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A Survey on Intelligent Optimization Approaches to Boiler Combustion Optimization

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ABSTRACT

This paper reviews the researches on boiler combustion optimization, which is an important direction in the field of energy saving and emission reduction. Many methods have been used to deal with boiler combustion optimization, among which evolutionary computing (EC) techniques have recently gained much attention. However, the existing researches are not sufficiently focused and have not been summarized systematically. This has led to slow progress of research on boiler combustion optimization and has obstacles in the application. This paper introduces a comprehensive survey of the works of intelligent optimization algorithms in boiler combustion optimization and summarizes the contributions of different optimization algorithms. Finally, this paper discusses new research challenges and outlines future research directions, which can guide boiler combustion optimization to improve energy efficiency and reduce pollutant emission concentrations.

KEYWORDS

boiler combustion optimization; circulating fluidized bed boiler; environmental protection; computational intelligence; intelligent optimization algorithm

With the fast development of economy and technology in recent decades, China's electricity demand has increased. Figures 1 and 2 depict information from various forms of power generation in recent years. Statistics show that a sizable share of China's power output still comes from thermal power. The boiler carrier in the thermal power plant is the circulating fluidized bed boiler (CFBB). Coal has become the primary fuel for CFBB in most countries due to its low price and abundant reserves[1, 2]. The pollution gas generated by coal combustion has seriously damaged the ecological environment. Many countries have formulated the corresponding laws and regulations to specify the pollution emission concentration of boilers[3,4].

The use of coal-fired power generation mainly causes the following two results: (1) a lot of energy consumption and (2)

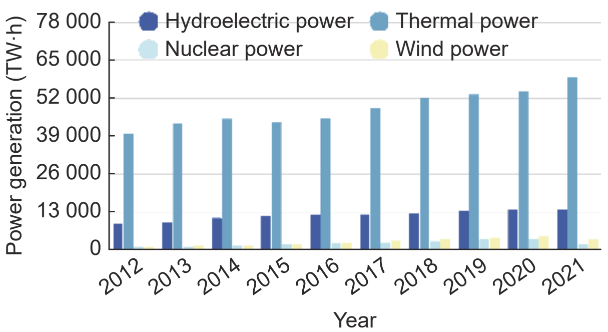

Fig. 1 Total power generation trend diagram of different power generation forms.

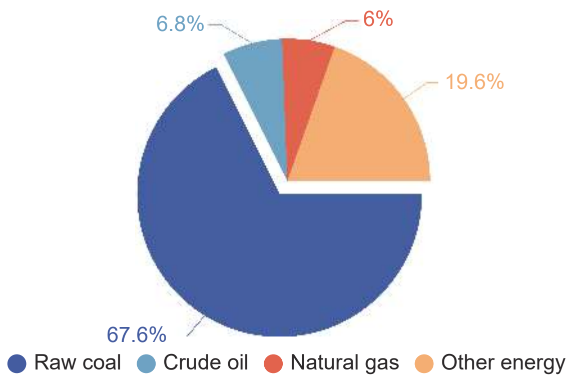

Fig. 2 Proportion of various raw materials used.

severe environmental pollution. Although coal reserves are relatively wealthy, they are not renewable resources. In addition, the current utilization rate of coal in thermal power plant boilers is relatively low, resulting in a waste of resources. Furthermore, a large number of harmful gases are generated after coal combustion, mainly including sulfide concentration (SO_x), carbon oxide (CO_x), and nitrogen oxide concentration (NO_x). These pollutants cause serious environmental problems such as acid rain, greenhouse effects, and the depletion of the earth's ozone layer. Therefore, how to effectively reduce pollutant emissions and enhance boiler thermal efficiency has essential significance for the sustainable development of the global economy. In the 1970s, research on boiler combustion optimization technology began. At first, Launder and Spalding[5] combined mechanics and combustion knowledge to obtain the mathematical model and numerical calculation method of the combustion process, which

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opened a new idea in combustion theory and applied research. Air cover is an effective method to ensure airflow uniformity in a CFBB boiler. In order to improve the thermal efficiency, Liu et al.[6] designed a 220 t/h CFBB small test bench, integrated with a new gas cap. The mathematical model was deduced, and cold experiments verified the accuracy. The experimental results showed that the thermal efficiency of CFBB increased from 86.4% to 91.8% after using the new gas cap. The early research is mainly divided into three categories, namely physical and chemical methods, numerical simulation, and burner design optimization. Representative works are shown in Table 1.

Although these methods improve the thermal efficiency of the boiler and reduce pollutant emissions to a certain extent, with the continuous increase of boiler capacity, the combustion process becomes more complex, and it is difficult to use mechanical methods to optimize the boiler combustion process. Therefore, an efficient intelligent optimization technology is needed to better solve the boiler combustion optimization problem. Evolutionary computing (EC) technology and data modeling (DM) technology have attracted a lot of attention in boiler combustion optimization problems due to their efficient performance[31, 32]. However, there is currently no complete guideline on the advantages, disadvantages, and usability of various algorithms[33]. This has led to the disconnection of research in this field, and the progress of practice has not been shared in time, resulting in the slow progress of boiler combustion optimization. This paper systematically summarizes the current achievements of boiler combustion optimization, aiming to provide guidance for interested researchers.

The use of intelligent optimization technology in boiler combustion optimization is mainly divided into two stages, namely, the establishment of the boiler combustion model and the optimization of the combustion process. Using the historical data of boiler combustion, the model is established by EC and DM technology, and then the combustion process is optimized by EC technology. The optimization flow chart is shown in Fig. 3.

Table 1 Works summary of mechanism methods.

Category	Reference
Physical and chemical methods	[5, 7–14]
Numerical simulation	[6, 15–24]
Burner design optimization	[25–30]

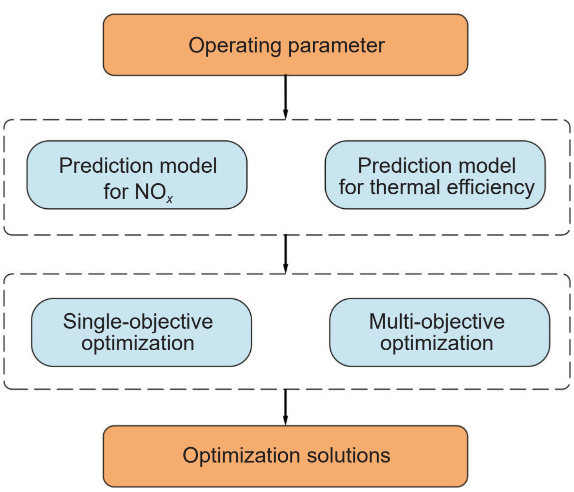

Fig. 3 Computational intelligence technologies to optimize boiler combustion processes.

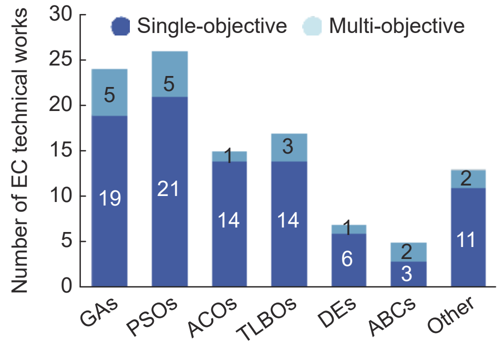

Fig. 4 Number of EC technical works in boiler combustion optimization.

Figure 4 shows the application of the main popular EC technologies in boiler combustion optimization. It can be clearly seen from Fig. 4 that genetic algorithms (GAs) and particle swarm optimization (PSOs) have relatively more research, while ant colony optimization (ACOs), teaching and learning-based optimization (TLBOs), differential evolution (DEs), and artificial bee colony (ABCs) are relatively few. The number of other EC technologies is small, mainly including grey wolf optimization (GWOs), whale optimization algorithm (WOAs), vortex search (VSs), and so on. In addition, the works on single-objective optimization are more than that on multi-objective optimization. (Please note that the data may not be absolutely complete, but are representative works. The data are from mainstream databases such as Google Scholar and Web of Science.) The goal of this paper is to conduct a comprehensive investigation of boiler combustion optimization research, hoping to further promote the research in the field of boiler combustion optimization.

The remaining sections are as follows. Section 1 introduces the structure and mechanism of CFBB. Section 2 introduces the existing researches on boiler combustion optimization. Section 3 presents future research directions and challenges. Section 4 summarizes the paper.

1 Background

This section introduces the basic structure and characteristics of boilers, the principle of NO_x generation, and the calculation method of thermal efficiency.

1.1 CFBB structure and combustion process

Figure 5 shows the structure of a CFBB boiler in a thermal power plant. The coal is first broken into small particles, and then sent into the furnace together with limestone and circulated under the action of primary and secondary air. To achieve full utilization of raw materials, the cyclone separator recycles unburned pulverized coal particles into the furnace. The high temperature and high-pressure gas produced by combustion will enter the turbine, driving the generator to generate electricity and converting heat and mechanical energy into electrical energy. Finally, the flue gas is filtered by the bag filter and discharged into the atmosphere.

Pulverized coal particles in a CFBB are fluidized under the action of graded wind, which is a unique feature different from the traditional pulverized coal boiler, and its unique characteristics have many advantages.

(1) It can adapt to various fuel types with a high fuel utilization rate. Some inferior fuels with low calorific value, high ash content, and low ash melting points, such as lignite and peat, can also be entirely burned in CFBB.

(2) In actual production, the CFBB bed temperature is strictly

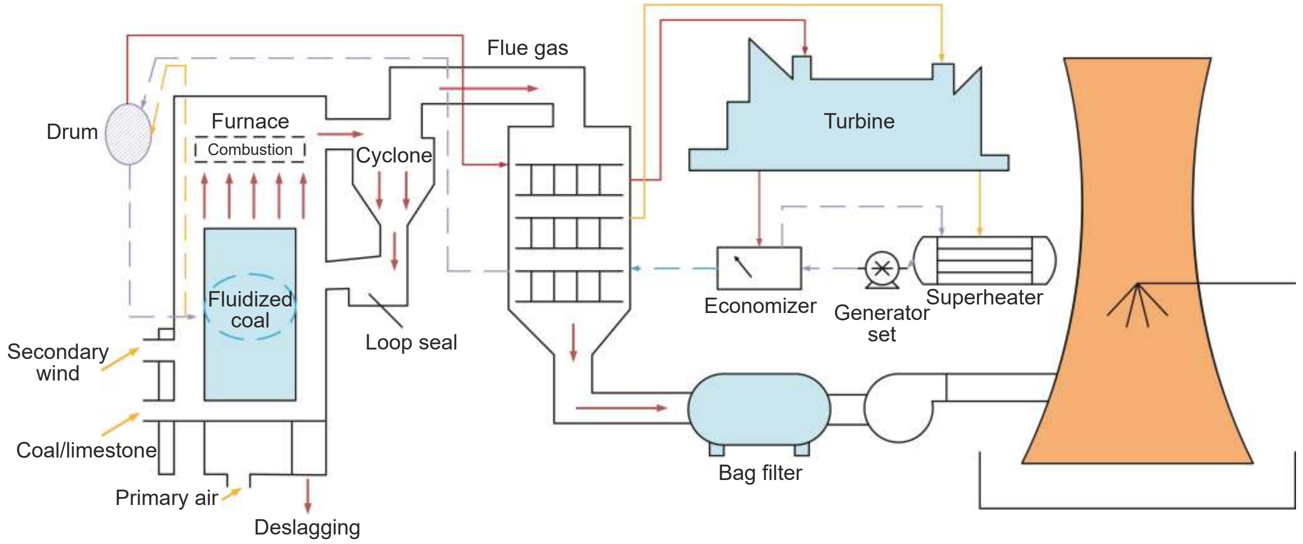

Fig. 5 Structure diagram of CFBB.

maintained at 850–950 ℃, lower furnace temperature, effectively avoiding the slag melting phenomenon. By adding limestone to the combustion process, the ash contains high calcium content, which can be used to make raw materials for cement and make the combustion residue recycled.

(3) The boiler has a wide range of manipulation conditions. This type of boiler load has an extensive mobilization range, which can meet the complex needs of the State Grid in different seasons and different periods.

(4) CFBB helps reduce pollutant emissions. The low-temperature combustion environment of CFBB makes it difficult for nitrogen (N) in the air to oxidize to NO_x. In addition, the staged combustion process can broadly inhibit the conversion of N into NO_x in the fuel and reduce some of the NO_x generated. Therefore, the combustion of CFBB is a kind of energy-saving and environmental protection combustion mode.

1.2 NO_x formation mechanism

NO_x is the main pollution gas in the CFBB combustion process, mainly including NO and NO_2, and NO accounts for about 90%. In order to prevent air pollution and protect the environment, it is necessary to strictly control its emission standards. CFBB combustion is a very complex process of physical and chemical changes. According to the NO_x formation mode, it can be roughly divided into three types: fuel type, thermal type, and fast type.

(1) Fuel NO_x is generated during the combustion process and is the dominant form. After a series of complex physical and chemical changes, numerous nitrogen ions and nitrogen-containing compounds will be decomposed. A series of chemical reactions occur between high-temperature conditions and carbon, hydrogen, and oxygen plasma, and NO_x is generated. This is also the main source of NO_x generated in the operation of CFBB, accounting for about 90% of the total NO_x production. The redox process of nitrogen in fuel is shown in Fig. 6.

Studies have shown that NO_x generated by coal combustion mainly comes from two ways, volatile ammonia and coke ammonia. In the early stage of the eruption, volatile coal ammonia produces some intermediate products in the rich zone. If oxygen is sufficient, NO_x is produced. If oxygen is insufficient, the precipitated nitrogen oxides are reduced to N_2. Because fuel NO_x accounts for a large proportion of total NO_x emissions, it is very important to study its formation and destruction mechanisms to control NO_x emissions.

(2) Thermal NO_x comes from the oxidation reaction of N_2 in the air at high temperature. The primary air and secondary air in the furnace are rich in N_2 and O_2. In a high-temperature environment, a series of chemical reactions occur between N_2 and O_2 to generate NO_x. The production process is shown in the following equation:

$$O + N_2 \rightarrow NO + N \tag{1}$$

$$N + O_2 \rightarrow NO + O \tag{2}$$

The production of thermal NO_x is greatly affected by temperature. If the temperature is higher than 1200 ℃, its production will be large. On the contrary, if the temperature is lower than 1200 ℃, its production is very small. Since the

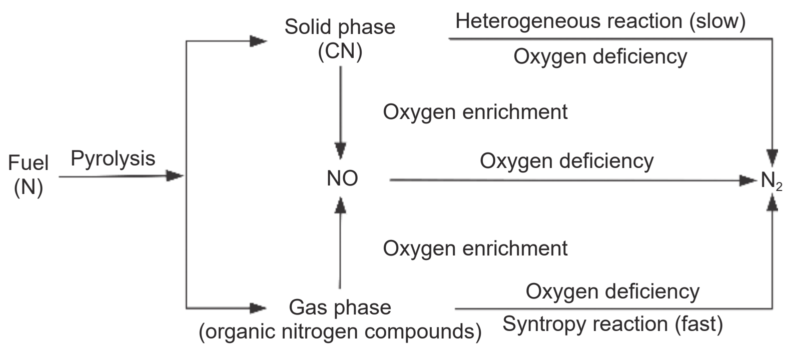

Fig. 6 Redox process of nitrogen.

temperature in the CFBB furnace is generally maintained at 850–900 ℃, the thermal NO_x production accounts for a small proportion of the CFBB.

(3) Fast NO_x is produced by the reaction of hydrocarbon ion clusters in fuel and N in the air according to the Fenimore mechanism. Fast NO_x production requires more hydrocarbons, and the oxygen concentration is relatively low. The production of rapid NO_x generally does not exceed 5% of the total NO_x production, so the production of rapid NO_x is less than that of thermal NO_x. Usually, only with gas-fueled burners can their production be considered.

1.3 Thermal efficiency calculation

Most of the heat generated during the regular operation of the boiler will be absorbed through the water wall. The absorbed heat is usually called adequate heat, and the part of heat lost through other ways is called heat loss. The thermal efficiency of a boiler is the percentage of heat energy converted to the total heat energy input. Thermal efficiency is not only the standard to evaluate the operation status of the boiler, but also an essential goal of boiler combustion optimization. The calculation method is shown as fouows:

$$\eta=\frac{Q_1}{Q_r}\times 100\% \tag{3}$$

where η is the thermal efficiency of the boiler, Q_1 is the effective heat, and Q_r is the total heat input.

(1) **Calculation method of thermal efficiency**. There are two methods to calculate thermal efficiency, the positive equilibrium method and the inverse equilibrium method. The positive balance method is to obtain Q_1 and Q_r through measurement and then calculate according to Eq. (3), namely, the thermal efficiency of the boiler. The inverse equilibrium method is also known as the heat loss method because it measures the heat loss value of the boiler combustion system and then calculates the percentage of total heat loss to Q_r, as well as the combustion efficiency. The calculation equation is as follows:

$$\eta=1-\frac{Q_s}{Q_r}\times 100\%=1-\sum q \tag{4}$$

where Q_s is the sum of all boiler heat loss.

Many thermal power plants obtain relevant data by measuring the speed of the coal feeder or using belt weighing and other rough means, so the measured data must have mistakes, resulting in within errors the calculated thermal efficiency. The equilibrium and anti-equilibrium methods are the main methods for calculating the thermal efficiency of boilers. Suppose the relative error is δ when the total heat input is Q_r, we have:

$$\varDelta_1=\frac{Q_1}{Q_r(1\pm\delta)}-\frac{Q_1}{Q_r}=\frac{\pm\delta\cdot Q_1}{(1\pm\delta)\cdot Q_r} \tag{5}$$

$$\varDelta_2=\left(1-\frac{Q_s}{Q_r(1\pm\delta)}\right)-\left(1-\frac{Q_s}{Q_r}\right)=\frac{\pm\delta\cdot Q_s}{(1\pm\delta)\cdot Q_r} \tag{6}$$

It can be found from Eqs. (5) and (6) that the difference between the error values $\varDelta_1$ and $\varDelta_2$ of the positive and negative balance methods is determined by the size of Q_1 and Q_s, respectively. The combustion efficiency of CFBB is relatively high. Generally, Q_1/Q_r is about 90%, and Q_s/Q_r is about 10%. It can be seen that the error $\varDelta_2$ obtained by the inverse equilibrium method is about 1/9 of that obtained by the positive equilibrium method $\varDelta_1$.

(2) **Anti-equilibrium calculation method**. Limestone is usually added as a desulfurized in the CFBB combustion process. The addition of limestone will affect the change of material composition and energy in the furnace, which is not conducive to calculating thermal efficiency. For the convenience of mathematics, the m_t kg desulfurized required for each kilogram of coal combustion is taken as the standard, and the changes of material and heat in the furnace brought about by the combustion process are equivalent to the corresponding mass of coal. The anti-equilibrium calculation Eq. (4) is transformed into Eq. (7).

$$\begin{aligned}\eta=1-&\frac{Q_2+Q_3+Q_4+Q_5+Q_6+Q_7}{Q_r}\times 100\%=\\&1-(q_2+q_3+q_4+q_5+q_6+q_7)\end{aligned} \tag{7}$$

where Q_2 is the physical heat loss of exhaust smoke $(\mathrm{kJ/kg})$. Q_3 is incomplete combustion heat loss of combustible gas $(\mathrm{kJ/kg})$. Q_4 is solid incomplete combustion heat loss $(\mathrm{kJ/kg})$. Q_5 is the boiler heat loss $(\mathrm{kJ/kg})$. Q_6 is the physical heat loss of ash $(\mathrm{kJ/kg})$. Q_7 is the heat loss of desulfurization reaction $(\mathrm{kJ/kg})$, $q_i(i=2,3,\ldots,7)$ is the Q_i percentage of Q_r.

It can be seen from Eq. (7) that when the inverse equilibrium method is used to calculate the thermal efficiency, the calculation results of each heat loss will affect the thermal efficiency of the boiler. Therefore, in order to obtain a more accurate thermal efficiency of the boiler, it is necessary to accurately calculate the heat loss of the boiler, to lay the foundation for the combustion optimization of the boiler. It should be noted that the detailed calculation of each index in Eq. (7) can be referred to in Ref. [34]. Among the six heat losses, exhaust heat loss Q_2 is the largest proportion of the heat loss in the combustion process, accounting for about 5%. The heat loss Q_4 caused by incomplete combustion of solids is second only to exhaust heat loss, and the proportion is also large. The ash physical heat loss Q_6 has a greater impact on the thermal efficiency of CFBB, and its impact on the index is small.

2 Existing Researches in Boiler Intelligent Optimization

This section summarizes the existing researches on boiler combustion optimization. It can be seen from Fig. 7 that according to different technologies, the works of boiler combustion optimization are divided into two categories, namely the EC paradigm and the DM paradigm. Mainstream EC technologies have been used in boiler combustion optimization. Genetic algorithm is a typical evolutionary algorithm, particle swarm optimization, ant colony optimization, and teaching and learning-based optimization are representative swarm intelligence algorithms. Other algorithms include differential evolution and vortex search, which are relatively lacking. DM paradigm is mainly used in boiler combustion modeling, including artificial neural networks (ANNs) and support vector machine regression (SVRs). Some other machine learning techniques such as ensemble learning and deep learning have less work.

2.1 EC paradigms

This subsection summarizes the works of EC technologies in boiler combustion optimization. It mainly includes GAs, PSOs, ACOs, TLBOs, and other EC techniques.

2.1.1 GAs for boiler combustion optimization

GAs are likely to be the first intelligent algorithm for boiler

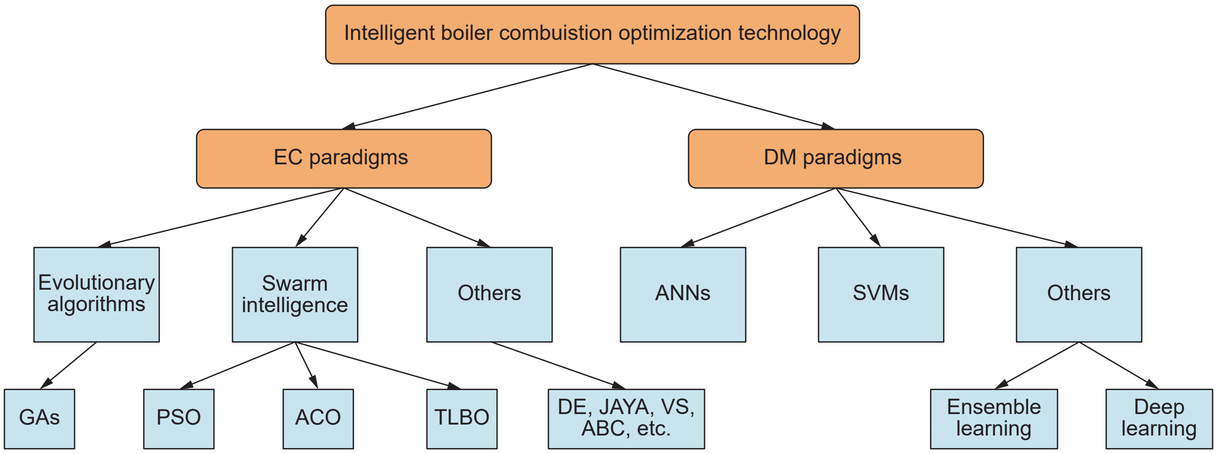

Fig. 7 Existing researches classification of intelligent boiler combustion optimization.

Table 2 Representative works of GAs in boiler combustion optimization.

Number of objectives	Reference
Single-objective	[35–49]
Multi-objective	[50–54]

combustion optimization. Since the 1990s, GAs have been applied to the optimization of boiler thermal efficiency. Table 2 lists some representative works on GAs optimization of boiler combustion. It can be seen in Table 2 that the number of single-objective optimization is more than that of multi-objective optimization.

In order to estimate the oxygen content in syngas generated by biomass in different types of facilities, Krzywanski et al.[55] considered the optimization of calcium oxide adsorption in syngas by bubble fluidized bed (FB) and CFBB. A non-iterative model was developed using GA and ANN to optimize hydrogen production. The experimental results showed that based on the established model, the thermal efficiency of CFBB was improved. The maximum hydrogen production rate was 67.4%, the temperature reached 775 ℃, and the molar ratios of CaO/C and H_2O/C were 2.40 and 3.12, respectively. Suresh et al.[56] used ANN and GA to study the thermal efficiency optimization of a high-ash coal-fired boiler in a supercritical power plant in order to maximize the thermal efficiency of the boiler. Wang et al.[57] have realized a safe and efficient explosion of boilers to some extent by using fuzzy association mining algorithms, ANN, and ECs in computational intelligence technologies. In Ref. [58], the established ANN-GA model was verified by historical combustion data and computational fluid dynamics. The experimental results showed that computational fluid dynamics was helpful to improve the performance of ANN and provided an effective tool for the combustion optimization of CFBB in practical industrial operations.

There are also many research works in multi-objective optimization. Chaudhari and Garg[59] used single-objective and multi-objective optimization techniques to study the adjustment model of maleic anhydride CFBB commercial plant reactor. Using the NSGA-II algorithm, the optimal productivity parameter combination was obtained. Buche et al.[60] proposed a multi-objective evolutionary algorithm capable of dealing with noise problems, which was applied to boiler combustion optimization to reduce the emission of NO_x and the pressure fluctuation of flame. In Ref. [61], based on the experimental data of coal-fired boilers, the hybrid model for predicting the efficiency and pollutant emissions of 360 MW boilers was established by using ANN. The GA was used to reduce the fuel and environmental costs as the optimization objective, and the optimal operation schemes such as excess air, primary airflow, and secondary air flow were obtained. This algorithm was combined with distributed control system (DCS) to realize the real-time coordinated and optimized control of power plant boilers. Shi et al.[62] used the computational fluid dynamics simulation method combined with ANN, the thermal efficiency and NO_x emission models of a 660 MW ultra-supercritical boiler were established, and the average prediction errors were 0.04% and 3.56 mg/Nm^3, respectively. Then the GA was used to optimize the air supply scheme to achieve the goal of high thermal efficiency and low NO_x emission.

In general, GA has played an excellent optimization effect in boiler combustion. However, GA still faces many challenges in boiler combustion optimization, such as difficulty in selecting hyperparameters, slow convergence speed, and easily falling into local minima.

2.1.2 PSOs for boiler combustion optimization

Table 3 lists the representative works of PSOs in boiler optimization. It can be seen in Table 3 that there are more studies on single-objective optimization than multi-objective optimization.

Because the original PSO has a fast convergence speed and is easy to converge to the local optimum, it is difficult to achieve a better optimization effect. Many scholars have used improved PSO combined with regression models such as ANN and SVR for boiler combustion optimization. In order to make full use of the potential of CFBB waste heat sources, Garg and Orosz[86] used PSO to search for the best trade-off between specific investment costs and energy utilization. A method for generating high entropy efficiency vortex geometry corresponding to the optimization period was proposed, and the optimization analysis was further extended to solar thermal applications. In Ref. [63], it focused on the use of PSO and SVR to minimize NO_x emissions and compared the performance with GA and ACO algorithms in this research. In Ref. [87], PSO with variable population size was used to optimize the reliability of the boiler furnace system. The results showed that the optimized reliability was as high as 99.9845%. In Ref. [88], a new hybrid jump particle swarm optimization

Table 3 Representative works of PSOs in boiler combustion optimization.

Number of objectives	Reference
Single-objective	[63–80]
Multi-objective	[81–85]

(HJPSO) was proposed to adjust the gain of the boiler proportional-integral (PI) controller. After introducing Gauss and Cauchy mutation, the optimization ability of HJPSO was greatly enhanced, and better PI controller gain was obtained in the comparison of other PSO variants. In Ref. [89], the distributed PSO based on MapReduce was used to optimize the thermal efficiency and NO_x emission of the boiler. The weighted coefficient method was used to convert multi-objective optimization into single-objective optimization. In Ref. [90], the control effects of PSO-proportional-integral-derivative (PID), modern controller fuzzy logic controller (FLC), and classical PID controller on CFBB bed temperature were compared. The results showed that the control establishment time of PSO-PID was shorter than that of other controllers.

In general, the application of PSO in boiler optimization is reflected in the improvement of PSO, and the optimization performance of PSO is improved by designing different strategies. However, most of the works do not consider the characteristics of boiler combustion to improve the algorithm.

2.1.3 ACOs for boiler combustion optimization

Table 4 lists the works of ACOs in boiler combustion optimization, the earliest work can be traced back to 2008[91]. There are not many studies on ACOs in boiler combustion compared with GAs and PSOs. In addition, it can be seen from the statistical data that more work focuses on single-objective optimization, and there are very few works on multi-objective optimization.

In Ref. [106], SVR was used to establish a model of the relationship between boiler NO_x emission concentration and boiler operating parameters. Then ACO was used to optimize the NO_x emission concentration. The experimental results showed that in the comparison of GA and PSO, the decision scheme optimized by ACO can effectively reduce NO_x emissions. In Ref. [107], a novel ACO-SVR model was proposed to establish a NO_x emission model. Experimental results showed that the proposed algorithm has higher prediction accuracy and training speed. Zheng et al.[108] introduced the combination of SVR and ACO to reduce NO_x emissions. Experiments showed that the method used effectively reduces NO_x by about 18.69%.

ACO has relatively less work in boiler combustion optimization. ACO has the characteristics of fast global convergence and strong robustness, but it is prone to stagnation and falls into local optimum in the later stage of evolution. Therefore, it is still necessary to study and design effective strategies to enhance the optimization efficiency of ACO in boiler optimization. In addition, it is necessary to further explore multi-objective optimization technology to meet the requirements of boiler optimization development.

2.1.4 TLBO for boiler combustion optimization

Table 4 Representative works of ACOs in boiler combustion optimization.

Number of objectives	Reference
Single-objective	[91–104]
Multi-objective	[105]

Table 5 Representative works of TLBOs in boiler combustion optimization.

Number of objectives	Reference
Single-objective	[38, 80, 110–118]
Multi-objective	[119–121]

As an efficient swarm-based search algorithm, TLBO is widely used in various industrial problems[109]. Table 5 shows the works of TLBO on boiler combustion optimization. In order to improve the optimization efficiency of boiler combustion, more improved TLBOs have been proposed.

In Ref. [122], a novel teaching-learning-based optimization algorithm (TLSO) was proposed, which dynamically adjusted the convergence speed according to the number of iterations and enhanced the global search ability of the algorithm. Compared with several other algorithms, such as PSO, ACO, TLBO, etc., the experimental results showed that TLSO achieves better results in NO_x emission optimization. Li et al.[111] proposed an improved A-TLBO algorithm to construct a 330 MW CFBB combustion model. The experimental results showed that the proposed method had good regression accuracy and generalization ability. In Ref. [123], the improved AELM model was combined with TLBO to establish a CFBB combustion NO_x model. The experimental results showed that compared with the other six models, AELM-TLBO had better prediction accuracy and provides a basis for reducing NO_x emissions. In Ref. [121], a multi-objective improved teaching optimization algorithm (MMTLBO) was proposed. Then, the thermal efficiency, NO_x, and SO_x in the boiler combustion process were comprehensively optimized. The experimental results showed that MMTLBO can find multiple sets of reasonable combustion schemes and provide meaningful guidance. In Ref. [114], an improved TLBO algorithm was used to optimize the NO_x emission of boiler combustion. The experimental results showed that the proposed method can effectively reduce the NO_x emission concentration. In Ref. [124], an improved TLBO algorithm (MTLBO) was proposed. The optimization ability and generalization performance of MTLBO were verified by 14 standard test functions. Finally, the NO_x emission of a 330 MW boiler was optimized. The experimental results showed that the proposed MTLBO algorithm has good optimization performance in NO_x emission optimization.

As an efficient optimization algorithm, the main advantage of TLBO is that it does not require parameter setting. Unlike PSO and GA, the optimization performance is greatly affected by algorithm parameters. However, the computational complexity of TLBO in boiler combustion optimization is relatively high, and it is necessary to further improve the computational efficiency to meet the requirements of complex and variable working conditions.

2.1.5 Others EC techniques for boiler combustion optimization

Table 6 lists other optimization techniques in boiler combustion optimization, including differential evolution (DE), artificial bee

Table 6 Other EC techniques for boiler combustion optimization.

Algorithm	Reference
DE	[70, 125–130]
ABC	[38, 131–134]
WOA	[135–137]
GWO	[138–140]
VS	[141, 142]
HS	[143]
JAYA	[144]
SSA	[145]

colony (ABC), whale optimization algorithm (WOA), sparrow search algorithm (SSA), grey wolf optimization (GWO), vortex search (VS), harmony search (HS), and some mathematical optimization techniques. Among them, DE has the most research results. In addition, Refs. [130, 131] are multi-objective optimization works.

Pattanayak et al.[146] developed a groundbreaking optimization system based on thermodynamics and an ANN model. The system used an optimization algorithm to refine the search for the optimal sequence of fan frequencies, which improved thermal efficiency and reduced pollutant emissions. In Ref. [147], a novel evolutionary multi-objective search algorithm was used to find the probability trade-off front between NO_x and fly ash carbon content based on a data-driven model, which effectively solves the problems of NO_x and thermal efficiency. In Ref. [148], the boiler efficiency was optimized using the optimal manipulated variable (MVs) decision algorithm.

In Ref. [149], multivariate analysis tools such as principal component analysis (PCA) and partial least square-regression (PLS-R) were used to establish the relationship between the input parameters of biomass gasification in a CFBB furnace. According to the optimization results, in order to obtain high quality, it was suggested to use olivine with a high carbon conversion rate and a low tar yield. Kusiak and Song[150] used a data mining method to optimize the complex, nonlinear, and non-stationary combustion process of CFBB. On this basis, a virtual test program was developed to verify the results of the optimization method. The results showed that the developed program improved combustion efficiency. Kim et al.[151] pointed out that the input parameters are related to the performance of the established model. When selecting the input parameters, not only the accuracy of prediction should be improved, but also the dimension of the model should be reduced. Therefore, one or more input parameters should be eliminated continuously. No less than 10 input parameters were saved out of the 36 initial input parameters. Finally, through the test of four commonly used models, it was found that the least squares support vector machine (LSSVM) combined with principal component analysis had the smallest prediction error of NO_x emission, which laid the foundation for boiler combustion optimization. In Ref. [152], a NO_x emission prediction model based on the combination of a feature selection method using an improved pollination algorithm and a random forest was proposed. The results showed that the model has high prediction accuracy and good robustness, which provides key technical support for combustion optimization. A model framework based on deep belief network (DBN) and JAYA was developed to obtain a 660 MW CFBB combustion model and optimize NO_x emission concentration[144]. In Ref. [138], GWO was used to optimize the CFBB operating parameters and improved the operating efficiency. In the comparison between GA and PSO, the proposed method effectively reduced the calculation time and improved the solution accuracy.

Although various intelligent optimization methods have promoted the research of boiler combustion optimization, the proposed algorithms are rarely aimed at boiler combustion characteristics, and the efficiency of the algorithm needs to be further improved.

2.1.6 Performance summary of EC technologies

Boiler combustion optimization refers to improving combustion efficiency and economy and reducing environmental pollution by adjusting boiler combustion parameters. As an effective tool to find the optimal solution, intelligent optimization algorithms have been widely used in boiler combustion optimization. This subsection discusses the effects of various EC algorithms in boiler combustion optimization and related connections and differences.

In boiler combustion optimization, GAs can optimize and adjust the adjustable parameters by modeling the fitness function of combustion parameters. GAs can solve multi-objective optimization problems and nonlinear problems to a certain extent, but for problems with a large distribution of decision space, it may lead to reduced search efficiency. PSOs find the optimal solution by simulating the movement and interaction of particles in the search space. PSOs have good search ability for problems with large search space, but for non-convex problems, they may fall into local optimal solutions and cannot obtain a significantly improved decision scheme. ACOs is a search algorithm based on the behavior of ants in finding food. In boiler combustion optimization, ACOs can find the optimal boiler combustion operating conditions by simulating the pheromone deposition and volatilization of ants during the search process. ACOs can deal with multi-objective optimization problems and constrained optimization problems, but they can not play a good optimization effect on problems with large search spaces. TLBOs find the optimal solution by simulating the behavior of teachers and students in the learning process. TLBOs can also handle multi-objective optimization problems and constrained optimization problems. TLBOs have good optimization ability in the early stage of the search stage, but the convergence speed is relatively slow in the later stage of the search.

Among the above four optimization algorithms, GAs, and PSOs are widely improved and applied to boiler combustion optimization. Due to the difference in the search performance of each algorithm, it can produce different optimization effects under different working conditions. In future work, it is necessary to further analyze the advantages and disadvantages of each algorithm in order to achieve better search performance in boiler combustion optimization.

2.2 DM paradigms

This subsection summarizes the works of DM algorithms in boiler combustion optimization. It mainly includes ANNs, SVRs, and other DM algorithms.

2.2.1 ANNs

Artificial neural networks (ANNs) have been proven to be an effective modeling method and have been widely applied to various fields of the power generation industry[153], boiler failure detection[154-156], noise anomalies[157], power output prediction[158, 159], and early abnormal behavior changes[160, 161]. This helps give untimely warnings during operations[162]. When some studies focus on monitoring and control[163-167], others investigate the possibility of optimization[168-170] and establish intelligent power plants[171]. Since the performance of ANNs in CFBB optimization was clarified in the 1990s[172], a large number of studies using ANNs applications have been produced. Table 7 shows the application of some

Table 7 Representative works of ANNs variants in boiler combustion optimization.

Algorithm	Reference
BP	[37, 68]
ELM	[159, 173–175]
DT	[157]
LSTM	[158, 176]

representative ANNs variants in boiler combustion optimization, including back propagation (BP), extreme learning machine (ELM), decision tree (DT), long short-term memory recurrent neural network (LSTM).

In Ref. [174], in order to improve the performance of ELM, an improved extreme learning machine was proposed. A new method was adopted to generate hidden layer input weights and deviations, and a new hidden layer activation function was presented. In order to verify the validity of the proposed model, a 330 MW boiler combustion process was modeled and good results were obtained. Liang et al.[72] established a multi-objective model of boiler combustion using an optimized extreme learning machine network to predict boiler thermal efficiency and NO_x emissions. In Ref. [177], a scheme for boiler combustion in functional power plants was proposed. In this study, the ANN and LSSVM were used to conduct Monte Carlo experiments and interval adjoint dominance analysis, which reduced some operating variables. The experimental results showed that the efficient generation of ANNs under the unit load of a power plant was obviously more effective. In Ref. [178], a CFBB gasifier/steam turbine/proton exchange membrane (PEM) fuel cell integrated system was developed. The system contains many thermochemical, biochemical, and physical processes. The ANN was established after combining the reaction principle and CFBB gasifier operating parameters. This model could accurately predict the output parameters of the PEM fuel cell and provide corresponding guidance. In Ref. [179], in order to predict the bed temperature of CFBB more accurately, after analyzing the chemical combustion process of coal-fired units, it is considered that different coal types have a great impact on the prediction of bed temperature. In order to solve this problem, the coal type information was added to the initial deep neural network (DNN) model. In the experiments on two real CFBBs, the proposed model accurately predicted the bed temperature. Booth and Roland[180] optimized boiler operation by using online learning neural networks, adjusted fuel quality fluctuations, and improved operational flexibility according to equipment performance changes caused by wear and maintenance activities. In addition, some boiler combustion optimization techniques have been applied at power plant sites. For example, Ultramar developed boiler combustion optimization software using statistical methods. The smart process of emerson company (SPEC) was based on ANN, used optimization techniques to optimize the boiler combustion process, and was successfully applied to the Warsaw Ostroleka power plant[181]. Pegasus has designed and developed the NeuSIGHT system and the PowerPerfect system. Using the data from DCS, the optimal control of boiler combustion is realized through the ANN[182]. Zhou et al.[183] established an ANN for low NO_x combustion performance of high-capacity boilers by using the nonlinear dynamic characteristics and self-learning characteristics of ANN. The model can predict the NO_x emission concentration and unburned carbon content under different working conditions. Combined with the optimization algorithm, the optimal operating conditions for low NO_x combustion were found. In Ref. [143], the improved ELM model was used to optimize the operation parameters of a 700 MW CFBB to reduce NO_x emissions. In addition, the proposed algorithm was compared with several other advanced algorithms to obtain better results and stronger robustness. The thermal efficiency of a 600 WM boiler was predicted using the ANN model, and the results demonstrated that the proposed method was more accurate in predicting the thermal efficiency of the boiler and other indicators. Finally, the model was tested using statistical methods[184].

2.2.2 SVRs

References [185-188] used different artificial intelligence optimization algorithms to optimize the hyper-parameters in support vector machines to obtain the optimal model of boiler combustion and then optimized the obtained model under multi-parameter conditions by using the optimization algorithm to achieve the goal of reducing the emission of boiler pollutants and improving the thermal efficiency of the boiler. An online combustion optimization system was designed to reduce the NO_x concentration generated by combustion. SVR and random forest models were used to verify the neural network model[69]. In order to meet the needs of bed temperature prediction, a dynamic model for predicting 300 MW CFBB by using LSSVM and delayed order group optimization technology[74]. On the basis of feature selection, the ensemble learning model was applied to decompose and combine the data subset based on LSSVM to predict NO_x emissions[189]. In Ref. [190], the adaptive LSSVM algorithm was used to establish the CFBB combustion model, and a two-step learning strategy was designed and verified by a nonlinear model. In Ref. [191], the Gaussian process model was used to establish the CFBB combustion model, and the SVM model was compared and verified.

2.2.3 Others DM techniques

In Ref. [192], the ensemble learning method was applied to CFBB historical combustion data to predict the unit. Random forest prediction results showed that radial position has the greatest impact on local mass flux and species separation. The overall mass flux had the greatest impact on local particle concentration, while the impact on local clustering characteristics was relatively weak. In addition, if large enough datasets were used, the ensemble learning model could be trained as a model with good predictive ability without any understanding of how it works. This study emphasized the value of machine learning methods in CFBB optimization. In Ref. [193], a NO_x emission prediction method based on the stacking generalized ensemble method (SGEM) was proposed. The PCA method was combined to select the relevant variables. In SGEM, the ensemble learning model was constructed with a back propagation neural network (BPNN), SVR, and DT as the basic models, and linear regression (LR) as the meta-model. Through experimental verification, the proposed method has high accuracy in predicting NO_x emissions. In order to predict the thermal efficiency and NO_x emission concentration of CFBB boilers, a deep bidirectional learning machine was proposed and compared with the same type of ELM[175]. In order to balance boiler thermal efficiency and emission control, a reinforcement learning architecture based on LSTM and deep Q-network structure was developed[176].

3 Future Direction and Research Challenge

With the continuous development of computer technology, many foreign companies have launched several boiler combustion optimization systems. In the 1990s, Pegasus Corporation of the United States developed the first NeuSIGHT system based on neural network modeling for power systems, which worked well in the capacity efficiency of coal-fired power plants at the time[194]. Based on this system, by adding a computer off-line simulation function and dynamic prediction function, the company has developed a Power Perfecter system with even better performance. This system can reduce NO_x emission by 10%–30% while improving boiler thermal efficiency by 0.5%−2.5%, and the optimization effect is very satisfactory. Ultramax has introduced the Ultramax system, which has been successfully used in more than 30 countries and regions[195]. Using multiple optimization algorithms to model artificial neural network parameters optimally, Emerson eventually developed a SmartProcess system that has improved thermal efficiency by approximately 0.6% and reduced NO_x emissions by approximately 13% for the 200 MW coal-fired unit at the Ostroleka power plant in Warsaw[196]. The GNOCISPLUS combustion optimization system, developed by Powergen based on historical operating data of power stations, has been applied in 37 power stations in the UK and the US. The system uses a neural network modeling approach as a tool to control emissions of NO_x and other pollutants by combining it with the plant's intelligent control system. This system uses neural network modeling as a tool to control the emission of polluting gases such as NO_x by combining it with the intelligent control system of the power plant. In addition, many DCS manufacturers, such as Honeywell, Siemens, Emerson, etc., have added combustion optimization control strategies to their mature control system products.

Although there are many combustion optimization systems available, the algorithms and techniques they use are relatively simple. On the other hand, these systems have made good impact abroad. However, China is a vast country with diverse coal quality conditions and a very complex combustion environments. Therefore, it is difficult for foreign systems to play a good role in guiding optimization in China. Further research and design of combustion optimization systems are needed in China[197]. Some of the mainstream research directions and challenges are listed below.

3.1 Combustion data processing

Most power plants are currently using DCS systems or SIS systems to upgrade their information technology, in which a large amount of historical boiler operation data is stored in the DCS system or SIS system. Although these massive data help to model the boiler combustion system, the boiler operation site is complex and the information collected by different testing devices is more chaotic and disorderly, which requires the use of effective data mining methods to process these system data and then select effective data to build the boiler combustion model.

Based on a data-driven model, Ref. [198] monitors the actual boiler efficiency and its desired efficiency. The method was based on an information-theoretic variable ordering of the massive data. In the data processing of ultra-supercritical units, the model structure is a transfer function matrix through dynamic analysis, and the data-driven multivariate model parameters are proposed in the form of intelligent identification combined with evolutionary algorithms for data mining, and the work done further provides a reference for boiler control[199].

For data models, the quality of the dataset is very important. It is important to extract more effective information from the large amount of data obtained from DCS for boiler combustion optimization.

3.2 Feature selection and feature reconstruction

The boiler combustion system is a nonlinear, strongly coupled, large hysteresis system. Its operating parameters are numerous and have complex coupling relationships with each other. If many parameters are directly used as inputs to the black-box model to construct the boiler combustion system model, it will inevitably make the input information of the model redundant and thus weaken the generalization ability of the model[200]. Therefore, when constructing the boiler combustion model, it is necessary to analyze the correlation between the operating parameters that affect the combustion characteristics of the boiler and then eliminate the correlation between the variables.

This study is divided into two main categories. One category is the use of feature extraction. Reference [201] uses a deep Q network (DQN) and an LSTM module to extract features of the combustion process from the DCS operating data. The other category is the use of feature reconstruction. Reference [92] used the mutual information (MI) algorithm to calculate the importance of the actual variables, analyzed them to determine the variables of interest, and then reconstructed the modeled data.

After using the feature selection technique for boiler parameters, the performance of the data model was improved[202, 203], and further research on the technique of boiler feature selection is important to improve boiler combustion optimization.

3.3 Boiler combustion modeling

Advanced computational intelligence techniques are introduced into boiler combustion optimization. Based on historical data of boiler combustion, combustion models are built using machine learning methods, such as neural networks[204], support vector machines[202, 205, 206], random forests[207, 208], etc. On the established model, the thermal efficiency and pollutant emission concentration of the boiler are optimized using population intelligence optimization techniques to achieve safe and efficient low-pollution combustion of the boiler.

These algorithms are capable of modeling the data of boiler combustion and have great advantages in modeling complex systems. It can extract the mapping relationship between the sample input and the target output by learning from a large amount of sample data. However, the traditional neural network relies too much on the random initial values of the network and also suffers from the problems of difficulty to determine the network model and slow learning speed. The parameters of support vector machines also rely too much on empirical knowledge. Therefore, its application in boiler combustion optimization needs to be further improved and perfected.

3.4 Knowledge-driven optimization

The data obtained from DCS are plagued by uncertainties and deficiencies. Hybrid prediction techniques for process control systems are the norm today and involve a combination of data-driven and knowledge-driven models.

Reference [209] generated an artificial neural network prediction tool using Visual Basic GUI and combined it with expert knowledge for predicting the spray values of a 500 MW boiler within the allowed tolerances. Reference [210] considers the structure of distributed support systems and proposes an integration framework based on a distributed architecture that includes expert knowledge and collaboration techniques, tools that work with decision-makers to enrich their knowledge.

The combination of expert knowledge and problem knowledge guides the combustion optimization of the boiler to good effect. It is of good practical importance to further study the combination approach.

3.5 Multi-objective optimization

Most of the current boiler combustion optimization methods and techniques are only optimized for a single objective, just optimizing boiler NO_x emissions or thermal efficiency. There are relatively few studies that simultaneously perform multi-objective integrated optimization of both. The existing algorithms mainly include immune cell subpopulation multi-objective optimization algorithm[211], multi-objective bee colony algorithm[212], multi-objective teaching and learning optimization algorithm[121], etc. However, these methods are not designed with the characteristics of combustion problems, and the comprehensive optimization capability needs further improvement.

3.6 Low carbon policy

To achieve the target task of carbon peaking and carbon neutrality, China has increased the efforts of boiler energy saving and emission reduction, and implemented a series of policy measures such as coal power structure optimization and transformation and upgrading, coal-fired industrial boiler energy saving and environmental protection comprehensive upgrading project, etc. The level of boiler energy saving and environmental protection has been significantly improved.

While reducing NO_x, SO_x, and other polluting gases, CO_2 emissions need to be further reduced. For example, CO_2 has been reduced by a new method of using flue gas heat in cascade[213]. A process simulation of a conventional plant was set up in Ref. [214] using Aspen plus, resulting in a CO_2 recovery rate of 96.24% for the whole system. In the future, the CO_2 emission concentration can be further reduced in terms of the structural design of power generation boilers[215] and optimization of various parameters[216].

4 Conclusion

This paper provided a complete investigation of the applications of intelligent optimization algorithms in boiler combustion optimization. It mainly included the commonly used EC algorithms and analyzed the advantages and disadvantages of each algorithm. In addition, the problems and challenges in future boiler combustion optimization were pointed out and discussed.

The survey shows that EC technologies are widely used in the field of boiler combustion optimization because of their high search efficiency. Each algorithm has its characteristics, e.g., GAs can retain genetic characteristics in the process of evolution, the update mechanism of PSOs is simple, the computational cost is relatively small, TLBOs have high global search ability, and so on. Therefore, the improved versions of these EC technologies can better optimize the boiler combustion process and deserve further study.

Although the current stage of works has achieved good optimization results, there are still many issues that need further in-depth research, such as, pre-processing of boiler combustion data, feature selection and feature reconstruction of combustion process parameters, numerical and data-based modeling, using knowledge-driven assisted optimization, and meeting low-carbon policy requirements. In addition, the algorithms need to have certain generalization performance as the corresponding policies are developed.

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