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Optimization of industrial boiler combustion control system based on genetic algorithm☆

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ABSTRACT

In the combustion process, the traditional furnace combustion control method cannot meet the control requirements with frequent variable loads. Firstly, for the combustion control system with the varying variable bias and bi-double crossing limit, the ranges of bias coefficients are analyzed gradually. Secondly, the objective function is designed based on the excess air coefficient and the main steam pressure deviation signal. Finally, the genetic algorithm is adopted to optimize the bias coefficients to achieve better control performance. The simulation results show that the presented method can effectively improve the response speed and keep the excess air coefficient in the optimal combustion interval.

1. Introduction

With the increasingly stringent requirements on the combustion systems in production process, the industrial boiler is becoming a more and more important factor in the production technologies. Recently, the research on the boiler combustion process control has been attracted more and more attention, in order to improve the combustion efficiency and economy performance [1].

The boiler is a complex multi-input and multi-output systems, and the input and output signals are closely related, and interact to each other. The objects of boiler control mainly include: 1) mutually regulate the amount of fuel, air volume (air intake) and the amount of air volume; 2) ultimately guarantee the main steam pressure and negative pressure become stabilization; 3) persistently keep the excess air coefficient in the expected interval. Considering the excess air coefficient is an important indicator of the industrial boiler combustion control system, hence, if the mixing ratio of the air intake and the fuel quantity can be well controlled, the burned condition can be achieved [2]. In general, the excess air interval of optimum combustion is (1.01–1.1). The combustion control system of the conventional industrial boiler is used to control the ratio and adjust the combustion characteristics. However, this system cannot effectively avoid the problems of oxygen burning and oxygen combustion [3].

In recent years, the artificial intelligence (AI) has been a hot topic, and lots of intelligent algorithms have gotten much attention and been adopted to more and more practical areas [4–6]. In this paper, the intelligent optimization algorithm is presented to optimize the key parameters in the combustion control system with varying bi-double crossing limit; and then,

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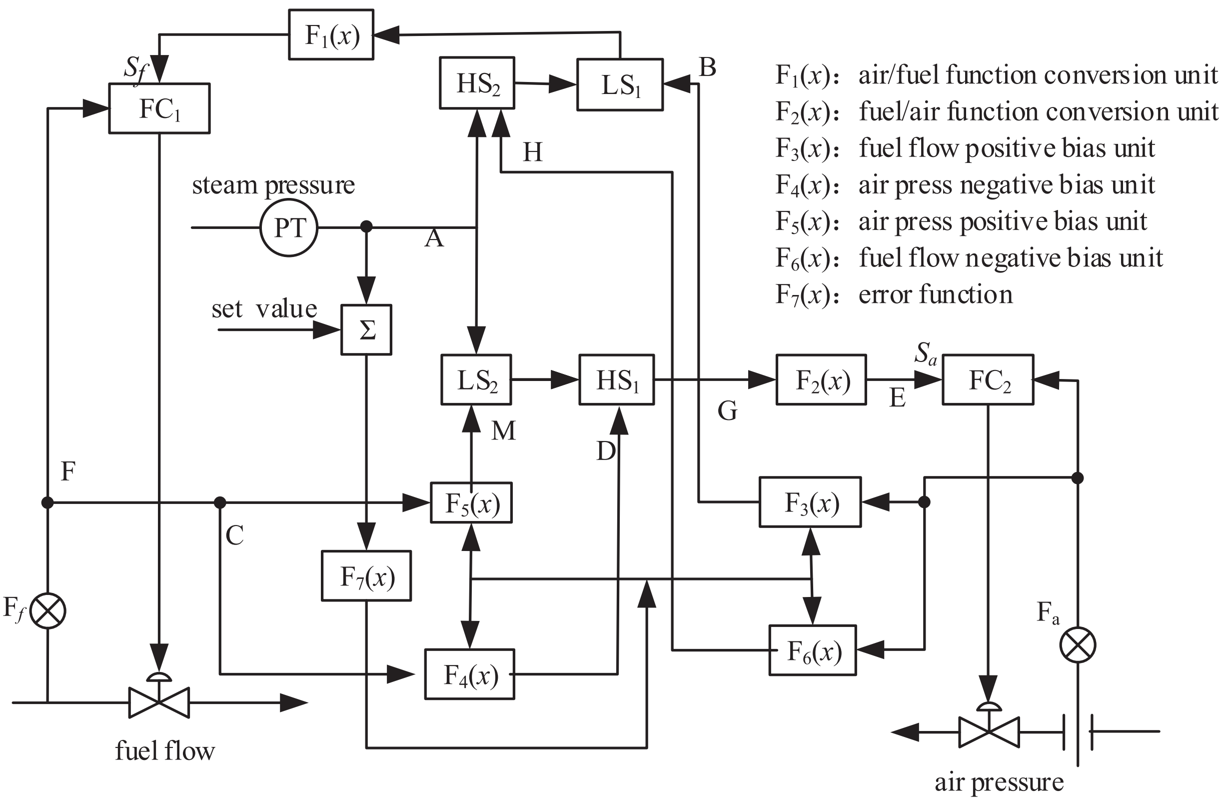

Fig. 1. The flow graph of varying bi-double crossing limit combustion control.

the appropriate fitness function is designed according to the control requirements of this system [7]. The simulation results show that, the thermal efficiency of the optimized combustion system has been improved significantly, and the peroxy and hypoxia combustion problems has also been solved perfectly.

This paper is organized as follows. In Section 2, the industrial boiler combustion control system and its working process are introduced briefly. Next, the optimization method based on the genetic algorithm (GA) is presented in Section 3. In Section 4, the comparison scheme is designed and the comparison results are shown in some figures and tables through the simulation examples. Finally, the paper ends with a summary (Fig. 1).

2. Variable biased double cross clipping principle analysis

The main control variable is the main steam pressure in the industrial boiler combustion control system. In order to guarantee the main steam pressure stabilize closely at the set value, and improve the combustion efficiency under varying load conditions, the variable bias method can be adopted [8]. For the design of varying bi-double crossing limit combustion control system, the selection of the bias variable is related to the production requirements, and in this paper, the main steam pressure error e is selected as a bias variable, e is the error between the set value of the steam pressure and the measured value of the actual steam pressure. When the boiler load changes in a large range, $|e|$ will increase, and reflect the boiler load change. Therefore, through changing e, a bias function can be corrected to make combustion system achieve stability [9]. The principle flow graph of varying bi-double crossing limit combustion control is shown in Fig. 2.

Using the error e as a bias variable, the bias function shown in Fig. 2 is corrected. The control effect of the varying bi-double crossing limit combustion control system is verified by analyzing the three load-changing processes (steady state, load up, load down) [9]. In order to guarantee the combustion safety, the combustion process must meet the principle: "when the load raises, the air pressure increases firstly; when the load decreases, the fuel flow decreases firstly". The system flow graph of load up and load down is analyzed as follows.

2.1. The load increasing process

1) The air pressure regulating loop: A > M, the low value selector LS_2 is switched to M.

- When the signal A increases persistently to larger than M, the low value selector LS_2 is switched to M, the signal A is turned off. Further, when M > D, the high value selector HS_1 is switched to M, which is converted as the set value of

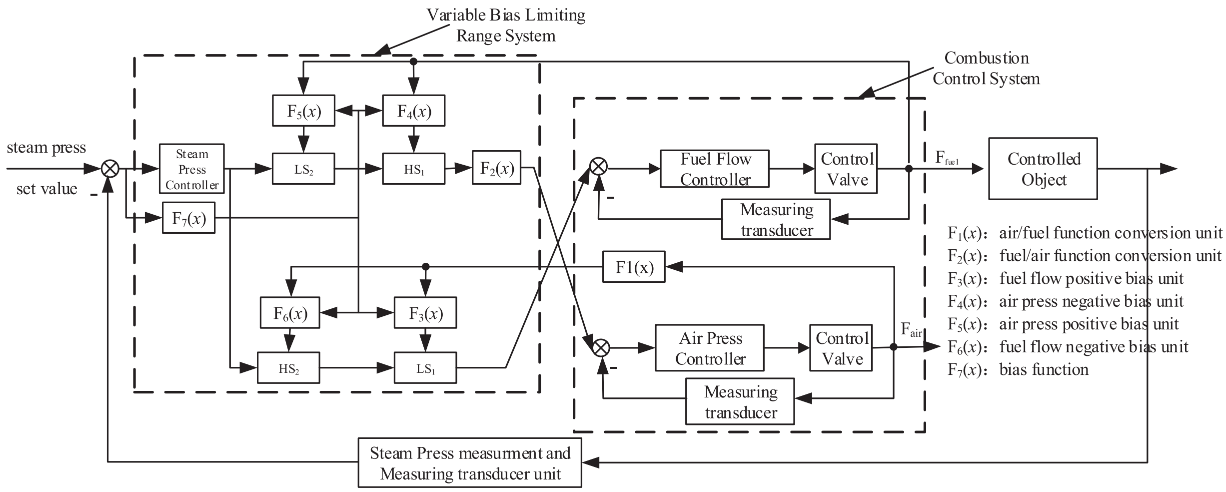

Fig. 2. The control block of varying bi-double crossing limit combustion control.

air pressure controller (FC_2) through $F_2(x)$, i.e., $S_a = M$. In other words, if $A > M > D$, the cross-limiting process begins, and in this process, the air pressure increases with the increasing of M.

- When the signal M increases to larger than A, the low value selector LS_2 is switched to A. M is cut off. Further, when $A > D$, the high value selector HS_1 is switched to A, and the signal A is converted as the set value of air pressure controller (FC_2) through $F_2(x)$, i.e., $S_a = A$. In other words, if $D < A < M$, the cross-limiting process ends, and the furnace combustion process returns to the steady state.

2) The fuel flow regulating loop: $A > H$, the high value selector HS_2 is switched to A.

- When the signal A increases persistently to larger than B, the low value selector LS_1 is switched to B, the signal A is cut off. Further, the signal B is converted as the set value of the fuel flow controller (FC_1) through $F_1(x)$, i.e., $S_f = M$. In other words, if $H < A < B$, the fuel flow increases with increasing of B, i.e., the fuel flow increases with the increasing of air pressure. The process of cross-limiting begins.
- When the signal A increases persistently to larger than H, the high value selector HS_2 is switched to the signal A. H is cut off. Further, when $B > A$, the low value selector LS_1 is switched to the signal A, and the signal A is converted as the set value of fuel flow controller (FC_1) through $F_1(x)$, i.e., $S_f = A$. In other words, if $B > A > H$, the cross-limiting process ends, and the furnace combustion process returns to the steady state.

2.2. The load decreasing process

1) The fuel flow regulating loop: $A < H$, the high value selector HS_2 is switched to H.

- When the signal A is smaller than H, and the high value selector HS_2 is switched to H. A is cut off. Further, when $H < B$, the low value selector LS_1 is switched to H, which is converted as the set value of the fuel flow controller (FC_1) through $F_1(x)$, i.e., $S_f = H$. In other words, if $A < H < B$, the cross-limiting process begins, and in this process, the fuel flow decreases with the decreasing of H.
- When the signal H decreases persistently to smaller than A, the high value selector HS_2 is switched to A. H is cut off. Further, when $A < B$, the low value selector LS_1 is switched to A, which is converted as the set value of the fuel flow controller (FC_1) through $F_1(x)$, i.e., $S_f = A$. In other words, if $H < A < B$, the process of cross-limiting ends, and the furnace combustion process returns o the steady state.

2) The air pressure regulating loop: $A < M$, the low value selector LS_2 is switched to A.

- When the signal A is lower than M, the low value selector LS_2 is switched to A. M is cut off. Further, when $A < D$, the high value selector HS_1 is switched to D, which is converted as the set value of air pressure controller (FC_2) through $F_2(x)$, i.e., $S_a = D$. In other words, if $A < M < D$, the cross-limiting process begins, and in this process, the air pressure decreases with the decreasing of A.
- When the signal A is lower than M, the lower value selector LS_2 is switched to A. M is cut off. Further, when $A < D$, the high value selector HS_1 are simultaneously switched to A, which is converted as the set value of air pressure controller (FC_2) through $F_2(x)$, i.e., $S_a = A$. In other words, if $D < A < M$, the process of cross-limiting ends, and the furnace combustion process return to the steady state.

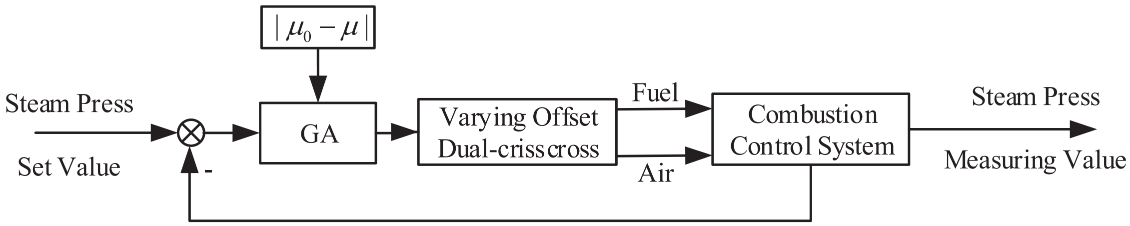

Fig. 3. The principle diagram of bias parameters by GA.

2.3. Overall analysis

Based on the above analysis, it shows that fuel flow and air pressure are cross-limiting, and mutually influenced in the furnace combustion process. In Fig. 2, the varying bi-double crossing limit combustion control system contains the low value selector (LS_1, LS_2), high value selector (HS_1, HS_2) and bias functions of $F_1(x)$– $F_7(x)$, where the function $F_7(x)$ is the error of main-steam pressure between actual measurement value and set value. Hence, $F_7(x)$ is considered as the bias variable of other function. Especially,

$$B = F_3(x) \tag{1a}$$

$$D = F_4(x) \tag{1b}$$

$$M = F_5(x) \tag{1c}$$

$$H = F_6(x) \tag{1d}$$

$$e = F_7(x) \tag{1e}$$

Through analyzing of Fig. 2, we can obtain the control block of varying bi-double crossing limit combustion control, which is shown in Fig. 2, and the conversion functions of positive and negative bias function of fuel and air are as follows:

$$F_3(x) = \lambda_3(1 + k_3 F_7(x)) \tag{2a}$$

$$F_4(x) = \lambda_4(1 + k_4 F_7(x)) \tag{2b}$$

$$F_5(x) = \lambda_5(1 + k_5 F_7(x)) \tag{2c}$$

$$F_6(x) = \lambda_6(1 + k_6 F_7(x)) \tag{2d}$$

$$F_7(x) = |SV - PT| \tag{2e}$$

where λ_3, λ_4, λ_5 and λ_6 are the theoretical correction coefficients, generally, $\lambda_3 = \lambda_5 = 0.5$, $\lambda_4 = \lambda_6 = 0.1$; and k_3, k_4, k_5 and k_6 are the bias coefficients, which are adopted to correct the conversion functions and can be determined according to Zhu et al. [10].

Generally, in order to meet the principle: "when the load raises, the air pressure increases firstly; when the load decreases, the fuel flow decreases firstly", the values of k_3 and k_5 are equal in the positive and negative bias function of the air pressure, the values of k_4 and k_6 are equal in the positive and negative bias function of fuel flow.

3. Optimization of industrial boiler combustion control system based on genetic algorithm

3.1. Improved varying bi-double crossing limit combustion control system

Considering the complexity of the bias coefficients selection in the varying bias function, the bias coefficients should be optimized during the load changing process to achieve the faster response speed and the better economic performance. In this paper, the genetic algorithm (GA) is used to optimize the parameters k_3, k_4, k_5 and k_6 according to the objective function, which is designed through using the excess air coefficient and the main steam pressure deviation signal. Fig. 3 shows the concrete realization process, and in Fig. 3, μ_0 and μ are the desired and the measured value of excess coefficient, respectively.

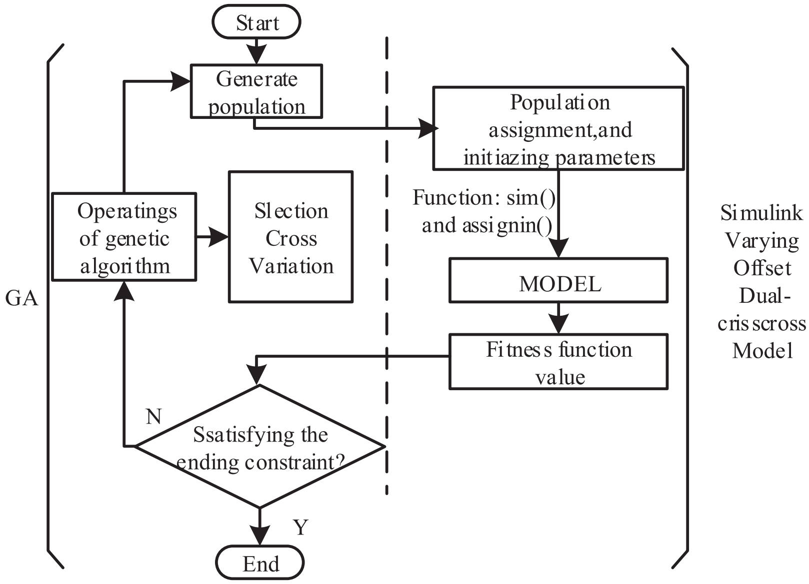

Fig. 4. The flow diagram of GA optimization.

3.2. Optimization of genetic algorithm based on parameters

GA is realized by the evolution rule of "survival of the fittest", and can be used to optimize the solution space in a given region [11,12]. In the optimization process, the initialization variables, the objective function and the judgment constraints are the key factors for the optimization problem. The variable initialization process transforms the optimization variables into appropriate population individuals by reasonable coding. The objective function is the key to reflect the optimization problem, and can achieve multi-objective optimization; judgment constraint is to achieve the optimization problem accuracy requirements.

The appropriate objective function can improve the optimization results. The fitness function guides the search direction of the genetic algorithm. Hence, the different search directions for the same group can achieve different optimization effect. In the process of the furnace combustion, it is necessary to ensure the stability of the main steam pressure, but also to ensure the excess air coefficient in the best combustion interval, to avoid the problem of peroxy and hypoxia combustion. Therefore, the design of the objective function should consider the above two factors.

In order to improve the response speed and the combustion efficiency of the system in condition of variable load, the Simulink implementation diagram of the optimization process of the bias coefficients using the genetic algorithm to optimize the bias coefficients is shown in Fig. 4. In order to obtain satisfactory control effect, the minimum objective function of genetic optimization problem is realized by using the optimal integrated time absolute error (ITAE) criterion.

In order to improve the stability and response speed of the output loads, the index of ITAE is used as part of the search direction of the GA, and the objective function is

$$J_1 = \int_0^{\infty} \omega_1 t|e_1(t)|dt + \omega_2\sigma \tag{3}$$

where $e_1(t)$ is the error of steam pressure between given value and the measured value, σ is the overshoot of steam pressure response curve.

In the combustion process, the error of excess air coefficient is used to correct the objective function to ensure the thermal efficiency of the combustion. So, the objective function of GA can be expressed as:

$$J_2 = 3\delta(t)^2 + 5\delta(t) \tag{4}$$

where $\delta(t)$ is the error of excess air coefficient between given value and the measured value. The given value of excess air coefficient $\mu_0 = 1.05$.

The above analysis shows that the selection of the objective function in the optimization process not only takes into account the trend of the steam pressure response, but also the influence of the excess air coefficient. Therefore, the total optimization function is obtained as follows:

$$J = \alpha J_1(t) + \beta J_2(t) \tag{5}$$

where α and β are the weights of J_1 and J_2, respectively, and $\alpha + \beta = 1$. In this paper, we chose $\alpha = 0.7$ and $\beta = 0.3$. The fitness function $\mathrm{F}(t)$ can be expressed as:

$$\mathrm{F}(t) = \frac{1}{1 + \gamma J(t)} \tag{6}$$

where γ is the coefficient of sensitivity control.

In the GA, the encoded mode affects the accuracy of optimization problem, and in this paper, the binary coding is adopted [11]. The length of the binary code determines the accuracy δ of optimization problem [7]. Suppose the range of optimization parameter is $[U_{\max}, U_{\min}]$, there are $2^l - 1$ different codes, where l is the length of the binary code. The calculation process is

$$\delta = \frac{U_{\max} - U_{\min}}{2^l - 1} \tag{7}$$

The overall algorithm is shown in Algorithm 1.

Algorithm 1 (The overall algorithm)**.**
The algorithm contains the off-line and on-line stages.
Off-line stage:
Step 1 Encode the bias coefficients. Using the binary coding, determine the coding length l according to the accuracy of the parameters;
Step 2 Initialize the population, design the fitness function. Using the fitness function (4), calculate the fitness of each individual in the population.
Online stage:
Step 1 GA operation: selection, crossover and mutation;
Step 2 Judge the termination condition. If the termination condition is satisfied, iteration is broken and jump to step 3; otherwise, jump to step 1;
Step 3 Obtain the bias coefficients k_3, k_4, k_5 and k_6;
Step 4 Run the simulation model.

4. Simulation results

4.1. Simulation of varying bi-double crossing limit combustion control system

According to the principle of varying bi-double crossing limit combustion control, the bias coefficients k_3, k_4, k_5 and k_6 in bias function affect the responses of the main-steam pressure and the excess air coefficient μ. Therefore, in order to find the effective range of the bias coefficients, the ranges of bias coefficients are obtained by manual test to guarantee the system response convergence.

In this simulation, the model of varying bi-double crossing limit combustion control system is built by Matlab Simulink Toolbox. Considering the furnace combustion process is complex, it is necessary to ensure the stability of the vapor pressure, but also to ensure the economy of combustion. Therefore, by considering the excess air coefficient to determine the combustion state, can effectively avoid the problem of peroxy combustion and anoxia combustion. Hence, when setting the bias coefficients $k_3 = k_4 = 0.1,$ the value of a is manually adjusted, the excess air coefficient response curve is shown in Fig. 5; when $k_3 = k_4 > 1.5$ or $k_3 = k_4 < 0.01,$ $\mu < 1$, this condition can product hypois combustion, reduce combustion efficiency.

When $k_3 = k_4 = 1.5,$ the values of k_5 and k_6 are manually adjusted, the response curve of excess air coefficient is shown in Fig. 6; when $k_5 = k_6 > 1.1,$ the product anoix combustion occurs, and this situation must be avoided in practical applications.

Considering the economy and stability in this process, the range of k_3, k_4, k_5, k_6 are: k_3, $k_4 \in (0.1, 1.5)$, k_5, $k_6 \in (0.1,\ 1.1)$. According to the above analysis, it can be known that, the response speed of control system is faster with the larger e; otherwise, the excess air coefficient is smaller and the furnace burning is more economic with the smaller e. Meanwhile, the larger k_3, k_4 are corresponding to the smaller μ; otherwise, the larger k_5, k_6 are corresponding to the larger μ. For varying bi-double crossing limit combustion control system, the changing of bias function is liner. Hence, the bias coefficients should be optimized, to get the optimal values and achieve the better response speed and economic performance.

4.2. Simulation of combustion control system based on genetic algorithm optimization

In order to obtain the suitable bias coefficients, for the range of k_3, k_4, k_5, k_6 obtained in Section 4.1, the GA can be adopted to optimize k_3, k_4, k_5, k_6 based on the initial population. According to the basic principle of GA, the related parameters are chosen in Table 1.

In order to compare the effectiveness of the presented algorithm, we give the comparison results of the following methods:

- In the first method (denoted as "**Manual**"), $k_3 = k_4 = 0.5000,$ $k_5 = k_6 = 1.1000$ are chosen manually;

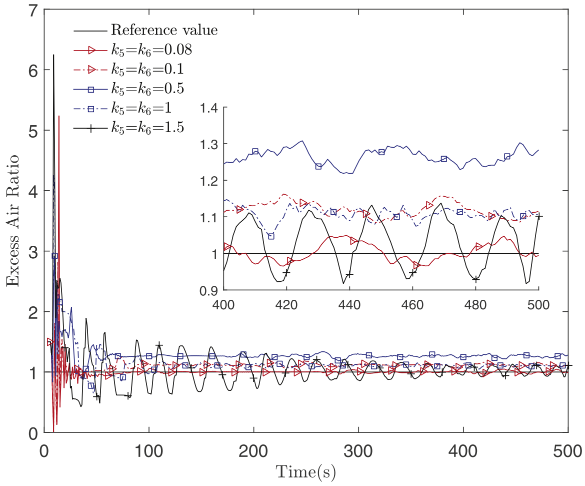

Fig. 5. The changes of μ with $k_3 = k_4 = 0.1$.

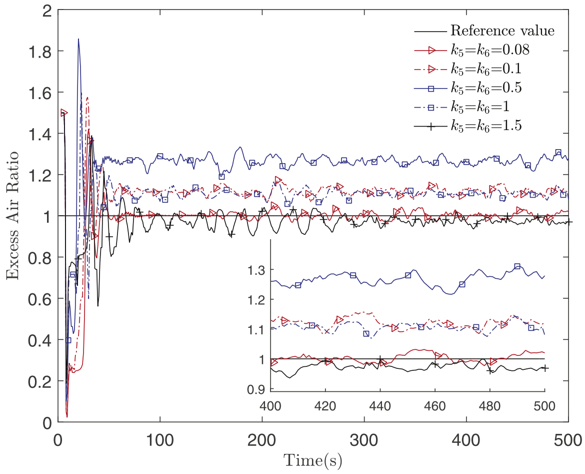

Fig. 6. The changes of μ with $k_3 = k_4 = 1.5$.

Table 1
Related parameters of genetic algorithm.

Parameters	Experssion	Parameters	Experssion
Encoding Method	Binary encoding	Maximum Evolutionary Algebra	100
Encoding Lengths	13	Fitness Function Value Deviation	1e-100
Initialize Population	Random product	Cross Progeny Ratio	0.6
Population Size	60	Objective Function	J
Number of Individuals	2	Update way	Roulette
Crossover Probability	0.6	Probability Mutation	0.0002
Maximum Value	[1.5,1.1]	Minimum Value	[0.1,0.1]

- in the second method (denoted as "**Non-optimized**"), $k_3 = k_4 = 0.3425,\ k_5 = k_6 = 0.5313$ are on-line optimized, but e is obtained by minimizing the fitness function at the first instant, and then it is fixed;
- in the third method (denoted as "**Optimized**"), $k_3 = k_4 = 0.3425,\ k_5 = k_6 = 0.5313$ are on-line optimized, and e is obtained by minimizing the fitness function on-line;

According to the range of k_3, k_4, k_5, k_6 the online optimization of these parameters is obtained, and then, the optimized bias coefficients k_3, k_4, k_5, k_6 are injected to the varying bi-double crossing limit combustion control system, and the system response is shown in Figs. 7–9.

After adopting GA optimization, the optimized values of bias coefficients are: $k_3 = k_4 = 0.3425,\ k_5 = k_6 = 0.5313$. According to the simulation results in Figs. 7–9, it can be found that, with the corrected bias coefficients k_3, k_4, k_5, k_6, the steam pressure response can achieve to the stable state quickly, and the overshoot is small. As can be seen in Fig. 8, the changes

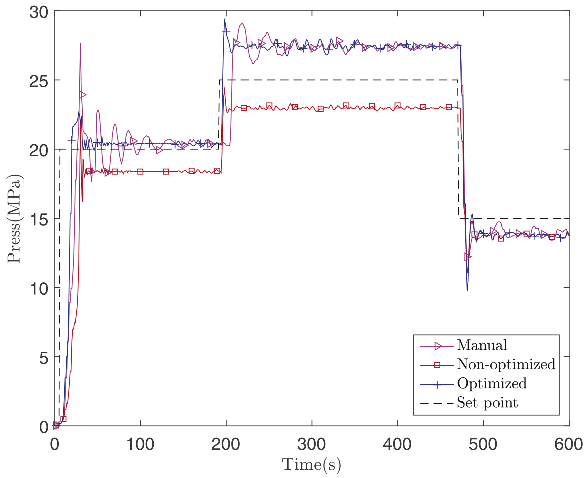

Fig. 7. The press response.

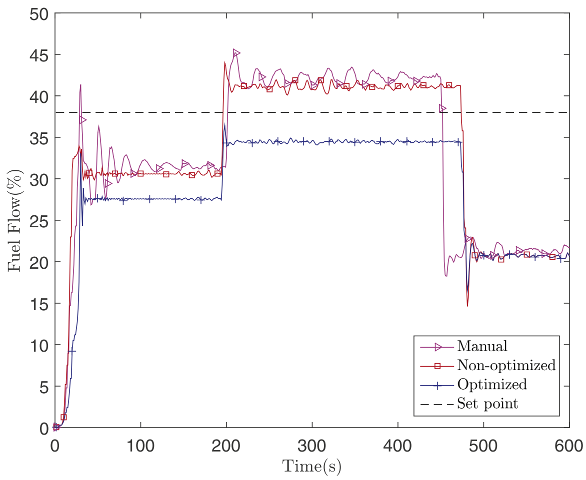

Fig. 8. The fuel flow response.

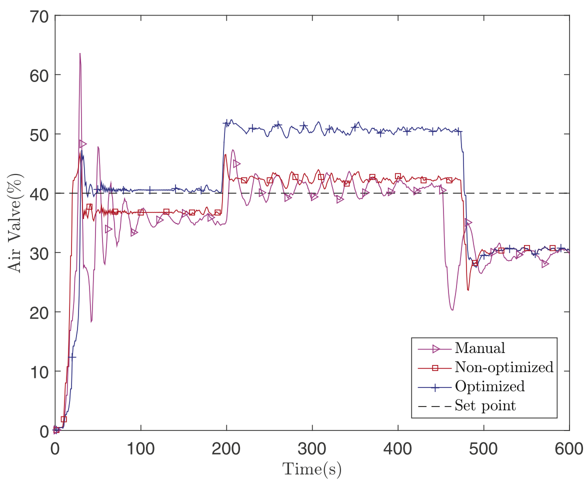

Fig. 9. The air press response.

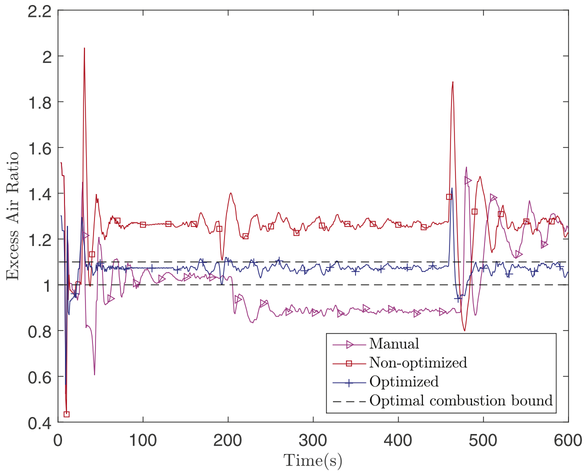

Fig. 10. The changing curve of excess air ratio.

Table 2
The performance comparisons of three methods.

Method	Bias coefficients		Performance indexes				
	$k_3 = k_4$	$k_5 = k_6$	e_s	t_r	e_{ss}	$\bar{g}_s$	σ_p
Manual	0.5000	1.1000	7860.7	50s	−4	1.33	40%
Non-optimized	0.3425	0.5313	6230.8	80s	+4	1.25	16.7%
Optimized	0.3425	0.5313	6182.7	40s	+1	1.07	5.0%

of the fuel and air can follow with the set points, and the excess air coefficient can finally be maintained in (1.01, 1.10) (Fig. 10).

In order to compare the control effect, the total deviation of excess air coefficient $\bar{g}_s$ and the total deviation of steam pressure output e_s in the simulation time(0–400 s) are analyzed, and the following evaluation criterion is adopted

$$e_s = \sum_{k=1}^{400} ||y(k) - y_0|| \tag{8}$$

where $y(k)$ is the output of steam pressure at kth instant, y_0 is the set value of steam pressure. According to (8), the optimized bias coefficients $k_3 = k_4 = 0.3425,\ k_5 = k_6 = 0.5313$ are injected to the varying bi-double crossing limit combustion control system to calculate the relevant performance indicators. The results are shown in Table 2.

Under the condition of variable load, the steam pressure response is basically stable. Compared with the second and third methods listed in the Table 2, for the improved method, the rise time t_r in the steam pressure response is shorter, the static residual capacity e_{ss} and the overshoot of main steam pressure σ_p are smaller, hence, the response performance of the system is better. The results show that the improved method with GA can not only improves the response speed, but also maintains the excess air coefficient in the best combustion interval.

5. Conclusion

In this paper, the combustion control system with varying bi-double crossing limit is analyzed firstly. Secondly, based on the analysis, the objective function, including the error signals of main steam pressure and the error signals of excess air ratio, is designed to improve the thermal efficiency and solve the peroxy and hypoxia combustion problems. Finally, the genetic algorithm is adopted to optimize the bias coefficients to maintain the excess air ratio at the optimal combustion interval under variable load conditions.

Acknowledgments

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Supplementary material

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.compeleceng.2018.03.003.

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