The Optimized Control of Steam Blowers in Coal-Fired Power Plant Boilers

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Abstract: The boiler soot blowing practices is the foundation for ensuring normal boiler operation and saving coal consumption. However, improper soot blowing strategies adopted by many power plants lead to decreased boiler efficiency and steam wastage. An effective ways to address this issue is to accurately monitor ash fouling and soot blowing in real-time. This paper investigates a comprehensive approach for monitoring ash fouling on the heating surface of boiler power plants and proposes an optimized soot blowing mechanism. Considering the time-series, variability, and complexity of the boiler heating surface data, an ensemble learning model is designed to monitor the cleanliness coefficient of the heating surface and thereby a boiler soot blowing optimization control strategy is proposed. This strategy combines the characteristics of steam sootblower in reality, using main steam flow rate as an environmental feedback variable, and designs a "virtual-real" dynamic reward mechanism. Experimental results demonstrate that the model can dynamically adjust control strategies based on real-time environmental feedback, ensuring higher net heat benefits and lower soot blowing costs.

1. Introduction

In most industrial processes, boilers play a crucial role in generating steam for power generation. In thermal power plants, boilers use a large amount of coal as fuel, and during the combustion process, the boiler's heating surface efficiently transfer the released heat energy to the steam. This generated steam is then used to drive turbines and produce electricity[1]. However, over prolonged operation, the boiler's heating surface may accumulate deposits of ash particles resulting from coal combustion, flue gas flow, and water circulation[2]. These deposits form sticky and glassy deposits on the boiler walls and heating surface. The continuous accumulation of these deposits increases the thermal resistance of the ash fouling, leading to a decline in heat transfer capacity and energy efficiency[3].

The sootblower is an effective and commonly used method to address the aforementioned issues. Sootblowing serves as a scheduled and quantified cleaning method that is widely applied in various industries[4]. However, the steam consumed during sootblowing is a part of the steam generation process, and frequent sootblowing requires more coal consumption for steam generation, resulting in increased economic costs and air pollution emissions. Moreover, conducting sootblowing in areas that are already clean may lead to pipeline corrosion and accelerate the degradation of pipeline surfaces, reducing their service life[5][6]. Therefore, the development of rational and scientific sootblowing optimization strategies to minimize scaling and reduce the overall costs of sootblowing operations has become an urgent problem in need of a solution[7].

The online monitoring of the boiler's various sections' fouling on the heating surface is an essential basis for formulating soot blowing strategies. Currently, there are two main approaches for predicting the state of boiler heating surface: mechanism-driven modeling and data-driven modeling. Mechanism-driven modeling methods primarily include the thermal equilibrium method. For instance, B. Peña et al. [8]developed a real-time calculation heat model using expert systems to assess the fouling rate of the superheater. Ma Z. et al.[9] validated the location of heating surface fouling through CFD simulations and experimental data comparison, thus evaluating slagging and fouling conditions in coal-fired boilers. Bilirgen et al.[10] formulated slagging mitigation strategies by monitoring flue gas emissions and analyzing coal composition, boiler operating parameters, and the effects of soot

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blowing behavior on the slagging formation process.

In the data-driven modeling aspect, Kumari et al.[11] used a dynamic nonlinear regression model to monitor the reheater and determine the critical cleanliness factor and the duration of soot blowing cycles. Xu L. et al.[12] established a fouling detection model based on thermal loss analysis and GA-BP neural networks. Shi Y et al.[13] proposed modeling a cleanliness factor to monitor the ash accumulation in the air preheater, aiming to obtain statistical fits of fouling status and assess optimized soot blowing strategies.

Mechanism-driven modeling requires not only detailed information about the heating surface, layout diagram, and steam-water flow provided by power plant boilers but also the processing of thermal parameters, which involves complex measurements of parameters such as heat transfer coefficients. This can lead to a description of the heating surface health status that may deviate from the actual situation. The regression model based on neural networks has shown great potential in solving complex problems such as ash fouling detection and optimized control of soot blowing. Non-linear models are commonly used to describe variables of the boiler heating surface, allowing information to be learned directly from data without relying on predefined equations. However, these individual models have some limitations when dealing with sudden changes in process conditions. Once the boiler operating environment undergoes sudden changes, the neural network requires some time to relearn and adapt to the new conditions. Moreover, using a single model is difficult to adapt to the complex and ever-changing boiler operating environment, resulting in limited predictive accuracy for industrial applications.

Based on the aforementioned issues, this paper proposes an improved AD_Stacking ensemble algorithm combined with the cleanliness coefficient G to establish a prediction model for boiler fouling on the heating surface. Furthermore, by integrating real-time feedback from the environment, the deep reinforcement learning TD3 algorithm is utilized to optimize the control of the sootblower. The core advantage lies in the ability to integrate the strengths of multiple models, explore based on historical experience, adapt to changing environments, and use reward signals to guide the learning direction, achieving control over the duration and frequency of soot blowing. The main contributions of this paper are as follows:

(1) Based on 44,640 continuous real-time data from a 600MW coal-fired boiler in Guangdong province, a boiler heating surface fouling prediction model was established. To address the issues of significant prediction errors of a single model under different operating conditions and the complexity of boiler heating surface data, we propose an improved AD_Stacking ensemble learning algorithm. This algorithm combines the Random Forest Regression (RFR), Gated Recurrent Unit (GRU), and LightGBM models to predict the cleanliness coefficient of the boiler heating surface, considering various operating conditions of the boiler heating surface.

(2) Building upon the aforementioned contributions, this study further explored the optimization control method for the soot blowing process based on the deep reinforcement learning TD3 algorithm. Taking into account the specific operating environment of the soot blowing system and using the main steam flow rate as the environmental feedback variable, a model was developed to predict steam losses. Moreover, a novel "virtual-real" reward mechanism was designed with the aim of ensuring normal boiler operation while maximizing the cleanliness of the boiler heating surface and minimizing the cost of using the soot blowing system.

(3) The established AD_Stacking ensemble algorithm is utilized as the parameter model for describing the boiler's heating surface fouling environment, combined with the real-time environmental feedback algorithm TD3 for optimal control of boiler soot blowing in power plants. Using R2 as the evaluation metric, experimental results show that within one soot blowing cycle, the model achieves an average accuracy of 95.7% in predicting the cleanliness coefficient and the steam loss by 99.5%. The reward value *MSL* increases by approximately 6% compared to the pre-optimized control, and the total steam consumption is reduced from 4.02t to 3.886t. These experimental results demonstrate the effective control of main steam flow and soot blowing steam cost while ensuring normal heat transfer efficiency of the boiler's heating surface.

2. Detection Of Ash Fouling Based On Ensemble Learning

2.1 The Cleanliness Coefficient G

During boiler operation, the heat absorption (Q) of the heating surfaces is closely related to the heat transfer efficiency, and its reduction directly reflects the degree of fouling and the decrease in heat transfer efficiency of the heating surfaces [14]. Therefore, the Q of the heating surfaces is used as a monitoring parameter. Meanwhile, the cleanliness coefficient (G) is introduced to quantify the degree of scaling on the heating surfaces, and its calculation equation is represented as Formula (1):

$$G = \frac{Q_{sj}}{Q_{clean}} \# \tag{1}$$

Where Q_{sj} represents the actual heat absorption on the convective heating surface during the real operation of the boiler, and Q_{clean} represents the heat absorption on the convective heating surface in the same operating state when it is clean. The numerical significance of the cleanliness coefficient G is the same as that of the cleanliness factor CF, both ranging from 0 to 1.

The formula for calculating the actual heat absorption on the working fluid of the convective heating surface is as follows:

$$Q_{sj} = (h'' - h') \# \tag{2}$$

Where h'' represents the enthalpy of the working fluid at the outlet of the heating surface, and h' represents the enthalpy of the fluid at the inlet of the heating surface. Modern power plants are typically equipped with comprehensive measurement points on the working fluid side, which allow for accurate calculation of the enthalpy values at the inlet and outlet of the heating surface. Based on equation (2), the actual heat absorption of the fluid, Q_{sj}, can be calculated.

2.2 AD_Stacking

During the operation of a boiler, the accumulation of ash on the heating surface causes changes in the heat transfer coefficient. As a result, the corresponding clean heat absorption Q_clean on the heating surface cannot be directly calculated through the heat transfer heat balance equation[15]. Therefore, considering the nonlinearity, temporal relationships among sample data, complexity, and dynamic variation of the boiler's heating surface, we adopt the Stacking ensemble learning algorithm[16]. The Stacking is an effective machine learning method that combines the predictions from multiple base models to obtain more accurate and stable predictions.

When selecting the base models, it is important to consider their strengths and weaknesses and choose them based on the specific problem at hand. For power plant boiler operational data, it contains rich temporal features and exhibits complex cyclic variations. To better utilize the temporal nature of the data and improve prediction accuracy, we choose to incorporate the Gated Recurrent Unit (GRU) [17]neural network model. Additionally, to balance model interpretability and prediction accuracy, we employ the Random Forest (RF)[18] algorithm model. RF possesses excellent robustness, can handle various data types, and is effective in handling missing and outlier values while mitigating overfitting. Lastly, to consider the generalization ability in the complex boiler environment and ensure the stability of the overall model, we select the LightGBM algorithm[19], which has fast training speed and lower memory consumption, as a base model. For the meta-model, we use a linear model (RL)[20] that provides good interpretability and has a lower computational burden.

In practical boiler fouling detection, the Stacking algorithm often faces challenges due to the complexity and dynamic variations of boiler heating surface. These challenges include:

(1) The monitoring and data acquisition of boiler heating surface usually require expensive and complex instruments, and they often face challenges such as data missing or noise interference during actual operation. In order to fully utilize the data features and mitigate the scarcity of data, we employed a five-fold cross-validation method to train various base models. Through the comprehensive learning of the meta-model, the predictive performance of the model can be further improved.

(2) The performance of the Stacking algorithm often relies on the generalization ability of the base models. Due to the involvement of multiple factors in power plant boilers, such as temperature, pressure, flow rate, and combustion efficiency, there exist nonlinear and variable relationships among these factors. An effective approach is to use weighted averaging to manipulate the predictions of the base models, adjusting their weights based on their performance, so that the models with better performance have a greater influence. This enables the meta-model to update its parameters more effectively during the training process. At the same time, the boiler operation data exhibits temporal characteristics, so we employ the sliding window method. This method divides the time series dataset into multiple sliding windows, where each window contains a segment of time series data, with a portion used for training and the remaining portion used for testing.

Based on the above discussion, the improved structure of the Stacking model is illustrated in Figure 1.

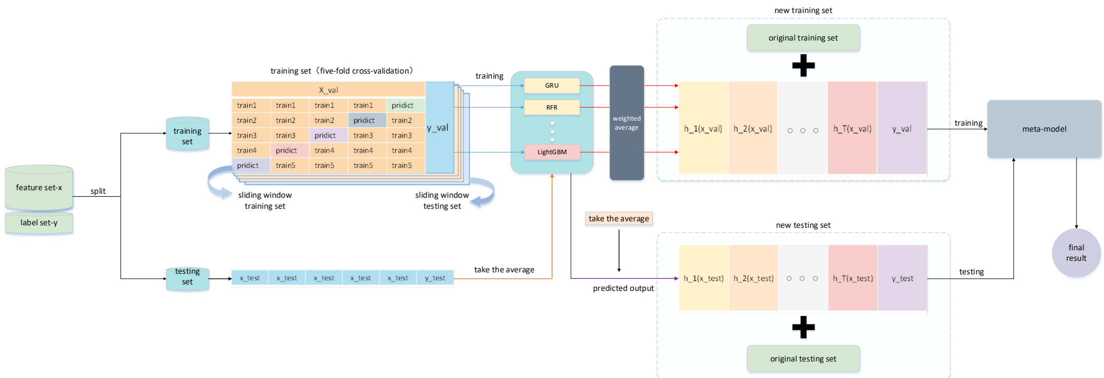

Figure 1. The Framework Of The Improved AD_Stacking Algorithm

3. Optimized Boiler Sootblower Optimization Control Model based on TD3 Algorithm

3.1 The TD3 Optimization Control

TD3 algorithm[21] is applied in optimization control tasks, and its learning process requires adjustments based on real-time feedback of the heating surface fouling status. For this purpose, the aforementioned AD_Stacking method is employed to construct a predictive model for the heating surface fouling status. The principle framework of the TD3 algorithm is shown in Figure 2. In the application scenario of the boiler soot blowing system in a power plant, the meaning of the experience data (s, a, s', r) is explained as follows: the environmental feedback variable s represents the descriptive parameter of the heating surface fouling status, which is the cleanliness coefficient G; the action space a represents the action performed by the soot blowing system, which is the blowing duration for the sootblower; the reward value r is designed as the main steam flow applied to power generation over a period of time; s' represents the next environmental feedback status after the action a is applied to the environment.

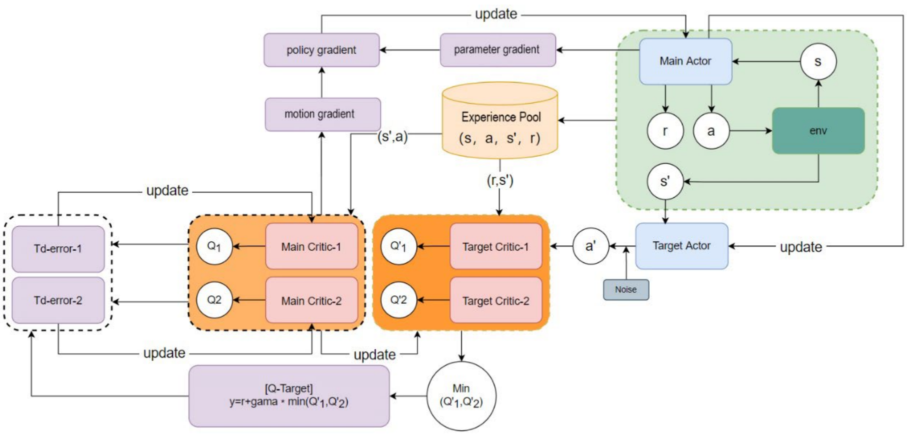

Figure 2. TD3 algorithm process framework

3.2 Principle of Establishing the Environmental Feedback Model

In the TD3 model, the feedback of environmental variable s plays a decisive role in the output of the reward mechanism[22]. However, the cleanliness coefficient itself cannot be directly used to design an appropriate reward mechanism. Considering the research subject is the steam sootblower, when the cleanliness coefficient of the heating surface area is low, it indicates severe ash accumulation, which reduces the heat transfer efficiency of the heating surface area, limits the evaporation of water inside the boiler, and consequently affects the magnitude of the main steam flow rate. Therefore, the main steam flow rate is closely related to the cleanliness coefficient of the heating surface area. To design a suitable reward mechanism, it is necessary to find the relationship between the cleanliness coefficient and the evaporation rate (D) and utilize parameters related to D in the design of the reward mechanism.

In the boiler's superheater, the steam sootblower extracts a portion of the superheated steam D_{ch} for the sootblower system, while the remaining steam is used to drive the turbine generator, known as the main steam flow rate (MSL) of the unit. Other steam losses, such as moisture loss, heat transfer loss, and blowdown loss, are collectively referred to as the steam loss D_{loss}, due to the complexity of their measurement. The actual steam evaporation rate D_{sj} per unit time can be represented by formula (3):

$$D_{sj} = D_{ch} + MSL + D_{loss}\# \tag{3}$$

Where D_{sj} , D_{ch}, and MSL represent the steam generation/consumption rate per unit time, which can be directly or indirectly obtained from power plant data. When the boiler is in a stable operating state with little load variation, the actual steam evaporation rate of the power plant boiler, D_sj, fluctuates around its rated evaporation rate, which is 1836 t/h. Based on the power plant data recorded, the MSL shows fluctuations between two sootblowing cycles, as illustrated in Figure 3.

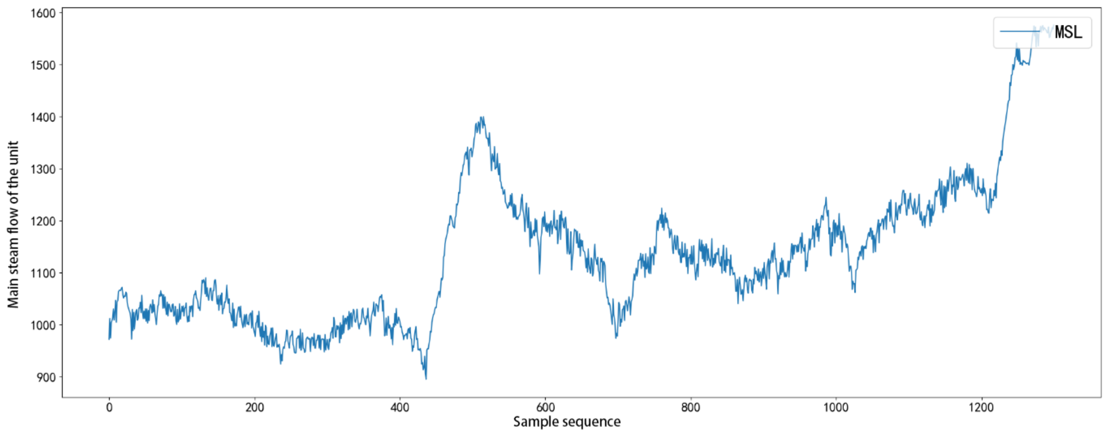

Figure 3. Change chart of main steam flow rate per unit time

From the above figure, it can be observed that the unit-time main steam flow rate of the unit varies with the change in the soot deposition status on the heating surface. However, in the optimization control process, the duration of sootblowing is not fixed. This implies that different values of D_{ch} and D_{loss} will result in different MSL values. In order to obtain a reward feedback that aligns with the description parameter of the soot deposition status on the heating surface, the MSL needs to be dynamically calculated. Since it is difficult to directly represent the boiler parameter variables associated with MSL, D_{ch} and D_{sj} can be calculated using mechanistic formulas. Among them, the steam loss D_{loss} is mainly related to the boiler's heat loss, cleanliness coefficient, and boiler load. The heat loss can be expressed by parameters such as the outlet flue gas temperature of the boiler's air preheater and the exhaust gas temperature, which can be substituted in the expression. Therefore, in conclusion, the AD_Stacking algorithm model can be employed to model and output D_{loss}, and the expression of D_{loss} after feature selection is as follows (4):

$$D_{loss} = f(G, MST, QO, MSP, K, Y)\# \tag{4}$$

Where G is the cleanliness coefficient, MST is the main steam temperature, QO is the total feedwater flow, MSP is the main steam pressure, K is the air preheater A side inlet flue gas temperature and Y is the flue gas flow rate.

Then, combining equations (3) and (4), the MSL is dynamically calculated during the operation of the TD3 optimization control model. It is used as a relevant variable in the reward calculation of the TD3 model, represented as $reward = f(MSL)$. The process of dynamically calculating MSL in the environmental model is shown in Figure 4.

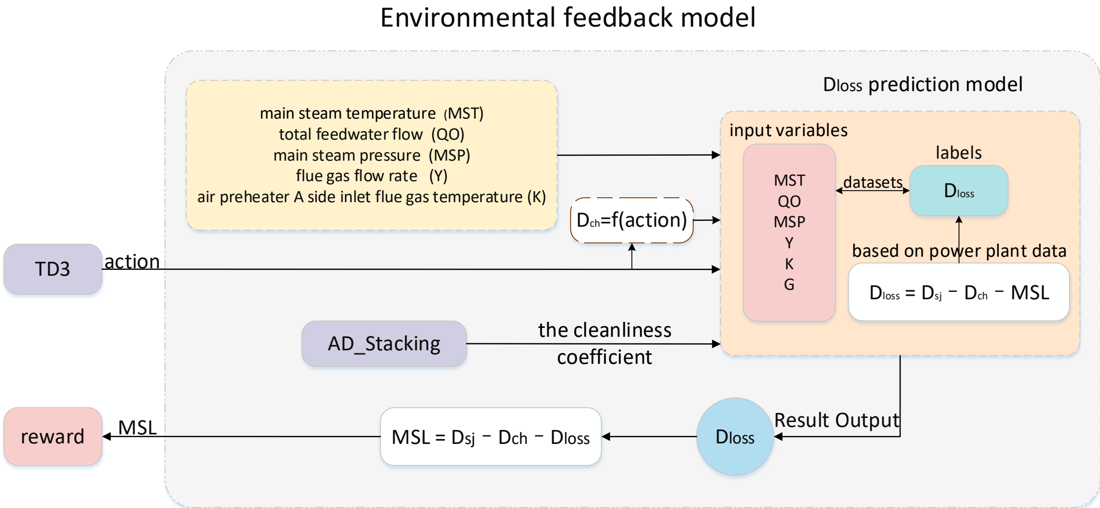

Figure 4. Schematic diagram of the reward mechanism system process

3.3 Reward Mechanism Design

In the steam sootblower optimization control model based on TD3 algorithm, in addition to obtaining feedback from the environment, it is necessary to understand the benefits or rewards generated by the sootblowing actions. The total steam produced by the boiler is represented by the actual evaporation amount D_{sj} . The operation of the sootblower extracts a portion of the steam D_{ch}, and there is also a certain steam loss consumption represented by D_{loss}. The remaining steam is used as the main steam flow rate MSL for boiler power generation. In the scenario where steam losses cannot be controlled, it is desired to maximize the utilization of steam for turbine power generation, specifically to maximize the main steam flow rate (MSL). Based on these considerations, a "virtual-reality" reward mechanism is designed, and the objective reward is denoted as X_r. as shown in equation (5).

$$X_r = \omega(X_a - X_{a'}) \# \tag{5}$$

Where X_a represents the main steam flow (MSL) after a certain period of time under the current action (assuming it is the blowing action); $X_{a'}$ represents the MSL after a certain period of time under the opposite action (not blowing); X_r represents the difference between the two as the reward value; ω is the correction parameter.

X_{MSL} represents the cumulative amount of steam, which can be calculated by accumulating the unit-time main steam flow. The specific calculation formula is shown in equation (6).

$$X_{MSL} = \sum_{i=pre}^{cur} (MSL_i + MSL_{i+1}) \,/\, 2 \, \# \tag{6}$$

The clean coefficient G of the heating surface is used as input to the TD3 algorithm, which determines the soot blowing action. If the action value is greater than 0, it represents the duration of soot blowing, followed by a 10-minute cleaning phase. The total amount of MSL (X_a) is calculated based on this. If the action value is negative, it indicates soot accumulation time, and the total MSL ($X_{a'}$) is calculated similarly. The final reward value X_r is derived by subtracting the two MSL values, with negative values indicating penalties and positive values representing rewards.

When G approaches 1, light soot coverage calls for minimal soot blowing to avoid negative rewards.

When G approaches 0, severe soot accumulation requires appropriate soot blowing to achieve positive rewards, while excessive or insufficient blowing can lead to negative rewards.

This reward mechanism and its processes are illustrated in Figure 5.

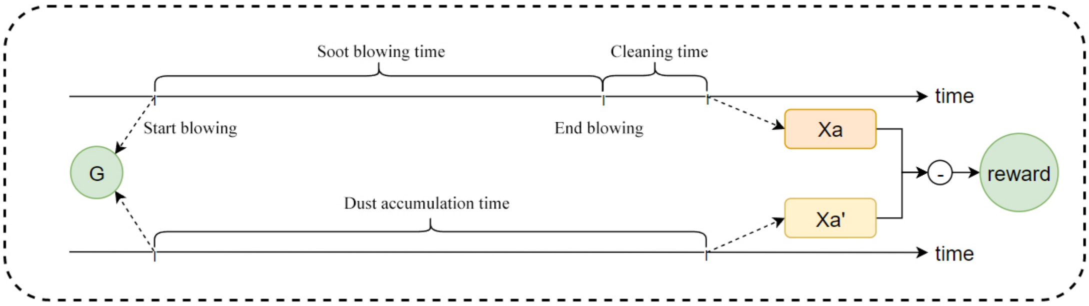

Figure 5. Schematic diagram of reward mechanism

4. Experimental results and analysis

4.1 Experimental datasets

This study validated the prediction and optimization control models using data from a 600MW coal-fired boiler. The focus was on modeling and predicting soot accumulation on the convective heating surface, with the economizer as an example for optimizing air preheater, economizer, superheater, and reheater sootblower control.

A dataset with 101 feature dimensions was collected from the actual boiler operation database, including heating surface impact and sootblower parameters. The Particle Swarm Optimization (PSO)-based Wrapper method[23] selected 10 key variables for predicting heat absorption, such as total coal quantity (M), total air flow (A), feedwater flow (QO), steam pressure (MSP), and flue gas flow rate (Y).

Data sampling occurred every 5 minutes, yielding 13,000 samples from July 1 to July 31, 2022, with a 60-second collection interval during normal operation. In total, 44,640 samples were obtained for model training.

4.2 Establishment and Prediction of the Heating Surface Fouling Status

Firstly, the prediction model utilizes the AD_Stacking algorithm to model each heating surface. The features related to the air preheater, economizer, superheater, and reheater are used as input variables for predicting the cleanliness of the heating surface. By inputting these variables into the cleanliness coefficient prediction model, the predicted total heat absorption, Q_{clean}, can be obtained. Then, combining with formulas (1) and (2), the cleanliness coefficient, G, for each heating surface can be calculated. The results are evaluated using the R2 score, as shown in the Figure 6.

According to the analysis of the modeling and prediction results of the four heating surface from Figure 6, it was found that the average accuracy of the prediction based on the AD_Stacking algorithm reached 0.979 for the economizer and air preheater. However, for the reheater and superheater, the average accuracy of the prediction results was 0.935, relatively lower with a decrease in accuracy of 4.4%. This difference can be attributed to various factors, such as the structural form of the heating surface, flue gas temperature and flow conditions, and ash deposition characteristics.

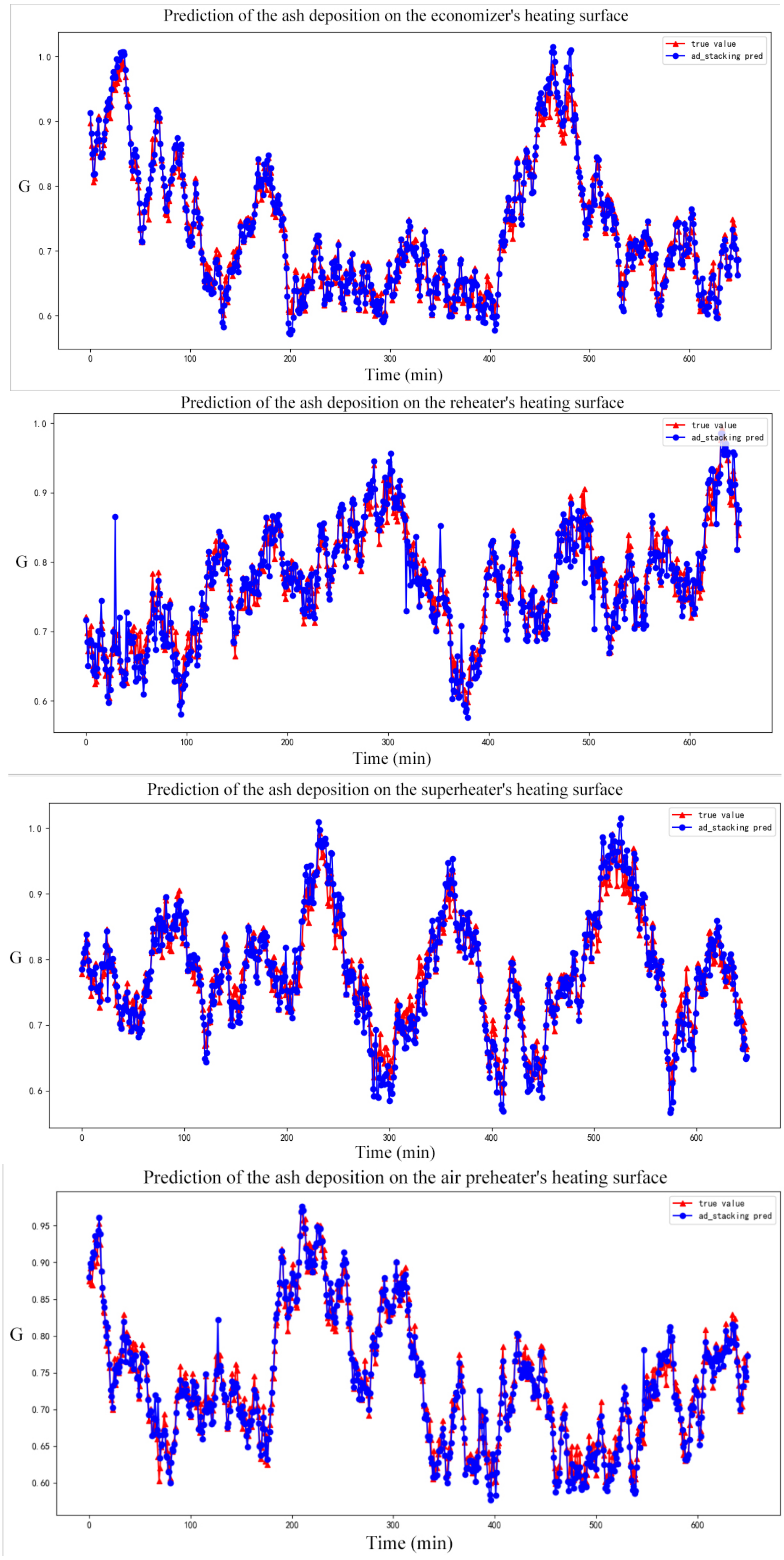

Figure 6. Schematic representation of the predicted cleanliness coefficients for each heating surface

Specifically, the characteristics and operating conditions of different heating surface can lead to differences in the accuracy of the model predictions. Economizers and air preheaters typically have relatively simple structures and a relatively single heat transfer mode, resulting in a more stable ash deposition status on their heating surface. Therefore, prediction results based on the AD_Stacking algorithm can achieve high accuracy for these surfaces. However, reheaters and superheaters have complex and variable ash deposition statuses on their heating surface. They are often subjected to the impact of high-temperature flue gas and high-speed flow, which leads to a complex heat transfer process with variable heat transfer modes. As a result, the prediction accuracy for these surfaces is relatively lower compared to the lower-temperature heating surface.

Overall, the high prediction accuracy of the boiler heating surface model established based on the AD_Stacking algorithm demonstrates its reliability.

4.3 Establishment and Prediction of Steam Loss Model

Based on the establishment and discussion results of the environmental feedback model in Section 3.2, in order to obtain the main steam flow rate related to the reward value, it is necessary to model the steam loss. Different values of D_{ch} and D_{loss} will result in different main steam flow rates. Therefore, a mechanistic analysis was conducted on the data from two consecutive soot blowing cycles, including D_{loss}, D_{ch}, MSL, and D_{sj}, which were randomly selected, as shown in Figure 7.

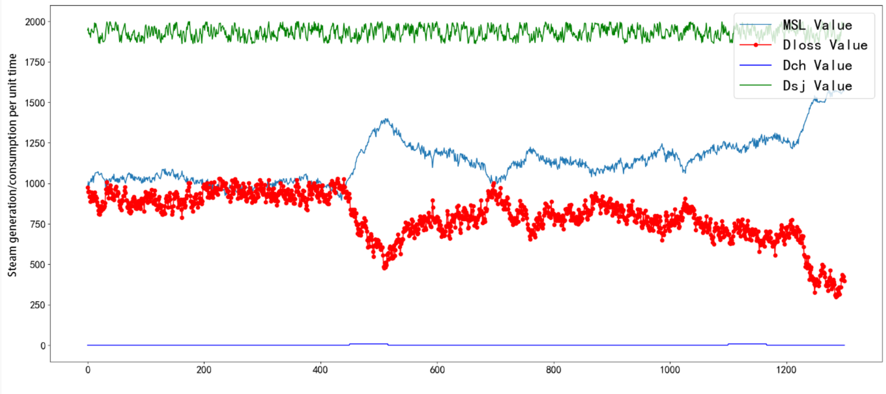

Figure 7. Schematic diagram of steam flow per unit time related parameters

From Figure 7, we can observe the fluctuation of the data. As mentioned earlier, the actual steam evaporation rate of the boiler, D_{sj}, fluctuates around its rated evaporation rate. On the other hand, the steam consumption rate for soot blowing varies periodically due to the adopted periodic blowing mode. It can be seen that the main steam flow rate, MSL, shows a significant peak from around the 450th time sample to the 510th time sample, indicating the occurrence of blowing and the cleaning state of the heating surface. Based on the characteristics of periodic blowing, it is not difficult to observe that the steam loss rate and the main steam flow rate exhibit a negative correlation trend. This explains the phenomenon of the two showing an inverse relationship while the evaporation rate remains constant.

Therefore, in the actual optimization control process, it is possible to calculate D_{loss} by obtaining real-time dynamic values, and use it to calculate MSL, thereby obtaining the feedback reward variable s for the TD3 model. Then, the D_{loss} prediction model is constructed by combining the AD_Stacking algorithm model. The dynamic acquisition of parameters is achieved, and the predicted results are shown in Figure 8.

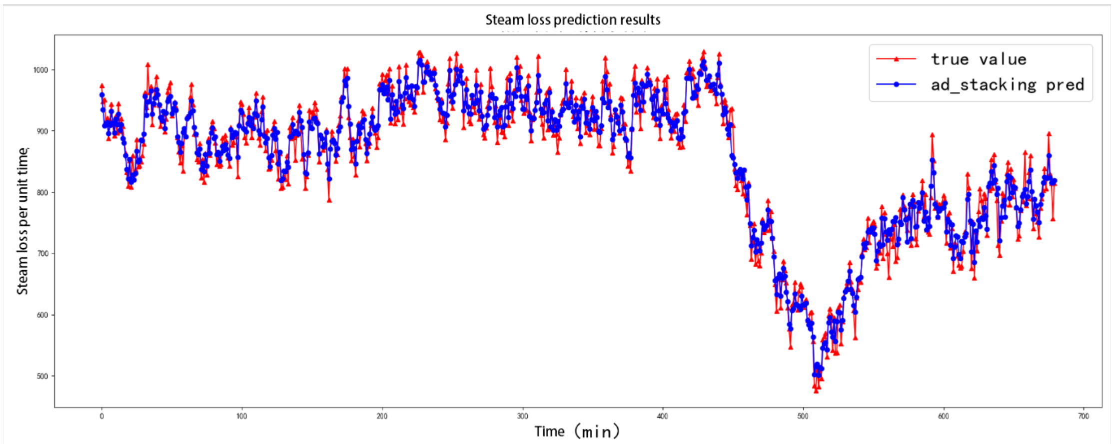

Figure 8. Comparison of the steam loss prediction results

The prediction model was evaluated using the R2 score, and the final prediction result achieved a score of 0.995. As shown in Figure 8, the D_{loss} prediction model based on the AD_Stacking algorithm exhibits a high level of fit, indicating a significant predictive performance.

4.4 Modeling and Experimental Optimization Control of Sootblower

Based on the cleanliness coefficient and reward values, the TD3 algorithm is utilized to dynamically control the soot blowing process in the power plant's boiler. The experimental dataset is divided into a training set and a testing set in an 8:2 ratio. Each training cycle consists of 200 training steps. The reward threshold is set to stop the episode if the reward falls below -150 or every 50 rounds. The testing results of the optimized control are presented in Figure 9-10.

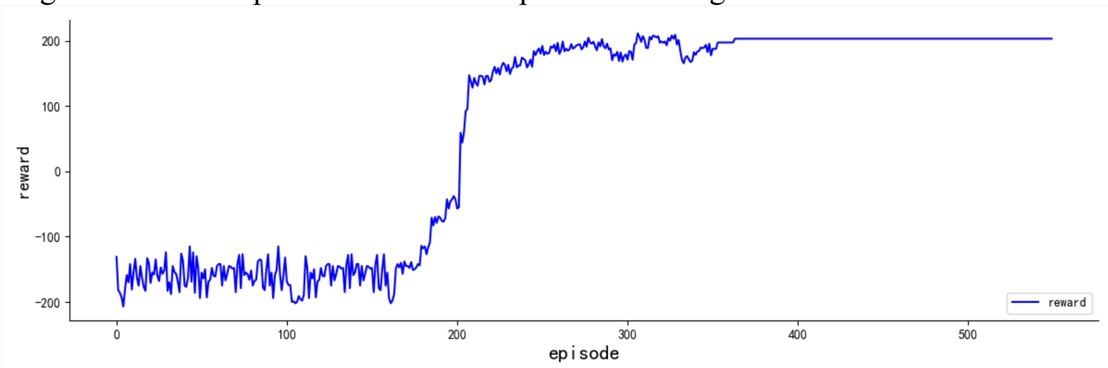

Figure 9. Change of reward values

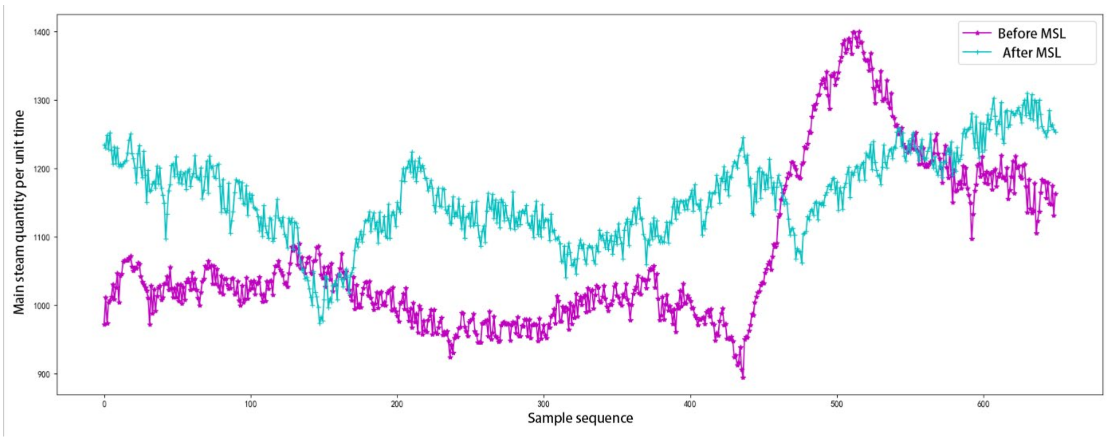

Figure 10. Comparison diagram of MSL optimization control before and after

Figures 9 and 10 show that after approximately 200 iterations, the reward value starts to increase and gradually reaches a stable state. The main steam flow rate generated by the unit after optimization control is significantly higher than before optimization. This indicates that based on the predefined reward mechanism, the model can effectively ensure the supply of the main steam flow rate in the power generation process of the boiler. It can also make appropriate soot blowing action choices based on environmental feedback and previous experience.

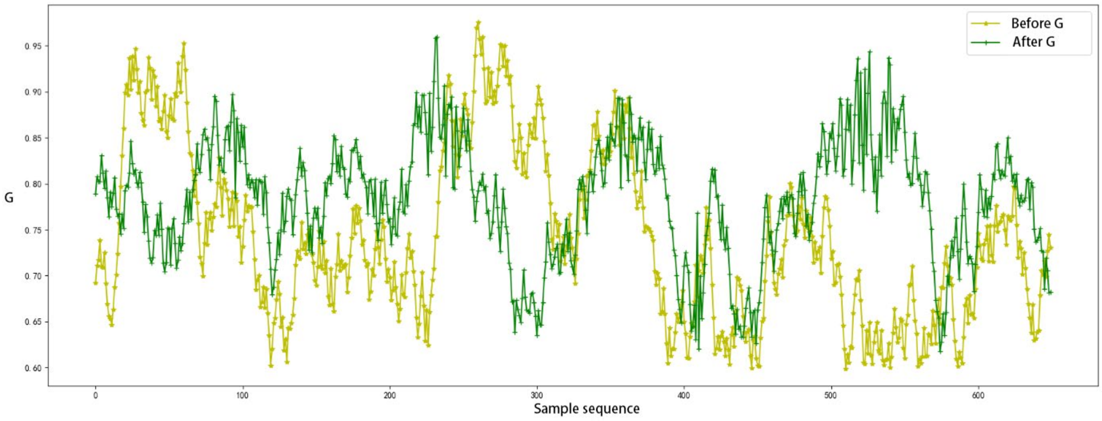

Figure 11. Comparison diagram of heating surface before and after grey optimization control

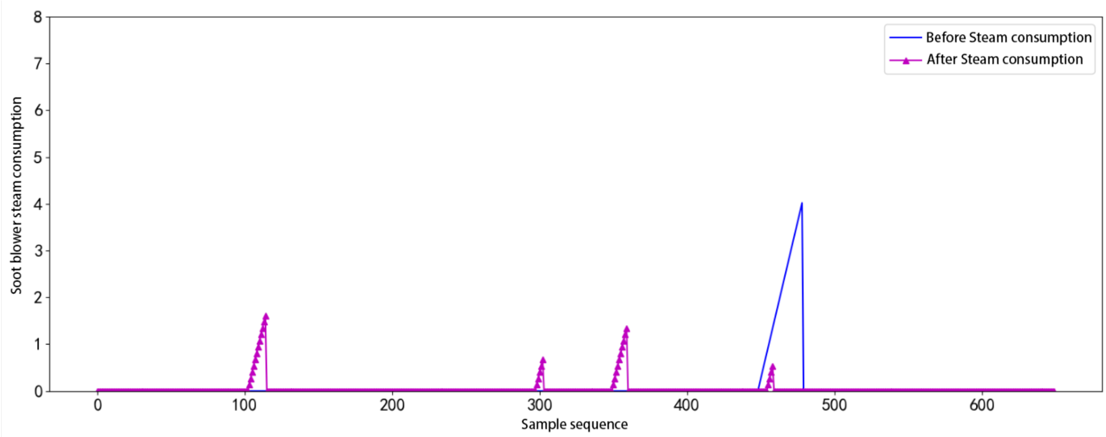

Figure 12. Comparison of accumulated steam consumption before and after optimization control of sootblower

Table 1 The MSL and total steam consumption before and after optimization

Comparing Parameters	Before Optimization	After Optimization
The Total Steam Consumption (t)	4.02	3.886
MSL (t)	11640.115849	12353.97544

Based on Figure 11 and 12, the reward values of the optimization control algorithm stabilize within a single random test cycle (650 time samples). Under stable rewards, the model dynamically adjusts its control strategy based on real-time feedback to maintain a cleanliness coefficient between 0.7 and 0.9. When it drops to 0.5, the model initiates soot blowing to keep the surface cleaner than before optimization. Conversely, when the coefficient approaches 0.9, it minimizes or shortens soot blowing to prevent excessive wear on equipment.

As shown in Table 1, optimization control increased the main steam flow rate (MSL) by 713.86 tons (about 6%), while total steam consumption decreased from 4.02t to 3.886t. This improvement enhances boiler energy efficiency, reduces coal consumption, and conserves energy resources.

5. Conclusions

This paper presents an optimization model for soot blowing heat transfer based on the TD3 reinforcement learning algorithm, aiming to improve the economic efficiency of coal-fired power plant boilers by balancing the clean heat absorption and the steam loss caused by soot blowing. Firstly, model for predicting the heat absorption of the boiler's clean heating surface is successfully established using an improved AD_Stacking algorithm. Then, considering the characteristics of steam sootblower, a reward mechanism is designed for the optimization control model. Finally, through the establishment of the steam loss model and experiments on the final soot blowing optimization model, the effectiveness of the optimization control model is demonstrated. The model can achieve a maximum supply of main steam flow while ensuring normal power generation of the boiler, and it aims to control soot blowing damage and costs as much as possible.

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