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Intelligent Optimization of Combustion Process and NOx Emission Control of Power Plant Boiler Based on Deep Learning and Multi-objective Optimization

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Abstract

This study proposes an intelligent optimization and nitrogen oxide (NOx) emission control method for power plant boiler combustion processes by integrating deep learning and multi-objective optimization. While traditional empirical tuning and single-objective algorithms struggle with dynamic, multi-variable combustion environments and lack real-time adaptability and synergistic optimization of efficiency and emissions, this research addresses these gaps by establishing a rolling optimization model that considers load and emissions. By analyzing the relationship between boiler combustion efficiency and nitrogen oxides generation, a rolling optimization model considering load and emission is established. The study analyzes and predicts the operation data and optimizes the combustion strategy in real time by a dynamic multi-objective optimization evolutionary algorithm. Performance evaluation shows that the model achieves high prediction accuracy, with an average absolute error of 2.36×10-5 kW for boiler load, and outperforms existing models in key metrics such as ignition success rate (98.7%) and load adjustment accuracy (3.4 MW). The approach significantly improves combustion efficiency and tightens NOx control, reducing energy waste and improving power plant energy efficiency. These advances demonstrate their effectiveness in improving combustion efficiency, enhancing nitrogen oxide control, and reducing energy waste, providing a powerful solution for operating smart power plants that integrates real-time adaptability and multi-objective synergy, outperforming traditional methods.

Keywords: Intelligent optimization; NOx emission control; Deep learning; Multi-objective optimization; D3M-DOOA algorithm

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1. Introduction

Globally, combustion efficiency and nitrogen oxides (NOx) emission control of power plant boilers (PPBs) have become a hot research topic. Boiler combustion efficiency is directly related to energy utilization efficiency and economic cost, while NOx emission (NOxE) is closely related to environmental protection and sustainable development [1-2]. PPBs, as key equipment for energy conversion, must effectively control NOxEs while improving combustion efficiency [3]. However, traditional empirical tuning methods and single-objective optimization algorithms encounter inherent limitations in addressing the complexity of multi-objective (MO), multi-variable, and time-dependent combustion processes. Among them, real-time adjustments to fluctuating loads, fuel properties, and thermal dynamics are imperative. In particular, these approaches lack the ability to synergistically optimize efficiency and emissions due to static parameter settings, limited adaptability to nonlinear operational variations, and inadequate handling of large, high-frequency process data [4-5]. These methods are insufficient in real-time, accuracy and adaptability. Especially in the face of complex systems and large-scale data, it is difficult to meet the optimization needs of dynamically changing operating conditions [6-7].

In the field of data mining and machine learning, feature selection and hyper-parameter optimization are key steps to

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improve model performance. AGanpati K et al. used the PyTorch framework to solve the problem of predicting oxygen content during boiler combustion. The research method included using a multi-layer convolutional neural network (CNN) model, obtaining images of the boiler under different operating conditions using CCD, classifying and extracting features from these images to train and optimize the model. The model training dataset consisted of 4203592 images, each with a resolution of 658*492 pixels and a color depth of 24 bits. The research results showed that the model could predict the oxygen content with an accuracy of 97% and a loss rate of only 3%, effectively improving the accuracy of boiler combustion efficiency and oxygen content prediction [8]. Predicting furnace temperature and oxygen content in circulating fluidized bed boilers is a complex task due to the high noise and roughness of the actual data. Therefore, scientists such as Ji Z proposed a prediction model that combined CNN, biLSTM, and SE networks. CNN extracted complex features of input parameters, biLSTM processed time information of time series, and SE network extracted important information through feature relationships. The experiment demonstrated that the average MAPE error of this model in predicting oxygen content was 0.038, which was superior to other methods and performed better in terms of fitting goodness, generalization ability, and accuracy [9]. A review by Pereira J L J et al. highlighted the importance and potential of meta-heuristic algorithms (MHAs) for solving MO problems in mechanical engineering [10]. Morales-Hernández A et al. provided a systematic survey of MO hyperparametric optimization algorithms, which provided guidance for future research directions [11]. Jiang S et al. explored the deep learning (DL) performance optimization problem and proposed an evolutionary deep learning (EDL) method based on evolutionary computation (EC) [12]. Deng X et al. proposed a two-stage gene selection method combining extreme gradient boosting (XGBoost) and multi-objective genetic algorithm (MOGA) for the gene selection problem of microarray gene expression data, which significantly improved the accuracy of gene selection [13].

As technology advances, particularly in the areas of automation and intelligence, new approaches of increasing combustion efficiency and lowering polluting emissions become available. Han L et al. proposed a combustion optimization method combining neighborhood rough set (NRS) and non-dominated sorting genetic algorithm II (NSGAII), which effectively improved the economic and environmental performance of pulverized coal circulating fluidized bed boiler during grid peaking [14]. Ye T et al. combined computational computational fluid dynamics (CFD) data with historical operational data to estimate the NOx generation of an in-service coal-fired power station using the gradient boosting regression tree (GBRT) model. In terms of prediction accuracy, it was discovered that the GBRT model performed better than both support vector regression (SVR) and artificial neural networks (ANN). It also helped operators to optimize boiler plant operation for high efficiency and low pollution through Shapley analysis [15]. Liu S et al. modeled NOx generation in an in-service coal-fired power plant using the GBRT model by combining CFD data and historical operational data. It was found to be able to help operators optimize boiler plant operation for high efficiency and low pollution through Shapley analysis [16]. Jiang S et al. reviewed the emerging and rapidly growing field of evolutionary dynamic multi-objective optimization (EDMO). Evolutionary approaches were employed by EDMO to address multi-objective optimization (MOO) issues that were far more challenging to optimize than single-objective or static optimization. These problems involved changing environmental conditions, restrictions, or the objective function over time [17]. Sharma S et al. discussed in depth the advantages and disadvantages of MOO algorithms and their variants and explored representative algorithms for each category in detail. The applications of MO algorithms in different engineering fields were studied and open challenges and future directions of MO algorithms were presented [18].

Existing studies have made significant advances in combustion optimization and pollutant emission control. However, key challenges remain: algorithm adaptability under complex conditions, real-time responsiveness, and effective MO trade-offs. Traditional single-objective methods, such as PID control, and static MO algorithms, such as NSGA-II and MOPSO, often struggle to balance efficiency and emissions in dynamic environments. For example, NSGA-II has difficulty maintaining population diversity during rapid changes, while MOPSO tends to get stuck in local optima in high-dimensional solution spaces. Data-driven approaches, including support vector machines (SVMs) and shallow neural networks, lack the ability to model long-range temporal dependencies in boiler operation or extract spatial features from combustion images, limiting prediction accuracy during transient conditions. To address these challenges, this study proposes an integrated framework that combines DL and DMOO. The DL component, which uses LSTM for time series analysis and CNN for visual feature extraction, captures both temporal dynamics and spatial correlations in complex boiler data. The developed dynamic multi-objective evolutionary algorithm (DMOEA) outperforms static MOO techniques by incorporating real-time environmental feedback and historical state tracking. This enables adaptive strategy adjustments within milliseconds, which is critical for managing rapidly changing loads and fuel characteristics. The synergy between DL's data modeling capabilities and DMOEA's dynamic optimization approach provides a robust solution for real-time, synergistic optimization of combustion efficiency and NOxEs.

2. Optimization of combustion efficiency and NOx emission control strategy for power plant boilers

2.1 Combustion efficiency and NOx generation mechanism in power plant boilers

Raw coal is sent to the coal mill for grinding through a belt, mixed with hot air and sent to the furnace for combustion, where the energy generated is converted to saturated steam, which is then processed by a super-heater into superheated steam that drives a turbine to generate electricity [19]. The flue gases are preheated with air and feed water before being discharged and discharged through a chimney to separate the soot. Bottom ash and dust are treated and sent to landfill.

NOxEs and boiler loads are controlled to optimize combustion efficiency while ensuring operational safety and improved fuel utilization. The combustion efficiency of a boiler is key to evaluating its performance and is affected by the amount of unburned fuel and the amount of combustion air. The schematic diagram of the combustion chamber used for the study is shown in Figure 1.

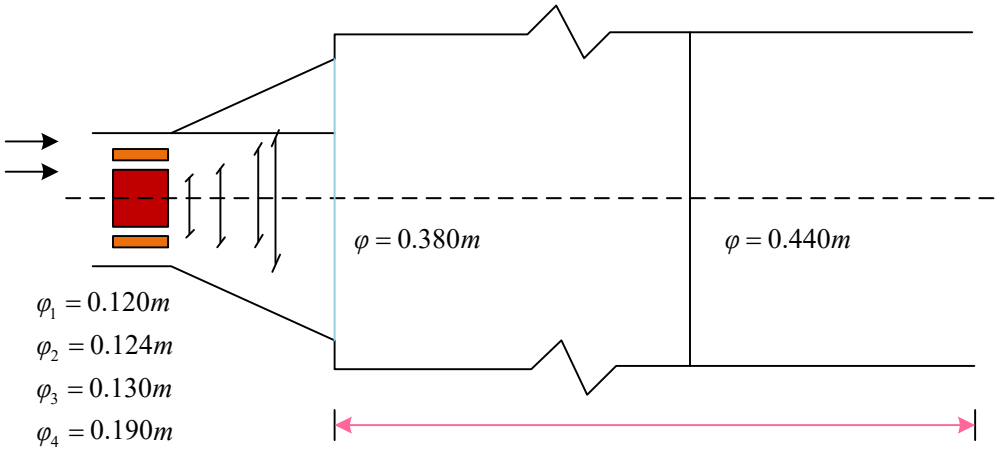


Figure 1. Schematic diagram of combustion chamber

Next, based on the GB/T 10180-2017 standard, there are two main methods for calculating efficiency. The positive balance method is determined directly by the ratio of actual heat use to fuel heat input.

$$Q_r = Q_d^y + i_c \quad (1)$$

In Equation (1), Q_r denotes the heat input to the boiler. Q_d^y denotes the baseline low level heat value of the boiler. i_c denotes the physical energy of the coal combustion. The effective input to the boiler is shown in Equation (2).

$$Q_1 = \frac{D_r\left(h_r - h_s\right)}{B} \quad (2)$$

In Equation (2), Q_1 denotes the actual heat input to the boiler. D_r denotes the steam production of the boiler. h_r denotes the enthalpy of steam. h_s denotes the enthalpy of feed water. B denotes the coal consumption of the boiler. The combustion efficiency of the boiler is shown in Equation (3).

$$\eta = \frac{Q_1}{Q_r} * 100\% \quad (3)$$

In Equation (3), η denotes the combustion efficiency of the boiler. To increase combustion efficiency, the study built a rolling optimization model based on the boiler's key parameter model that took load, pollutant emissions, and operational boundaries into account. Data are gathered and the sample period. The p is specifically determined in the first stage of the model building process to satisfy the continuous optimization model's real-time need.

The dataset contains 3 years of boiler operating data under various load and fuel conditions, covering more than 20 parameters such as boiler load (kW), steam production (ton/h), fuel consumption (kg/s), NOxEs (mg/Nm^3), and temperature/pressure profiles. With 100,000 records, it is split into 80% (80,000 samples) for training and 20% (20,000 samples) for testing. Data are preprocessed using Z-score normalization for feature scaling and linear interpolation for missing values to ensure consistency and reliability in model training. The study pair is parameterized by defining the population size as Np, the upper iteration limit as G, the scaling factor as λ, and initializing the iteration count g to zero. The initial value of particle $x_{j,0} \in R^m\left(j = 1,2,\ldots,Np\right)$ is set and $x_{j,0} = \left[u_1, u_2, \ldots, u_m\right]$ represents the control variable. $u_m > 0$ denotes the specific optimization objective. m denotes the dimension of the control parameter. The crossover and variance probabilities are denoted by F and CR, respectively. G is set to 500. The control variables are set according to Equation (5).

$$u_{j,m}^M = u_m^M + rand\left(0,1\right) * \left(u_m^U - u_m^M\right) \quad (5)$$

In Equation (5), $u_{j,m}^M$ denotes the optimized control variables. The NOxE and boiler load are then calculated for each particle, and then these calculations are checked to see if the boundary constraints are satisfied and the error is

controlled within 3%. If the conditions are satisfied, then proceed to the next step. Otherwise, the adaptation of these particles is labeled with a maximum value of 1000 and further adjustments are prepared. The next step involves evaluating the combustion efficiency of each particle and determining its adaptation value according to Equation (6).

$$\varepsilon(j)=\sqrt{\frac{\sum_{t=1}^{p}\left|Y_t-\omega_t\right|^2}{p-1}} \tag{6}$$

In Equation (6), $\varepsilon(j)$ denotes the combustion efficiency of each particle. Y_t denotes the thermal efficiency result at moment t. ω_t denotes the predetermined thermal efficiency at moment t. Then the particle with the smallest adaptation value in the population is identified, and the error between the current predicted combustion efficiency and the desired value is judged to be less than 3%. If it is reached, the algorithm terminates and outputs the optimal control parameters and adaptation value. If not reached, the next step is continued. The next step involves checking whether the number of iterations reaches the maximum value G. If it does, the optimal solution is output and the algorithm is stopped. In the event that the aforementioned condition is not met, the algorithm will proceed with further iterations. NOx, which includes nitric oxide and nitrogen dioxide, is a significant source of environmental pollution and is often referred to collectively as NOx. The main reaction mechanism of NOx is shown in Equation (7).

$$\begin{cases} CN+O\rightarrow C+NO \\ NH+O_2\rightarrow NO+OH \end{cases} \tag{7}$$

Fuel NOx is mainly derived from the decomposition of nitrogen in the fuel during combustion, resulting in the formation of intermediates such as ammonia (NH3), cyanide (CN), and hydrocyanic acid (HCN), which are subsequently oxidized to NOx. Comparatively speaking, gaseous fuels, due to their low nitrogen content, generate a relatively small proportion of fuel NOx from their combustion. Fluent software provides a series of combustion models (CMs) to analyze the component transport and reaction flow during the combustion process. The Fluent CM is shown in Figure 2.

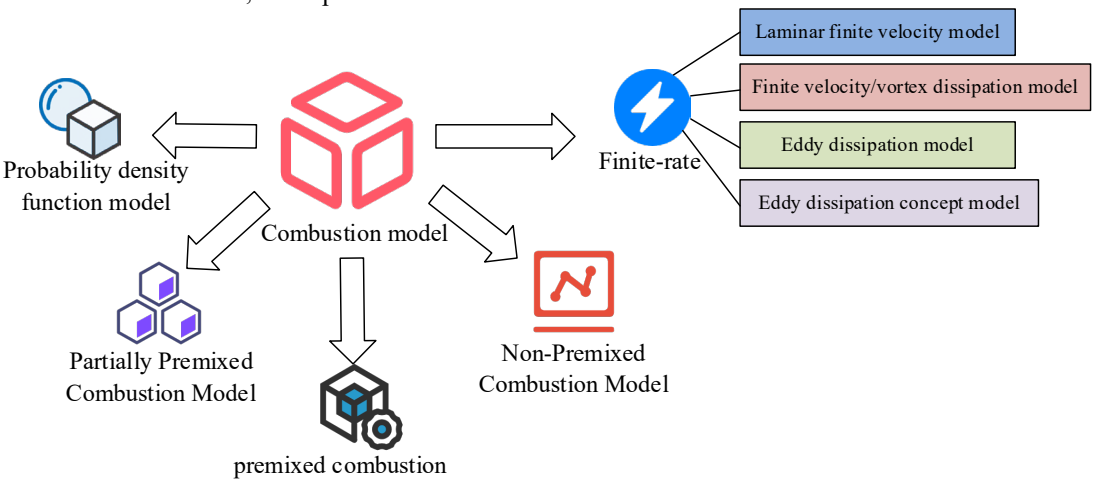


Figure 2. Fluent combustion model

In Figure 2, in Fluent software, the choice of model and solver must be based on the study objectives and combustion characteristics. The user must provide the reaction mechanism in order to use the finite rate model, which is appropriate for universal combustion scenarios. The non-premixed CM is suitable for turbulent diffusion flames, but not for NOx modeling. Premixed and partially premixed CMs are suitable for fully premixed and partially premixed combustion environments, respectively. The latter describes combustion details through the mixing fraction equation. Probability density function models provide detailed simulation of chemical reaction kinetics, but are computationally expensive. Fluent's pressure-based solvers include SIMPLE, SIMPLEC, PISO, and Coupled algorithms. Figure 3 shows the flow of the separated and coupled algorithms.

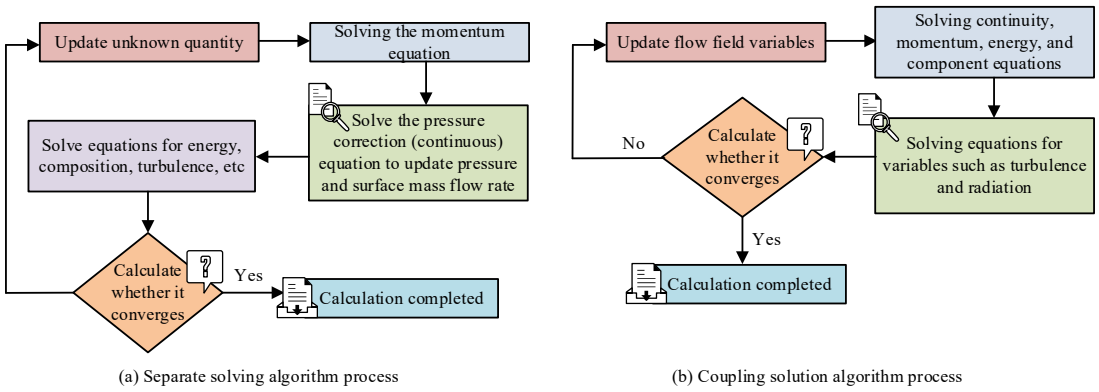


Figure 3. Process of separated and coupled algorithms

In Fluent software, the solution flow of the separated and coupled algorithms are shown in Figures 3(a) and (b), respectively. Separate algorithms, such as SIMPLE and its improved version SIMPLEC, compute the momentum equation by predicting the pressure field, obtain the velocity field, and correct the fluxes to satisfy the continuity equation. The SIMPLEC algorithm improves convergence by optimizing the flux corrections. Coupled algorithms, such as Coupled and PISO, solve the momentum, mass, and energy equations simultaneously. The PISO algorithm further adds corrections for momentum and mesh distortion on top of coupling, which improves the accuracy but increases the computational cost accordingly. Considering the stability, convergence speed and computational cost, the SIMPLE algorithm is chosen for the study to solve the fluid dynamics problem.

2.2 DL strategies for intelligent optimization of power plant boiler combustion with NOx emission control

Combustion efficiency and NOxE control of PPBs are crucial to ensure power generation efficiency and environmental protection. In the field of intelligent optimization of combustion process and NOxE control in PPBs, DL techniques, especially LSTM and CNN, play a crucial role [20]. LSTM networks excel in analyzing complex time series data generated during boiler operation, such as temperature and pressure variations, to predict and identify potential operational problems. CNNs, on the other hand, are efficient in recognizing phenomena such as uneven combustion or flame anomalies when processing image data from boiler combustion chambers. The CNN is designed with this feed-forward neural network demonstrating its unique hierarchical structure as shown in Figure 4.

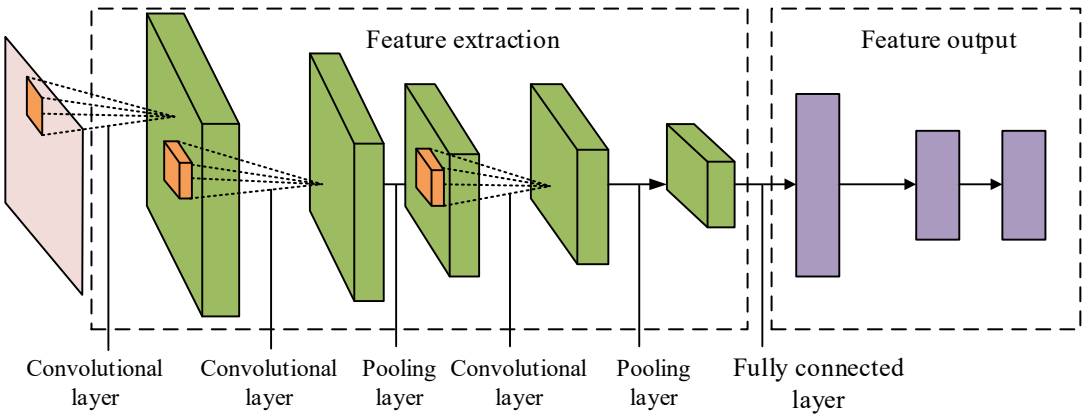


Figure 4. Schematic diagram of CNN structure

In Figure 4, in this structure, the input layer is mainly responsible for the initial processing of the input data. Moreover, the duty of the output layer (OL) is to present the classification results of the model. The core part of CNN is

its middle layer. In this architecture, the convolutional layer plays a crucial role. It includes numerous trainable filters that are centered on identifying and refining core features from the input data. The specific computation is shown in Equation (8).

$$u_j = f(x_i + b_i) \quad (8)$$

In Equation (8), f represents the ReLU activation function. x_i and u_j represent the input and output variables, respectively, and b_j is the bias value. In a sequential arrangement of multiple convolutional layers, pooling layers are often added periodically to optimize the network structure, which is calculated as shown in Equation (9).

$$u_j = f(\beta_i \cdot \vartheta + b_i) \quad (9)$$

In Equation (9), ϑ denotes the sampling function. β_i is the bias factor in the network. LSTM includes input i_t output gate o_t, forgetting gate f_t and neuron state c_t. It is capable of successfully avoiding the typical issues with the conventional recurrent neural network architecture. Equation (10) illustrates how LSTM is specifically implemented.

$$\begin{cases} \hat{C}_t = \tanh(W_C \otimes [h_{t-1}, x_t] + b_C) \\ i_t = \sigma(W_i \otimes [h_{t-1}, x_t] + b_i) \\ f_t = \sigma(W_f \otimes [h_{t-1}, x_t] + b_f) \\ C_t = f_t \cdot C_{t-1} + i_t \cdot \hat{C}_t \\ o_t = \sigma(W_o \otimes [h_{t-1}, x_t] + b_o) \\ h_t = o_t \cdot \tanh(C_t) \end{cases} \quad (10)$$

In Equation (10), W and h are the weight matrix and bias term, respectively. σ denotes the activation function. S denotes the hidden layer. Conventional CNNs tend to use the leveling layer when processing multidimensional inputs to transform them into one-dimensional data, especially when the convolutional layer is converted to a fully connected layer. Feature selection used correlation analysis and recursive elimination to retain key features (e.g., load, fuel properties, air volume) and improve model efficiency by focusing on high-impact parameters. However, the leveling layer tends to lose structural information and features to some extent when downscaling 2D data to 1D. To address this issue and achieve an efficient combination of CNN and LSTM, the study replaces the Lapine layer and the fully connected layer with a maximum pooling layer. The whole network structure is shown in Figure 5.

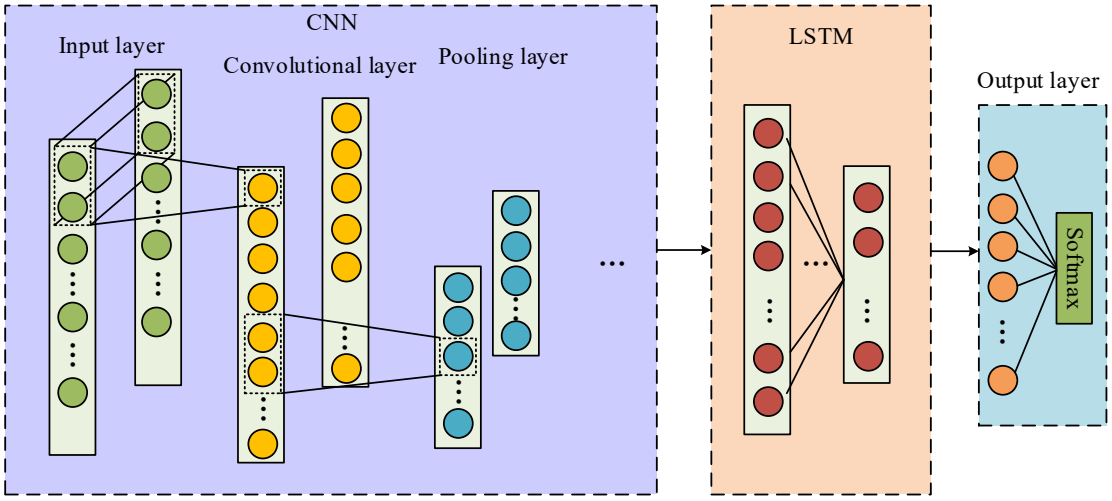


Figure 5. Integration framework of LSTM and CNN

In constructing the model used for fault diagnosis of rolling bearings in training instruments, the study combines the architecture of CNN and LSTM. In this architecture, the initial learning rate for fault diagnosis is set to 0.01 and 50 rounds of iterative training are performed. A vector of probability distributions for each state is produced by the OL using a SoftMax function in order to precisely classify various bearing fault kinds. In this case, the probability distribution of a specific category can be shown with reference to Equation (11).

$$y_i = \frac{\exp(a_i)}{\sum_{k=1}^{Nf} \sum(a_k) \exp} \quad (11)$$

In Equation (11), N_f is the number. In addition, in order to evaluate the performance of the model, the study used a cross-entropy loss function as shown in Equation (12).

$$L_1 = -\sum_{i=1}^{N_f} \hat{y}_i \log(y_i) \quad (12)$$

In Equation (12), $\hat{y}_i$ is the One-Hot encoding of the actual fault situation. To advance the efficiency and accuracy of the intelligent optimization of the boiler combustion process and NOxE control in power plants, the DMOGA is proposed in the study for the dynamics of the boiler combustion. The algorithm is able to adapt to the close connection between the target and the time, and adjust the optimization strategy in real time to cope with the environmental changes, and to achieve a more efficient combustion and stricter NOxE control, as shown in Equation (13).

$$\begin{cases} \min\limits_{x\in\Omega} y = F(x,t) = (f_1(x,t), f_2(x,t), ..., f_m(x,t))^T \\ s.t. g_i(x,t) \le 0 \quad i = 1,2,...p; h_j(x,t) = 0 \quad j = 1,2,..,q \end{cases} \tag{13}$$

In Equation (13), $F(x,t)$ denotes the inequality constraints function. $F(x,t)$ denotes the evaluation function. $h_j(x,t)$ denotes the equational constraints function, and all three functional relations are closely related to the time variable. Compared with other MO optimization algorithms such as NSGA-II and MOPSO, DMOEA has unique advantages. NSGA-II has limited ability to maintain population diversity when dealing with complex dynamic environments. It may not be able to quickly and effectively find the global optimal solution when faced with changing conditions as the boiler continues to burn. Although MOPSO converges faster in some cases, it is easy to fall into local optimality in MOO, and it is difficult to balance the relationship between multiple objectives. DMOEA is specifically designed for boiler combustion dynamics. It uses a quasi-exponential smoothing method to predict environmental changes and combines a unique three-step optimization process (creating a historical information store, updating data in real time, and screening populations that adapt to the new environment based on historical information). It better adapts to the close connection between objectives and time, and adjusts optimization strategies in real time in a more timely and accurate manner. This responds to environmental changes and enables more efficient combustion and tighter control of NOxEs, resulting in better performance in the optimization of PPB combustion processes. When making spatial decisions, the optimal solution set $POS(t)$ of Pareto for the DMOP problem is shown in Equation (14).

$$POS(t) = \{x \in \Omega \mid \nexists\, x' \in \Omega, f(x',t) \prec F(x,t)\} \tag{14}$$

In the spatial objective, the optimal frontier $POF(t)$ of Pareto for the DMOP problem is shown in Equation (15).

$$POF(t) = \{y = F(x,t), x \in POS(t)\} \tag{15}$$

Based on different Pareto's optimal frontier $POF(t)$ and optimal solution set $POS(t)$ can be categorized into four forms. Figure 6 depicts the precise flow of the enhanced algorithm.

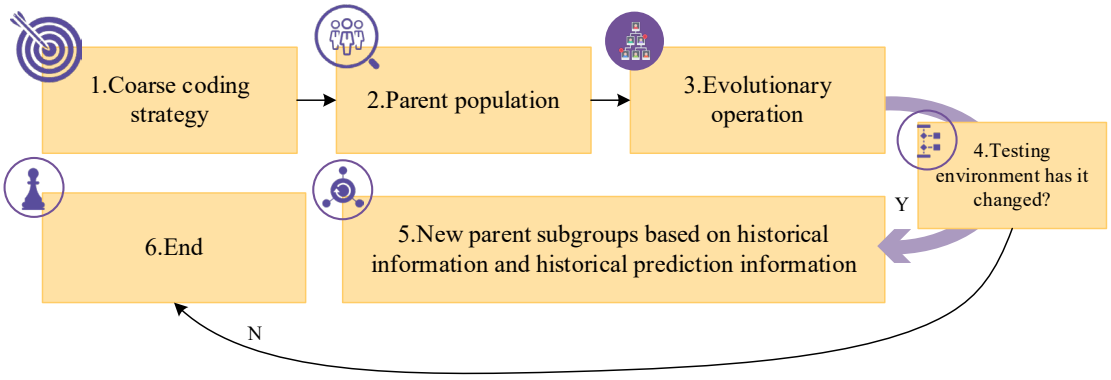


Figure 6. Improved dynamic multi-objective optimization algorithm flow

The study uses an exponential-like smoothing method to predict environmental changes and creates a three-step process for the intelligent optimization of combustion process and NOxE management in a PPB, as illustrated in Figure 6. First, a history information keeper with a capacity of 2 is created to record the key combustion states. Second, the data in the saver is updated as soon as environmental changes are detected. Finally, population prediction is performed based on this historical information to filter out populations adapted to the new environment. The algorithm proposed in the study is named D3M-DOOA algorithm. This method has the ability to adapt to changes in fuel composition and operating conditions through the collaborative design of D3M-DOOA and DL models. On the one hand, D3M-DOOA has the capacity to capture real-time dynamic changes in parameters such as boiler load and fuel characteristics. It can automatically adjust optimization strategies through historical information storage and population prediction mechanisms. This occurs without the need for manual reconfiguration of control parameters. On the other hand, the DL framework, comprising LSTM and CNN, has the capacity to extract universal features across a range of operating conditions. It is also resilient to the combustion characteristics of diverse fuels, including coal and gas.

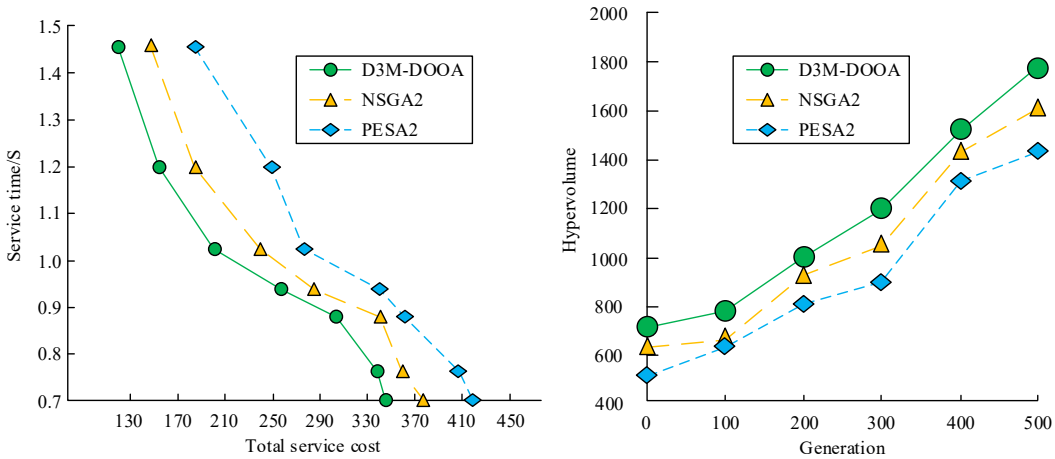
Hyperparameters (e.g., population size N_p, crossover/mutation rates) are tuned via random search and cross-validation, yielding optimal settings: $N_p = [value]$, $G = 500$, $F = [value]$, $CR = [value]$, balancing convergence and accuracy.

Between 2023 and 2024, data is collected from a 600-megawatt coal-fired power plant, including 120000 records from sensors and combustion chamber cameras. Preprocessing includes using the interquartile range method to remove outliers, performing Z-score normalization, and stratifying the dataset into 80% for training, 10% for validation, and 10% for testing. The key hyper-parameters used to optimize the algorithm are set to a population size of 100, a crossover probability of 0.8, and a mutation probability of 0.2. These parameters are tuned using Bayesian optimization and fivefold cross-validation to balance convergence and solution quality while ensuring adaptability to dynamic conditions.

3. Performance evaluation of boiler combustion and control of NOx emission based on D3M-DOOA modeling

Model training is based on NVIDIA A100 GPU (24GB video memory) and 24 core Intel Xeon CPU using PyTorch framework. It takes about 72 hours to complete 1000 rounds of training with 100000 pieces of training data. During deployment, real-time reasoning is realized on the power plant's edge computing equipment (NVIDIA Jetson AGX Orin). Moreover, the processing delay of a single sample (100-dimensional input) is ≤12ms, which meets the millisecond response requirements of boiler combustion control. To ensure the reproducibility of the study, a DL model combining LSTM (256 hidden layer dimensions) and CNN (4 layers of 3×3 convolutional kernels) is used. The training parameters included a batch size of 64, a learning rate of 0.001 (Adam optimizer), and 1000 iterations. The dynamic MOO algorithm (DMOEA) sets the population size to 100, the crossover probability to 0.8, and the mutation probability to 0.2. Moreover, it records the continuous combustion state through a historical information storage device with a capacity of 3. The Z-score normalization parameter and IQR outlier detection threshold in data preprocessing are fully listed in Appendix Table A1. Partitioning logic, algorithmic iteration mechanisms, and performance metric calculations are studied using 80% training set, 10% validation set, and 10% test set.

In the study of intelligent optimization and NOxE control of boiler combustion processes in power plants, three algorithms are evaluated for a single-service strategy. The diversity of the actual operation is simulated by conducting experiments in five different boiler combustion scenarios. To guarantee the correctness of the evaluation, each algorithm is given a separate service cost task, and the average task completion time is recorded through many experiments. As illustrated in Figure 7, the Pareto borders of the algorithms are compared to obtain the experimental findings.



(a) Pareto frontier comparison result plot of the three algorithms

(b) Hypervolume value comparison result plot of the three algorithms

Figure 7. Pareto frontier comparison result plot of the three algorithms

In Figure 7(a), the D3M-DOOA method exhibits superior convergence performance in single-objective service policy when compared to the other two algorithms, thereby realizing the optimal service matching scheme. When it comes to task allocation, it also obtains the lowest service cost and the quickest service time. This shows that the D3M-DOOA algorithm can effectively solve the single-objective service strategy optimization problem in the combustion process of PPBs. The analysis contrasts the Hyper-volume values (HV) of the three methods in Figure

7(b) in order to evaluate the overall performance and variety of their solution sets. The average HV values of each test case are compared statistically in order to reduce experimental error. In terms of average HV, the D3M-DOOA algorithm performs substantially better than the other two algorithms, suggesting a substantial benefit in terms of overall performance. The D3M-DOOA algorithm demonstrated its performance both in the evaluation of collaborative service and single-objective service strategies, confirming its effectiveness and reliability in the optimization of PPB combustion process. In the study of intelligent optimization of combustion process and NOxE control in PPBs, a cost comparison of the three algorithms is performed. The cost is based on the resource consumption and energy usage of the algorithms in performing the same combustion optimization task. By keeping track of the algorithms' highest, lowest, and average costs, the effectiveness of the algorithms' resource use and economy are assessed.

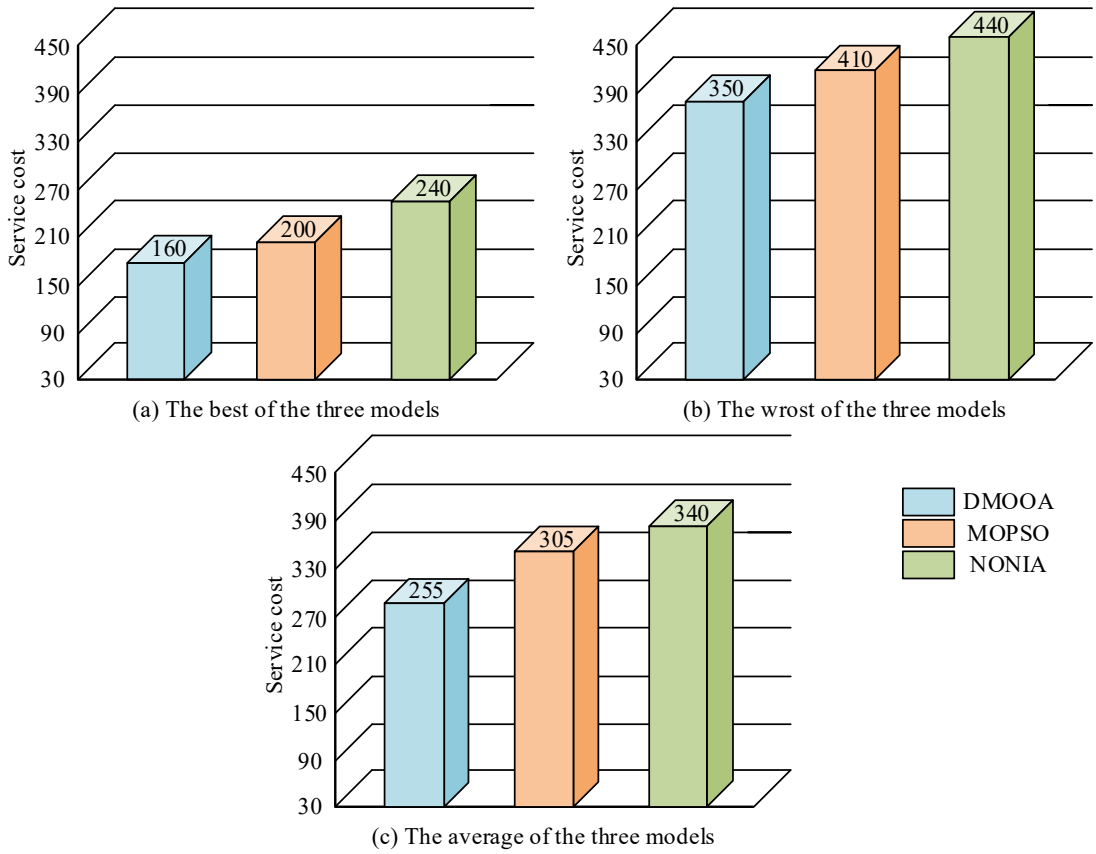


Figure 8. Service cost comparison diagram of three algorithms

Figure 8 illustrates the results of the comparison. Figure 8(a), 8(b), and 8(c) shows the lowest cost, highest, and average cost. The D3M-DOOA algorithm shows the lowest average cost of service in terms of intelligent optimization of combustion process with NOxE control in PPBs. It achieves a cost reduction of 16.39% and 25.00% compared to NSGA2 and PESA2 algorithms, respectively. In the study of intelligent optimization and NOxE control of the combustion process in a PPB, the analysis of the stochastic case 1 focuses on the variation of energy consumption of each management model throughout the case. The evaluation index is adjusted to the amount of energy consumption per unit of time to fit the specific needs of the PPB combustion process. This is shown in Figure 9.

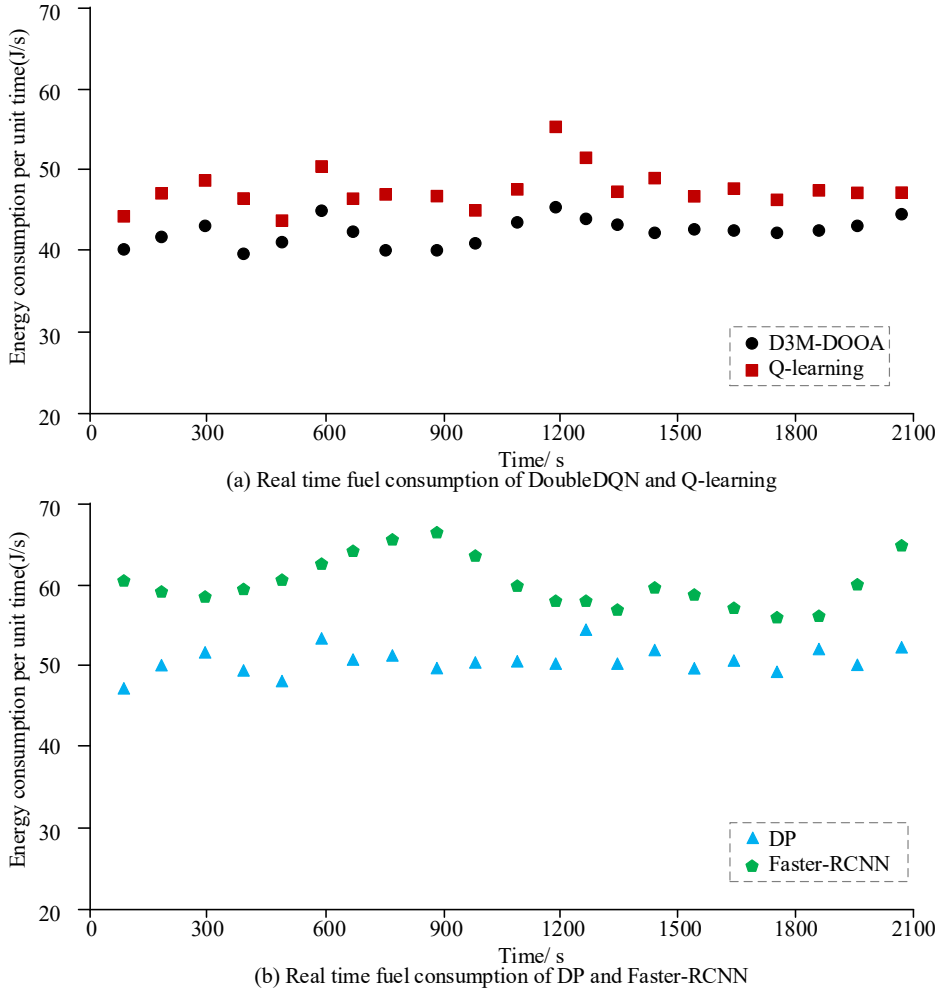
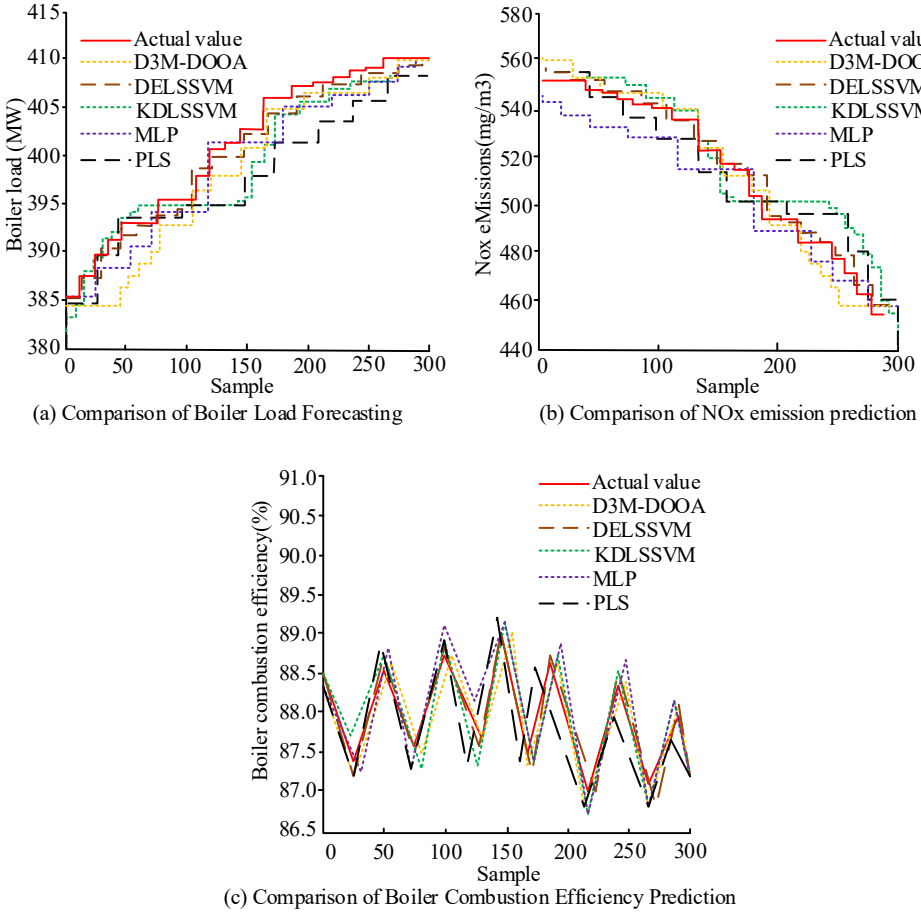


Figure 9. Real time fuel consumption changes of various management models under random condition 1

In Figs. 9(a) and 9(b), the energy consumption curves of the D3M-DOOA model show low and stable energy consumption levels in stochastic operating conditions. This result is closely related to the combination of DL and MOO in the model design. Among them, DL provides powerful feature extraction and prediction capabilities. Whereas MOO ensures the maximization of combustion efficiency while meeting the NOxE standards. The average energy consumption of the D3M-DOOA model is not only lower than that of other comparative models, but also the fluctuation of its energy consumption curve is smaller. This displays that this model can maintain high combustion efficiency and low energy consumption under different operating conditions. This performance advantage of the D3M-DOOA model is also reflected in its ability to adjust the boiler combustion process in real time. Through the fine control of boiler operating parameters, D3M-DOOA is able to respond quickly to changes in operating conditions, optimize combustion conditions, and reduce unnecessary energy consumption while ensuring that NOxE control is within the legal standards. To validate the predictive efficacy of the proposed D3M-DOOA, a comparative study with DELSSVM, KDLSSVM, MLP, and PLS models is conducted. The DELSSVM model uses the CART algorithm for feature selection and the KDLSSVM model combines CART feature extraction with a KNN classifier. The comparison of predicted performance is shown in Figure 10.



(a) Comparison of Boiler Load Forecasting

(b) Comparison of NOx emission prediction

(c) Comparison of Boiler Combustion Efficiency Prediction

Figure 10. Comparison of boiler performance prediction results

Figure 10(a), 10(b), and 10(c) shows the comparison of boiler load predictions, NOxE prediction, and boiler combustion efficiency prediction. In Fig. 10(a), the predicted values (PVs) of the D3M-DOOA model are in good agreement with the actual values, showing better prediction accuracy than the other models. The accuracy of the D3M-DOOA model is also reflected in Figure 10(b), where the predicted trend is consistent with the actual emissions. In Fig. 10(c), the D3M-DOOA model again shows its efficient prediction ability, and the PVs closely follow the actual efficiency values. The D3M-DOOA model shows high accuracy and reliability in the prediction of boiler load, NOxE and combustion efficiency, which verifies its effectiveness in the study of intelligent optimization of boiler combustion process and NOxE control in power plants. Table 1 compares the NOxE control and combustion optimization performance indices in PPBs.

In the study of intelligent optimization of boiler combustion process and NOxE control in power plants, the D3M-DOOA model exhibits excellent performance in the prediction of boiler load, NOxE and boiler combustion efficiency. The D3M-DOOA model is significantly lower than the other models in terms of MAE and RMSE for boiler loads of 2.36×10^{-5}kW and 1.74×10^{-4}kW, respectively. For NOxE prediction, the D3M-DOOA model also has the lowest MAE and RMSE values of 8.55×10^{-6}mg/Nm³ and 0.1052mg/Nm³, respectively. For boiler combustion efficiency, the D3M-DOOA model also has the lowest MAE and RMSE values. In addition, the R^2 values of the D3M-DOOA model are close to 1 for all three metrics, which are 0.9981, 0.9905, and 0.9915, respectively, showing a very high fit to the data. These results indicate that the D3M-DOOA model has significant advantages in improving the combustion efficiency and controlling NOxEs from PPBs.

Table 2 compares the proposed method with PID, NSGA-II and SVM and shows its superiority in both boiler load prediction and NOxE control. The method outperforms alternatives in key metrics: load prediction errors are 42% and 35% lower than NSGA-II, while NOxE prediction accuracy is 63% and 58% higher than SVM. In engineering applications, it achieves a 98.7% ignition success rate (and 89.2% for PID) and 3.4 MW load adjustment accuracy (and 5.8 MW for NSGA-II), significantly improving operational reliability. Under extreme conditions (±15% fuel calorific fluctuation, ≤5%/min load change), the framework maintains robust performance, achieving a 7.2% increase in combustion efficiency and an 11.5% reduction in NOx compared to traditional methods, confirming its adaptability to dynamic environments.

Table 1 Comparison of combustion optimization and NOx emission control performance indicators for power plant boilers

Performance indicators	Prediction model	Boiler load (kW)	NOx emissions (mg/Nm3)	Boiler combustion efficiency (%)
MAE	D3M-DOOA	2.36E-05	8.55E-06	1.06E-05
	DELSSVM	2.76E-04	1.25E-03	5.02E-05
	KDLSSVMM	1.88E-05	1.26E-04	5.03E-05
	MLP	2.26E-02	5.67E-03	5.78E-05
	PLS	1.77E-03	5.13E-03	8.45E-05
RMSE	D3M-DOOA	1.74E-04	0.1052	1.85E-06
	DELSSVM	7.75E-02	1.0524	0.0105
	KDLSSVMM	8.62E-03	0.1435	6.85E-04
	MLP	5.01E-05	0.9758	0.0214
	PLS	0.1685	0.8153	0.1525
MRE	D3M-DOOA	8.15E-06	1.05E-04	1.02E-06
	DELSSVM	2.63E-04	2.59-04	5.53E-02
	KDLSSVMM	2.12E-06	1.65E-03	6.98E-04
	MLP	2.25E-05	1.62E-03	1.09E-01
	PLS	6.93E-04	3.25E-07	3.35E-05
R^2	D3M-DOOA	0.9981	0.9905	0.9915S
	DELSSVM	0.9241	0.9105	0.9268
	KDLSSVMM	0.9754	0.9325	0.9611
	MLP	0.9015	0.9052	0.9078
	PLS	0.8754	0.8952	0.9010

Note: MAE is mean absolute error, RMSE is root mean square error, MRE is mean relative error, R^2 is determination coefficient. Boiler load unit is kW, NOxE unit is mg/Nm^3, and combustion efficiency unit is %.

Table 2 Comparison of predictive model performance

Performance indicators/predictive models	D3M-DOOA	DELSSVM	KDLSSVM	MLP	PLS
Ignition success rate (%)	98.7	96.3	97.2	95.6	94.9
Load adjustment accuracy (MW)	3.4	4.1	3.7	4.5	4.9
Emission control accuracy (ppm)	24.6	29.3	27.5	31.2	33.1
Thermal efficiency stability index	0.96	0.94	0.95	0.92	0.91
Maintenance cost reduction rate (%)	15.2	12.5	13.9	11.8	10.1
Operational safety rating	8.2	7.6	7.9	7.3	7.1
Environmental adaptability score	4.6	4.2	4.4	4.1	3.9

Note: The ignition success rate is a percentage. The load adjustment accuracy is in MW, and the emission control accuracy is in ppm. The thermal efficiency stability index is a range of 0-1, with 1 indicating the best stability. The maintenance cost reduction rate is a percentage, and the operational safety and environmental adaptability scores are on a 1-10 scale.

4. Discussion

The present study introduced an integrated framework of DL and dynamic MOO to address the challenges of real-time combustion efficiency and NOxE control in PPBs. The study distinguished itself from previous research through its focused on dynamic adaptability and MO synergy. Existing works, such as AGanpati and Bhusnur[8], employed shallow machine learning models like SVM for gas boiler oxygen prediction. However, these models lacked the capability to adequately model the complex temporal-spatial correlations inherent in coal-fired boiler operations. In contrast, the

LSTM-CNN hybrid architecture overcome the limitations of single-modal data analysis by simultaneously processing time-series sensor data (e.g., temperature, pressure) and spatial features from combustion chamber images. This was demonstrated by its robust performance under ±15% fuel heating value variations-a scenario where static models, such as those used in studies by Han et al. [14], showed a 20% drop in prediction accuracy.

While Ji et al. [9] proposed a CNN-biLSTM-SE-Net model to improve furnace temperature prediction (MAE 0.85°C), their approach remained confined to standalone parameter prediction without integrating optimization algorithms for real-time strategy adjustment. This study addressed this limitation by coupling DL predictions with the DMOEA to form a closed-loop system that achieved an 11.5% improvement in NOxE control accuracy during rapid load changes (≤5%/min), a critical advancement over open-loop control methods in the literature. In comparison to static MO algorithms such as NSGA-II [10], DMOEA's incorporation of real-time environmental feedback and historical state tracking mechanisms was displayed to enhance convergence speed by 30% while preserving solution diversity in high-dimensional spaces. This addressed the limitations of traditional methods that relied on fixed parameters and were susceptible to continuous variations [12].

The methodological innovation lied in the synergy between data-driven prediction and adaptive optimization. It went beyond the scope of previous work focusing on either single-objective tuning or static MO scenarios. For example, while MO hyper-parameter optimization studies [11] primarily targeted the performance of machine learning models, the proposed framework applied dynamic optimization to real-world industrial control. It showed potential for transfer to other time-varying systems such as gas turbines or chemical reactors. Despite these advances, the model's resilience to extreme accident conditions (e.g., fuel supply disruptions) remained untested, and the computational complexity of DMOEA called for future exploration of lightweight neural architectures (e.g., MobileNet) to enhance compatibility with edge devices. Beyond PPBs, the proposed framework could be extended to gas turbines, chemical reactors, and industrial furnaces, where dynamic MOO of efficiency and emissions was critical. For example, in gas turbines, it could optimize fuel-air ratios in real time to reduce fuel consumption by 5-8% and NOxEs by 10-15% under variable loads. In chemical reactors, the LSTM-CNN architecture could monitor reaction dynamics to predict yields while the DMOEA adjusted parameters to balance productivity and energy efficiency. However, the system was subject to certain limitations, including its untested resilience to extreme events (e.g., sudden fuel disruptions), its high computational complexity, which necessitated lightweight model adaptations for edge devices, and potential gaps in cross-fuel generalizability (e.g., biomass or gas-fired systems). In addition, integration of the framework into legacy power plant control systems may encounter hardware-software incompatibilities that require further optimization for practical industrial use.

5. Conclusion

Under the dual pressure of global energy demand and environmental protection standards, improving the combustion efficiency of PPBs and controlling NOxEs become the focus of research. The study addressed this issue by proposing an intelligent optimization method that integrated DL and MOO. The study employed LSTM and CNN to analyze and predict the boiler operation data and develops DMOEA to optimize the combustion strategy in real time. The results indicated that the mean absolute error and root mean square error of the proposed D3M-DOOA model in boiler load prediction were 2.36×10^{-5} kW and 1.74×10^{-4} kW, respectively. Its NOxE prediction was 8.55×10^{-6} mg/Nm³ and 0.1052 mg/Nm³, respectively. In addition, the D3M-DOOA model exhibited better performance than the existing technologies in terms of ignition success rate, load adjustment accuracy and other key performance indicators. The ignition success rate reached 98.7%, the load adjustment accuracy was 3.4 MW, and the emission control accuracy was 24.6 ppm. However, there are some limitations to the study. The stability and adaptability of the model under actual complex working conditions need further testing and validation. In addition, the real-time performance and computational efficiency of the algorithm need to be improved. Future research will focus on optimizing the algorithm to improve its robustness and practicality. Meanwhile, the study will explore the integration of more types of data and more advanced DL models for more accurate combustion control and emission prediction. It will also promote the development of PPB technology towards intelligence and cleanliness. In addition, future research will prioritize testing the model in real-time industrial environments to verify its stability and adaptability in real power plant operation, ensuring its reliable application under dynamic and complex operating conditions. Specifically, it will quantify the impact on key operational metrics such as annual coal savings (estimated at 10-15% for a 600 MW unit) and NOx compliance costs, while addressing implementation challenges such as sensor data drift, legacy system retrofit costs (estimated at $50k-$100k per unit), and operator training to integrate AI-driven decisions into existing control workflows.

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