

Article

Intelligent Deep Learning Modeling and Multi-Objective Optimization of Boiler Combustion System in Power Plants

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Abstract

The internal combustion process in a boiler in power plants has a direct impact on boiler efficiency and NO_x generation. The objective of this study is to propose an intelligent deep learning modeling and multi-objective optimization approach that considers NO_x emission concentration and boiler thermal efficiency simultaneously for boiler combustion in power plants. Firstly, a hybrid deep learning model, namely, convolutional neural network–bidirectional gated recurrent unit (CNN-BiGRU), is employed to predict the concentration of NO_x emissions and the boiler thermal efficiency. Then, based on the hybrid deep prediction model, variables such as primary and secondary airflow rates are considered as controllable variables. A single-objective optimization model based on an improved flow direction algorithm (IFDA) and a multi-objective optimization model based on NSGA-II are developed. For multi-objective optimization using NSGA-II, the average NO_x emission concentration is reduced by 5.01%, and the average thermal efficiency is increased by 0.32%. The objective functions are to minimize the boiler thermal efficiency and the concentration of NO_x emissions. Comparative analysis of the experiments shows that the NSGA-II algorithm can provide a Pareto optimal front based on the requirements, resulting in better results than single-objective optimization. The effectiveness of the NSGA-II algorithm is demonstrated, and the obtained results provide reference values for the low-carbon and environmentally friendly operation of coal-fired boilers in power plants.

Keywords: boiler combustion system; hybrid deep learning model; multi-objective optimization; CNN-BiGRU; improved flow direction algorithm



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1. Introduction

The issue of controlling pollutant emissions from thermal power plants has received increasing attention and focus [1]. Coal-fired boilers in thermal power plants produce large amounts of nitrogen oxides (NO_x) during combustion. NO_x, comprising nitric oxide (NO) and nitrogen dioxide (NO₂), significantly contributes to severe air pollution [2]. NO_x is an acidic gaseous pollutant that can cause significant damage to the human respiratory system when emitted into the air in large quantities. It forms fine particles of nitric acid and nitrate, causing atmospheric pollution and, in severe cases, acid rain, which can affect the surrounding animals and plants [3]. The use of coal-fired boilers in power

plants to generate electricity has caused environmental pollution problems, and many power plants have sought to reduce NO_x emission concentrations. However, incomplete combustion in boilers results in wasted fuel calorific values, which, in turn, leads to lower combustion efficiency and increased fuel consumption, thus increasing costs [4]. Measures to reduce NO_x emissions often reduce boiler efficiency and affect the economic efficiency [5]. Therefore, a balance between NO_x emission and boiler efficiency must be considered to find a solution that will reduce NO_x emissions without unduly sacrificing boiler efficiency and plant economics.

As society continues to develop, many power plants have been equipped with plant-level real-time monitoring information systems (SISs), which store much of the operational data during boiler operation, such as the operating conditions and parameters, and provide data support for developing boiler combustion optimization technology [6]. The ever-evolving field of artificial intelligence and machine learning has recently introduced several techniques to enhance boiler combustion optimization technology. NO_x emission levels and boiler thermal efficiency are crucial performance indicators for evaluating boiler operation. A machine learning-based predictive model can be created for the NO_x emission concentration and boiler thermal efficiency using historical data on boiler operations [7]. In addition, an intelligent evolutionary algorithm can be employed to optimize controllable operational parameters of the boiler combustion system. This will help lower the NO_x emission concentration and enhance boiler thermal efficiency, ultimately improving the economic efficiency of power plants [8].

NO_x production and thermal efficiency during boiler combustion depend on various factors, including the coal feed, boiler load, primary and secondary airflow, etc. Therefore, the boiler combustion model is a complex multivariable and nonlinear system, making it challenging to develop an optimal model using traditional methods. Therefore, many scholars have conducted intelligent modeling through historical data to predict NO_x concentration emissions and boiler combustion efficiency [9]. Currently, the main approaches for data modeling are machine learning and deep learning models.

Li et al. [10] proposed a model of Extreme Learning Machine (ELM) based on an artificial bee colony algorithm for predicting the thermal efficiency of boilers. After experimental verification, the model is capable of markedly increasing the reliability of forecasting results and provides strong support for boiler operation. Tan et al. [11] found through experiments that the long short-term memory (LSTM) model outperformed support vector machines (SVMs) in predicting NO_x emissions from coal-fired boilers. Liu et al. [12] employed a generalized correlation (GC) entropy-based hybrid LSTM model to predict NO_x emission concentrations, which yielded satisfactory outcomes. Wang et al. [13] developed a hybrid model by utilizing an attention mechanism with an LSTM model and also introduced the complete ensemble empirical mode decomposition with adaptive noise (CEEMDAN) method for the decomposition of raw historical data. Wang et al. [14] introduced a new regression method, the convolutional neural network (CNN), which utilizes convolutional neural networks to enhance NO_x emission prediction accuracy and efficiency in both steady-state and transient scenarios for coal-fired boilers. The CNN-BiGRU model was proposed by Ma et al. [15] for the NO_x concentration prediction of a 660 MW coal-fired boiler. The model displays excellent prediction performance and accurately predicts NO_x concentrations. Based on this, this paper will use the CNN-BiGRU model to construct a NO_x concentration and boiler combustion efficiency prediction model and, subsequently, to conduct research. Li et al. [16] developed a CNN-LSTM model augmented with a channel-wise attention module to predict NO_x emissions from coal-fired boilers, achieving improved accuracy and robustness over standard deep learning models. Wan et al. [17] applied a

CNN-LSTM-attention framework to forecast the boiler load in CHP plants, reporting a MAPE of below 1%.

Based on the application of machine learning algorithms to model and simulate boiler combustion processes, some researchers have used intelligent evolutionary algorithms to optimize controllable boiler operating parameters under different operating conditions, aimed at boosting boiler efficiency and lowering nitrogen oxide emissions. According to the boiler operation requirements, there are two main methods for optimizing coal-fired boilers [18]: One is to use single-objective optimization to improve boiler efficiency or to reduce the NOx emission concentration. The other is to use multi-objective optimization to balance the NOx concentration and improve boiler efficiency. The single-objective optimization methods for boiler combustion systems include the simulated annealing genetic algorithm (SAGA) [19], genetic algorithm (GA) [20], ant colony optimization algorithm (ACO) [21], and other algorithms [22]. Dirik [20] developed a NOx emission model using a neuro-fuzzy inference system. The model used the GA algorithm to optimize boiler combustion by determining optimal values for the operating parameters. Wei et al. [19] proposed a support vector regression (SVR) model to predict the concentration of NOx emissions and employed SAGA for optimizing the operating parameters of coal-fired boilers. Yao et al. [23] implemented a genetic algorithm to improve system operations, aiming to suppress NOx emission levels. Zhou et al. [21] obtained optimal operating parameters based on the ACO algorithm for reducing NOx emissions.

During the last several years, many multi-objective optimization algorithms have been introduced to solve the problem of optimizing the control of systems such as boiler combustion and denitrification systems [9]. A predictive model is built based on the raw data, and multiple objective functions are established, such as the system efficiency, pollutant emission concentration, operating cost, etc. By solving the objective functions using multi-objective optimization algorithms, multiple Pareto optimal fronts are found, and feasible solutions for the corresponding controllable parameters are obtained, providing reliable recommendations for the operation and production of the equipment.

The most commonly used multi-objective optimization algorithms include non-dominated sorting genetic algorithm II (NSGA-II) [24], multi-objective particle swarm optimization (MOPSO) [25], multi-objective differential evolution (MODE) [26], etc. Xu et al. [25] proposed an improved multi-objective particle swarm optimization (IMOPSO) to optimize boiler combustion to simultaneously enhance thermal efficiency and reduce NOx emissions. Zheng et al. [26] suggested employing a multi-objective evolutionary algorithm (MOEA/D) in combination with a kernel extreme-learning machine (KELM) prediction model for optimal control. The aim was to reduce pollutant emissions and enhance energy efficiency, and the simulation results confirmed the efficacy of this approach. Wu et al. [27] proposed a design for a steam power system (SPS) that incorporated pollutant reduction technology. The NSGA-II algorithm was used to obtain the Pareto optimization curve, and simulation results verified the applicability of NSGA-II. In this study, the NSGA-II multi-objective optimization algorithm is applied to enhance the boiler combustion performance. Tang et al. [28] developed DYNA-A3C, a dynamic-weight reinforcement learning model, to optimize combustion performance under deep peak-shaving scenarios, effectively improving NOx control. Meanwhile, advanced multi-objective optimization algorithms such as MOEA/D and SPEA2 have been employed to handle the trade-off between emission reduction and efficiency. Zheng et al. [26] applied MOEA/D integrated with a kernel extreme learning machine (KELM) for combustion optimization, yielding a diverse and efficient set of solutions.

Motivated by the preceding techniques, this paper proposes a research method for intelligent modeling and multi-objective optimization of boiler combustion based on deep hybrid learning. The scientific contributions made by this study are set out below:

- (1) A hybrid deep learning model, known as CNN-BiGRU, is constructed using historical operational data to accurately predict the NOx emission concentration and to optimize the boiler combustion efficiency of a 300 MW coal-fired boiler. This advanced model integrates convolutional neural networks (CNNs) and bidirectional gated recurrent units (BiGRUs) to capture complex temporal and spatial patterns in boiler combustion. Compared with prior works using LSTM, GRUs, or basic CNN models, the CNN-BiGRU model demonstrates superior prediction accuracy.
- (2) The NOx emission concentration and boiler combustion efficiency are identified as the optimization objectives. Boiler combustion is optimized with the single goal of using the improved flow direction algorithm (IFDA). The IFDA incorporates iterative local search (ILS) and chaotic initialization to enhance the optimization capabilities, outperforming the original FDA algorithm. The controllable variables and the optimization interval are determined, and the optimal solution is found by continuously adjusting the values of the controllable variables to reduce the NOx emission concentration or to improve the thermal efficiency of the boiler.
- (3) To optimize the combustion performance of coal-fired boilers, the non-dominated sorting genetic algorithm II (NSGA-II) is employed as a multi-objective optimization tool. The NSGA-II algorithm is utilized to balance NOx emission reduction and boiler efficiency improvement, generating a Pareto optimal front that provides practical solutions for real-world applications. This approach overcomes the limitations of the single-objective optimization methods previously used. The resulting Pareto front is compared against single-objective optimization outcomes, thereby validating the superiority and practicality of the multi-objective approach. The NSGA-II algorithm achieves a significant reduction in NOx emissions and an increase in boiler thermal efficiency, demonstrating the model's potential for promoting the low-carbon and environmentally sustainable operation of coal-fired boilers.

In this study, Section 2 provides an introduction to the case study and data sources. Section 3 describes the improved FDA algorithm, the NSGA-II algorithm, and the general process of this paper. The results of the prediction model for the boiler combustion system is presented in Section 4. Next, Section 5 compares and analyzes the simulation results obtained from single-objective and multi-objective optimization approaches applied to coal-fired boilers. A summary of the experimental results is presented in Section 6.

2. Methods

2.1. Improved Flow Direction Algorithm (IFDA)

Karami et al. [29] developed the flow direction algorithm (FDA), which is based on tracking the flow movement to the basin outlet. The flow direction algorithm (FDA) employs a specific policy for allocating search duration to balance global and local searches. This is accomplished through two key components: gradually reducing the neighborhood radius to negligible values and implementing a sink-filling process that aids in escaping local solutions. The steps involved in the FDA can be summarized as follows:

$$F1_I = \begin{bmatrix} i_1^1 & i_2^1 & \cdots & i_s^1 \\ i_1^2 & i_2^2 & \cdots & i_s^2 \\ \vdots & \vdots & \ddots & \vdots \\ i_1^w & i_2^w & \cdots & i_s^w \end{bmatrix} \quad (1)$$

where $F1_I$ denotes the location of the flow, s denotes the dimension of the problem, and the population size is w .

Each flow undergoes objective function evaluation, with the exit point determined by identifying the most favorable value. The corresponding matrix representation of the objective functions is shown as follows:

$$F1_fit = \begin{bmatrix} fit1 \\ fit2 \\ \vdots \\ fitw \end{bmatrix} \quad (2)$$

A set of neighboring flows is constructed for each stream element based on a predefined neighborhood radius Δ . The position of the neighborhood is calculated as follows:

$$N1_I(n) = F1_I(m) + randn * \Delta \quad (3)$$

where $N1_I$ denotes the n th position of the neighbor and $randn$ is a random value. $F1_I(m)$ denotes the m th position in the flow direction.

The value of the objective function is computed for each neighbor, and the best neighbor is determined using the following approach:

$$\Delta = rand * Irand - rand * F1_I(m) * BestX - F1_I(m) * W \quad (4)$$

$$r_d = \sum_{a=1}^A R_a - \varphi \Delta t \quad (5)$$

where $rand$ stands for a random location and $Irand$ is a random location determined by the direct runoff. W is a non-linear weight, r_d denotes the direct runoff, R_a denotes the rainfall, Δt denotes the time interval, and m denotes the time step.

An update of the flow velocity vector is performed using Equation (6) when the optimal neighbor exhibits a better objective function value than the current flow. A new flow position is generated according to the relations outlined in Equation (7). The expression for the flow velocity vector can be found in Equation (8):

$$F1_newX(m) = f_X(m) + V * \frac{F1_X(m) - N1_X(n)}{\|F1_X(m) - N1_X(n)\|} \quad (6)$$

$$V = [v_1 \ v_2 \ \dots \ v_s] \quad (7)$$

$$V = randm * S_0 \quad (8)$$

where $F1_newX(m)$ represents the location of the new flow, $randm$ represents a randomly generated number, and the variable S_0 indicates the slope linking the neighbor to the current flow.

The position of the flow is updated according to the following formula:

$$\begin{cases} \text{if } F1_fit(r) < F1_fit(m) \\ F1_newX(m) = F1_X(i) + randm * (F1_X(r) - F1_X(m)) \\ \text{else} \\ F1_newX(m) = F1_X(m) + 2randm * (Best_X - F1_X(m)) \end{cases} \quad (9)$$

where r is a random integer.

The final part calculates the objective function for the new flows. The resulting results are compared with the existing flows, and if the effect improves, the objective function and the positions of the flows are updated, and the optimal answer is returned. Conversely, the number of neighborhoods with neighborhood radius Δ is recreated for each flow, and the subsequent steps are repeated.

The original FDA algorithm has yielded relatively excellent results in the study of many optimization problems, but it also suffers from some drawbacks. For this reason, Ma et al. [15] added iterative local search (ILS) strategies and chaotic initialization to improve the FDA algorithm.

The FDA algorithm is frequently employed for swarm intelligence optimization and relies on random distribution for the initial population generation. However, this approach can compromise population diversity, leading to premature convergence, especially for more intricate problems where the algorithm may rapidly converge to a suboptimal local solution. Escaping local optima can present a significant challenge when seeking better solutions. Various strategies have been proposed to overcome the tendency of the FDA algorithm to fall into local optimization during location updates. One such method involves implementing a chaos strategy to determine the initial population distribution [29], which leverages the random behavior of chaotic systems to increase the initial population diversity. An alternative strategy to combat early local optimum convergence and improve the global search ability of the FDA algorithm involves utilizing an ILS technique [30]. Essentially, the ILS approach introduces perturbations to the current local optimum solution and conducts a new search to identify a superior global optimum solution [31]. A key advantage of the ILS approach is its ability to rapidly jump out of local optima, facilitating the solution exploration capabilities of the FDA. An ILS strategy is adopted and integrated at the end of each iteration to counter the issue of local-optimum-solution trapping in the FDA algorithm. This strategy enables the algorithm to more effectively bypass local optima, resulting in a quicker convergence rate.

The improved flow direction algorithm has an optimization search flow, as shown in Figure 1.

2.2. Non-Dominated Sorting Genetic Algorithm-II (NSGA-II)

Deb et al. [32] introduced the non-dominated sorting genetic algorithm-II (NSGA-II), which incorporates crowding distance calculations to identify the complete Pareto optimal front. This approach also ensures that solutions along the front are evenly distributed, thereby maintaining population diversity throughout the optimization process. The NSGA-II algorithm avoids the loss of the best individuals in the population by introducing an elite strategy and expanding the sampling space while also increasing the computational speed of the algorithm. The NSGA-II algorithm steps are described below:

Step 1: Produce an initial population with N number of individuals;

Step 2: Determine whether to generate new individuals by calculating fitness values and rank them;

Step 3: Generate a second-generation population through strategies such as cross and variation, and use an elite strategy to merge the first- and second-generation populations to form a new population;

Step 4: Perform non-dominated sorting on the new population and calculate the crowd level. Select the best individuals to form a new population again, and keep repeating the above operations until the end conditions are met.

Figure 2 shows the flow of the NSGA-II algorithm.

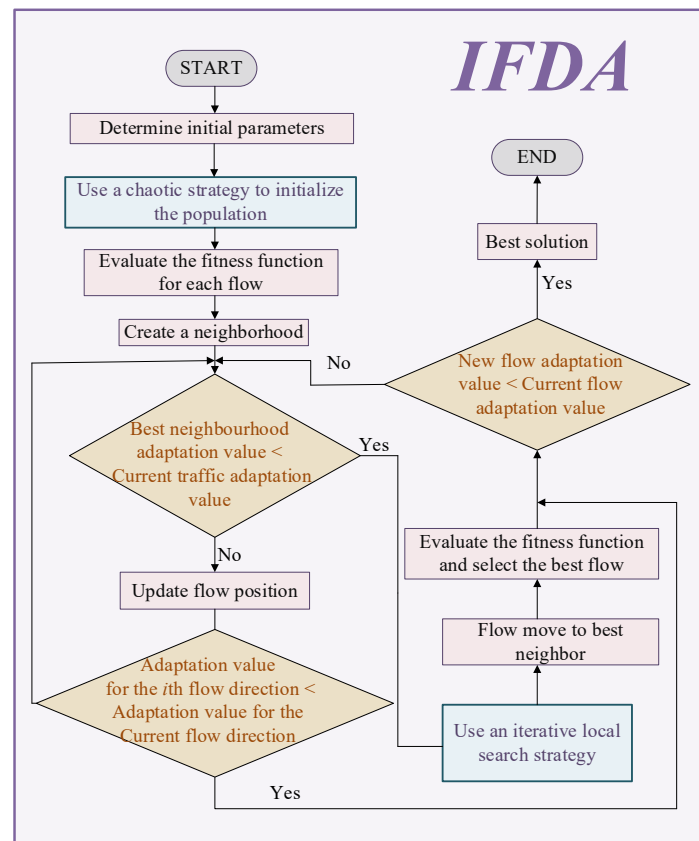


Figure 1. Flow chart of the improved flow direction algorithm.

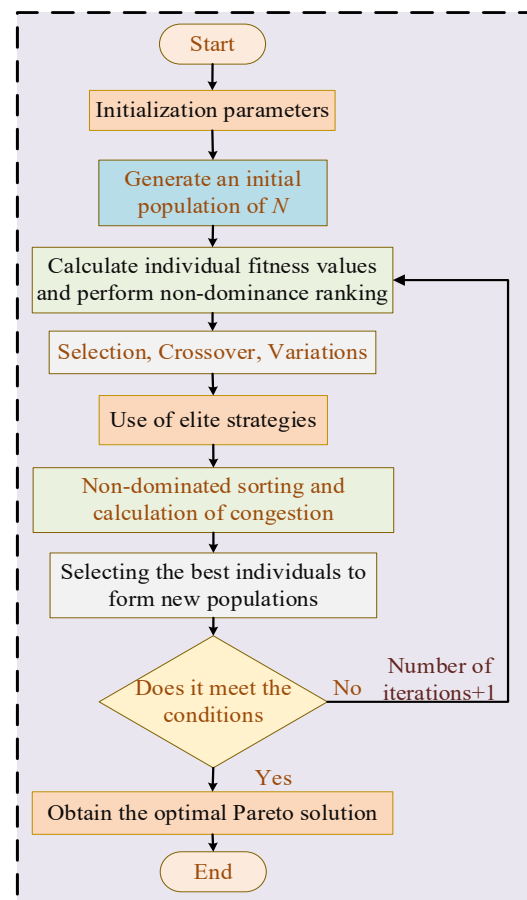


Figure 2. NSGA-II algorithm calculation flow chart.

2.3. The CNN-BiGRU Prediction Model

Ma et al. [15] employed a convolutional neural network (CNN) to extract deep features from a dataset before utilizing the BiGRU model to predict NOx. Then, the hyperparameters of the CNN-BiGRU are optimized using the IFDA algorithm. In this paper, based on Ma et al. [15], a NOx concentration and coal-fired boiler efficiency prediction model will be constructed based on 300 MW boiler operation data as the research object. Figure 3 shows the final construction of the CNN-BiGRU model.

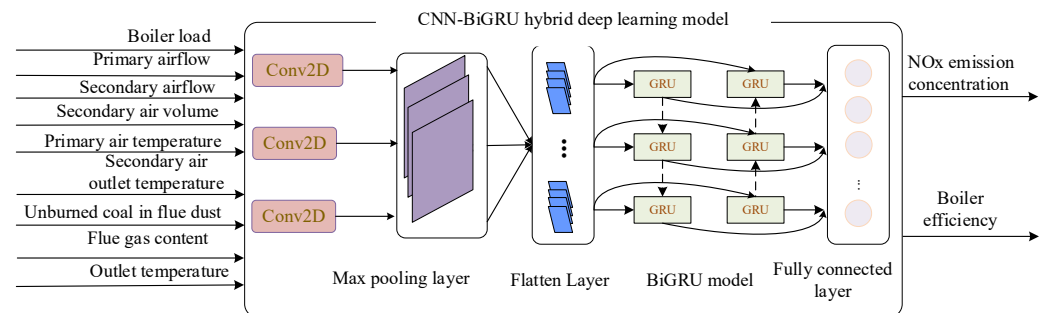


Figure 3. A boiler combustion prediction model based on the CNN-BiGRU.

The CNN-BiGRU model comprises two convolutional layers with kernel sizes of 3 and 5, respectively, followed by ReLU activation. The BiGRU layer contains 128 hidden units, followed by a dense output layer. The model is trained for 100 epochs with a batch size of 64, using the Adam optimizer and a learning rate of 0.001. The IFDA algorithm is applied to optimize key hyperparameters, including the learning rate, number of filters, and hidden units by minimizing the validation RMSE.

2.4. Boiler Efficiency Calculations

Boiler efficiency is defined as the ratio of useful heat output to the total heat input during the coal combustion process in a boiler [33]. Boiler efficiency is used to assess the economics of coal-fired boilers. Improving boiler efficiency increases energy efficiency and is one of the main objectives of this study for optimal control. Two main methods for calculating boiler thermal efficiency are currently used in the actual generation process, namely the positive- and negative-balance method [34].

When the boiler efficiency is calculated using the positive balance method in the actual production process, it is necessary to obtain the total heat input value of the boiler QH_2 and the effective heat value QH_1 and to obtain the boiler efficiency from the ratio of the two. The calculation formula is shown in Equation (10):

$$\eta = \frac{QH_1}{QH_2} \quad (10)$$

where QH_1 and QH_2 represent the effective heat value per kilogram of fuel and the total heat input, respectively.

However, in practice, the errors in the effective heat obtained and the total heat input are too large to accurately calculate boiler efficiency, so plants generally use the negative balance method to calculate boiler efficiency. The negative balance method differs from the forward balance method in that the negative balance method indirectly calculates boiler efficiency by obtaining various heat loss values for coal-fired boilers. This calculation method not only gives a more accurate picture of the boiler efficiency but also allows the

current operating conditions of the boiler to be known from the heat loss values. The calculation formula for the negative balance method is shown in Equation (11).

$$\eta = 100 - \sum_{j=3}^7 QH_j \quad (11)$$

where QH_j represents various heat loss values, mainly for the following types of heat loss: exhaust heat loss QH_3 , gas incomplete combustion heat loss QH_4 , solid incomplete combustion heat loss QH_5 , heat loss QH_6 , and ash physical heat loss QH_7 .

Exhaust heat loss QH_3 refers to the heat in the flue gas emitted from the boiler; more heat is lost the higher exhaust temperature is. Gas incomplete combustion heat loss QH_4 refers to the combustible gases remaining in the flue gas emitted from the boiler; such gases do not burn and release heat during the boiler operation, resulting in heat loss. The solid incomplete combustion heat loss QH_5 and ash physical heat loss QH_7 refer to the coal in the combustion process; some slag and leakage of coal contain unburned coal material, thus causing heat loss; the more unburned coal material generated by the heat loss, the more significant this will be. Heat loss QH_6 is the heat loss caused by the heat dissipation of the equipment to the outside due to the combustion process of the boiler; this heat loss generally accounts for a relatively small amount.

3. General Flowchart of the CNN-BiGRU and NSCA-II for Boiler Combustion Modeling

The general process of the CNN-BiGRU and NSCA-II (CNN-BiGRU-NSCA-II)-based study is shown below:

- (1) Firstly, the study object was identified as a 300 MW circulating fluidized bed boiler, and 3000 samples were selected as the raw data from its historical operation data, of which 70% were classified as the training set and 30% as the test set. There were 25 input variables, while the model output variables mainly involved boiler thermal efficiency and NOx emission concentration.
- (2) A CNN-BiGRU-based boiler combustion prediction model was constructed and employed to forecast the concentrations of NOx emissions and the thermal efficiency of the boiler.
- (3) A total of five variables, namely the primary airflow rate ($y_6 \sim y_7$), secondary airflow rate ($y_{12} \sim y_{13}$), and flue gas oxygen content (y_{20}), were selected as controllable variables according to the actual situation, and the optimization interval was determined.
- (4) The boiler thermal efficiency and NOx emission concentration were denoted as the optimization objectives.
- (5) The NSGA-II algorithm was employed to identify the optimal solution for controllable variables within the defined optimization range, with the best parameter set corresponding to the minimum fitness value achieved by the algorithm.
- (6) Simulation analyses were performed to evaluate and compare the outcomes of the IFDA under single-objective and multi-objective optimization scenarios.

The specific process based on the CNN-BiGRU-NSGA-II is shown in Figure 4.

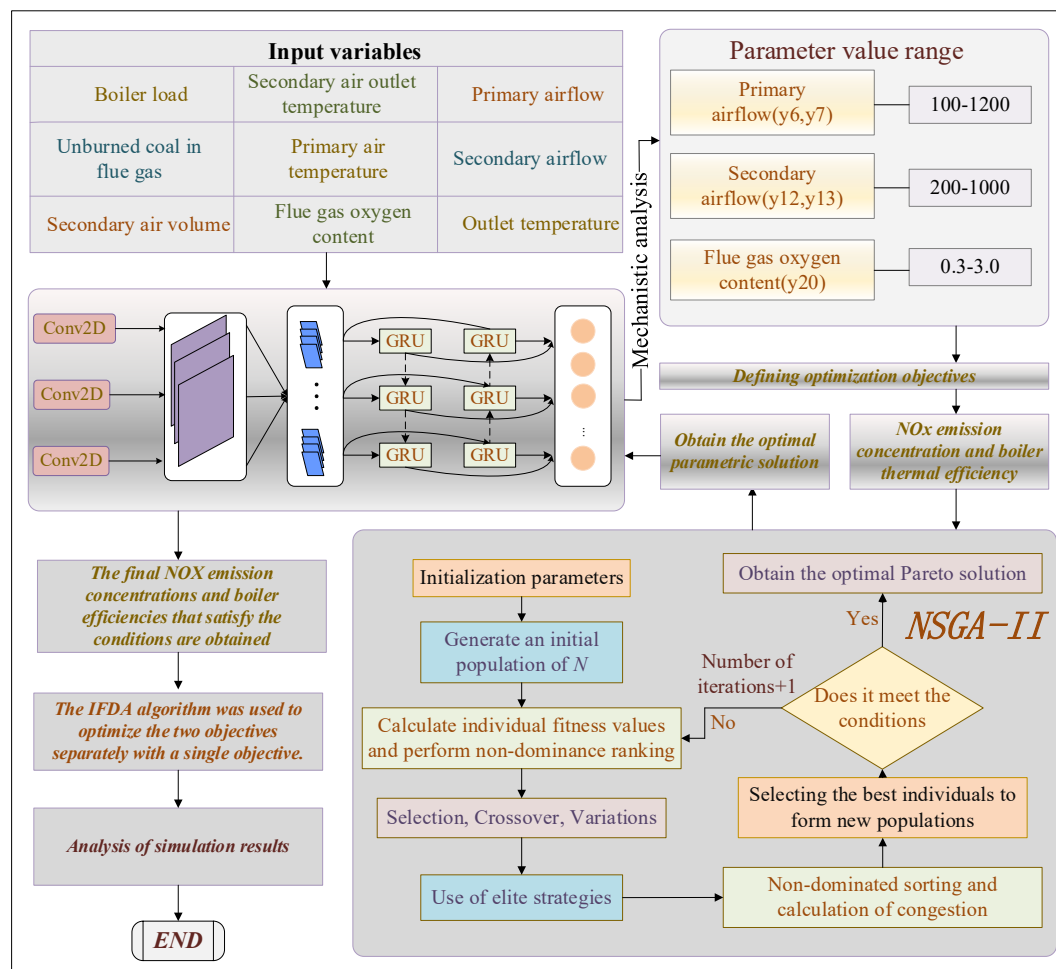


Figure 4. General flowchart of the CNN-BiGRU and NSGA-II for boiler combustion modeling.

4. Case Study

4.1. Data Source and Preprocessing

In this study, operational data were collected from a 300 MW circulating fluidized bed (CFB) boiler, based on historical combustion operation records. A total of 3000 samples were selected as the original dataset after preprocessing. The dataset was divided into 70% for training and 30% for testing. Twenty-five key variables were selected as inputs, including the boiler load (y_1), coal feed rates (y_2 – y_5), primary airflow at the burner inlets (y_6 – y_7), primary air temperature (y_8 – y_9), primary fan inlet temperature (y_{10} – y_{11}), secondary airflow (y_{12} – y_{13}), secondary air outlet temperature (y_{14} – y_{15}), motor currents (y_{16} – y_{17}), flue gas oxygen content (y_{18}), flue gas temperature (y_{19}), and outlet temperature of slag cooler (y_{20} – y_{23}). The two output variables were NOx emission concentration and efficiency. The dataset was provided by Hu et al. [26] and was a real dataset from the monitoring information system (SIS) of circulating fluidized bed boilers (CFBBs).

To guarantee the reliability of the combustion model used in this study, a meticulous selection process was employed to screen and process accurate operating data from the power plant for testing and training purposes. The primary factors influencing NOx generation in coal-fired boilers included the direct airflow, secondary airflow, coal feed, load, and oxygen content. A comprehensive analysis was conducted on these factors to determine the input variables for subsequent experiments. Based on the generation mechanism of NOx, 23 variables were selected as input variables, and NOx emission

concentration and boiler thermal efficiency were selected as the output variables of the model. The initial selection of 23 variables is presented in Table 1 below:

Table 1. Coal-fired boiler inputs and outputs.

	Variable Name	Unit	Variable
Input	Load	%	y_1
Ambient pressure	Coal quantity of the coal feeder	t/h	y_2 – y_5
Ambient humidity	Primary airflow of the burner inlet	kNm^3/h	y_6 – y_7
Air-filter pressure difference	Primary air temperature of the burner inlet	$^{\circ}\text{C}$	y_8, y_9
Gas-turbine exhaust pressure	Primary air fan inlet temperature	$^{\circ}\text{C}$	y_{10}, y_{11}
Turbine inlet temperature	Distribution flow of the secondary air	kNm^3/h	y_{12}, y_{13}
Turbine after temperature	Distribution flow of secondary air	kNm^3/h	
Compressor discharge pressure	Air preheater secondary air outlet air temperature	$^{\circ}\text{C}$	y_{14}, y_{15}
Turbine energy yield	Limestone powder conveying motor current	AMP	y_{16}, y_{17}
Carbon monoxide	Flue gas oxygen content	%	y_{18}
Nitrogen oxides	Flue gas temperature	$^{\circ}\text{C}$	y_{19}
	Outlet temperature of slag cooler	$^{\circ}\text{C}$	y_{20} – y_{23}
Output	NOx emission concentration	mg/m^3	
	efficiency	%	

4.2. Performance Metrics

Four evaluation metrics were used in this study to assess the effectiveness of the prediction model: Root Mean Square Error (RMSE), Correlation Coefficient (R), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE).

$$RMSE = \sqrt{\frac{1}{p} \sum_{a=1}^p (Y_{c_a} - G_{e_a})^2} \quad (12)$$

$$R = \frac{\sum_{a=1}^p (Y_{c_a} - \overline{Y_{c_a}})(G_{e_a} - \overline{G_{e_a}})}{\sqrt{\sum_{a=1}^p (Y_{c_a} - \overline{Y_{c_a}})^2 \times \sum_{j=1}^p (G_{e_a} - \overline{G_{e_a}})^2}} \quad (13)$$

$$MAE = \frac{1}{p} \sum_{n=1}^p |Y_{c_n} - G_{e_n}| \quad (14)$$

$$MAPE = \frac{1}{p} \sum_{n=1}^p \left| \frac{Y_{c_n} - G_{e_n}}{G_{e_n}} \right| \times \frac{100}{p} \quad (15)$$

where G_{e_a} is the observed value and p is the total number of predicted samples. Y_{c_a} is the predicted value, and $\overline{Y_{p_i}}$ and $\overline{O_i}$ represent the average observed and average predicted values, respectively.

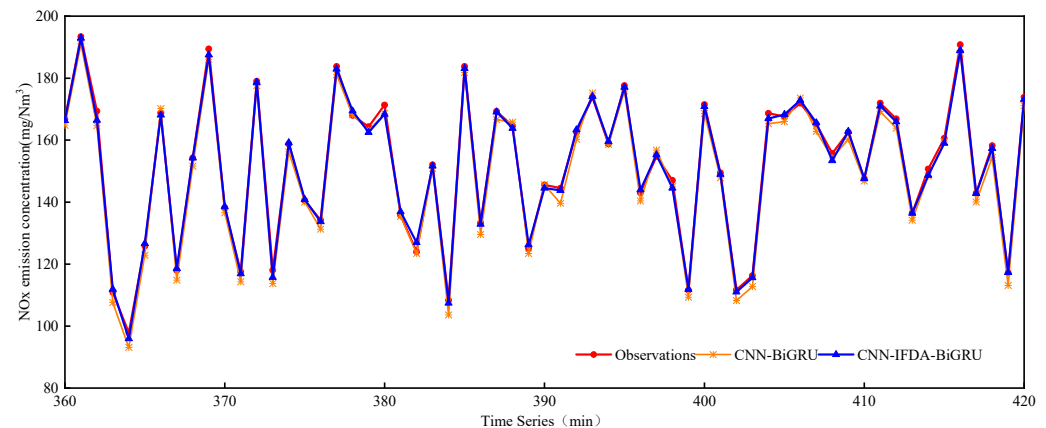
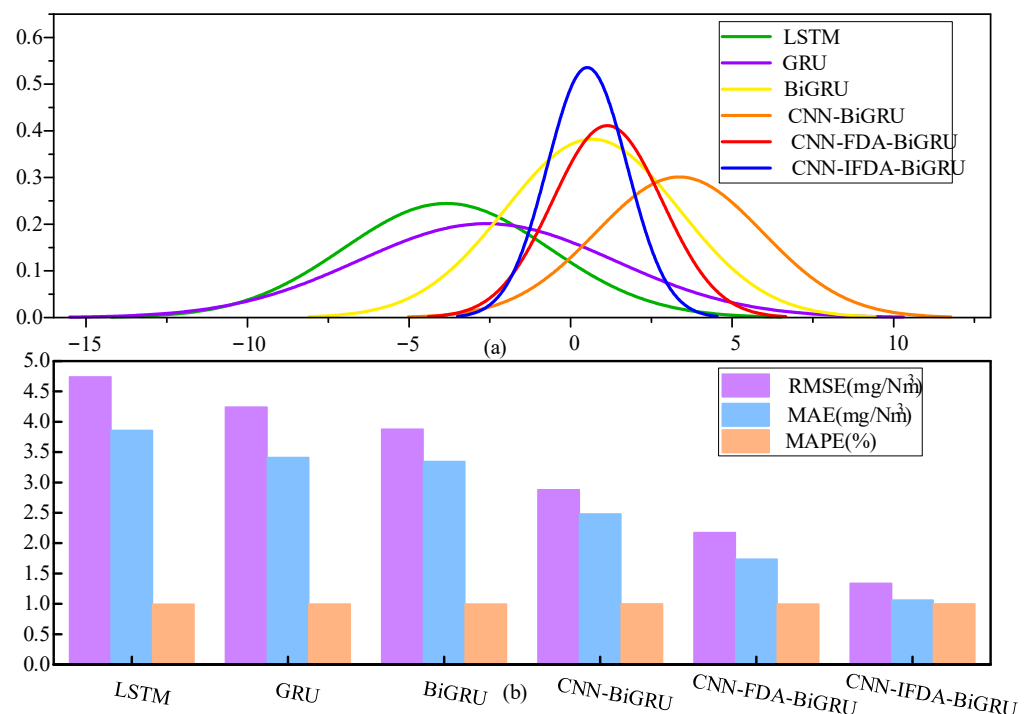
5. Comparison Results

5.1. Analysis of the NOx Prediction Results

In this research study, a novel hybrid deep learning model dubbed CNN-BiGRU was utilized in constructing boiler combustion prediction models. Table 2 displays the NOx emission concentration prediction-error evaluation index values for each model. To present the NOx prediction outcomes more transparently, this subsection employs a sample size of 60 consecutive forecast results to generate comparative graphs depicting the model prediction performance, as shown in Figures 5 and 6.

Table 2. Evaluation index of the prediction error for the NOx emission concentration in each model.

NOx Emission Prediction Model	RMSE	MAE	R	MAPE
LSTM	4.7415	3.8592	0.9953	0.0266
GRU	4.2426	3.4098	0.9964	0.0274
BiGRU	3.8799	3.3472	0.9977	0.0228
CNN-BiGRU	2.8784	2.4829	0.9991	0.0199
CNN-FDA-BiGRU	2.1745	1.7395	0.9985	0.0137
CNN-IFDA-BiGRU	1.3396	1.064	0.9992	0.0078

**Figure 5.** Comparison of NOx emission concentration prediction results from the hybrid deep learning model.**Figure 6.** Probability distribution diagram and error index comparison. (a) Probability density of the prediction errors. (b) Bar-chart comparison of RMSE, MAE and MAPE for each model.

For the NOx emission concentration prediction experiment, the CNN-IFDA-BiGRU model achieved RMSE, MAE, R, and MAPE values of 1.3396, 1.064, 0.9992, and 0.0078, respectively, as detailed in Table 2. This model demonstrates the lowest error metrics—including for the RMSE, MAE, and MAPE—while also attaining the highest correlation coefficient R. When comparing the CNN-BiGRU model to the standalone BiGRU model, the former clearly outperforms the latter, exhibiting reduced RMSE, MAE,

and MAPE values, which indicates its superior predictive capability. Furthermore, as illustrated in Figure 5, the IFDA-optimized model surpasses the FDA-optimized model in prediction accuracy. These results confirm the effectiveness of the IFDA algorithm in minimizing prediction errors and enhancing the overall performance of the CNN-BiGRU model. To provide a more comprehensive evaluation, Figure 6 presents the normal distribution of the NO_x prediction results alongside a comparative analysis of the error metrics across all the models.

Observing the probability distribution in Figure 6, it becomes evident that the CNN-IFDA-BiGRU model exhibits a higher frequency of error values close to zero compared with other models. On the other hand, the LSTM model displays the smallest error values. This further indicates that the proposed model has better results in predicting NO_x emission concentrations. The error indicator bar chart clearly illustrates a consistent decreasing trend in the simulation results of each model. This trend is strong evidence of the effectiveness of the methods proposed in this study.

5.2. Analysis of the Thermal Efficiency of Coal-Fired Boilers Prediction Results

Like in Section 4.1, the boiler combustion prediction models were constructed using the hybrid deep learning model CNN-BiGRU. Table 3 shows the values of the boiler thermal efficiency prediction-error evaluation metrics for each model. The thermal efficiency prediction results for coal-fired boilers are shown in Figures 7 and 8.

Table 3. Comparison of evaluation indicators for the prediction error for the thermal efficiency of coal-fired boilers in various models.

Thermal Efficiency Prediction Model	RMSE	MAE	R	MAPE
LSTM	0.0573	0.0453	0.9935	0.00050
GRU	0.0527	0.0404	0.9927	0.00045
BiGRU	0.0470	0.0348	0.9938	0.00038
CNN-BiGRU	0.0421	0.0365	0.9984	0.00040
CNN-FDA-BiGRU	0.0273	0.0189	0.9981	0.00021

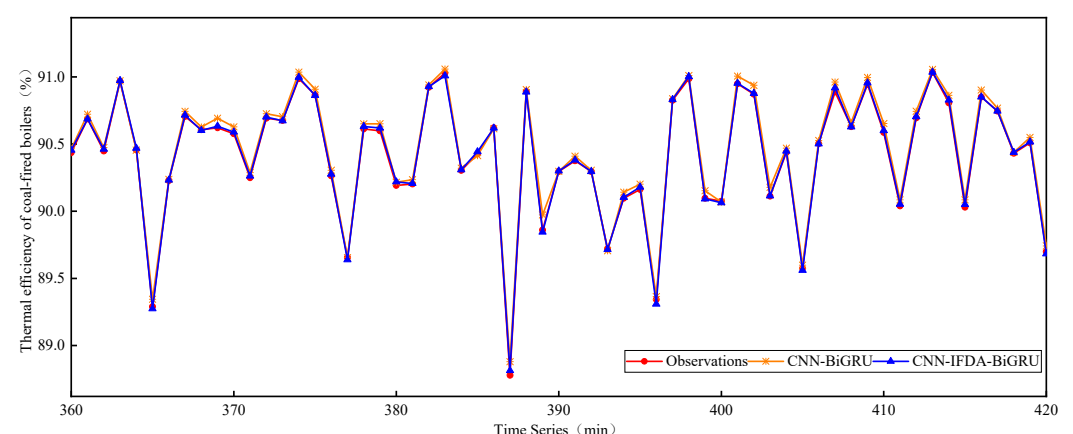


Figure 7. Comparison of boiler thermal efficiency prediction results of the hybrid deep learning model.

In the boiler thermal efficiency prediction experiments, the CNN-IFDA-BiGRU model achieved RMSE, MAE, R, and MAPE values of 0.0144, 0.0113, 0.9996, and 0.00012, respectively. Among all the control groups, this model exhibits the lowest error metrics—including for the RMSE, MAE, and MAPE—along with the highest correlation coefficient R. As illustrated in Figure 7, the IFDA-optimized model outperforms the FDA-optimized model in terms of prediction accuracy. To further compare the performance of each model in boiler thermal efficiency prediction, a plot of the normal distribution of the NO_x prediction results and a comparison of error indicators for each model were plotted, as shown in

Figure 8. The probability distribution plot in Figure 8 shows that the CNN-IFDA-BiGRU model has the most error values close to zero and the LSTM model has the least, further indicating that the proposed model has the better performance in predicting boiler thermal efficiency. The histogram of error indicators demonstrates a consistent decreasing trend in the simulation results of each model, implying the effectiveness of the proposed methods in predicting the thermal efficiency of boilers.

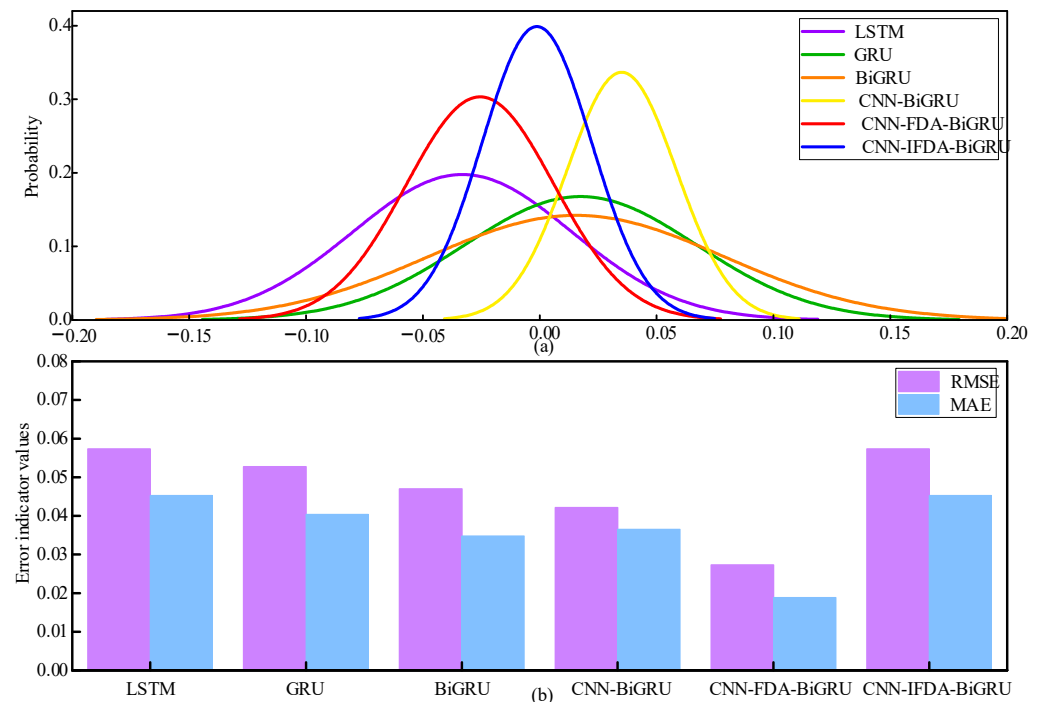


Figure 8. Performance comparison in boiler thermal-efficiency prediction. (a) Probability-density distribution of the prediction errors. (b) Bar-chart comparison of RMSE and MAE for each model.

5.3. Coal-Fired Boilers with Multiple Objectives

In practice, reducing NO_x emissions from boilers can reduce the boiler thermal efficiency, thus affecting the efficiency of the power plant. Therefore, during boiler combustion operations, it is imperative to consider not only the limits of NO_x emission concentrations but also the efficiency of the boiler. This study starts with these two objectives. In combination with the previous prediction model of the boiler combustion system based on the CNN-BiGRU, a single-objective optimization of these two objectives is carried out first. Then a multi-objective optimization model considering NO_x emission concentration and boiler combustion efficiency as optimization objectives are constructed using NSGA-II, and the simulation results are analyzed.

This study utilizes real-world boiler operating data as the foundation for the model, employing an algorithm to identify the optimal boiler operating parameters that fulfil the requirements. This approach facilitates optimal control over boiler efficiency and NO_x emission concentration. In this study, only the primary airflow ($y_6 \sim y_7$), secondary airflow ($y_{12} \sim y_{13}$), and flue gas oxygen content (y_{20}) parameters are optimized in the given optimization range. In contrast, the other operating parameters are kept constant during optimization.

5.3.1. Single-Objective Optimization of NOx Emission Concentrations from Coal-Fired Boilers

Single-objective optimization is the optimization of only one objective function, within a given range, by finding the optimal solution for the parameter variables to satisfy the objective function. Single-objective optimization can be expressed by the following Equation (16):

$$\begin{aligned} & \text{Min(orMax)} \quad \text{fun}(x) \\ & \text{s.t.} \\ & x = [x_1, x_1, \dots, x_m, \dots, x_M] \\ & x_{m\min} \leq x_m \leq x_{m\max} \end{aligned} \quad (16)$$

where $\text{Min(orMax)} \text{ fun}(x)$ is the approximate objective function, $x = [x_1, x_1, \dots, x_m, \dots, x_M]$ is the constraint condition, and $x_{m\min} \leq x_m \leq x_{m\max}$ is the range of the parameter variables.

Using Equation (17), a single-objective optimization model of the NOx emission concentration using the FDA algorithm and the IFDA algorithm is constructed as

$$\begin{aligned} & \text{Minfun}(y) \\ & \text{s.t.} \\ & y = [y_1, y_1, \dots, y_m, \dots, y_{13}] \\ & y_{m\min} \leq y_m \leq y_{m\max} \end{aligned} \quad (17)$$

where $\text{fun}(y)$ is the NOx emission concentration and $y = [y_1, y_1, \dots, y_m, \dots, y_{13}]$ represents the input variables.

Certain parameter variables are not adjustable during the practical operation of boilers [32]. The dataset in this paper shows that boiler load and temperature are uncontrollable parameter variables. Accordingly, based on practical considerations, five variables were chosen as controllable parameters in this study: primary airflow (y_6 – y_7), secondary airflow (y_{12} – y_{13}), and flue gas oxygen content (y_{20}). The optimal ranges for these controllable variables are presented in Table 4.

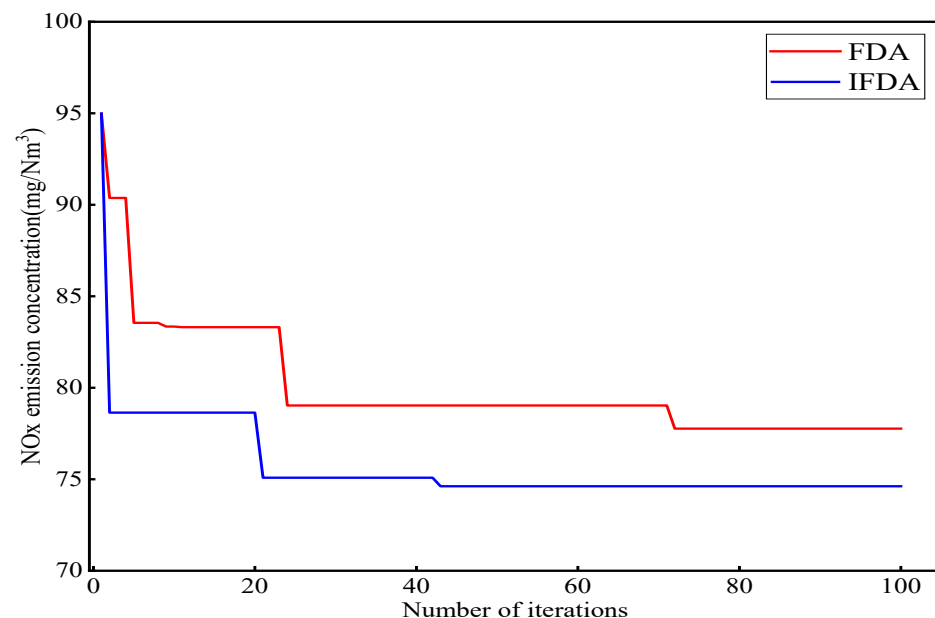
Table 4. The optimization interval of the selected controllable variables.

Controllable Variables	Flue Gas Oxygen Content (%a)	Primary Airflow (KNm ³ /h)	Secondary Airflow (KNm ³ /h)
Controllable interval	0.3–3.0	1200–1000	100–1200

This study first used the CNN-BiGRU model to predict NOx emission concentrations. Then the FDA algorithm and the modified FDA algorithm were used to continuously search for the best values within the selected optimization intervals of the five variables until their optimal values were found. The populations of the IFDA algorithm were set to 20, the neighbors to 5, and the maximum number of iterations to 100. The minimum value of the NOx emission concentration obtained during the optimization process was taken as the optimal solution. Finally, optimal values of the controllable variables were obtained based on this optimal solution. In this section, the original FDA algorithm with the same parameter settings is used as a comparison to demonstrate the optimality-finding capability of the IFDA algorithm. The optimization process is depicted in Figure 9, with the corresponding results shown in Table 5.

Table 5. Optimization results of controllable variables for NOx emission concentration.

Variables	Primary Airflow		Secondary Airflow		Flue Gas Oxygen Content
	y_6	y_7	y_{12}	y_{13}	y_{18}
Observations	866.15	864.27	540.70	947.79	1.06
FDA	853.03	793.89	521.58	896.28	1.01
IFDA	847.51	680.05	526.79	877.91	0.86

**Figure 9.** NOx emission concentration optimization process.

As can be seen from the information in Table 5 and Figure 9, the distribution of the blue and red curves represents the optimization process of the IFDA and FDA for the pair of NOx emission concentrations. This indicates that the IFDA algorithm has a better optimization capability and can find more suitable parameter variables for the boiler; thus, it can effectively achieve the optimization goal of reducing NOx emission concentrations.

5.3.2. Single-Objective Optimization of Thermal Efficiency in Coal-Fired Boilers

As in Section 5.3.1, this subsection uses the IFDA algorithm to perform a single-objective optimization of the boiler thermal efficiency, with the single-objective optimization function constructed as

$$\begin{aligned}
 & \text{Min } fun(y) \\
 & \text{s.t.} \\
 & y = [y_1, y_1, \dots, y_m, \dots, y_{13}] \\
 & y_{m\min} \leq y_m \leq y_{m\max}
 \end{aligned} \tag{18}$$

where $fun(y)$ is the thermal efficiency of the boiler and $y = [y_1, y_1, \dots, y_m, \dots, y_{13}]$ represents the input variables.

To ensure the accuracy and validity of the experiment, this summary also uses the sample data from Section 5.3.1. Also, it selects the five variables of primary airflow ($y_6 \sim y_7$), secondary airflow ($y_{12} \sim y_{13}$), and flue gas oxygen content (y_{20}) as control variables, with the variable optimization range shown in Table 4. After determining the variables to be optimized and the optimization target, the IFDA algorithm is used to continuously search for the optimum value within the optimization interval of these five variables based on the boiler thermal efficiency prediction model until the best value is found. Throughout the optimization procedure, the optimal solution is identified by maximizing the thermal

efficiency of the coal-fired boiler. Subsequently, the optimal values of the controllable variables are derived based on this solution. The algorithm's optimization process is illustrated in Figure 10, while the corresponding results are summarized in Table 6.

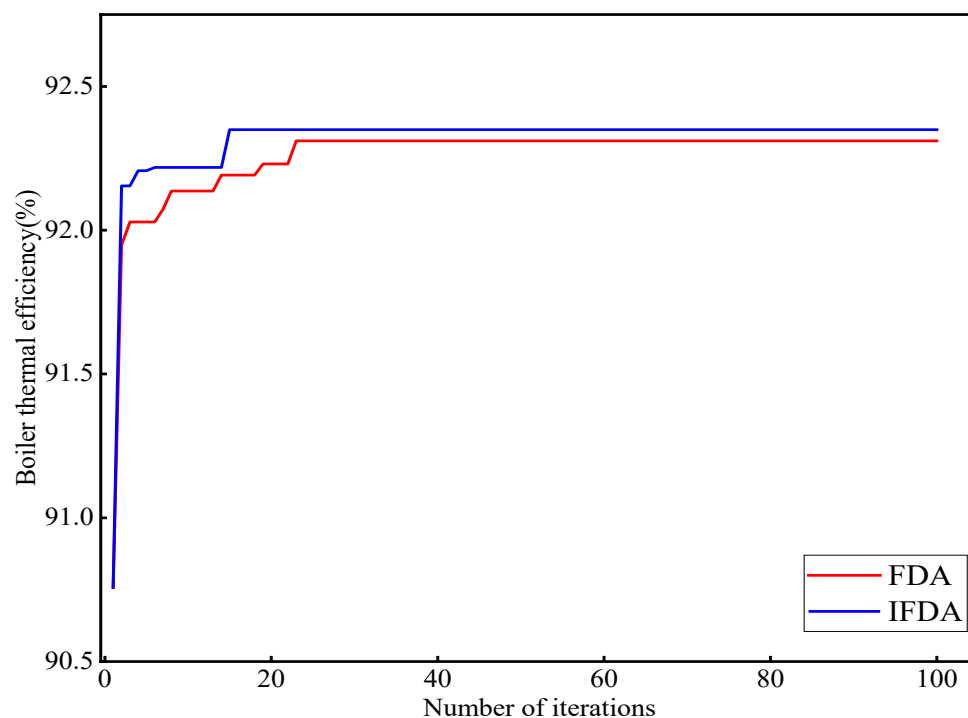


Figure 10. Thermal efficiency optimization process for coal-fired boilers.

Table 6. Optimization results of controllable variables for boiler thermal efficiency.

Variables	Primary Airflow		Secondary Airflow		Flue Gas Oxygen Content
	y_6	y_7	y_{12}	y_{13}	y_{20}
Observations	866.15	864.27	540.70	947.79	1.06
FDA	896.72	868.02	560.38	952.09	1.31
IFDA	921.51	980.05	596.79	977.91	2.09

As illustrated in Table 6 and Figure 10, the blue and red curves correspond to the IFDA and FDA optimization processes for the boiler thermal efficiency, respectively. Following optimization of the boiler's controllable parameters by the FDA algorithm, the thermal efficiency increased from 90.75% to 92.31%. With the improved IFDA algorithm, the thermal efficiency similarly rose from 90.75% to 92.31%. These results further confirm that the IFDA optimization algorithm is more effective in identifying optimal parameter values to enhance boiler thermal efficiency.

5.3.3. Multi-Objective Optimization for Boiler Combustion

The main objective of coal-fired boiler combustion optimization is to minimize NO_x emissions while increasing the boiler efficiency as much as possible. Therefore, this study uses the multi-objective optimization algorithm NSGA-II to find the optimal solution for the controllable parameter variables within the optimization range. The optimal parameter solution is obtained when the algorithm is minimally adaptive. Through this optimal parameter, the operation process of the coal-fired boiler is controlled, and finally, the NO_x emission concentration and boiler efficiency satisfying the conditions are obtained.

The multi-objective model constructed in this study is shown in Equation (19).

$$\left\{ \begin{array}{l} \text{Min } 100 - \text{fun}_1(y) \\ \text{Min } \text{fun}_2(y) \\ \text{s.t.} \\ y = [y_1, y_1, \dots, y_m, \dots, y_{13}] \\ a \leq y_m \leq b \end{array} \right. \quad (19)$$

where $100 - \text{fun}_1(y)$ is the boiler thermal efficiency loss value and $\text{fun}_2(y)$ is the NOx emission concentration.

Among the Pareto optimal solutions, the middle point is selected as the recommended solution, balancing NOx emission and thermal efficiency. This approach assumes equal preference for emission reduction and energy performance, aligning with practical decision-making scenarios in power plants. Choosing endpoints on the Pareto front, in contrast, would prioritize either strict emission control or maximum efficiency, potentially sacrificing the other objective.

The range for the controllable parameter variables used in this study is the same as when single-objective optimization was carried out. To verify the effectiveness of the NSGA-II algorithm, three samples—with low NOx emission concentration, medium NOx emission concentration, and high NOx emission concentration—were selected as experimental control groups in the original data, named Sample A, Sample B, and Sample C, respectively. The optimized results are shown in Figure 11. The two endpoints and the middle point of the Pareto optimal front for samples A, B, and C were selected for analysis, and the specific results are shown in Table 7.

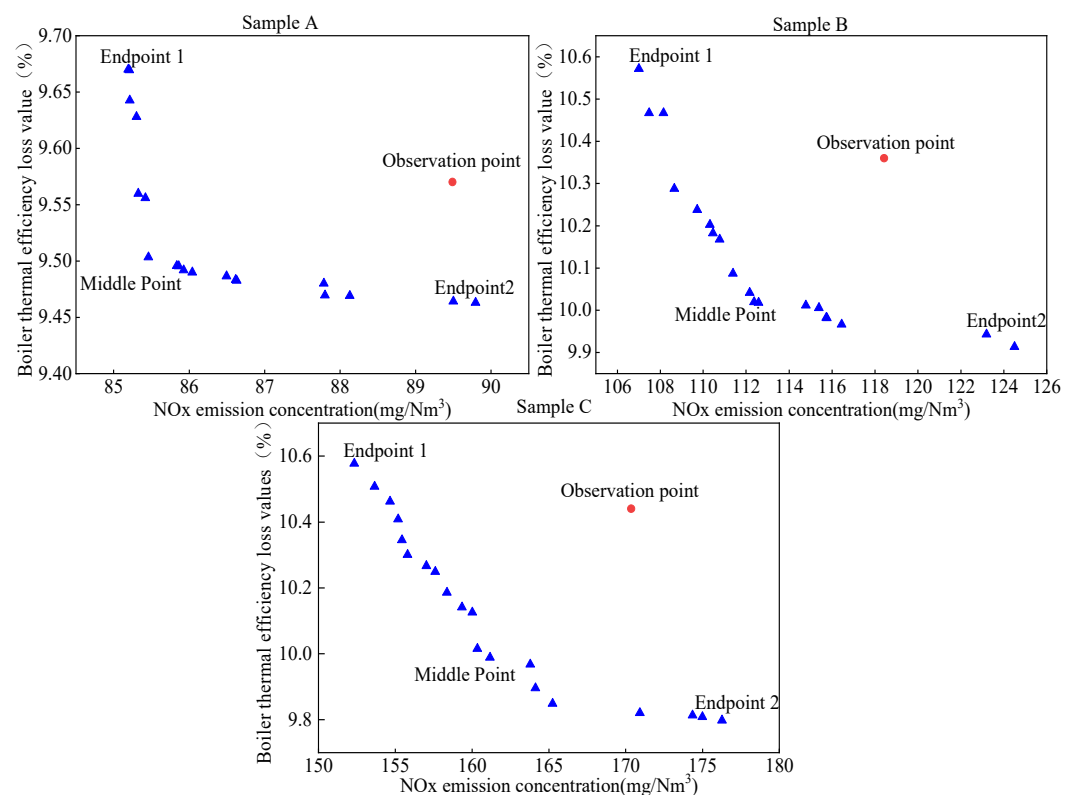


Figure 11. Pareto optimal front of the different samples.

Following the application of the NSGA-II algorithm for optimization, significant reductions in NOx emission concentrations for the coal-fired boiler are evident when comparing the data in Figure 11 and Table 7 with pre-optimization results. Concurrently, an improvement in boiler thermal efficiency is also observed. Analysis of endpoints 1 and 2 from the three sample datasets reveals a trade-off: when NOx emissions reach their minimum, boiler combustion efficiency declines relative to observed values, whereas the highest combustion efficiency corresponds to an increase in NOx emissions compared with observations. This indicates that single-objective optimization can only satisfy one goal at a time. To overcome this limitation, a multi-objective optimization algorithm is employed to generate the Pareto optimal front, from which a recommended intermediate solution is selected.

Table 7. Optimization results of the samples.

Sample	Optimization Objectives	NOx Emission Concentration (mg/Nm ³)	Thermal Efficiency (%)
Sample A	Observations	89.49	90.43
	Endpoints 1	85.19	90.34
	Endpoints 2	89.79	90.54
	Middle Point	85.46	90.50
Sample B	Observations	118.43	89.64
	Endpoints 1	107.01	89.43
	Endpoints 2	124.50	90.09
	Middle Point	112.37	89.98
Sample C	Observations	170.36	89.56
	Endpoints 1	152.33	89.42
	Endpoints 2	176.27	90.20
	Middle Point	161.17	90.01

The middle point of the Pareto optimal front, selected from samples A, B, and C, is chosen as the recommended point for analysis. The original data for sample A shows a NOx emission concentration of 89.49 mg/Nm³ and a thermal efficiency of 90.43%. After optimization, the values obtained are 85.46 mg/Nm³ for the NOx emission concentration and 90.50% for thermal efficiency. This represents a 4.5% reduction in the NOx emission concentration and a 0.07% increase in boiler thermal efficiency. For sample B, the original data shows a NOx emission concentration of 118.43 mg/Nm³ and a thermal efficiency of 89.64%. After optimization, the values obtained are 112.37 mg/Nm³ for the NOx emission concentration and 89.98% for thermal efficiency. This represents a 5.12% reduction in the NOx emission concentration and a 0.38% increase in boiler thermal efficiency. For sample C, the original data shows a NOx emission concentration of 170.36 mg/Nm³ and a thermal efficiency of 89.64%. After optimization, the values obtained are 161.17 mg/Nm³ for the NOx emission concentration and 90.01% for thermal efficiency. This represents a 5.40% reduction in the NOx emission concentration and a 0.50% increase in boiler thermal efficiency. By calculating the average of the middle points of the three samples, it is determined that the average reduction in NOx emission concentration is 5.01%. In contrast, the average increase in boiler thermal efficiency is 0.32%. These results demonstrate that the NSGA-II algorithm can effectively optimize and control combustion in boilers.

6. Conclusions

This study develops a predictive model for boiler combustion systems by employing a hybrid deep learning approach to accurately forecast NOx emission concentrations and boiler thermal efficiency. Following this, the NSGA-II multi-objective optimization algorithm is applied to optimize the controllable parameters within specified ranges, identifying

the optimal values and deriving the Pareto optimal front. The proposed method demonstrates superior predictive accuracy and robust generalization capabilities, successfully achieving NO_x emission levels and boiler efficiencies that satisfy the targeted criteria. The key contributions of this research are summarized as follows:

- (1) A prediction model for the boiler combustion system was developed based on the operating data generated by a 300 MW boiler, which was used to predict the NO_x emission concentration and thermal efficiency of the boiler. For the CNN-IFDA-BiGRU model, the MAPE for predicting the NO_x emission concentration is 0.78%, while the MAPE for predicting the boiler thermal efficiency is 0.012%.
- (2) The boiler combustion system utilizes the FDA and IFDA for single-objective optimization of the boiler thermal efficiency and NO_x emission concentration, respectively. Simulation results indicate that the IFDA possesses superior optimization capabilities, effectively achieving the optimization goals of reducing the NO_x emission concentration and improving the thermal efficiency of coal-fired boilers separately and efficiently.
- (3) The NSGA-II algorithm was employed to optimize the boiler combustion process through an analysis of simulation results. The primary goals were to reduce NO_x emission concentrations, improve boiler thermal efficiency, and achieve effective control over the boiler's combustion system. Utilizing operational data from coal-fired boilers, the proposed approach generated a Pareto optimal front tailored to specific objectives. The findings provide valuable insights for promoting the low-carbon and environmentally sustainable operation of coal-fired boilers. The effectiveness of the NSGA-II algorithm was validated by comparing NO_x emission concentrations and boiler thermal efficiencies across various samples before and after optimization, supported by detailed simulation analyses.

Author Contributions: C.H.: Conceptualization, Data curation, Methodology. Y.Z.: Methodology, Investigation, Software, Writing—original draft. H.Z.: Writing—review and editing. J.Z.: Software, Visualization. Y.F.: Visualization, Writing—review and editing. Z.T.: Writing—review and editing. C.Z.: Conceptualization, Writing—review and editing. T.P. Conceptualization, Methodology. All authors have read and agreed to the published version of the manuscript.

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Abbreviations

ICGO	Improved Chaos Game Optimization	CGO	Chaos Game Optimization
BiGRU	Bidirectional Gated Recurrent Unit	PSO	Particle Swarm Optimization
NO	Nitric Oxide	NO _x	Nitrogen Oxides
ML	Machine Learning	ACO	Ant Colony Optimization Algorithm
ELM	Extreme Learning Machines	IGOA	Improved Grasshopper Optimization Algorithm
SAGA	Simulated Annealing Genetic Algorithm	NSGA-II	Non-dominated Sorting Genetic Algorithm II
SVM	Support Vector Machine	MOPSO	Multi-objective Particle Swarm Optimization
NO ₂	Nitrogen Dioxide	MODE	Multi-objective Differential Evolution
RMSE	Root Mean Square Error	ILS	Iterative Local Search
CNN	Convolutional Neural Network	MAE	Root Mean Absolute Error
ANNSVR	Support Vector Regression Artificial Neural Network	MAPE	Mean Absolute Percentage Error
LSTM	Long Short-Term Memory	EMD	Empirical Mode Decomposition
RNN	Recurrent Neural Network	R	Correlation Coefficient
CEEMDAN	Complete Ensemble Empirical Mode Decomposition with Adaptive Noise	LSH	Locality Sensitive Hashing
SPS	Steam Power System	FDA	Flow Direction Algorithm

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