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# Methods and research status of energy consumption analysis and optimization for coal-fired generator units

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**Abstract.** Reducing the energy consumption of coal-fired generator units (CFGN) is an inevitable choice for the transformation of the power industry to low-carbon. Starting from the analysis of the energy consumption evaluation index of CFGN, the main factors affecting the energy consumption of CFGN are analysed. It is proposed that the operation optimization is an important way to reduce the energy consumption of CFGN. From the aspects of hierarchical measurement and reconstruction of process parameters, the establishment of equipment thermodynamic characteristic model, and the determination of benchmark operating conditions, the methods and research status of energy consumption analysis and operation optimization of CFGN are discussed. It is pointed out that the application of data mining information technology is the development direction of CFGN operation optimization.

## 1. Introduction

The power industry has always been the world's largest energy consumption and carbon emissions industry. In 2017, power generation accounted for 40% of the global primary energy consumption [1], and by 2040, this proportion is expected to rise to 50%. At present, CFGN accounts for 38% of global power generation. Despite the rapid growth of renewable energy, coal is expected to remain the main source of energy for power in the next two decades due to the low proportion of renewable energy (only 8% in 2017) [2]. Therefore, reducing the energy consumption of CFGN can not only reduce the production cost of power plants, but also reduce carbon emissions, which have significant economic and social benefits.

Firstly, this paper analyzed the evaluation index and the main constraint factors of energy consumption for CFGN. Secondly, it discussed the methods and research status of energy consumption analysis and operation optimization for CFGN from three aspects: hierarchical measurement and reconstruction of process parameters, equipment thermodynamic characteristics modeling, and determination of benchmark operating condition.

## 2. The energy consumption evaluation index of CFGN

It is usually chosen standard coal consumption rate of power supply (SCR) (Eq. 1) as the energy consumption evaluation index.

$$b = \frac{HR}{29.3076 \times \eta_b \times \eta_p \times (1 - r_a)} \quad (1)$$



Where  $b$  is SCRP,  $\text{g}/(\text{kW}\cdot\text{h})$ ;  $HR$  is the turbine heat rate,  $\text{kJ}/(\text{kW}\cdot\text{h})$ ;  $\eta_b$  is the boiler efficiency;  $\eta_p$  is the pipeline efficiency, usually takes a value of 0.99;  $r_a$  is the auxiliary power consumption rate of power plant.

Analytical Eq. 1 shows that reducing the turbine heat rate, improving boiler efficiency, and reducing the auxiliary power consumption rate of power plants are the main ways to achieve energy saving and consumption reduction of CFGN.

### 3. Energy consumption constraints of CFGN

For a CFGN set with fixed equipment, the factors affecting boiler efficiency, turbine heat rate and auxiliary power consumption rate of the power plant can be divided into the following three categories [3], as shown in Table 1.

- *Uncontrollable external constraints.* Including load, coal composition, ambient temperature, humidity, etc.
- *Operational controllable factors.* The adjustable process parameters, such as main steam pressure, main steam temperature, reheat steam temperature, exhaust-gas oxygen and water-coal ratio, as well as the operation strategy of auxiliary equipment, such as coal mills and circulating water pumps.
- *Energy efficiency index of equipment.* Such as turbine cylinder efficiency, pump efficiency, fan efficiency, heat transfer coefficient of condenser, air leakage rate of air preheater, etc. These indexes are mainly determined by the health status of the equipment, depending on the economic performance of the equipment itself and the level of equipment maintenance. It is necessary to strengthen and improve the quality of maintenance as well as other measures to ensure that the energy efficiency indexes are in good condition.

Table 1. Energy consumption constraints of CFGN.

category	parameters and indexes		
Uncontrollable external constraints	load	coal composition	ambient pressure
	ambient temperature	ambient humidity	...
Operational controllable factors	main steam pressure	main steam temperature	reheat steam temperature
	boiler gas oxygen	water-coal ratio	operation strategy of coal mills
	operation strategy of circulating water pumps	operation strategy of circulating vacuum pumps	...
Energy efficiency index of equipment	turbine cylinder efficiency	pump efficiency	fan efficiency
	heat transfer coefficient of condenser	air leakage rate of air preheater	shaft seal leakage
	milling unit consumption	desulfurization unit consumption	...

In the process of CFGN, in response of the change of external constraints, operators should first adjust the operation of mode of main equipment such as coal mill, draught fans, induced draft fans, feed water pump and circulating water pump. After determining the unit load, air-fuel ratio and water-fuel ratio, other process parameters should be adjusted to the optimum value in time.

Compared with retrofitting or maintenance in order to improve the energy efficiency of equipment, the way of reducing energy consumption by adjusting operation parameters and operation strategies of equipment has the advantages of less investment and higher profit. Therefore, operation optimization has always been one of the most important means of energy saving and consumption reduction of CFGN.

#### 4. Energy consumption analysis and optimization

The basis of energy consumption analysis and optimization of CFGN is the accurate measurement of process parameters, and the core is to establish an accurate thermodynamic characteristic model of equipment and to determine the target values of process parameters and the optimal operation strategy of auxiliary equipment.

##### 4.1 Hierarchical measurement and reconstruction of process parameters

At present, due to the requirement of control, the setting of measurement of the process parameters focuses on ensuring reliability and trend accuracy, which cannot fully meet the needs for energy consumption analysis and optimization. Therefore, it is necessary to hierarchically measure and reconstruct the process parameters.

The measurement of process parameters needs a wide range of detection technologies. Besides the conventional measurement of pressure, temperature, flow rate, electric power, voltage and current, it also needs the support of new detection technologies such as coal-fired components and flue gas components.

*4.1.1 Classification of parameters.* According to the importance of energy consumption analysis, process parameters can be divided into three levels. The basic idea of classification is illustrated by taking process parameters of steam turbine as an example.

- Core parameters. Process parameters describing uncontrollable external constraints.
- Important parameters. Parameters whose accuracy significantly affects the steam turbine energy calculation result. Including main steam pressure, main steam temperature, reheat steam temperature, vacuum, final feed water temperature, feed water flow, etc.
- General parameters. Parameters whose accuracy has little influence on the calculation results, including steam extraction pressure and temperature, outlet temperature and hydrophobic temperature of heater, etc.

*4.1.2 Validation of data validity.* Different verification methods should be used to verify the validity of the measured results of the classified parameters.

- The core parameters and important parameters are verified by the redundant measurement results.
- For general parameters, redundant test point verification can be used as the main method, and soft measurement verification as the auxiliary method.

*4.1.3 Reconstruction of failure and missing data.* Soft measurement should be adopted to reconstruct the missing and failed points. At present, soft measurement technology has been widely used in the field of data reconstruction. Reference [4] presented a neural network model for on-line soft measurement of carbon content in fly ash of boiler was established, which could accurately describe the response characteristics of carbon content in fly ash. Reference [5] presented an on-line soft measurement method for steam turbine exhaust dryness, which is more accurate than the calculation method based on flow. Reference [6] presented an on-line soft measurement model for the capacity of storage coal pulverizing system based on grey entropy and chaos analysis (GECA) and support vector machine (SVR). It was proved that the model has high accuracy and can reflect the actual working conditions of pulverizing system. Reference [7] presented a soft measurement of main steam flow based on measurement data, which takes into account the error distribution of measurements and the energy balance of the unit. This method had been applied to the SIS system of 300 MW units.

##### 4.2 Establishment of equipment thermodynamic characteristic model

Thermodynamic characteristics refer to the response of process parameters of equipment to external constraints. Taking the steam turbine system as an example, the thermodynamic characteristics model of the equipment needed for energy consumption analysis is as follows:

- The characteristic model of turbine flow. The response characteristics of steam extraction pressure and temperature with the change of main steam flow.
- The characteristic model of steam turbine regenerative system. The response characteristics of water outlet temperature and hydrophobic temperature of heaters with the change of load.
- The characteristic model of condenser. The response characteristics of condenser pressure with the change of load, circulating water temperature and circulating water flow.
- The characteristic model of turbine heat rate. The response characteristics of turbine heat rate with the change of load.

At present, there are two main modeling techniques: mechanism analysis and data mining. The mechanism model is a mathematical model reflecting the transfer mechanism of material flow and energy flow in the production process. The mechanism modelling is generally based on energy balance and mass balance, and some assumptions are adopted to simplify the constraints of the model. The mechanism model has the advantages of clear structure and strong universality. However, due to the variability of constraints of CFGN and the complexity of the process, the calculation results of the mechanism model often deviate considerably from the actual operation data.

Establishing the thermal characteristic model based on data mining algorithm does not need to analyse the mechanism of process, but to get equipment response characteristics from historical data. Reference [8] presented a condenser vacuum prediction model based on generalized regression neural network optimized by drosophila algorithm, and the model could accurately predict the variation of a 600MW CFGN. Reference [9] established a back-pressure prediction model of the direct air-cooled condenser by using BP neural network. The model takes fan power, ambient temperature and load as input and condenser back pressure as output. The accuracy of the prediction can meet the control requirements. Reference [10] established the sensitivity model of energy consumption by using fuzzy rough set and SVR, and obtained the sensitivity coefficient of process parameters to the SCRП under different loads, which provides guidance for unit energy saving and operation optimization.

#### *4.3 Determination of benchmark operating condition*

Generally, the set of all process parameters of CFGN is called operation condition, and the benchmark operating condition refers to the operation condition corresponding to the lowest energy consumption of CFGN under certain uncontrollable external constraints. Therefore, it is the ultimate goal of energy consumption analysis and operation optimization of CFGN to determine the energy consumption benchmark conditions.

The common methods to determine the benchmark conditions are design value method, thermodynamic test method, intelligent optimization with off-design calculation method (IOFC) and data mining method. The design value method is to set the design condition of unit as the benchmark operating condition. This method is suitable for the new unit which is always operated at the design load, but not for the unit whose load changes frequently or the equipment is aging. Thermodynamic test method is to determine the benchmark conditions under typical constraints by the thermodynamic test. However, the cost of the test is high and the optimized conditions are limited.

IOFC is based on the thermodynamic characteristics model of the equipment, using intelligent optimization algorithms to determine the benchmark conditions under certain constraints. The accuracy of IOFC depends on the accuracy of the equipment characteristic model and the ability of global optimization of the optimization algorithm. Reference [11] established the prediction model of SCRП and  $NO_x$  emission of 300MW CFGN by using SVR, and established the optimization model of boiler combustion with genetic algorithm. The optimization results can guide the efficient and clean operation of CFGN. Reference [12] an improved distance learning particle swarm optimization algorithm was proposed to overcome the premature problem and it was applied to the optimization of  $NO_x$  emission reduction. The optimization results show that the algorithm can make the emission of  $NO_x$  lower and the optimization results more stable. In reference [13], based on SVR and artificial bee colony optimization algorithm, an optimization model was established, which takes total air volume, secondary baffle opening degree and rotating separator speed as the optimized parameters and takes

the net efficiency of the boiler as the objective. The optimum exhaust-gas oxygen and the secondary air distribution mode under different loads are given.

Data mining method uses clustering or association rule algorithm to find the lowest energy consumption condition group in a large number of historical data, extract parameters characteristics, and finally determine the benchmark operating condition. In reference [14], based on fuzzy C-means clustering algorithm, the benchmark values of exhaust-gas oxygen, exhaust-gas temperature and unburned carbon content of a 300 MW unit at the highest boiler efficiency under various typical loads were excavated. Reference [15] implemented the parallel calculation of association rule algorithm on MapReduce architecture of Hadoop platform, which improves the processing speed of dealing with a large amount of data. Taking a 1000MW unit as an object, the benchmark values of steam turbine system operation parameters aiming at minimizing *HR* were excavated. In reference [16], based on the fuzzy sets and association rule algorithm, a method of mining fuzzy association rules suitable for dynamic data flow was established, which was applied to determination of benchmark operating condition and the study of the most economical coal type decision-making method. Compared with IOFC, the data mining method does not need to establish the thermodynamic characteristics model of the equipment, so the optimization results are not affected by the characteristics model. The benchmark condition determined by data mining method is historical optimum condition rather than theoretical optimum condition, so the optimization result is more realizable, but may not be the actual optimum condition.

## 5. Conclusion

### *5.1 Operation optimization is an important way to tap the energy-saving potential of CFGN*

Under certain external constraints, the energy-saving potential of CFGN should be excavated from two aspects: operation optimization and intensive maintenance. The operation optimization has the advantages of low investment and high profit.

### *5.2 The application of information technology is the development direction of CFGN operation optimization*

Due to the large system and complicated process, CFGN still has problems including that some key parameters cannot be measured, certain mechanism process characteristics are unknown, and obtaining economic operation targets is difficult. With the maturity of intelligent information technology with data mining algorithm as the core, a lot of scholars have introduced it into the field of energy-saving optimization of CFGN and achieved good results by utilizing its characteristics of data-driven. According to the technical characteristics of CFGN, further research on energy-saving strategy and operation optimization based on advanced intelligent information technology should be carried out at different levels such as system, process and unit.

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