in Figure 11.

It can be clearly seen from Figure 11 that PID control algorithm takes a long time to reach a steady state and has a large overshoot. The HSIC control algorithm process response is very stable without overshooting, showing strong robust performance.

When the time delay parameter changes from $\tau = 20$ to $\tau = 60$, the process step response curves of these two algorithms are shown in Figure 12 under the action of a step excitation with an input amplitude of 3 in the process.

It can be seen from Figure 12 that the process step response curve of PID control algorithm produces a large overshoot and a strong oscillation with a high oscillation frequency. It is impossible to control to a stable desired state. The HSIC control process responds very smoothly, and there is no overshoot. The response curve shows that even when the time delay parameter is increased by 3 times, HSIC control still shows strong robustness and excellent control quality.

6. Conclusion

Waste incineration is an ideal method for harmlessness, reduction, and recycling of municipal solid waste, but the temperature control of incineration process is extremely critical. Existing strategies have poor control effects and are prone to secondary pollution of flue gas. Therefore, this paper proposes an intelligent optimization control strategy for secondary pollution of flue gas in municipal solid waste incineration. HSIC algorithm is proposed by combining the control difficulties and cybernetic characteristics of waste incineration. Moreover, IPSO is used to optimize the parameter settings in HSIC algorithm to achieve optimal temperature control during the incineration process and reduce the secondary pollution of flue gas. Experimental demonstration based on MATLAB simulation platform shows that the control performance of proposed strategy is the best when K_{P1}, K_{D1}, K_{P2}, K_{D2}, K_{P3}, and K_{D3} of HSIC algorithm are set to 6.340, 8.854, -6.707, 0.148, 26.486, and 3.053, respectively. Besides, when the delay parameters and time constant change greatly and there is a large disturbance, the process response is fast and stable, which is better than PID control strategy. Thus, it is feasible, reasonable, and usable to use the optimized HSIC algorithm for temperature control in the incineration process.

Domestic awareness and systems regarding waste sorting and disposal are not perfect, and there are many types of waste, which will result in low-quality waste that can be used for incineration. In the next study, a control strategy will be designed for different types of waste to achieve intelligent temperature control, so as to achieve high-quality incineration of waste and ensure that it will not cause secondary pollution.

Data Availability

The data included in this paper are available without any restriction.

Conflicts of Interest

The author declares that there is no conflict of interest regarding the publication of this paper.

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