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Application of Multivariate Reinforcement Learning Engine in Optimizing the Power Generation Process of Domestic Waste Incineration

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Abstract: Garbage incineration is an ideal method for the harmless and resource-oriented treatment of urban domestic waste. However, current domestic waste incineration power plants often face challenges related to maintaining consistent steam production and high operational costs. This article capitalizes on the technical advantages of big data artificial intelligence, optimizing the power generation process of domestic waste incineration as the entry point, and adopts four main engine modules of Alibaba Cloud reinforcement learning algorithm engine, operating parameter prediction engine, anomaly recognition engine, and video visual recognition algorithm engine. The reinforcement learning algorithm extracts the operational parameters of each incinerator to obtain a control benchmark. Through the operating parameter prediction algorithm, prediction models for drum pressure, primary steam flow, NO_x, SO_2, and HCl are constructed to achieve short-term prediction of operational parameters, ultimately improving control performance. The anomaly recognition algorithm develops a thickness identification model for the material layer in the drying section, allowing for rapid and effective assessment of feed material thickness to ensure uniformity control. Meanwhile, the visual recognition algorithm identifies flame images and assesses the combustion status and location of the combustion fire line within the furnace. This real-time understanding of furnace flame combustion conditions guides adjustments to the grate and air volume. Integrating AI technology into the waste incineration sector empowers the environmental protection industry with the potential to leverage big data. This development holds practical significance in optimizing the harmless and resource-oriented treatment of urban domestic waste, reducing operational costs, and increasing efficiency.

Keywords: Multivariable reinforcement learning engine; Waste incineration power generation; Visual recognition algorithm

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1. Introduction

Waste incineration is an ideal method for the eco-friendly and resource-driven treatment of urban domestic waste. However, current domestic waste incineration power plants generally require much more stable steam production and high production costs [1,2]. Research shows that the complex combustion control objects of municipal solid waste have characteristics such as unknown, time-varying, random, and dispersive system parameters, as well as elusive and variable system time lags. These systems exhibited pronounced nonlinearity and interdependencies among their various variables. Additionally, environmental interference introduces unknown, diverse, and random factors into the equation. For the control problem of this uncertain and complex object (or process), traditional control methods based on mathematical models make it difficult for effective control, hence strategies with more effective control must be explored [3].

The algorithms constructed by various control strategies exhibit variations in complexity, robustness, and decoupling performance. Additionally, there are disparities in software and hardware resource costs within the realm of technical implementation. What people seek is a cost-effective control strategy. The available strategies encompass neural network control, fuzzy logic control, expert system control, and artificial intelligence control [4]. The multivariate reinforcement learning algorithm comprises three components: feature input, decision algorithm engine, and decision output [5]. It utilizes operating parameters to characterize waste incineration. The relationship between relevant equipment instructions at each operational point is established based on multidimensional historical data extraction. This approach provides benchmark operating parameters, eliminating the need for numerous test experiments typically required in conventional control. Consequently, it swiftly generates benchmark characteristic data for each furnace. By mining and reconstructing data from waste incineration power plant operations, algorithms are developed to control variables such as steam flow, feeder speed, upper grate cycle times, lower grate cycle times, primary air frequency, secondary air frequency, primary air temperature, and the coordination of each furnace. These algorithms also address control of nitric oxide and nitrogen dioxide (NO_x), sulfur dioxide (SO_2), and hydrochloric acid (HCl) emissions, facilitating automatic control of the waste incinerator's combustion process in the power plant. The incorporation of AI technology empowers the environmental protection industry with the potential to harness big data. This development carries practical significance by reducing costs and enhancing efficiency in the optimization of eco-friendly and resource-driven urban domestic waste treatment [6].

2. Multivariate reinforcement learning algorithm

Reinforcement learning is an end-to-end method that combines perceptual decision-making with continuous iterative optimization through trial and error and has strong autonomous learning capabilities [7-10]. In recent years, inspired by biological groups and artificial intelligence, reinforcement learning algorithms have evolved from solving individual decision-making problems to optimizing collaboration problems in clusters, injecting new momentum into enhancing the convergence and emergence of cluster intelligence [11]. The multivariable reinforcement learning algorithm includes feature input, decision algorithm engine, and decision output. The algorithm principle in waste incineration process optimization is to select steam flow, primary air volume, pressure of each air chamber, central steam pressure, furnace smoke temperature, and push. Main operating parameters such as feeder stroke and stroke are used as indicators of waste incineration conditions. The corresponding relationships of relevant equipment instructions under each working condition point are summarized through multi-dimensional historical data extraction, and benchmark operating parameter guidance values are given.

By extracting features from historical data, the corresponding relationship between changes in primary steam flow rate and feeder speed instructions, grate cycle times, and primary and secondary air frequency instructions can be obtained to form a benchmark for control instructions. It avoids using many test experiments to obtain benchmark data in conventional control and quickly obtains the benchmark characteristic data of each furnace.

3. Execution of the parameter prediction algorithm

Waste incineration boilers have large fluctuations in waste calorific value and substantial delay and inertia characteristics. It is difficult for traditional industrial controllers to solve the control lag problem caused by considerable delay and large inertia. In addition, the waste calorific value fluctuates wildly and is uncertain, further increasing the difficulty of control. Making use of data-driven advantages and combining the principles of industrial processes, we develop an industrial prediction engine. Based on the prediction results and combined with recommended algorithms, we guide the control system or operators to take early actions to alleviate the poor control performance caused by considerable delays, large inertia, and model uncertainty, as well as the problem of large fluctuations in operating parameters.

3.1. Alibaba Cloud prediction engine

The industrial prediction engine needs to analyze the relationship between input and output based on the principle of the production process and historical operation data, construct characteristic variables, and combine different system characteristics; characteristic variables (original characteristics + structural characteristics) and target variables are the parameters to be predicted. The industrial forecasting engine is the core of the algorithm. It is constructed through machine learning and deep learning algorithms. The industrial forecasting engine will regularly train and update the model according to the operation of the forecast results to maintain the model with high forecasting accuracy.

The Alibaba Cloud prediction engine involves parameters such as central steam temperature and main steam flow forecast. Based on the prediction model, each control parameter is optimized to improve the boiler stability further. The steam flow prediction relies on the Alibaba Cloud Industrial Brain deep learning platform algorithm. It uses historical operating data (pushing stroke, pushing action, primary air volume, primary air pressure, secondary air volume, furnace temperature, flue gas content (oxygen, feed water flow, drum level, central steam pressure, and other dozens of operating parameters) have established a steam volume prediction model, which can accurately predict the steam volume after 180 seconds in the future, and provide predictions and predictions for subsequent steam volume trends. The time decision provides a practical basis, which alleviates the impact of large fluctuations in steam volume caused by the uncertainty of the calorific value of waste, which is difficult to control effectively.

3.2. Prediction of drum pressure

Applying Alibaba Cloud's big data analysis technology and combining it with the operating mechanism of the unit, a correlation analysis was conducted on historical data encompassing steam drum pressure. This analysis also encompassed determinants such as feed rate, primary air volume, primary air temperature, TX1 temperature, TX2 flue inlet temperature, and flue gas content, including oxygen content. These parameters were identified as key indicators affecting drum pressure. Leveraging the Alibaba Cloud prediction engine and employing a residual modeling method, the study aimed to find the influence characteristics of the drum pressure generation when the aforementioned characteristic parameters change, and as a result, a drum pressure prediction model after 5 minutes was finally established. The prediction model is shown in **Figure 1** below:

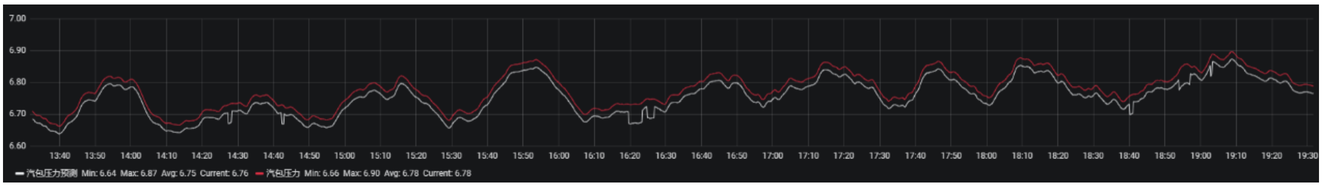

Figure 1. Real-time effect curve of steam drum pressure prediction

It can be seen from the drum pressure prediction curve that the overall fluctuation of the drum pressure predicted value is consistent with the actual value. However, the overall trend phase is about 2 minutes ahead of the actual drum pressure value, which can better predict the future drum pressure. This predictive capability has the practical advantage of anticipating changes in the boiler steam load through prediction, enabling the adjustments of air volume based on the prediction results, which then facilitates proactive steam load adjustments.

3.3. NO_x content prediction

Utilizing Alibaba Cloud‘s big data analysis technology, coupled with an understanding of the unit's operational intricacies, a comprehensive correlation analysis of historical NO_x data was conducted. This analysis considered variables such as feed rate, flue gas oxygen content, primary and secondary air volumes, primary air temperature, TX 1 temperature, TX2 flue inlet temperature, ammonia (NH_3) flow rate, dilution water flow rate, and other parameters identified as characteristic indicators of NO_x content. By harnessing the predictive capabilities of the Alibaba Cloud prediction engine and employing a residual modeling approach, the study aimed to ascertain the impact characteristics on NO_x generation resulting from changes in the aforementioned characteristic parameters. Consequently, a NO_x content prediction model was successfully developed to forecast NO_x content level two minutes in the future. The prediction model is shown in **Figure 2** below:

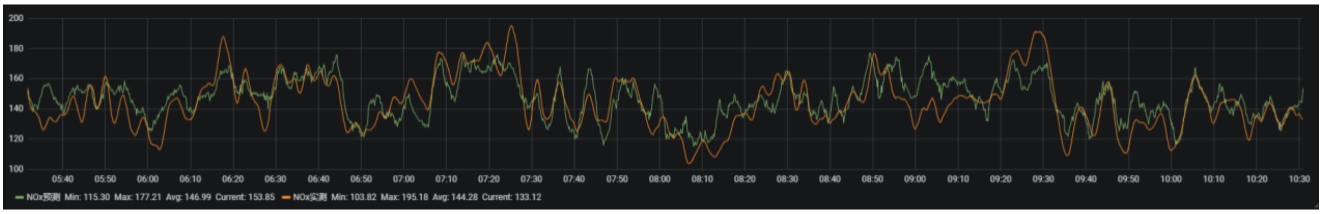

Figure 2. NO_x prediction effect curve

In **Figure 2**, the green curve represents the predicted NO_x content values, while the yellow curve represents the actual NO_x content values. The predicted values closely align with the overall fluctuation of the actual values. Notably, there exists a consistent phase difference of approximately 2 minutes, with the predicted values showing trends ahead of the actual NO_x content values. This advanced prediction capability significantly enhances the capacity to anticipate forthcoming fluctuations in NO_x content trends and it holds practical advantages by enabling the proactive sensing of changes in boiler steam load through prediction. Subsequently, it allows for the implementation of control instructions, such as NH_3 water flow and secondary air volume adjustments, based on prediction results. This proactive approach facilitates advanced NO_x control adjustments.

3.4. SO_2 content prediction

Similarly, Alibaba Cloud's big data analysis technology is used to conduct SO_2 data correlation analysis on the unit's historical data and targeted test adjustment data and determine the parameters based on the feed rate, flue gas oxygen content, and primary and secondary air volumes, primary air temperature, TX1 temperature, TX2 flue inlet temperature, lime volume, dilution water flow, and other parameters that are used as SO_2 content characteristic parameters. Applying the Alibaba Cloud prediction engine and residual modeling method to find the impact characteristics on SO_2 production when the aforementioned characteristic parameters change, a prediction model for SO_2 content after 2 minutes was finally established. The prediction model is shown in **Figure 3** below:

Figure 3. SO_2 prediction effect curve

In **Figure 3**, the green curve is the predicted value of SO_2 content, and the yellow one is the actual value of SO_2. The overall fluctuation of the predicted value is consistent with the actual value, but the overall trend phase is about 2 minutes ahead of the actual value, which can better predict the future fluctuation of the NO_x trend; through prediction, the changing trend of boiler steam load can be perceived in advance, and then according to the prediction result, the lime supply command can be acted in advance to realize the advance adjustment of SO_2.

4. Anomaly identification algorithm engine

The anomaly identification algorithm mainly uses unsupervised learning methods from massive historical data to identify normal and abnormal states under different operating conditions. It then uses big data machine learning algorithms to learn and model the differentiated operating conditions. Through historical data learning, we can identify the thickness deviation of the material layer at a specific primary air volume, identify the abnormal temperature of a particular section of the grate under a specific primary air volume and primary air temperature, and then reflect the garbage humidity. Through abnormal recognition and sensing, it is ensured that the system can make automatic and targeted adjustments, promptly discover problems during operation, and maintain the stability of operating parameters. The primary architecture process of the algorithm is as follows in **Figure 4**:

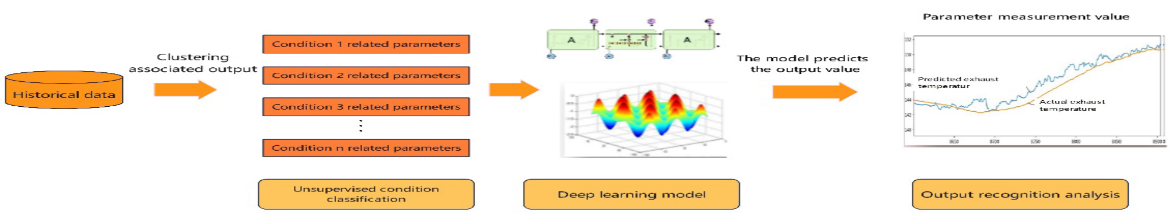

Figure 4. Primary structure of anomaly recognition algorithm

As shown in **Figure 4**, after obtaining the operating history data, the anomaly identification algorithm divides the working conditions through unsupervised clustering algorithms such as K-means and K-MEDOIDS, eliminates the abnormal working condition data, and obtains data within the normal generalized working conditions range. At the same time, the Alibaba Cloud modeling engine is used to model the standard working condition data and obtain the big data black box model of the target variable. The theoretical standard value can be calculated in real-time, and after comparing it with the actual value, it can judge whether the current state deviates from the standard value.

In the power generation process of waste incineration, the consistency in the quantity of waste fed into the furnace is a critical factor that determines the quality of the combustion process. If an excessive amount of waste is introduced into the furnace, it poses the risks of overtemperature, overloading, and exceeding environmental protection standards. Conversely, if insufficient waste is fed into the furnace, it can lead to burnout, causing the furnace temperature to drop rapidly or fall below the range of 8–50°C, which poses environmental protection hazards. However, accurately assessing the quantity of garbage inside the furnace presents challenges due to the complex and changeable nature of waste. Factors such as blockages, slippage, and bridging of garbage can obscure the direct measurement of garbage feeding rates. Additionally, issues such as garbage non-ignition and deflagration can lead to operator misjudgment, resulting in either overfeeding or underfeeding of waste, leading to material buildup or shortages. Accurately and effectively determining the garbage level within the furnace has thus emerged as a key factor in determining the feasibility of implementing automated combustion processes.

In this project, an effective method for gauging the quantity of garbage being introduced into the furnace was devised. It relies on the incinerator's furnace structure, specifically using the wind pressure within the drying section as a key indicator for estimating the garbage level within the furnace. However, it's worth noting that the wind pressure in the drying section is affected by both the primary air volume and the damper settings of the drying section. Yet, the instantaneous value of this parameter cannot directly represent the amount of garbage due to the varying openings of different dampers, including those in the combustion section. To address this challenge, the Alibaba Cloud anomaly identification algorithm engine was introduced. It employs wind pressure as an indicator of garbage feed quantity and conducts extensive big-data modeling of the wind pressure in the drying section. This process involves selecting 3–5 months' worth of historical operational data, utilizing unsupervised learning methods to filter out abnormal operating conditions, and obtaining standardized data for normal working conditions. Within these normal conditions, parameters such as primary wind frequency feedback, primary wind pressure, and the openings of each section's damper are selected as input features for the model. The Alibaba Cloud data modeling engine is then employed to establish a wind pressure model for the drying section. The model leverages the deviation between the predicted wind pressure ($P_{predicted}$) and the actual win pressure (P_{actual}) to ascertain the current amount of waste being fed into the furnace, followed by adjusting the feeder's feeding speed dynamically, ensuring a consistent feed volume. **Figure 5** illustrates the wind pressure model and the feed speed control curve for a drying section of the incinerator.

As shown in **Figure 5**, the upper diagram presents the actual wind pressure values in blue and the predicted wind pressure values in red, while the purple curve represents the difference between the actual value minus the predicted value. The lower diagram shows the corresponding feeder speed value. In the yellow box within the figure, it is evident that the actual wind pressure values significantly exceed the predicted value, resulting in a substantial deviation. This signifies an excessive amount of garbage within the drying section, prompting a reduction in feeder speed and a decrease in the feeding quantity. On the other hand, the red box within the figure reveals instances where both the wind pressure and actual compression values are significantly lower than the predicted value, with a minimal deviation. This indicates an insufficient amount of garbage in the drying section, leading to an increase in feeder speed to swiftly replenish the material. Through the wind pressure prediction model, the condition of garbage within the furnace can be continually monitored and assessed in real-time. Adjustments to the feeding speed can then be made as needed, effectively addressing the challenges associated with assessing furnace garbage levels and ensuring uniform feeding.

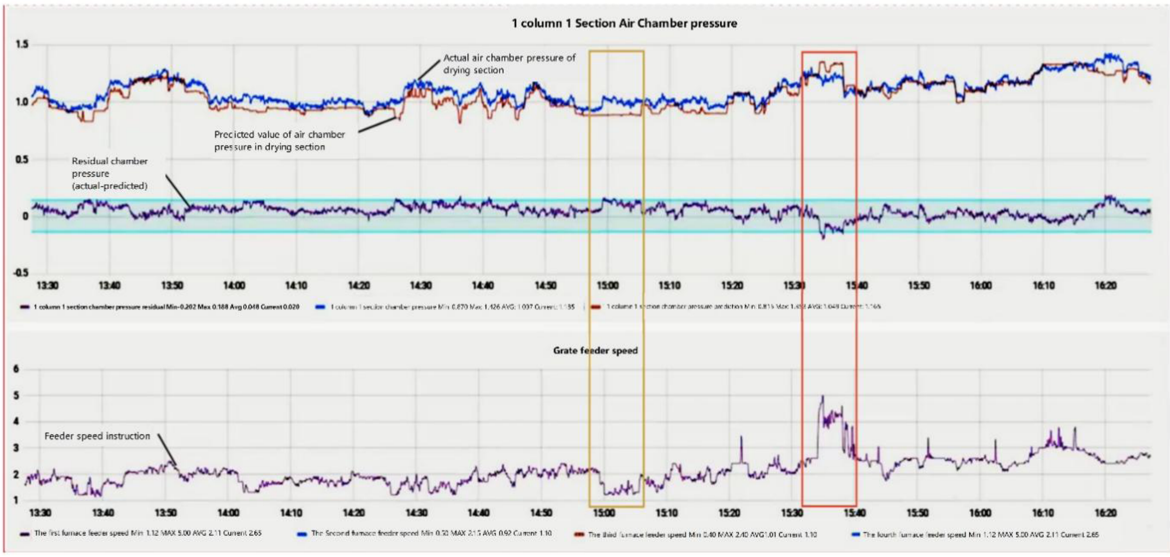

Figure 5. Wind pressure model and feed speed control of a row of drying sections

5. Visual recognition algorithm engine

The primary function of the visual recognition algorithm is to identify flame video images. Through visual recognition, it can promptly detect the burning conditions and burning locations of the garbage within the furnace, and then facilitates quick adjustments to the grates and primary fans of each section to ensure a stable combustion process. Within this project, the visual recognition algorithm primarily employs image classification and image segmentation techniques to analyze various aspects of the flame image, including the fire line, flame area, smoke, and brightness. This information is then subjected to post-processing to enable real-time analysis of the combustion status of the grate flame, which serves as input for subsequent control optimization algorithms. The overall algorithm flow is depicted in **Figure 6** below:

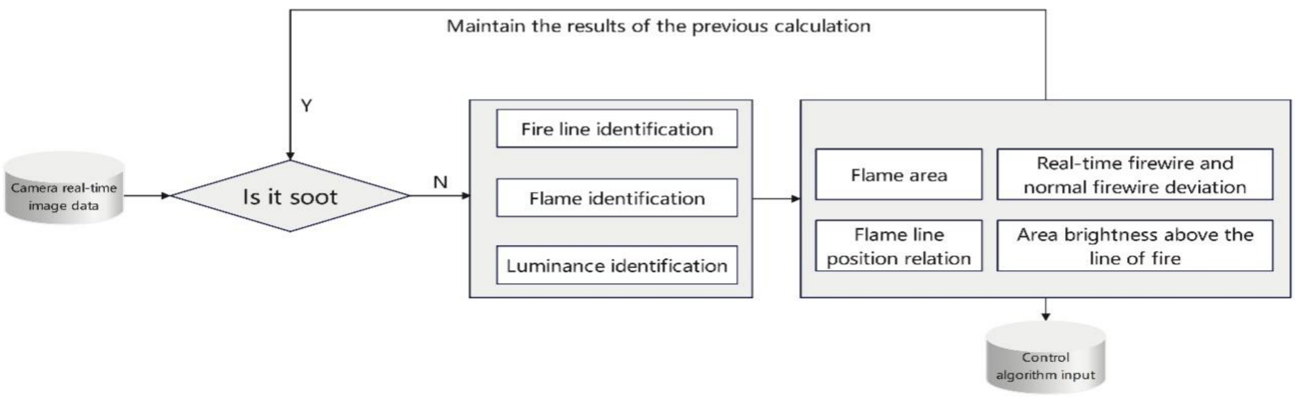

Figure 6. Visual recognition algorithm flow chart

A recognition algorithm is developed utilizing on-site flame image conditions, and the identified flame, fire line area, and corresponding position relationship are divided into images to conduct a more detailed analysis of the flame-burning state, as shown in **Figures 7** and **8**.

Figure 7. Flame image recognition algorithm: left side of the flame in furnace #1

Figure 8. Flame image recognition algorithm: right side of the flame in furnace #2

When the camera is clear, the current combustion situation in the furnaces and the material layer in the combustion section can be evaluated based on the flame width and brightness to make targeted combustion adjustments.

6. Discussion and conclusion

To assess the performance of the AI automation system, an 18-day evaluation test was carried out. During the test, the system was operated in the automatic and manual modes for nine days, respectively, while ensuring the unit remained under consistent operating conditions with similar waste calorific values. Based on the operational data analysis during the test period, the AI control system primarily demonstrated efficiency improvement in four aspects, including optimizing and transforming a total of 45 control loops across the feeding system, wind and smoke system, and exhaust gas treatment system. Moreover, parameter tuning yielded positive outcomes in five aspects: improving the automation level of the unit, improving combustion stability, reducing manual operation intensity, reducing plant power consumption, improving variable load performance, and achieving the expected goals.

6.1. Automatic operation rate of unit

After debugging and optimizing the early modeling prediction algorithm and control algorithm, debugging and optimizing the video image algorithm, switching deployment between the edge and the cloud, and the overall trial operation test, the combustion control algorithm can be put into operation, the automatic operation rate is about 97%, and the specific data of the comparative test are shown in **Table 1**.

Table 1. Automatic operation table of the unit

Furnace number	Operation time (hour)	Total time (hour)	Operation rate (%)
1	205	216	94.9
2	212	216	98.1
3	206	216	95.4
4	209	216	96.8
Total	832	864	96.3

6.2. Furnace header steam flow

It is seen from **Table 2** that during the operation of the combustion optimization automatic control system, it can effectively improve the stability of the steam volume while ensuring that the steam volume is consistent. The average steam volume is the same compared to the manual operation period. The stability of the steam volume of furnaces #1–#4 is increased by 27.48%, 22.12%, 26.12%, and 21.06%, respectively, with an average increase of 24.2 %, indicating a stable combustion optimization control system. It can improve combustion stability while ensuring the overall load.

While the steam volume stability is improved, the header pressure stability is also greatly improved. The overall pressure stability of the #1–#4 furnace headers increased by 4.1%. The stability of the steam pressure effectively improved the stable operation of the steam turbine unit. The specific data are as follows.

In addition, the stability of critical parameters such as furnace temperature and oxygen content has also been improved. The T2X furnace temperature stability increased by 6.0% after operating the system. When the above vital parameters are stable, combustion stability can be improved, pollutants exceeding standards can be reduced, and furnace coking can be reduced, thereby effectively improving unit operation and equipment health.

Table 2. Steam flow in furnace header

	#1 Furnace header		#2 Furnace header		#3 Furnace header		#4 Furnace header	
	Average pressure	Pressure standard deviation	Average pressure	Pressure standard deviation	Average pressure	Pressure standard deviation	Average pressure	Pressure standard deviation
Automatic	6.31	0.038	6.33	0.045	6.34	0.041	6.35	0.041
Manual	6.31	0.041	6.33	0.043	6.35	0.043	6.36	0.045
Increase (%)	0.0%	7.3%	0.0%	-4.7%	0.2%	4.7%	-0.2%	8.9%

6.3. Improvement of manual operation intensity

Table 3 lists system operation numbers before and after implementing the automatic control system. It can be seen from the table that after the combustion optimization, an automatic control system is put into operation; it can control the feeder, each grate, and primary and secondary air in real-time according to the current working conditions. The desuperheated water, SNCR, and other systems are automatically adjusted, requiring only a small amount of manual intervention under abnormal working conditions such as equipment failure, maintenance, garbage not catching fire, and stacking, significantly reducing operators' workload.

Statistics were made on the number of operations of each control quantity of the combustion system during the manual operation period, the number of interventions during the operation of the combustion optimization automatic control system, and the total number of operations was calculated. The statistical results are shown in the figure and table below. During manual operation, the total number of operations of the combustion system in 9 days was 18,080. After the automatic control system was implemented, the total number of operations was 1,295, and the amount of manual operations was reduced by 93%. It significantly reduced the labor intensity of operators and was able to respond to on-site emergencies such as insufficient workforce in the central control room.

Table 3. List of system operation numbers before and after the automatic control system is integrated into the system

#1–#4 Furnaces	**Manual**	**Automatic**
Control amount	**Operation amount**	**Operation amount**
Feeder speed	3,016	851
Number of grate cycles	1,114	154
Number of lower grate cycles	1,112	0
Primary fan frequency	1,917	175
Secondary fan frequency	9,862	74
SNCR ammonia water regulating valve opening	361	15
SNCR dilution water regulating valve opening	15	0
Opening degree of the first stage desuperheating water regulating valve	616	26
Opening degree of the secondary desuperheating water regulating valve	67	0
Total	18,080	1,295
Decline (%)	93%	

6.4. Optimization of the environmental reagents dosage and environmental parameters control

With the implementation of the combustion optimization control system, the production and operational conditions exhibited greater stability compared to manual control. Moreover, the system achieved automated control over SCR/SNCR/activated, leading to more consistent control of pollutant parameters, closely aligning them with the predefined set values. As a result, the permissible outlet NO_X and SO_2 values could be moderately increased within the environmental protection assessment requirements, thus effectively reducing the consumption of consumables such as ammonia and activated carbon while still meeting environmental protection standards. **Table 4** shows the average NO_X value and ammonia consumption based on the production operation report during the 18-day experiment. It can be seen from the table that the average NO_X value during automatic operation is the same as that during manual control and is within the environmental protection standards.

Table 4. NO_X average value and ammonia water consumption table during the experiment

	Total garbage disposal volume (t)	**Total ammonia consumption (kg)**	**Ammonia consumption per ton of garbage (kg/t)**	**Average NO_X value (mg/m^3)**
Automatic	26,647	84,570.51	3.17	95.99
Manual	28,516	84,873.12	2.98	95.00
Increase (%)	6.6%	0.36%	-6.63%	-1.03%

Table 5 shows the consumption of activated carbon and slaked lime based on the production operation

report during the 18-day experiment. The average values of SO_2 and HCl are the same between automatic and manual, and ammonia escape is reduced by 11.6%. Slaked lime and the dosage of activated carbon are similar.

Table 5. Activated carbon and slaked lime consumption table during the experiment

	Total activated carbon consumption (kg)	Activated carbon consumption per ton of garbage (kg/t)	Total slaked lime consumption (kg)	Slaked lime consumption per ton of garbage (kg/t)	SO_2 average (mg/m^3)	HCl mean (mg/m^3)	NH_3 escape average value (mg/m^3)
Automatic	11,274	0.4 2	138,830	5.21	1.76	0.57	6.72
Manual	11,438	0.4	138,810	4.87	2.08	0.44	7.6
Increase (%)	1.43%	-5.48%	- 0.01%	-7.02%	15.3%	-29.1%	11.6%

6.5. Energy consumption optimization and gas production indicators per ton

The test showed that during the 18-day experiment, due to more accurate oxygen adjustment and more stable furnace negative pressure, the power consumption of the secondary fan increased by 4.5%, the power consumption of the induced draft fan decreased by 4.7%, and the power consumption of the primary fan decreased by 5.1%; the overall fan power consumption is reduced by 4.1% (**Table 6**), and the average daily power consumption is reduced by 2,620 kWh. Based on this, it is estimated that the annual electricity bill will be saved approximately 620,000 CNY (based on 0.65 CNY per kWh), hence reducing operating costs.

Table 6. Statistics table of fan power consumption

	Primary fan power consumption (kWh)	Secondary fan power consumption (kWh)	Electricity consumption of induced draft fan (kWh)	Total power consumption of the fan (kWh)
Automatic	31,024	44,939	481,038	557,001
Manual	32,697	43,021	504,863	580,581
Increase (%)	5.1%	-4.5%	4.7%	4.1%

During the 18-day experiment, the critical indicators of the boiler's gas production per ton increased by 4.5 %, and the thermal ignition rate decreased by 3.1 % (**Table 7**), which proves that in the fully automatic state, while improving operational stability and reducing production costs, the operation indicator can still be controlled in a stable state.

Table 7. Statistical table of boiler gas production per ton and heat loss rate

	Average gas production per ton of furnace #1–#4	#1–#4 Furnace thermal ignition rate average
Automatic	2.57	2.36
Manual	2.46	2.29
Increase (%)	4.5%	-3.1%

6.6. Conclusion

Intelligent waste incineration control better integrates traditional industrial control and big data artificial intelligence in large-scale grate furnace control. Alibaba Cloud's big data modeling and prediction technology is applied. The operator's operating benchmark parameters are obtained through reinforcement learning algorithms, and the operation control benchmarks for each load section are obtained. Anomaly identification algorithms are used to build an identification model of material layer thickness for the drying section, and the thickness of the feed material is evaluated. Rapid and effective evaluation realizes the feed uniformity control and solves the most fundamental and core feed problem in grate furnace control such as constructing prediction models of steam drum pressure, NO_x, and SO_2 through operation parameter prediction algorithm, and realizes operation parameters. The short-term prediction realizes advanced adjustment and improves the control performance; through a visual recognition algorithm, the flame image recognition is used to obtain the flame-burning status and combustion line position in the furnace, and the flame-burning status in the furnace is understood in real-time. The grate and air volume are then adjusted to optimize the combustion conditions in the furnace, and through comparing the data before and after commissioning, the fluctuations of parameters such as steam volume and turbine pressure have been significantly improved, and the control effect is ideal.

In the future, with the continuous accumulation of operating data after commissioning, the system model will be continuously optimized in combination with the operating process data, and the control effect will be further optimized and improved.

Disclosure statement

The authors declare no conflict of interest.

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