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Research on thermal performance optimization of regenerative organic waste gas incinerator

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SUMMARY: *Aiming at the problems of temperature oscillation, high exhaust heat loss and insufficient fuel utilization in regenerative organic waste gas incinerator under load fluctuation conditions, a thermal system model was constructed, and an intelligent optimization method of multi-source thermal parameters was proposed, which was compared with PID control on the test platform. The results show that the mean absolute temperature deviation is reduced by 43.8%, the auxiliary fuel flow rate is reduced by 12.6%, the comprehensive thermal efficiency is increased by 4.1 percentage points, and the VOC removal rate is 98.6%. The results show that the proposed method can take into account temperature stability, waste heat recovery and energy consumption control, which provides a new technical path for the efficient operation of regenerative organic waste gas incinerator.*

KEYWORDS: *regenerative organic waste gas incinerator; Thermal performance optimization; Intelligent control; Waste heat recovery*

1 Introduction

The stable operation of the regenerative organic waste gas incinerator depends on the coordination and matching between the temperature field of the combustion chamber, the heat transfer efficiency of the regenerative bed, the fluctuation of the exhaust gas concentration and the switching rhythm of the system. Once the thermal performance is out of balance, it will not only cause the temperature deviation of the furnace, the increase of fuel consumption and the decrease of heat storage efficiency, but also cause the fluctuation of purification efficiency, local overheating and shortening of equipment life. With the increasingly complex composition of industrial waste gas, the operation condition of incinerator has changed from relatively single to multiple disturbance coupling. The traditional control method relying on experience setting and fixed value adjustment has been difficult to adapt to the operation environment of temperature response lag, frequent flow disturbance and nonlinear enhancement of heat recovery link. Focusing on regenerative incineration and waste gas treatment process optimization, Park et al. realized low emission combustion based on high heating device, and verified the engineering feasibility of regenerative heat oxidation equipment in temperature maintenance and waste gas purification [1]. Dal Hwan improved the structure of 100 CMM regenerative thermal oxidation device, which improved the operation stability in the process of volatile organic compounds treatment [2]. Starting from the multi-source waste gas treatment scenario, Han et al. used dynamic cumulative correlation analysis to trace the overheating fault of regenerative thermal oxidation system, indicating that there was a significant time-series coupling relationship between thermal variables [3]. In

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terms of fault diagnosis and operation identification, Han et al. further constructed an uncertain causality diagram model integrating early anomaly detection, which provided a new calculation path for the state monitoring of complex incineration systems [4]. Baskaran et al. discussed the development direction of volatile organic treatment equipment from the perspective of technology integration, and pointed out that heat treatment, catalysis and digital collaboration are becoming an important trend to improve treatment efficiency [5]. Hammerschmid et al. proposed Thermal twin 4.0 digital support tool to combine thermal process modeling and operation optimization, providing digital twin ideas for thermal tuning of hazardous waste incineration equipment [6]. Wajda et al. and Jaworski et al. respectively optimized the energy recovery and operation performance of incineration facilities through special applications, proving that computer-aided decision making has practical value in the efficiency improvement of thermal systems [7, 8]. Lips et al. used Bayesian optimization for closed-loop identification, showing strong data-driven ability in model input selection and structure determination [9]. Adibimanesh et al. applied machine learning to sludge incineration process monitoring and showed that intelligent algorithms could improve the accuracy of energy consumption analysis and condition identification [10].

The existing research has laid a foundation for the thermal efficiency improvement, fault identification and energy recovery optimization of incineration equipment, but there are still two shortcomings. One kind of research focuses on the structural improvement of the device or the analysis of single link heat recovery, and the overall thermal coupling between the regenerator bed, combustion chamber and valve switch is not fully described. Although the other type of research introduces digital tools and intelligent algorithms, it mostly serves for fault early warning or parameter identification, and the research on continuous optimization of thermal performance, dynamic regulation mechanism and control effect comparison is insufficient. Based on this, this paper takes the regenerative organic waste gas incinerator as the object, constructs the thermal system modeling and performance control mechanism, designs an intelligent optimization algorithm for thermal performance improvement based on the fusion of multi-source thermal parameters, and tests its optimization effect in temperature stability, heat recovery efficiency and energy consumption control through the experimental platform. In order to provide a calculable and implementable technical path for the efficient operation of regenerative organic waste gas incinerator.

2 Thermal system modeling and performance control mechanism construction of regenerative organic waste gas incinerator

In order to improve the thermal performance of regenerative organic waste gas incinerators, it is necessary to establish a thermal model that can reflect the combined effects of heat release from combustion, heat transfer from storage, smoke exhaust loss and switching disturbance. This kind of equipment is not a single combustion unit, but a coupling system composed of combustion chamber, thermal storage bed on both sides, switching valve group, air induction system and monitoring and execution module. Once the exhaust gas concentration, inlet temperature, air volume ratio and valve switching cycle change, the temperature field in the furnace and the heat storage and release process of the regenerator bed will be adjusted accordingly, which will affect the heat recovery efficiency, auxiliary fuel consumption and outlet purification stability. Therefore, the modeling of thermal system should not stop at static heat accounting, but turn to the calculation expression oriented to dynamic regulation. Combined with the multi-source monitoring information during the operation of the incinerator, the system status is expressed as follows.

$$x(t)=\left[T_c(t),T_{b1}(t),T_{b2}(t),F_g(t),C_{voc}(t),O_2(t),\tau_s(t)\right]^T \tag{1}$$

where, T_c represents the characteristic temperature of the combustion chamber, T_{b1} and T_{b2} represent the average temperature of the regenerative beds on both sides, F_g is the exhaust gas flow rate, C_{voc} is the concentration of organic matter, O_2 is the oxygen content, and τ_s is the valve switching time. The state vector not only retains the core variables of the thermal process, but also provides a uniform interface for subsequent data fusion, state recognition and control output on the computer side.

The heat input of the incinerator mainly comes from the oxidation heat of the combustible components in the exhaust gas and the compensation heat of the auxiliary fuel. After considering the sensible heat contribution of exhaust gas, the total heat input of the system per unit time can be written as follows.

$$Q_{in}=F_g\rho_g c_{pg}(T_{in}-T_0)+\eta_v F_g C_{voc}H_{voc}+\eta_f m_f H_f \tag{2}$$

Among them, pg is the exhaust gas density, c_{pg} is the specific heat capacity of exhaust gas at constant pressure, T_{in} is the inlet exhaust gas temperature, T_0 is the environmental reference temperature, η_v is the effective combustion coefficient of organic components, H_{voc} is the converted heat value of volatile organic compounds per unit concentration, η_f、m_f and H_f represent the auxiliary fuel utilization coefficient, injection mass flow rate and low temperature heat value, respectively. This expression shows that the heat release capacity of the system is not simply determined by the burner, and the load fluctuation of the exhaust gas itself also directly changes the heat balance in the furnace.

The regenerative bed undertakes two tasks: waste heat recovery of high temperature flue gas and preheating of low temperature exhaust gas, and its heat exchange state determines the thermal efficiency level of the system. Considering the average temperature change of the bed and the gas-solid heat transfer process, the heat storage and release rate of the regenerator bed can be expressed as follows.

$$Q_{reg}=k_r A_r(T_c-T_b)-M_b c_b\frac{dT_b}{dt} \tag{3}$$

where, k_r is the equivalent heat transfer coefficient, A_r is the effective heat transfer area of the heat storage bed, T_b is the average temperature of the current heat transfer bed, M_b and c_b are the mass and specific heat capacity of the heat storage medium respectively. Equation (3) shows that the regenerator bed is not a passive heat absorber, and its temperature rise rate is closely related to the current temperature difference, medium heat capacity and switching time. When the switching period is not set properly, the bed will not fully release or absorb heat before entering the next stage, and the heat will be weakened in the reciprocating flow, resulting in outlet temperature fluctuations and decreased energy utilization. In addition to heat storage and utilization, the system also has smoke loss and furnace surface heat dissipation. For the convenience of unified analysis, the main heat loss is approximately written as follows.

$$Q_{loss}=F_{ex}\rho_{ex}c_{pex}(T_{ex}-T_0)+U_w A_w(T_c-T_a) \tag{4}$$

where, F_{ex} is the exhaust flow rate, ρ_{ex} and c_{pex} are the density of flue gas and the specific heat capacity at constant pressure respectively, T_{ex} is the exhaust temperature, U_w is the total heat transfer coefficient of the furnace wall, A_w is the heat dissipation area of the furnace body, T_a is the ambient temperature. If the exhaust temperature is too high for a long time, it means that the recovery of high temperature flue gas is insufficient in the regenerative bed. If the furnace wall loss continues to expand, it often means that the furnace temperature control overshot, the deterioration of the insulation state or the uneven distribution of the local flow field. On this basis, the temperature of the combustion chamber can be dynamically written into the equivalent energy balance form:

$$C_{eq}\frac{dT_c}{dt}=Q_{in}+Q_{reg}-Q_{loss}-Q_{sw} \tag{5}$$

where, C_{eq} is the equivalent heat capacity of the system and Q_{sw} represents the additional heating disturbance caused by valve switching, flow reversal and short-time mixing. This equation reflects that the combustion chamber temperature is not the result of unidirectional rise and fall, but a dynamic response process shaped by input heat, heat storage feedback, various loss terms and switching disturbances. Because of this, the empirical fixed value control is often difficult to take into account the temperature stability and energy saving requirements: when the controller is only adjusted around a single point temperature, the state and switching effects of the regenerator bed are often ignored, and the system is prone to the phenomenon of "temperature reaches the target but energy consumption is high" or "temperature oscillation after fuel reduction".

Based on the above model, this paper further constructs the regulation mechanism for thermal performance improvement. The core idea is not to impose rigid constraints on a single temperature variable, but to send the temperature, flow, concentration, oxygen content and switching state to the state estimation module in real time under the collaborative architecture of industrial computer and PLC, forming a closed-loop link of "perception, modeling, evaluation and adjustment". Its modeling and regulation relationship is shown in Figure 1.

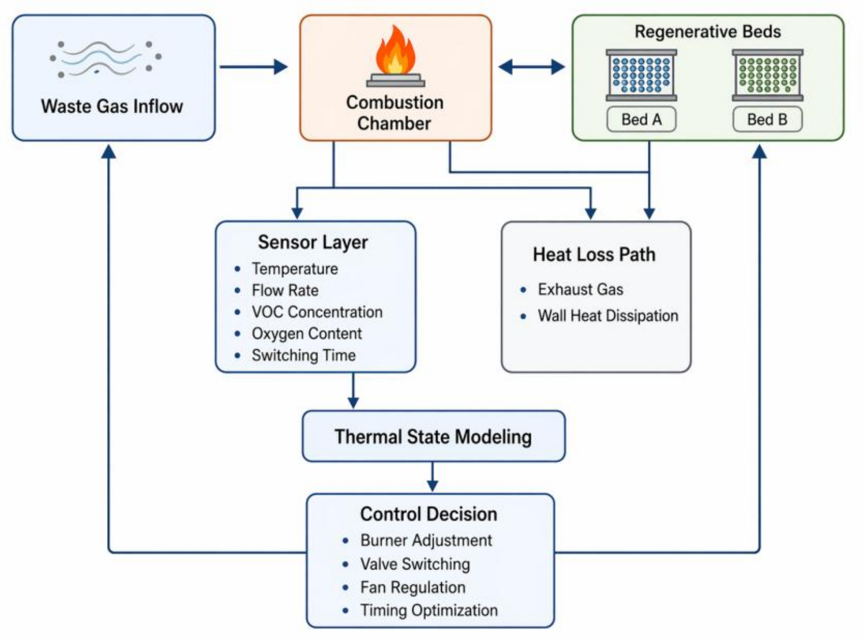

Figure 1: Framework of thermal system modeling and performance regulation mechanism for regenerative organic waste gas incinerator

In order to truly transform the thermal model into an executable regulation basis, this paper sets up a comprehensive performance index:

$$J=\omega_1\left|T_c-T^*\right|+\omega_2(T_{ex}-T_{ex}^*)^2+\omega_3 m_f+\omega_4\sigma_T \tag{6}$$

Here, T^* is the target combustion temperature, T_{ex}^* is the expected exhaust temperature, m_f represents the auxiliary fuel consumption intensity, σT represents the standard deviation of the combustion chamber temperature fluctuation in a period of operation window, and ω_1~ω_4 are the weight coefficients. The index integrates temperature control, waste heat utilization, fuel economy and operation stability into the same evaluation framework, which can avoid the deviation caused by too single control target.

The resulting performance regulation mechanism has two meanings. One is the coupling of heat conservation and heat transfer at the mechanism level, which explains why the system heats up, drops down and where heat loss occurs. The other layer is the state recognition and control mapping of the calculation level, which is used to determine when to adjust the burner load, when to correct the valve switching time, and when to change the air inlet intensity. After the combination of the two, the operation process of regenerative organic waste gas incinerator is no longer a passive response relying on artificial experience, but can be transformed into a dynamic optimization process supported by data-driven and constrained by thermal mechanism, which also lays a clear model foundation for subsequent intelligent optimization algorithm design.

3 Intelligent optimization algorithm design of regenerative organic waste gas incinerator for thermal performance improvement

3.1 Multi-source thermal parameter fusion and feature expression

The intelligent optimization for thermal performance improvement of regenerative organic waste gas incinerator is not only a single variable correction of the temperature at a certain measurement point, but also needs to incorporate the combustion chamber, regenerative bed, smoke exhaust channel and intake side into a unified parameter expression framework. During the operation of the incinerator, there is an obvious sequential linkage relationship between the furnace temperature, bed temperature difference, inlet exhaust gas concentration, oxygen content, air intake, valve switching time and exhaust temperature. If the control is only based on a single temperature value, it is easy to ignore the information such as heat transfer lag, residual heat storage state and load fluctuation accumulation, which makes the controller appear high energy consumption or temperature swing back when the local standard is reached. Therefore, before the intelligent optimization algorithm enters the regulation decision, it is necessary to complete the fusion and feature expression of multi-source thermal parameters, and convert the discrete monitoring quantities into state characteristics that can be calculated, comparable, and input to the model.

Combined with the online monitoring structure of the incinerator, this paper selects the temperature of the combustion chamber T_c, the temperature of the regenerative bed A T_{bA}, the temperature of the regenerative bed B T_{bB}, the exhaust temperature T_{ex}, the exhaust gas flow F_g, the organic matter concentration C_{voc}, the oxygen content O_2 and the valve switching cycle τ_s as the basic input quantities, and constitutes the original parameter vector:

$$p(t)=\left[T_c,T_{bA},T_{bB},T_{ex},F_g,C_{voc},O_2,\tau_s\right]^T \tag{7}$$

Due to the obvious differences in dimension, amplitude range and fluctuation frequency of each variable, it is easy to cause excessive dominance of high-magnitude variables on the results if they are directly input into the optimization model. To this end, this paper uses standardization processing to map each parameter to a unified scale, and its expression is as follows.

$$p_i(t)=\frac{p_i(t)-\mu_i}{\sigma_i} \tag{8}$$

Here, μ_i and σ_i represent the mean and standard deviation of the ith thermal parameter in the training sample window, respectively. After standardization, monitoring data from different sources can be compared in a unified numerical space, which provides a basis for subsequent feature fusion.

Static values alone are not sufficient to characterize the thermal behavior of the incinerator. The prominent feature of the regenerative system is "state migration with time", and the corresponding operation meaning of the same temperature level in the heating stage and cooling stage is not the same. Therefore, this paper further introduces the parameter change rate to characterize the short-term dynamics, which is defined as follows:

$$v_i(t)=\frac{p_i(t)-p_i(t-\Delta t)}{\Delta t} \tag{9}$$

where, $v_i(t)$ represents the change rate of the ith parameter between adjacent sampling moments. This quantity can reflect the heating speed of the combustion chamber, the falling trend of the exhaust temperature and the disturbance intensity of the exhaust gas concentration, so as to make up for the shortage of the observation value at a single time in trend identification.

Considering that the thermal performance of the incinerator is not only determined by a single variable, but also affected by the cross-variable coupling relationship, this paper further constructs the thermal correlation feature. In order to highlight the heat matching state between the furnace and the regenerative bed, the temperature difference coupling index and combustion matching index are defined as follows.

$$r_1(t)=T_c-\frac{T_{bA}+T_{bB}}{2},r_2(t)=\frac{C_{voc}\cdot F_g}{O_2+\varepsilon} \tag{10}$$

$r_1(t)$ is used to measure the deviation degree between the average heat potential of the combustion chamber and the regenerative bed. A large value usually means inadequate heat recovery or unbalanced switching rhythm. $r_2(t)$ describes the exhaust gas heat load intensity under the condition of unit oxygen supply, which can more directly reflect the coordination between combustion load and oxygen supply state, and ε is a minimal constant set to prevent the denominator from being zero. Compared to the original variables, this type of constructed features are closer to the thermal relationships that control decisions really care about.After extracting standardized features, dynamic features and correlation features, we concatenate them to form a multi-source fusion input vector:

$$f(t)=[\hat{p}(t),v(t),r_1(t),r_2(t)] \tag{11}$$

The vector not only retains the thermal state of the system at the current time, but also contains the short-term change direction and key coupling information, which can be directly used as the input of the subsequent adaptive thermal regulation module. For the implementation of industrial computer, this expression has two advantages. One is that it is easy to form continuous sample sequence through the data buffer window to improve the recognition ability of the algorithm for fluctuation conditions. Secondly, the features can be added, deleted or extended according to different working conditions to maintain the openness and engineering adaptability of the model interface. In order to make the parameter fusion process clearer, this paper summarizes the multi-source thermal parameter fusion and feature expression process as Figure 2.

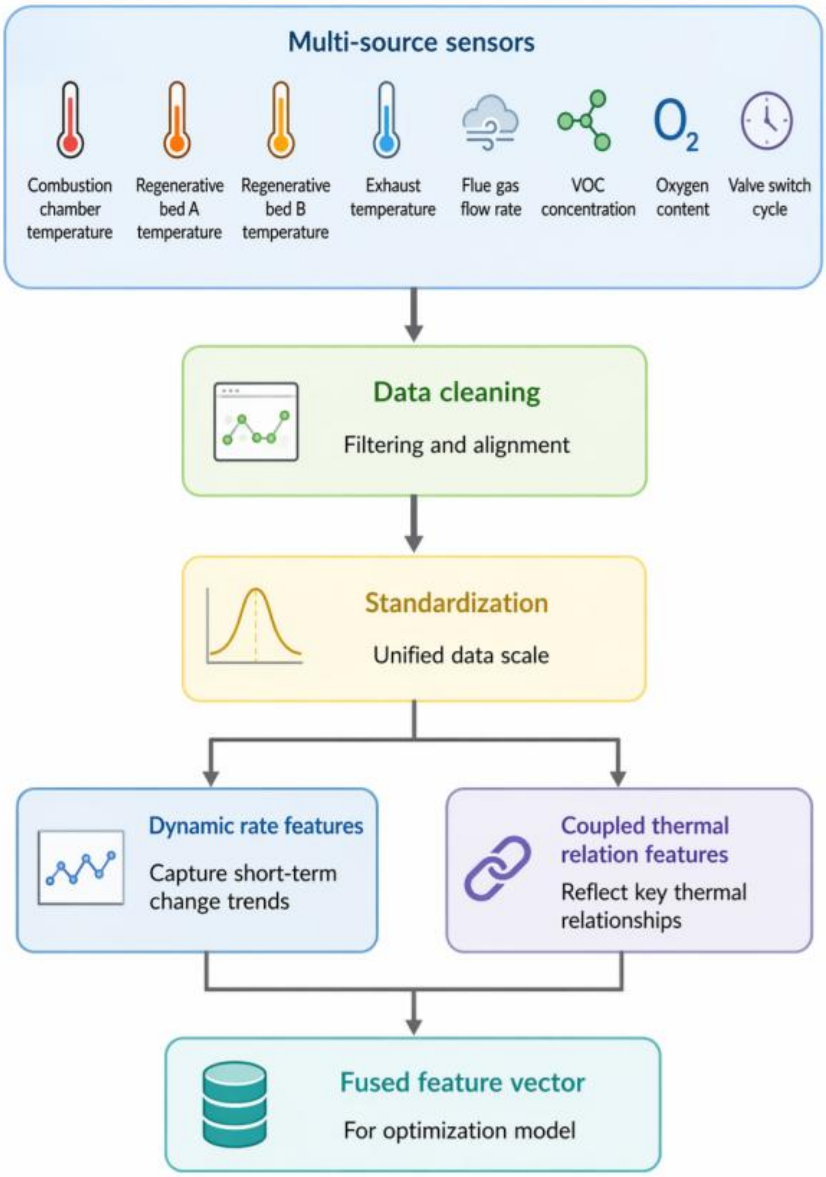

Figure 2: Process of multi-source thermal parameter fusion and feature expression

3.2 Adaptive thermal regulation mechanism

After the multi-source thermal parameter fusion and feature expression, the key of the algorithm design is no longer to simply identify the thermal state of the system, but to modify the control quantity in real time according to the state change results, so that the combustion temperature, heat storage and recovery efficiency and energy consumption level are kept in a relatively coordinated interval. The operation process of regenerative organic waste gas incinerator has obvious nonlinear and time-varying characteristics. On the one hand, the fluctuation of exhaust gas concentration and flow will directly change the heat load of the furnace. On the other hand, the valve switching and the residual heat storage and release of the regenerator bed will make the temperature response lag and inertia. If the controller still adopts the fixed parameter strategy, it can only maintain the temperature stability under local working conditions. Once the load disturbance is enhanced, it is prone to problems such as temperature overshoot, high exhaust waste heat and excessive auxiliary fuel compensation. Therefore, it is necessary to construct an adaptive thermal regulation mechanism that can be dynamically modified with the change of operating conditions. In this paper, the regulation objective is defined as the minimization of the comprehensive performance deviation within a given time window, and its performance index is written as follows.

$$J_t=\lambda_1(T_c(t)-T_c^{ref})^2+\lambda_2(T_{ex}(t)-T_{ex}^{ref})^2+\lambda_3 m_f^2(t)+\lambda_4(\tau_s(t)-\tau_s^{ref})^2 \tag{12}$$

where, T_c^{ref} is the target combustion chamber temperature, T_{ex}^{ref} is the expected exhaust temperature, $m_f(t)$ is the current auxiliary fuel injection amount, τ_s^{ref} is the target switching period, and λ_1~λ_4 is the weight coefficient. The index does not regard the temperature standard as the only goal, but takes the exhaust heat loss, fuel consumption and switching stability into the evaluation at the same time, so that the control results are more in line with the actual needs of incinerator thermal optimization. In the control input design, the burner opening, the induced draft fan adjustment and the switching cycle correction are uniformly expressed as control vectors:

$$u(t)=[u_b(t),u_a(t),u_s(t)]^T \tag{13}$$

Among them, $u_b(t)$ represents the combustion compensation control quantity, $u_a(t)$ represents the cooperative adjustment quantity of air and suction air, and $u_s(t)$ represents the correction quantity of valve switching cycle. Considering the existence of time-varying disturbances and model mismatch in the incinerator, this paper does not adopt a fixed mapping relationship, but introduces a parameter self-updating mechanism, so that the controller can correct the control gain according to the real-time error. Let the regulation parameter vector be $\theta(t)$, then its online update rule is written as follows.

$$\theta(t+1)=\theta(t)-\eta\nabla_\theta J_t \tag{14}$$

where η is the learning step and $\nabla_\theta J_t$ is the gradient of the performance index with respect to the regulation parameter. The meaning of this update method is that when the system temperature is high, the smoke exhaust loss is increased or the fuel consumption is abnormal, the control parameters will be gradually modified along the direction of reducing the comprehensive cost, so as to enhance the adaptability of the control strategy to the change of working conditions.

In order to avoid the controller overreacting only based on the instantaneous error, this paper further introduces a disturbance compensation term to feedforward correct the fluctuation of the exhaust gas concentration and the change of the inlet heat load. The control output is expressed as follows.

$$u(t)=K(t)f(t)+D(t)w(t) \tag{15}$$

Here, f(t) is the fusion feature vector obtained in Section 3.1, K(t) is the adaptive feedback gain matrix, w(t) is the disturbance vector composed of inlet concentration, flow rate and oxygen content, and D(t) is the feedforward compensation matrix. In this way, the controller can not only implement feedback correction according to the current thermal state, but also respond to the upcoming thermal load change in advance. As shown in Figure 3, after the input of multi-source thermal characteristics, the system first completes the performance evaluation and parameter update, and then acts the adjustment results on the burner, fan and switch valve, and then continues the feedback correction according to the thermal response of the incinerator, forming a continuous closed-loop adaptive regulation process.

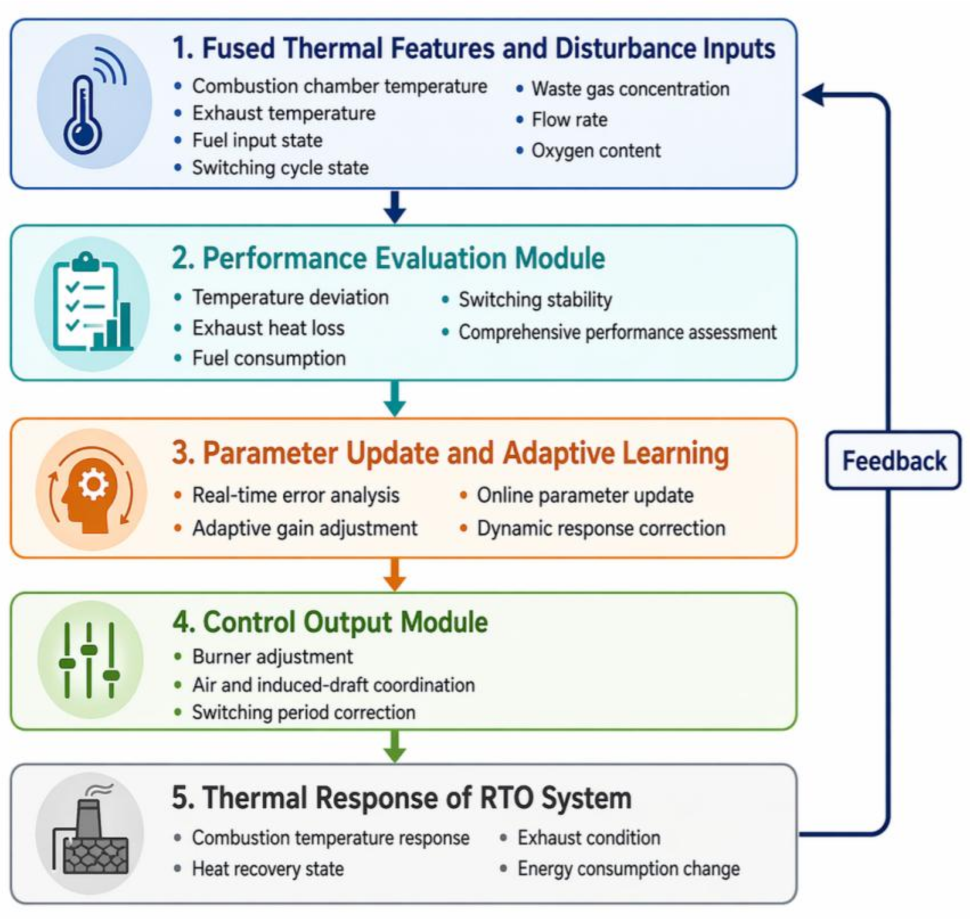

Figure 3: Schematic representation of the adaptive thermal regulation mechanism structure

3.3 Implementation of optimization algorithm flow and structure

After the fusion of multi-source thermal parameters and the construction of adaptive thermal regulation mechanism, the focus of the optimization algorithm turns to how to organize state recognition, rule inference, control generation and online correction into a continuous calculation process. Regenerative organic waste gas incinerator is not a static equipment, and the exhaust gas concentration, flow load, heat storage state of the regenerative bed and valve switching rhythm will change with time. Therefore, the algorithm structure cannot stay at the single-step discrimination level, and should form a cyclic link of "input update - rule activation - control synthesis - execution feedback - online correction". Only in this way, the system can continuously output regulation commands that match the thermal state under different working conditions. In this paper, the continuous observation features at time t are organized into a state window of length L, denoted as follows.

$$S_t=[f(t-L+1),f(t-L+2),\ldots,f(t)] \tag{16}$$

where, f(t) is the fused feature vector obtained in Section 3.1. The function of window processing is to retain the short-term evolution trajectory of the thermal state, instead of making a judgment only based on a single sampling point. Due to the obvious lag of the incinerator thermal response, whether the current temperature needs to be corrected is often related to the concentration disturbance, smoke exhaust change and temperature difference of the regenerator bed in the previous stage. Therefore, the use of state window is more conducive to the algorithm to identify the real trend of the system.

In the rule inference stage, the corresponding control rule center c_j is configured for each type of typical thermal state, and the activation strength is determined according to the distance between the current window state and the rule center, which is expressed as follows.

$$\alpha_j(t)=\frac{\exp\left(-\frac{\|S_t-c_j\|^2}{2\sigma_j^2}\right)}{\sum_{m=1}^{M}\exp\left(-\frac{\|S_t-c_m\|^2}{2\sigma_m^2}\right)} \tag{17}$$

Here, $\alpha_j(t)$ is the activation weight of the JTH rule at time t, σ_j is the parameter of the scope of the rule, and M is the total number of rules. The method does not use the rigid decision of "satisfied or not satisfied", but assigns different influence weights to multiple rules according to the similarity degree of the state, so that the algorithm can adapt to the continuous change characteristics of the incinerator under transition conditions.

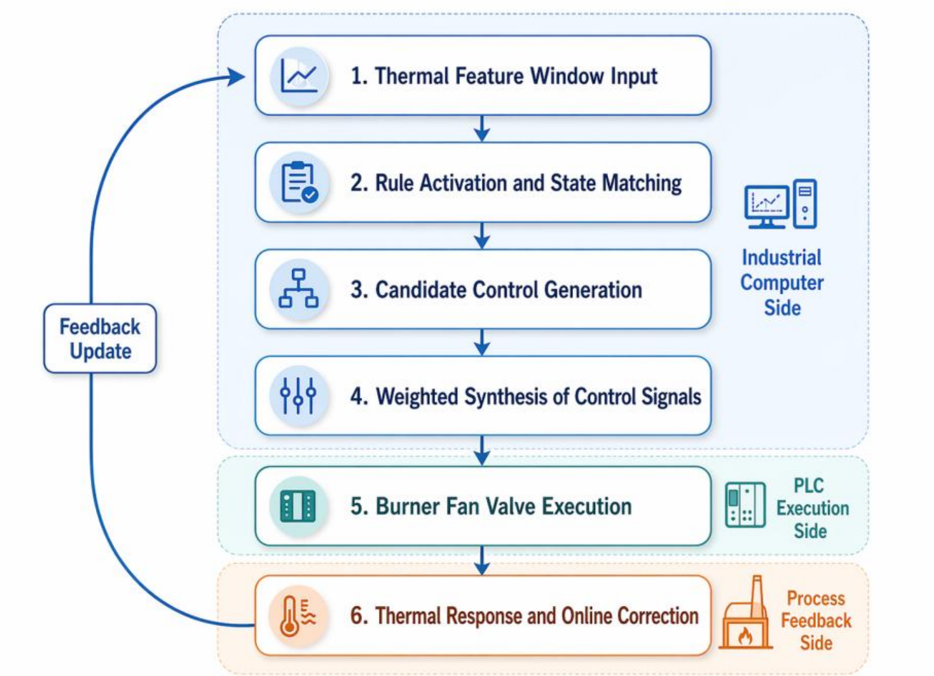

Figure 4: Implementation of optimization algorithm flow and structure

As shown in Figure 4, when the algorithm runs, the control result is not directly output by a single rule, but after the input of the state window, the rule activation and candidate control generation are completed first, and then the execution instructions are obtained through weighted synthesis, and the system feedback is sent back to the parameter update module. In this way, the continuity of control decisions can be maintained, and the abrupt regulation dominated by a single rule can be avoided. Let the candidate control vector corresponding to rule j be $u_j(t)$, then the synthesis control output can be expressed as follows.

$$u^*(t)=\sum_{j=1}^{M}\alpha_j(t)u_j(t) \tag{18}$$

where, $u^*(t)$ contains three components: combustion compensation, air volume adjustment and switching cycle correction. The result obtained after weighted synthesis can integrate the local judgment of multiple rules, and is more suitable for dealing with the complex state of the incinerator under the condition of concentration fluctuation, temperature backswing and alternating commutation of the regenerative bed. Considering that the execution of industrial control still needs to meet the requirements of stationarity and safety boundary, this paper further applies smoothness constraints and interval restrictions to output instructions, and its execution control quantity is written as follows.

$$u(t)=\mathrm{clip}(\rho u(t-1)+(1-\rho)u^*(t),\ u_{min},u_{max}) \tag{19}$$

where ρ is the smoothing factor, u_{min} and u_{max} are the minimum and maximum control bounds allowed by the device, respectively, and clip($\cdot$) is used to restrict the result to the executable interval. After this process, the controller will not produce too large command transitions due to sharp fluctuations in input at a certain time, so as to avoid additional impact on the equipment caused by frequent adjustment of the burner, excessive response of the fan or sudden shortening of the switching period.

From the view of structure realization, the optimization algorithm is composed of state calculation module, rule inference module, control synthesis module and PLC execution module. The industrial computer is responsible for receiving real-time data such as temperature, flow rate, concentration, oxygen content and valve status, and completes the update of characteristic window and the calculation of control quantity. PLC drives the burner, induced draft fan and switching valve group according to the output command, and feeds back the thermal response to the algorithm module. The operation link formed in this way makes the thermal regulation of regenerative organic waste gas incinerator no longer rely on static experience, but can realize the integration of state recognition, control generation and structural correction in continuous feedback. Through this process, the algorithm not only has the dynamic adaptation ability under thermal disturbance, but also provides a complete implementation basis for the subsequent experimental comparison to verify its temperature stability, heat recovery performance and energy consumption control effect.

4 Thermal performance optimization experiment and test analysis

4.1 Experimental platform and parameter setting

In order to test the actual effect of the proposed intelligent optimization algorithm in the thermal performance adjustment of regenerative organic waste gas incinerator, a small experimental platform is built and continuous operation tests are carried out under controllable disturbance conditions. The purpose of the experiment is not limited to whether the furnace temperature reaches the set value, but to evaluate the combustion stability, heat storage and recovery status, smoke exhaust temperature change and auxiliary fuel consumption level synchronously, and compare the method in this paper with the conventional PID control strategy. The experimental platform is composed of incinerator body, temperature and flow monitoring unit, gas concentration detection unit, industrial computer, PLC controller and actuator. The industrial computer is responsible for deploying the thermal optimization algorithm proposed in this paper, receiving the data of each measurement point in real time and outputting the adjustment instructions. The PLC is responsible for the low-level execution of the burner opening, air inlet frequency and switching valve action to ensure the continuity and repeatability of the control link.

The experimental object is a set of double regenerative bed organic waste gas incinerator test equipment, the upper limit of the combustion chamber design temperature is 900 °C, and the rated treatment air volume is 3000 m^3/h. In order to ensure the integrity of the thermal state identification, K-type thermocouples are arranged in the center of the combustion chamber, the upper and middle of the thermal storage bed on both sides, the air intake and the smoke exhaust, and the VOC concentration analyzer, oxygen content sensor, mass flow meter and valve position feedback module are equipped. The data acquisition and control program was developed using Python 3.11, running on Ubuntu 22.04 environment, and the core algorithm was deployed on the industrial computer. The sampling period was set to 1 s, and the control refresh period was set to 2 s. The PID parameters of the control group were set as K_p=3.8、K_i=0.42、K_d=11.6 according to the pre-experiment tuning results, and the integral limiting mechanism was added to avoid cumulative saturation under high temperature conditions. See Table 1 for the composition of the experimental platform.

Table 1: Composition and configuration of the experimental platform

Module Category	Main Equipment or Software	Function Description	Key Parameters
RTO furnace body	Dual-regenerative-bed RTO experimental device	Completes waste gas preheating, oxidation combustion, and waste heat recovery	Rated air volume: 3000 m^3/h; maximum design temperature: 900 ℃
Combustion execution unit	Gas burner, regulating valve set	Provides auxiliary heat and performs load regulation	Combustion power: 80–180 kW
Ventilation execution unit	Induced draft fan, frequency converter	Regulates waste gas transport and the negative pressure state inside the furnace	Frequency range: 20–50 Hz
Switching execution unit	Pneumatic switching valve	Controls the alternating operation of the regenerative beds on both sides	Adjustable switching cycle: 30–90 s
Temperature monitoring unit	K-type thermocouple	Monitors the temperatures of the combustion chamber, regenerative bed, inlet and outlet, and exhaust gas	Accuracy: ±1.5 ℃
Gas detection unit	VOC analyzer, oxygen content sensor	Acquires inlet concentration and excess air status	VOC range: 0–3000 mg/m^3; O_2 range: 0–25%
Flow monitoring unit	Mass flow meter	Monitors waste gas flow rate and auxiliary fuel flow rate	Accuracy: ±1.0% F.S.
Control and computing platform	Industrial computer, PLC	Realizes algorithm computation, data exchange, and execution control	Ubuntu 22.04; Python 3.11; PLC scan cycle: 100 ms

In order to ensure the validity of the comparison results, all the experiments were started under the same initial conditions: the initial temperature of the combustion chamber was stable at about 760 ℃, the average temperature of the regenerator bed was controlled at about 680 ℃, the exhaust gas temperature at the inlet was 45 ℃, the initial VOC concentration was set at 1200 mg/m³, and the oxygen content was maintained at about 8.5%. On this basis, load disturbances are constructed by changing the exhaust gas concentration, inlet flow rate and switching period to investigate the thermal response ability of the control strategy under continuous fluctuation conditions. The test is divided into stable condition test and disturbance condition test. The stable condition test is used to compare the steady-state temperature deviation and average energy consumption of different control methods. In the case of disturbance, step disturbance and periodic disturbance are used to test the adaptability of the controller to sudden load and fluctuating load. To avoid the contingency of a single experiment, each set of conditions was run continuously for 120 min, the test was repeated three times, and the average value was taken as the final result. See Table 2 for the specific parameter Settings.

Table 2: Experimental operation parameters and disturbance Settings

Parameter Category	Setting Content	Value Range or Condition
Target combustion chamber temperature	Temperature control target	780 ℃
Initial average temperature of the regenerative bed	Stable state before start-up	670–690 ℃
Inlet exhaust gas temperature	Initial test condition	40–50 ℃
Initial VOC test condition		40–50 ℃
Initial VOC concentration	Baseline load	1200 mg/m³
VOC disturbance range	Step-change and fluctuation test	800–2000 mg/m³
Exhaust gas flow rate range	Operating condition switching test	2200–3200 m³/h
Oxygen content control range	Oxygen supply regulation condition	7.5%–10.5%
Valve switching cycle	Alternating time of the regenerative bed	30 s, 45 s, 60 s, 75 s, 90 s
Sampling cycle	Sensor data acquisition	1 s
Control refresh cycle	Algorithm output update	2 s
Duration of each experiment group	Continuous operating time	120 min
Number of repetitions	Repetitions for each test group	3

The above platform and parameter Settings enable the incinerator to present the typical characteristics of temperature inertia, heat storage delay, load fluctuation and switching disturbance at the same time in the experimental process, thus providing a relatively complete test basis for the data analysis of subsequent thermal operation process and the comparison of optimization results. Such an experimental design also makes the evaluation of the proposed algorithm no longer stop at static set-point tracking, but can more truly reflect its adaptability and stability in complex industrial thermal scenarios.

4.2 Analysis of data fluctuation characteristics in thermal operation process

After the completion of the experimental platform construction and parameter setting, it is necessary to further investigate the thermal fluctuation characteristics of regenerative organic waste gas incinerator under optimal control from the continuous operation data. The improvement of thermal performance is not only reflected in the combustion chamber temperature reaches the set value at a certain time, but also reflected in whether the system can maintain a small amplitude, a faster recovery speed and a smoother control output when the disturbance comes. Based on the test conditions described in Section 4.1, a continuous operating window of 120 min was selected in this paper to track and analyze the combustion chamber temperature, exhaust temperature, temperature difference of the regenerator bed, oxygen content and auxiliary fuel flow, and a representative fluctuation curve was drawn with a 1-min mean sequence.

From the dynamic relationship between the combustion chamber temperature and the target temperature, the optimization algorithm can quickly enter the stable adjustment interval after the end of the initial heating. Figure 5 shows that the system completed the transition from the start-up phase to the steady-state operation phase in the first 12 min, and then the actual temperature of the combustion chamber basically fluctuated around the target value of 780 ℃, and there was no continuous amplification oscillation in the overall trajectory. Around 30 min and 65 min, due to the superposition of inlet concentration disturbance and flow switching, the temperature curve appeared two times more obvious dip, but did not form a long time offset after falling back, and the disturbance around 30 min returned to the range of ±2 ℃ within about 3 min. The recovery time for stronger disturbances around 65 min is also controlled at around 6 min. There is a slight positive uplift around 95 min, which is related to the enhanced short-term residual heat release after the regenerator bed switch, but its peak amplitude is still in the controlled range. According to the statistical results, the average temperature of the combustion chamber in the stable operation stage is 779.9 ℃, the standard deviation is 2.28 ℃, and the peakto-peak value is 11.03 ℃, which indicates that the algorithm has a good buffer ability for heat load fluctuations. Further observation shows that 81.7% of the sample points remain within the range of ±3 ℃, and 95.4% of the sample points fall within the range of ±5 ℃, indicating that the system is in a relatively stable thermal state most of the time, and the prominent deviation is mainly concentrated in a few high disturbance periods.

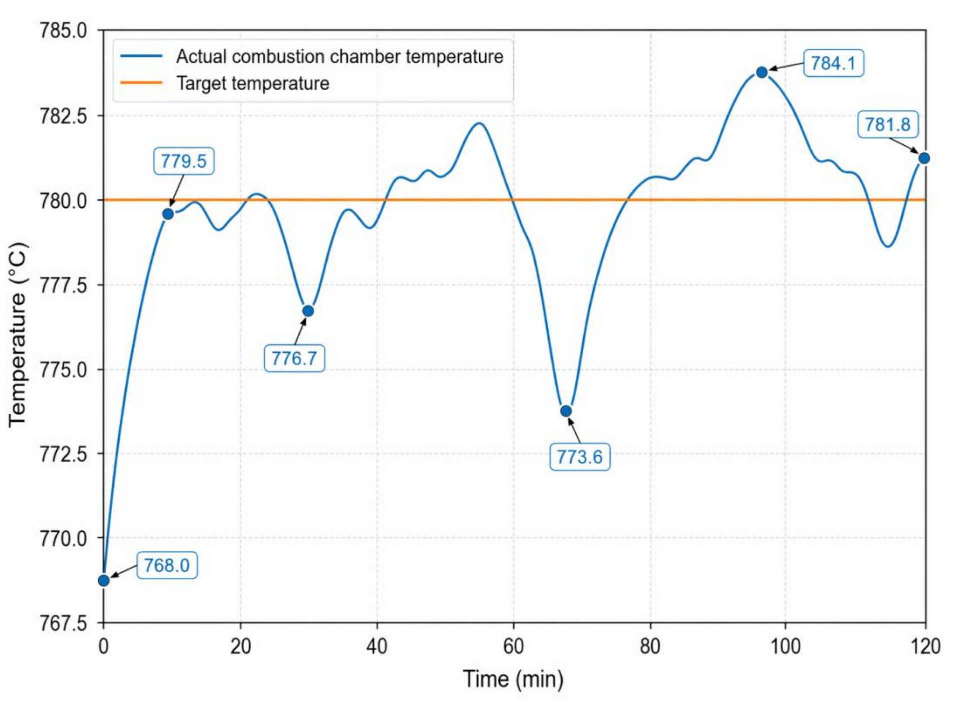

Figure 5: Actual and target temperature tracking curves of the combustion chamber

From the temperature trajectory reflected in Figure 5, it can be seen that the fluctuation of regenerative incinerator is not random, but has obvious characteristics of operating condition triggering. The local temperature drop mainly occurred in the period near the high-concentration exhaust gas input and valve switching, which indicated that the thermal disturbance was not only from the change of inlet heat value, but also affected by the heat release rhythm of the regenerative bed and the flow reversal process. Different from the traditional univariate temperature control, the proposed algorithm does not give a large combustion compensation immediately after the temperature deviation occurs, but combines the oxygen content, the exhaust temperature and the state of the regenerator to make a collaborative correction. Therefore, although the curve falls back, it does not show the phenomenon of sharp rebound after overshoot. In other words, the controller emphasizes the suppression of continuous deviations rather than overresponding to instantaneous fluctuations, which is beneficial to avoid secondary oscillations caused by frequent increases and decreases in auxiliary fuel.

According to the distribution pattern of temperature error, the system error is concentrated around zero, but the distribution is not completely symmetric. Figure 6 shows that the error mainly falls in the range −2 ℃ to 2 ℃, indicating that the optimization algorithm is able to compress the temperature deviation within a small range most of the time. Compared with the ideal fully symmetric distribution, the left tail of the error distribution is slightly longer, indicating that a few large negative deviations do exist, which is consistent with the temperature drop in the stronger disturbance phase around 65 min. At the same time, the proportion of positive error samples is about 55.0%, indicating that the system still maintains slightly high operation in most periods. This strategy is reasonable for the organic waste gas incineration device, because the temperature slightly higher than the target value is more conducive to the stable oxidation and decomposition process. However, from the mean value, the average error is only −0.09 ℃, indicating that the positive overestimation is not continuously amplified, but is pulled back to the level closer to zero in the stage of negative large disturbance. On the whole, the error distribution shows the characteristics of "concentrated in the center and limited extension in the tail", and there is no large-area discrete expansion, which reflects that although the system is affected by the disturbance of the working condition, the control stability remains within an acceptable range.

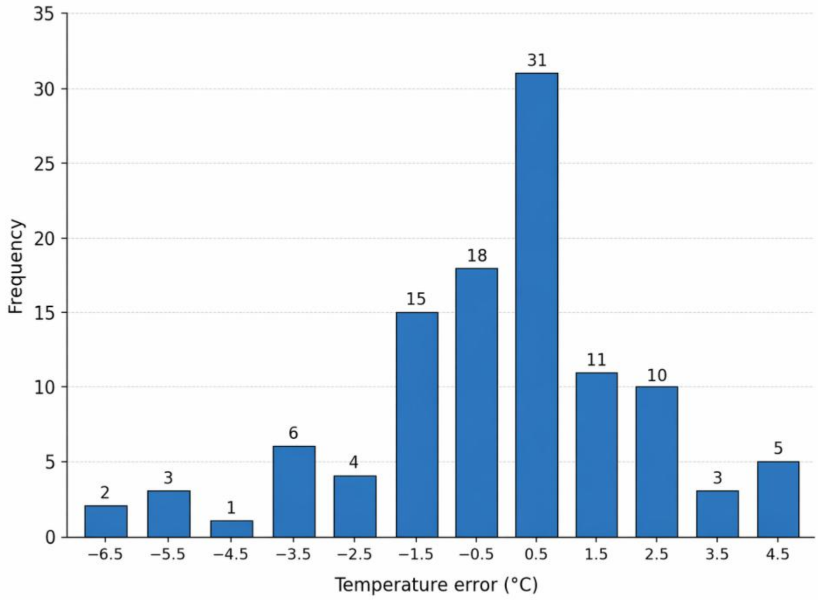

Figure 6: Temperature error distribution diagram of the combustion chamber

Figure 6 also shows that the main problem of the system is not that the steady-state error is too large, but that there is still a short-time compensation lag in the individual burst conditions. When the high-concentration exhaust gas input is superimposed with the switching action, the support of the heat release of the regenerative bed to the combustion chamber will be transiently reduced. In order to avoid increasing the combustion compensation too quickly, the controller often first uses the matching of air volume and oxygen supply to suppress, and then gradually increases the combustion input, so the negative error tail will be slightly longer than the positive error tail. This indicates that the current algorithm adopts a somewhat robust trade-off between stability and response speed, which has the advantage of reducing overshoot and fuel waste at the expense of slightly deeper temperature valleys under strong disturbance conditions. In terms of the thermal operation law, this deviation structure is understandable, which also indicates that the subsequent optimization can be further carried out around the feedforward compensation under high disturbance conditions.

Table 3: Statistical results of fluctuation of main thermal variables

Variable Name	Mean	Standard Deviation	Fluctuation Range or Peak-to-Peak Value
Combustion chamber temperature / °C	779.9	2.28	11.03
Exhaust gas temperature / °C	209.4	7.80	31.6
Regenerative bed temperature difference / °C	17.6	3.40	25.1
Oxygen content / %	8.71	0.43	7.8–9.6
Auxiliary fuel flow rate / $Nm^3 \cdot h^{-1}$	13.2	1.05	11.0–15.9

Combined with Table 3, it can be further seen that the combustion chamber temperature is not the only indicator that can reflect the thermal state. The standard deviation of flue gas temperature is significantly higher than that of furnace temperature, indicating that under optimal control conditions, the system prefers to release part of the disturbance to the waste heat recovery link rather than direct conduction to the core temperature zone of the combustion chamber. This phenomenon is advantageous from an engineering point of view because the stability priority of the combustion chamber, as a critical region of the purification reaction, is higher than the short-term fluctuations at the exhaust end. The periodic variation of the temperature difference of the regenerative bed shows that the alternating operation of the two beds is very obvious, and the heat is not continuously and evenly distributed, but dynamically switched between heat storage and heat release. If the algorithm cannot identify such structural fluctuations, it will often misjudge normal switching fluctuations as abnormal deviations, which will lead to excessive control. The proposed method maintains the combustion chamber temperature within a narrow fluctuation band when the temperature difference of the regenerator bed and the exhaust temperature are not excessively amplified, which indicates that the multi-source parameter fusion strategy has a good discrimination effect.

4.3 Comparison between optimization results and conventional control methods

After completing the fluctuation analysis of the thermal operation process, it is necessary to further investigate the comprehensive regulation effect of the optimization algorithm proposed in this paper compared with the conventional PID control method. The experimental platform and disturbance mode set in Section 4.1 are still used in the comparison test. Under the same initial temperature, same inlet flow and same target temperature, the operation results of the two control methods under different VOC concentrations and complex disturbance conditions are recorded respectively. The comparison content not only includes the temperature deviation of the combustion chamber, but also covers the dynamic recovery capacity, exhaust heat loss, auxiliary fuel consumption and comprehensive thermal efficiency, so as to more completely evaluate the influence of control strategies on the thermal performance of regenerative organic waste gas incinerators.

From the temperature control deviation under different VOC concentrations, the proposed algorithm shows a more stable regulation effect in each working condition. As the inlet concentration increases from 800 mg/m^3 to 2000 mg/m^3, the average temperature deviation of the two methods increases, but the increase of the optimization algorithm is significantly slower. As shown in Figure 7, the mean absolute temperature deviation of the proposed algorithm is 1.42 ℃, while that of PID control is 2.36 ℃ under low concentration condition. When the concentration rises to 2000 mg/m^3, the deviation of the proposed algorithm increases to 1.95 ℃, and the PID increases to 3.74 ℃. This shows that the conventional PID is more prone to the phenomenon of control lag and excessive adjustment in the face of the increase of exhaust gas heating value and combustion load, while the proposed algorithm can maintain the temperature deviation in a relatively narrow interval with the help of multi-source thermal parameter fusion and adaptive correction mechanism. In other words, the optimization algorithm not only has better temperature control accuracy under the benchmark condition, but also has stronger stability maintenance ability under the condition of high load fluctuation.

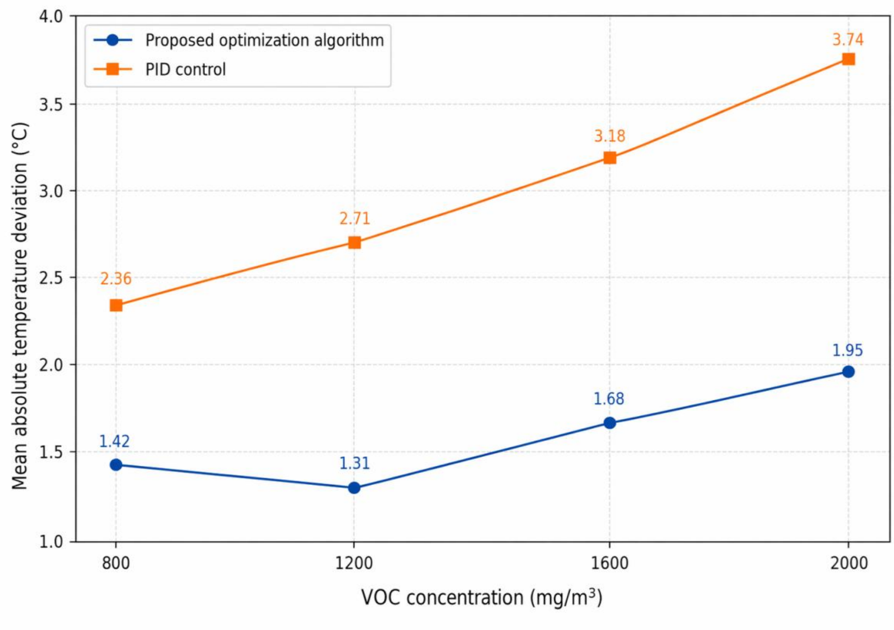

Figure 7: Comparison of temperature control deviations between the two control methods at different VOC concentrations

It is still not sufficient to judge the control quality only from the single concentration condition, so this paper further summarizes and compares the key performance indicators under the compound disturbance condition. The compound disturbance condition refers to the operation state in which the inlet concentration, exhaust gas flow rate and valve switching cycle change simultaneously, which is closer to the dynamic environment faced by the exhaust gas treatment system in the actual production process. The test results show that the proposed algorithm is superior to the conventional PID control in temperature stability, response speed and energy saving performance. Table 4 lists the main operating indices of the two methods under compound disturbance conditions.

Table 4: Comparison of the thermal performance of the two control methods under the compound disturbance condition

Indicator	Optimization Algorithm	PID Control	Variation Characteristics
Mean absolute temperature deviation / °C	1.73	3.08	Deviation reduced by 43.8%
Temperature standard deviation / °C	2.28	3.94	Fluctuation amplitude decreased significantly
Maximum overshoot / °C	4.62	8.35	Better overshoot suppression
Disturbance recovery time / min	4.3	8.0	Faster recovery speed
Average exhaust gas temperature / °C	209.4	223.8	Lower exhaust heat loss
Auxiliary fuel flow rate / $Nm^3 \cdot h^{-1}$	13.2	15.1	Fuel consumption reduced by 12.6%
Overall thermal efficiency / %	92.8	88.7	Heat utilization level increased by 4.1 percentage points
VOC removal rate / %	98.6	97.9	Purification stability improved slightly

It can be seen from Table 4 that the mean absolute temperature deviation of the proposed algorithm under the compound disturbance condition is only 1.73 ℃, which is 43.8% lower than that of PID control, indicating that its tracking of the target temperature of the combustion chamber is more accurate. The standard deviation of temperature decreases from 3.94 ℃ to 2.28 ℃, which indicates that the overall fluctuation of the system is obviously convergent, and the thermal state in the combustion process is more stable. The maximum overshoot and disturbance recovery time also decrease synchronously, which indicates that the optimization algorithm can complete the error correction faster and avoid a new round of oscillation caused by the reverse temperature overshoot when the working condition changes abruptly. For incineration thermal equipment, this comprehensive feature of "smaller deviation, faster recovery and weaker overshoot" is more practical than the simple pursuit of returning to the set value in a short time, because it can take into account the safety of equipment and long-term operation stability.

In terms of energy utilization, the proposed algorithm also shows obvious advantages. Under the condition of compound disturbance, the average exhaust temperature of the optimization algorithm is 209.4 ℃, which is lower than the PID control of 223.8 ℃, indicating that the waste heat recovery of high temperature flue gas is more adequate in the regenerative bed, and the sensible heat loss at the exhaust end is effectively compressed. At the same time, the average flow rate of auxiliary fuel decreased from 15.1 $Nm^3 \cdot h^{-1}$ to 13.2 $Nm^3 \cdot h^{-1}$, indicating that the algorithm did not maintain temperature stability by merely improving the combustion compensation, but formed a more reasonable coordination relationship among heat storage and recovery, oxygen supply matching, and combustion compensation. Because of this, the comprehensive thermal efficiency of the system is increased to 92.8%, 4.1 percentage points higher than that of PID control. It should be pointed out that although the VOC removal rate is only increased by 0.7 percentage points, in high-temperature incineration equipment, this improvement often means that the temperature field is more uniform and the oxidation reaction is more continuous, and its process value is not low.

5 Conclusion

Focusing on the thermal performance optimization problem of regenerative organic waste gas incinerator, this paper constructed a research framework consisting of thermal system modeling, multi-source thermal parameter fusion, adaptive thermal regulation and optimization algorithm implementation, and systematically tested its operation effect on the experimental platform. The results show that the thermal performance of the regenerative incinerator is not simply determined by the temperature of the combustion chamber, but is affected by the exhaust gas concentration, flow load, heat storage and release state of the regenerative bed, exhaust heat loss and valve switching rhythm. By incorporating these factors into the unified modeling and control link, the system can more accurately identify the thermal state changes, and output more targeted regulation instructions accordingly.

The experimental results show that the proposed optimization algorithm is superior to the conventional PID control method in terms of temperature stability, disturbance response speed and comprehensive thermal efficiency. Under different VOC concentration and complex disturbance conditions, the optimization algorithm can maintain the combustion chamber temperature within a small deviation range, significantly weaken the temperature fluctuation and overshoot phenomenon, and shorten the recovery time after disturbance. Compared with PID control, the proposed method shows better control quality in mean absolute temperature deviation, temperature standard deviation and maximum overshoot, which indicates that it has stronger adaptability to thermal inertia and time-varying disturbance under complex working conditions. In addition to the improvement of temperature control effect, the proposed method also shows obvious advantages in energy saving and heat utilization. The test results show that the optimization algorithm can reduce the exhaust temperature and auxiliary fuel consumption, improve the waste heat recovery efficiency of the regenerator bed, and improve the comprehensive thermal efficiency of the system while ensuring the stable VOC removal rate. This shows that the intelligent optimization control for thermal performance improvement can not only improve the running stability of the incinerator, but also help to reduce energy consumption and operating costs.

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