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Multi-objective thermodynamic performance optimization of thermal power generation

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Abstract:

To study the relationship of the conventional power plant and the pollutant emission restrict, a simulated thermodynamic system model of traditional supercritical coal-fired units coupled with environment protect equipment is designed on the platform of Ebsilon. A multi-objective algorithm model is established to weigh up the relationship between boiler efficiency and environmental impact of pollutant. Practical operating parameters of an actual Chinese power plant are set as the reference state of simulation model, which can be summarized as: load rate, ambient state, fuel composition. The pollutant emission of NO_X, SO_x and dust is acquired with the help of support vector machine (SVM) from the historical record of that power plant. The restriction of pollutant emission in Chinese newly policy is taken into account as constraints condition. By considering energy and environment as the multi-objective, the simulation, which evaluates the solutions by interfacing with the programmed optimization algorithm, is developed. And corresponding total system performance and characteristic of pollutant emission in flue gas is derived. The result show that the performance of system and environment protect equipment will be influenced as boundary conditions changed. Boiler efficiency can reach about 93.8% with minimum environmental impact in the case of our testing power plant.

Keywords:

Multi-objective Optimization, Pollutant Emission, support vector machine, Genetic Algorithm.

1. Introduction

The optimization of thermal power generation usually concentrates on the boiler efficiency, economic and environmental aspects. Specifically the objective of boiler efficiency, abided by thermodynamic laws, should be the chief target for analysis. And when the investment or retrofit of equipment is considered, an economic objective indicator is usually introduced. Moreover, if the pollutant emissions should be taken into account, an environmental indicator needs to be defined to evaluate the effect of pollutant emission to the ambient.

Multi-objective optimization techniques optimize the operation performance according to more than one objective at a time, which is quite suitable when we concerning efficiency, economy or environment at the same time. The multiple objectives, however, may perform opposite characteristics when selecting the optimized operating state, which makes it controversial to identify the better situation. Hence, the concept of Pareto optimal solution, also called Pareto frontier, is introduced to consider the multiple objectives simultaneously. The so called Pareto optimal solution basically refers to the solution that no other feasible solution has a strictly better performance at least in one of the objectives[1]. It is wise to search the Pareto frontier by heuristic-based evolutionary algorithm[2,3]. Multi-objective evolutionary algorithms (MOEAs) has been proposed and developed continually[4-6]. For instance, one study [7] shows how a thermal system design can be optimized using energy, economy and environment as separate objectives. Evolutionary algorithm has been adjusted to find the surface of optimal solutions defined by three objective functions simultaneously. And Dincer[8] investigated exergoenvironment analysis and optimization of a cogeneration plant system using multimodal genetic algorithm. Actually, single-objective optimization also can deal with multi-objective problem since it can weigh the multiple objectives into an overall single-objective function.

Data mining has been used in the optimal design of coal-fired power plants years ago. Correlation analysis of operational data is used in [9] to establish the correlation ship between boiler efficiency and exhaust temperature. Artificial Neural Network (ANN) has been widely used in the complex nonlinear system and applied in energy consumption of power unit with gratifying successes. In reference [10], the relationship between unburned carbon content in fly ash and the emission of NO_x is analysed. ANN method, however, is lack in computational complexity and have excessive studying effect. To overcome these problems, SVM is first introduce in 1992[11] and has acquired significant effect in the study of thermal power generation[12].

Actually, according to the Emission Standard of Air Pollutants for Thermal Power Plants (GB 13223-2011) in China, all the coal-fired power plants should operating under the new pollutant emission limit value after Jan. 2014. Therefore, pollutant emission situation under newly strict standards is worth to be studied. As far back as 1997, Rosen and Dincer have introduced and discussed the relationships between exergy and environmental impact[13].Reference [14] investigated the economic parameters variations on the carbon dioxide emission and fuel consumption of the power plant to increase exergy efficiency while decreasing CO_2 emission. In the optimization approach of reference [15], the exergetic, economic and environmental aspects have been considered. In their multi-objective optimization, the three objective functions, including the boiler efficiency, total cost rate of the system production and CO_2 emission, have been considered.

For each multi-objective optimization problem, objective functions should be determined first. In this paper, we choose boiler efficiency as one of the thermodynamic objectives. Support vector machine (SVM) and Ebsilon simulation is used in the optimization process. And environmental impact of pollutant has been chosen as one of the objective functions. To our knowledge, this paper is the first attempt to analyze the coal fired power plant according to thermodynamics and pollutant emission objectives with the latest Chinese policy.

2. Coal-fired power generation system

2.1. Plant model

The supercritical coal-fired power plant used to perform the optimization is shown in Fig.1, which is a conventional single-reheat water cooling plant with a capacity of 600 MW. To calculate the environmental effects of pollutant emission, coal with a lower heating value (LHV) of 22000kJ/kg and an ultimate analysis of C(57.5%),H(3.1%),O(2.8%),N(1.1%),S(0.91%),H2O(7.1%) is used in reference state. The main steam condition and reheated steam condition is set to 24.2MPa/566℃ and 4.2MPa/566℃.

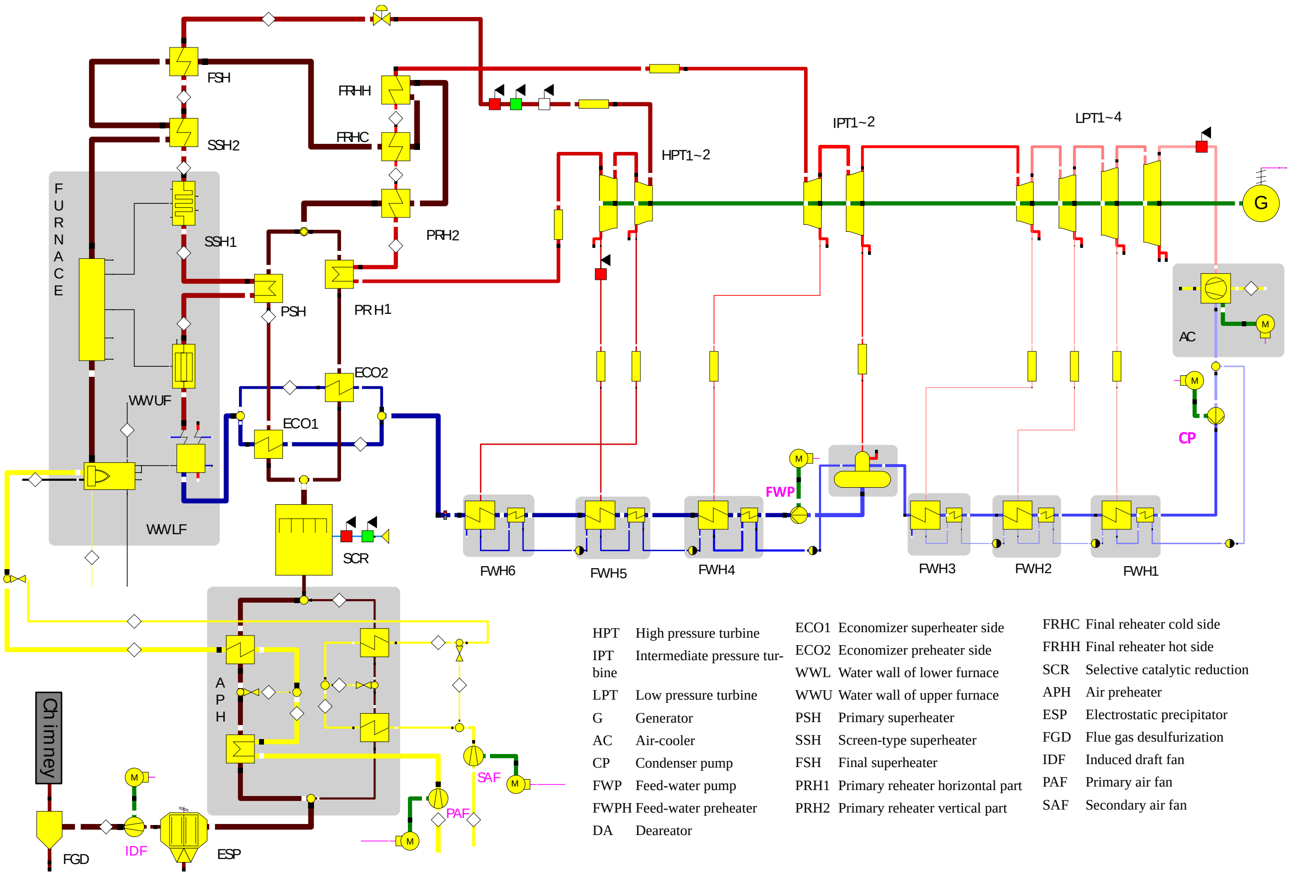

Fig. 1. Schematic diagram of the power plant under consideration

The main stream generated in the boiler is expanded in the high-pressure turbine (HPT) and then is reheated. The reheated steam passes through the intermediate-pressure (IPT) and the low-pressure turbines (LPT) and finally being condensed in a surface condenser (COND) which is used to remove the low temperature heat to the environment. HPT is split into two parts to realize the regenerated cycle and so does the IPT and LPT, which is divided into two and four parts, respectively. The feedwater is preheated in H1-H3, deaerator (DA) and H5-H7 to increase the thermodynamic average temperature. The flue gas, which has generated in combustion chamber, pass through SCR, air preheater (AH), ESP and FGD. Environment protection devices (SCR, ESP and WFGD) to minimize the damage to the environment are considered as dissipative devices. Carbon capture and storage devices are not considered in this paper.

2.2. Method of exergy analysis

Exergy analysis is used to evaluate the performance of each component in this real coal-fired power plant. The method mainly base on the reference[16].It is assumed that reference environmental temperature of the system boundaries is 1bar/0℃.Therefore, exergy of each steam can be calculated and exergy balance of each component can be expressed as:

$$\dot{E}_{F,k} = \dot{E}_{P,k} + \dot{E}_{D,k} \qquad (1)$$

Where subscripts *F*, *P* and *D* represent as fuel exergy, product exergy and exergy destruction of kth component, respectively. When it comes to the overall system, however, the exergy loss term appears and the exergy balance equation becomes:

$$\dot{E}_{F,sys} = \dot{E}_{P,sys} + \sum_{k} \dot{E}_{D,sys} + \dot{E}_{L,sys} \qquad (2)$$

The exergetic efficiency of kth component is defined as:

$$\varepsilon_k = \frac{\dot{E}_{P,k}}{\dot{E}_{F,k}} \quad (3)$$

Another crucial ratio is defined to identify the part of total fuel exergy input destroyed within the kth component, which is defined as:

$$y_{D,k} = \frac{\dot{E}_{D,k}}{\dot{E}_{F,sys}} \quad (4)$$

3. Multi-objectives optimization

The heuristic-based evolutionary algorithm which is interfaced with Ebsilon and the definition of energetic and environmental objectives as well as input variables are introduced in details in this section.

3.1. Defining the energetic and environmental objectives

The boiler efficiency, expressed as (5), is fairly suitable as the definition of energetic objective when the environmental impact is considered at the same time

$$\eta_b = \frac{Q_1}{Q_r} \quad (5)$$

Where $\eta_b \dot{W}_{net}$ is the boiler efficiency. Q_1 and Q_r are the boiler input heat and effective used heat of per kg fuel (kJ/kg). LHV is the low heating value of corresponding coal.

The environmental objective is defined to describe the total impact of pollutant emission, which including the amount of NOx, SOx and dust.

$$I_{\mathrm{env}} = \lambda_{NO_x} C_{NO_x} + \lambda_{SO_x} C_{SO_x} + \lambda_{\mathrm{dust}} C_{dust} \quad (6)$$

Where the objective function I_{env} expresses the environmental impact due to NO_x, SO_x and dust. C_{NO_x}, C_{SO_x} and C_{dust} denote the effluent concentration of NO_x, SO_x and dust (mg/Nm^3), separately. λ_{NO_x}, λ_{SO_x} and λ_{dust} are appropriate weighting factors to describe the impact of per mg pollutant by multiplying each effluent concentration by their corresponding weighting factors. Regrettably, these weighting factors are assigned more or less arbitrarily by our analyst, which may let the result influenced by the values of weighting factors.

3.2. Input variables and constraint conditions

The input variables involve various types of boundary conditions, such as load rate, ambient state and fuel composition. Science the input variables vary during the multi-objective optimization procedure, constraint conditions of each parameter are listed in Table 1, which mainly based on the historical data. The parameters of pollutant emission are concerned as the input variables as well, which is restricted to the requirement of GB13223-2011. Hence, the concentration of NOx, SOx and dust in flue gas is limited in 100 mg/Nm^3, 100 mg/Nm^3 and 30 mg/Nm^3 separately.

Table 1. List of input variables and its constraint conditions

Input variables	Symbol	Constraint conditions	unit
concentration of NOx in the inlet of SCR	$c_{SCR,in}$	200~450	mg/Nm^3
concentration of NOx in the outlet of SCR	$c_{SCR,\mathrm{out}}$	<100	mg/Nm^3
concentration of SOx before desulfuration	$c_{SO_x,in}$	1200<2400	mg/Nm^3
Load of boiler	W_{net}	540~650	MW
Temperature of primary air at the outlet of APH	$t_{APH,out}$	270~300	℃
Opening degree of primary Air	x_A, x_B	30~70	%
Temperature of coal mill	$t_{mill,out}$	20~80	℃
Outlet temperature of main steam	$t_{sh,out}$	500~600	℃
Temperature of reheat steam	$t_{rh,o}$	500~600	℃
Pressure of main steam	$P_{sh,o}$	230~330	Bar

3.3. Algorithm and interface with SVM and Ebsilon

Genetic algorithm is the most widely applied one for solving multi-objective optimization. And the structure of MOEA used in the paper is shown in Fig. 2. In first step, totally 2×Ns feasible solutions are randomly generated as the first initialized generation. Ns represent the number of individuals in each generation and are calculated as 100 in this case. Ns parent population is selected among 2×Ns initial population with the same probability to process a parent population. Then the parent population is reproduced to generate the offspring population by a crossover and mutation strategy. The objective function values of offspring population are then evaluated with the help of Ebsilon and SVM, which is shown in details in Fig3. Then Ns best ranked solutions are selected to survive. If the termination condition is met, the frontier solutions are presented; otherwise the surviving solutions become the starting population for the next generation.

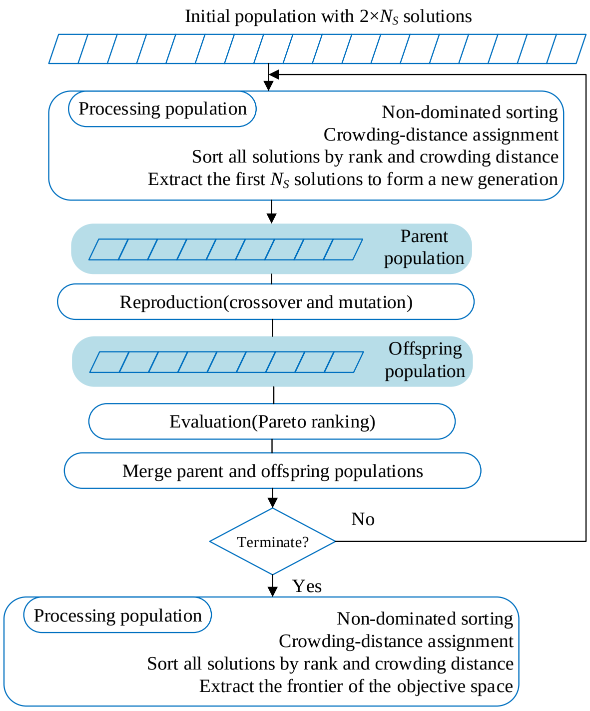

Fig. 2. Scheme for the multi-objective evolutionary algorithm used in this paper

For each individual in any generations, objective function values is calculated from its input variables in the process of Fig. 3.This process was completed by interfacing with SVM and Ebsilon when the values of objectives are needed. Environmental impact of pollutant is obtained according to (1), the pollutant parameters of which are acquired by SVM. And the simulation procedure to calculate the energetic objectives was performed by a simulation and optimization software named Ebsilon Professional[], which is calculated according to the thermodynamic laws.

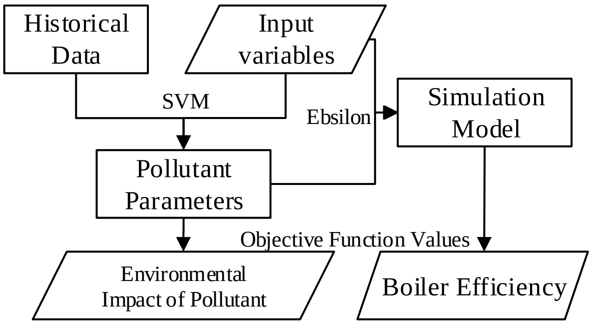

Fig. 3. Scheme for getting the objective function values by SVM and Ebsilon

More specifically, all the operating parameters have been set in Ebsilon as the reference state based on the actual values of real power plant in a steady state. To optimize the operating situation from the perspective of boiler efficiency and the impact of pollutant, a group of parameters have been selected as the input variables (e.g. the out let pressure of each turbine, parameters of main and reheat steam etc.). Besides, pollutant parameters are also the input value for Ebsilon to complete to simulation procedure. By changing the values of input variables in genetic algorithm, Pareto frontier can be acquired to determine the optimum operating parameters.

Since it is rather difficult to accurately predict the pollutant emissions from simulation model, SVM is used to estimate the pollutant parameters. From which we acquired the necessary input variables both for simulation model and the objective function of environmental. The training model of SVM to establish the concentration of NO_x, SO_x and dust based on the historical data of a 600MW power plant is shown in fig.4.

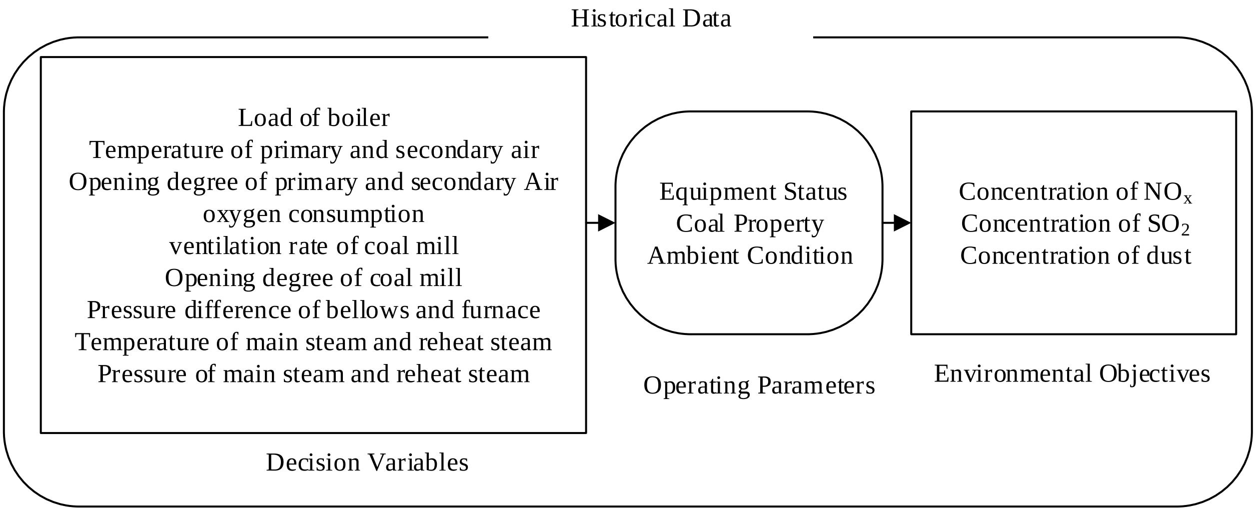

Fig. 4. Model of SVM to analyse the environmental impact of pollutant

Support vector regression (SVR) is the most widely used method for SVM, which could carry out nonlinear fitting between input vector x (input variables and operating parameters) and output data y (environmental objectives). In the training process, the historical data is regard as m samples with n dimensional vectors. Each sample is a real-time record by measuring that power plant once a minute. Each dimension refers to the values of one input variables or operation parameters. This concept can be expressed as $(\mathrm{x}_1, \mathrm{y}_1), \ldots, (\mathrm{x}_m, \mathrm{y}_m) \in R^n \times R$, and fitting function can be written as:

$$f(\mathrm{x}) = \omega\varphi(\mathrm{x}) + b \qquad (7)$$

Where x is input vector including input variables and operating parameters, and $\varphi(x)$ is nonlinear function for mapping. ω is weight vector. Totally three groups of $f(x)$ have been trained to calculate the concentration of NO_x, SO_x and dust.

4. Result and discussion

4.1. Exergy analysis

It can be seen from Table 2 that nearly 37% of the total input fuel exergy is destroyed in the furnace, which is mainly result from the combustion process in the reaction zone. Besides, a high temperature difference will also cause unwanted irreversible exergy loss. Other components with higher exergy loss include air preheater, heat exchanging equipment in boiler system and turbines. The irreversibility of one component shows the priority when improving the efficiency of overall system. Boiler system, especially the reaction zone, should be the first priority for the reduction of the performance of power plant. It should be noticed that Air cooler, SCR, ESP and FGD are treated as dissipative devices and are not listed in Table 2.

Table 2. Results of exergy analysis of each component

	Comp Name	$\dot{E}_{F,k}$ (MW)	$\dot{E}_{P,k}$ (MW)	$\dot{E}_{D,k}$ (MW)	ε_k	$y_{D,k}$
Turbine system	HTP1	172.06	163.52	8.54	95.04%	0.58%
	HTP2	39.38	37.18	2.20	94.41%	0.15%
	IPT1	118.92	112.94	5.98	94.97%	0.41%
	IPT2	89.48	84.94	4.54	94.93%	0.31%
	LPT1	104.09	95.92	8.17	90.81%	0.48%
	LPT2	77.62	70.49	7.13	92.15%	0.55%
	LPT3	62.41	48.28	14.13	77.35%	0.96%
	CP	7.62	6.53	1.09	85.70%	0.07%
	H1	13.90	12.04	1.85	86.66%	0.13%
	H2	23.70	20.39	3.31	86.02%	0.22%
	H3	25.97	23.08	2.89	88.89%	0.20%
	DA	24.68	22.10	2.58	89.53%	0.18%
	H4	37.03	33.53	3.50	90.55%	0.24%
	H5	70.52	65.89	4.63	93.43%	0.31%
	H6	31.91	30.17	1.74	94.56%	0.12%
	FWP	27.36	24.12	3.24	88.17%	0.22%
Boiler system	FURNACE	976.40	428.69	547.71	43.91%	37.11%
	ECO1	48.77	41.36	7.41	84.80%	0.50%
	ECO2	20.25	17.38	2.87	85.84%	0.19%
	APH	82.27	57.47	24.80	69.86%	1.68%
	IDF	13.86	11.98	1.88	86.42%	0.13%
	PSH	77.02	67.34	9.68	87.43%	0.66%
	SSH2	72.12	58.98	13.13	81.79%	0.89%
	FSH	65.69	55.91	9.78	85.11%	0.66%
	PRH1	83.21	70.47	12.74	84.69%	0.86%
	PRH2	26.54	20.68	5.86	77.91%	0.40%
	FRHC	62.65	52.60	10.05	83.96%	0.68%
	FRHH	23.83	19.40	4.43	81.41%	0.30%
	PAF	8.97	7.68	1.29	85.62%	0.09%
	SAF	8.75	7.49	1.26	85.59%	0.09%
System($\dot{E}_{L,sys}$ =129.06)		1475.75	589.66	757.03	39.96%	51.30%

4.2. Algorithm and interface with SVM and Ebsilon

Fig.5 presents the details of the optimization process for finding the frontier solution when considering energy efficiency and environmental impact. After 200 generations , the first 2×Ns initial population have converged and form an front, which result from a trade-off between minimum environmental impact and maximum boiler efficiency. It should be noted that the constraint conditions do not affect the mutation and crossover process. Therefore, the mutation and crossover operations assure the generation of almost any possible solution within the objective space. In the each generation, the solutions near the frontier of the decision space are preserved and the frontier gradually formed. The frontier can be visualized at the 30th generation but is not smooth enough. With continued evolution, the frontier solutions become more uniformly and densely dispersed, leading to a smooth frontier at the end.

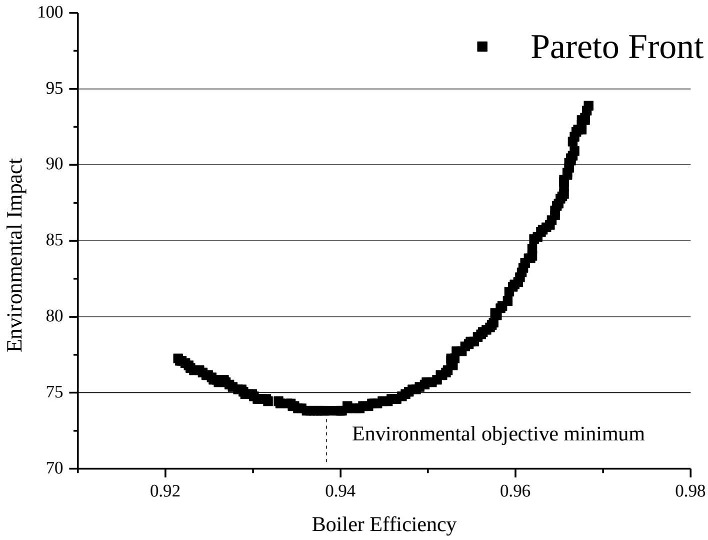

Fig. 5. Evolution result of Pareto Front

All the solutions on the Pareto front, especially on the right-hand side of the minimum point of environmental impact, are significant in the decision-making process. The minimum environmental impact solution is acquired when the boiler efficiency is 93.8%. This point separates the frontier to the left-hand side and right-hand side. In the left hand side, the environmental impact gradually decreased with increasing boiler efficiency. And the curve seems to be flat around the point of 93.8%, which means the solutions around this area can be regarded as optimal designs. In the right-hand side, the two objectives oppose each other, forming a Pareto front where the environmental impact increases sharply with the increasing of boiler efficiency.

4.3. Comparisons between the reference state and optimal designs

Table 2 shows the key values of reference state of the actual power plant and the optimal values of simulation. Reference state is listed in the second column. The last three columns are three Pareto solutions near the minimum environmental impact point, which can be chosen as optimal designs. To minimum the environmental impact, the boiler efficiency is slightly decreased compared to the reference state. Actually, exergy destruction of boiler subsystem is about half of the total system fuel in reference state. In addition, the boiler efficiency of plant is 94% in this condition. The cost of energy and resources consumption for remove the pollutant only account for a little part in the thermodynamic viewpoint. The performance of system and environment protect equipment will be influenced as boundary conditions changed. Emission controlling equipment influences each other while single boundary condition varies, and the desulfurization subsystem in the terminal of flue gas process is affected notably.

Table 3. Comparisons between the reference values and optimal values

	reference state	optimal designs		
		1	2	3
Boiler Efficiency/%	94	93.82	93.84	93.82
average concentration of SOx in flue gas/(mg/Nm^3)	24.08	22.75	22.68	22.12
average concentration of NOx in flue gas/(mg/Nm^3)	31.89	27.59	30.82	28.67
average concentration of dust in flue gas/(mg/Nm^3)	7.76	7.68	7.79	7.53
concentration of NOx in the inlet of SCR/(mg/Nm^3)	202.51	197.85	195.71	197.11
concentration of NOx in the outlet of SCR/(mg/Nm^3)	47.97	45.94	45.18	45.50
concentration of SOx before desulfuration/(mg/Nm^3)	2598.03	2520.85	2535.59	2522.96
Load of boiler/MW	600	614.27	603.90	613.37
Temperature of primary air at the outlet of AH/℃	25	24.26	24.31	24.39
Temperature of main steam/℃	560	564.19	565.06	565.74
Temperature of reheat steam/℃	560	565.94	566.02	565.96
Pressure of main steam/MPa	24.2	25.92	25.93	25.99
Opening degree of primary Air x_A/%	55	54.14	53.05	53.46
Opening degree of primary Air x_B/%	55	54.05	53.05	53.21
outlet temperature of coal mill/℃	25	23.94	24.00	23.97

To be specific, the exergy destruction in the boiler system is significantly affected by the air preheating process.

5. Conclusion

Exergy analysis shows the energy saving potential of each component. Boiler system, especially the reaction zone, has largest operational exergy destruction. The optimal design of traditional coal-fired power plants was optimized from the perspectives of efficiency and environment aspects. Genetic algorithm is used to analyze this multi-objectives problem. However, more accurate weighting factors to describe the impact of per mg pollutant are needed to describe the objectives with higher accuracy.

The following conclusions can be drawn:

(1) Exergy analysis shows that nearly 37% of total input fuel exergy is destroyed in the furnace, which is mainly result from the combustion process in the reaction zone. Boiler efficiency was set as one of the objectives, which can reach about 93.8% with minimum environmental impact in the case of our testing power plant.

(2) In the optimal design, the energy-saving effects achieved as the boiler efficiency of the higher pressure and higher temperature steam extraction is much better than that of the reference state of steam extraction.

(3) It is concluded that the environmental impact can be reduced though the current industrial design is not far away from the optimal design. And it is not necessary to blindly improve the boiler efficiency as the pollutant effect will be increased dramatically.

Nomenclature

Letter symbols

Greek symbols

ε exergetic efficiency

y_D exergy destruction ratio

Subscripts and superscripts

F fuel

P product

D destruction

L loss

Sys system

k kth component

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