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Research on the Optimization of Boiler Efficiency based on Artificial Bee Colony Algorithm

Jun-Ta Wu[1,3], Yuan-Biao Zhang[2,3], Gui-Sen Xu[1], Yi Lin[4] & Xin-Guang Lv[2,3]

[1] Electrical and Information School, Jinan University, Zhuhai 519070, China

[2] Packaging Engineering Institute, Jinan University, Zhuhai 519070, China

[3] Key Laboratory of Product Packaging and Logistics of Guangdong Higher Education Institutes, Jinan University, Zhuhai 519070, China

[4] International Business School, Jinan University, Zhuhai 519070, China

Correspondence: Jun-Ta Wu, Key Laboratory of Product Packaging and Logistics of Guangdong Higher Education Institutes, Jinan University, Zhuhai 519070, China. E-mail: 418655377@qq.com

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Abstract

This paper is to seek effective scheme of boiler efficiency optimization, it uses Artificial Bee Colony (ABC) algorithm to optimize boiler efficiency based on the model of boiler combustion efficiency. First, an optimization model of boiler efficiency, which takes boiler efficiency function as optimization objective, is set up according to the heat loss of boiler combustion. Moreover, the operating parameters affecting boiler efficiency is determined. Then ABC algorithm is used to solve the optimal value of boiler efficiency. The result of the research shows that the optimization of boiler efficiency based on ABC algorithm can quickly obtain optimal parameters for running boiler, so that the optimal boiler efficiency can be got.

Keywords: boiler efficiency, optimization, artificial bee colony algorithm, genetic algorithm

1. Introduction

Boiler is a typically complex system which is multi-input, multi-output, nonlinear as well as non-self-balanced, and boiler combustion of power station is complex physical and chemical process. Therefore how to improve the combustion efficiency of boiler has always been an important issue in this field (Shi, 2010).

At present, researches on the optimization of boiler efficiency have been in-depth. Zhang et al. (1999) proposed a new computational model of boiler efficiency on the basis of the research on operating parameters of boiler combustion; Hao et al. (2004) used a method based on artificial network (ANN) and genetic algorithm (GA) for modeling the carbon burnout behavior in a pulverized coal fired boiler and optimizing boiler efficiency; Kusiak and Song (2006) introduced a data-mining approach to optimize combustion efficiency of a coal-fired boiler; Zhao and Wang (2009) combined support vector regression (SVR) with simplified model of boiler efficiency to improve boiler efficiency and to reduce the NOx emission. Gu et al. (2010) set up the boiler combustion model of power station with least squares support vector machine (LS-SVM) and used GA for optimization. Zhang et al. (2012) introduced the partial least squares vector machine (SVM) to set up boiler efficiency model of coal-fired power plant.

For the present, the optimization of boiler efficiency based on GA is common. However, GA is unstable during the process of optimization. On the basis of the established model of boiler efficiency, this paper introduces ABC algorithm for the research on the optimization of boiler efficiency, which conquers the unsteadiness of GA.

ABC algorithm is a meta-heuristic algorithm on the basis of group theory, which was proposed by Karaboga and Basturk in 2005 and improved by Karaboga et al (Shen, 2012). Now this algorithm has received much attention. Karaboga et al. used ABC algorithm for optimizing multivariable functions (2007) and compared the performance of ABC algorithm with that of Differential Evolution(DE), Particle Swarm Optimization (PSO) and Evolutionary Algorithm (EA) for multi-dimensional numeric problems (2009). Xu and Duan (2010) used ABC in visual target recognition for aircraft at low altitude. Omkar et al. (2011) introduced ABC for multi-objective design optimization of composite structures. Akay and Karaboga (2012) introduced modified versions of ABC algorithm for efficiently solving real-parameter optimization problems.

This paper introduces ABC algorithm into the field of the optimization of boiler efficiency and verify its effectiveness. First, we research heat loss of running boiler and set up the optimization model of boiler efficiency based on anti-balance method. In this way, the operating parameters which affect boiler efficiency are determined. Then boiler efficiency is optimized based on ABC algorithm with boiler efficiency function as optimization objective. Finally, we research on the performance of ABC algorithm according to the optimization result and compare ABC algorithm with GA.

2. The Optimization of Boiler Efficiency

2.1 Establishment of the Optimization Model of Boiler Efficiency

2.1.1 Background Information of Boiler

Boiler is one of the key equipment for thermal power station, whose efficiency has direct impact on the economy of the station. In modern power station, boiler efficiency is the key performance indicator to reflect the operating conditions of boiler. Additionally, power station uses anti-balanced method to compute boiler efficiency, that is:

$$\eta_{gl} = q_1 = 100 - \sum_{i=2}^{6} q_i \quad \% \tag{1}$$

due to unburned gas q_3, heat loss due to unburned carbon q_4, heat loss due to radiation q_5, heat loss due to sensible heat in slag q_6 .Where, $q_i(i=1,2,\cdots,6)$ respectively represent net heat q_1, heat loss due to exhaust gas q_2, heat loss

2.1.2 Heat Loss of Boiler

1) Heat loss due to exhaust gas

In the thermal balance test, in order to simplify the calculation, the following empirical equation for calculating heat loss due to exhaust gas is used (Wu, 2006):

$$q_2 = (m + n\alpha_{py})(1 - \frac{q_4}{100})\frac{\theta_{py} - t_{amb}}{100} \quad \% \tag{2}$$

Where $m = 0.5$, $n = 3.45$, α_{py} is excess air coefficient, θ_{py} is exhaust gas temperature, t_{amb} is ambient temperature.

2) Heat loss due to unburned gas

Heat loss due to unburned gas comes from inflammable gas in exhaust smoke, such as CO H_2, CH_4, heavy hydrocarbons and so on, which do not emit their combustion heat. In order to simplify the calculation, we assume CO is the only product of incomplete combustion gas. Therefore, the following empirical equation is used to calculate heat loss due to unburned gas based on content of CO (Sun, 2008):

$$q_3 = \lambda \alpha_{py} V_{CO} \quad \% \tag{3}$$

Where, factor $\lambda = 3.2$, V_{CO} is volume percentage of CO in exhaust smoke.

From relevant literature (Gao, 2009), we know that:

$$V_{CO} = \frac{21 - (1+\beta)V_{RO_2} - V_{O_2}}{0.605 + \beta} \quad \% \tag{4}$$

Where $\beta = 0.102$, $V_{RO_2} = 13.05(\%)$, V_{RO_2} is volume percentage of SO_2 and CO_2 in exhaust smoke, V_{O_2} is volume percentage of O_2. Then we can get the relational expression between V_{CO} and V_{O_2} :

$$V_{CO} = \frac{\mu - V_{O_2}}{\omega} \quad \% \tag{5}$$

In the above equation, $\mu = 6.6189$, $\omega = 0.707$. Substituting Equation (5) into Equation (3), then we can get Equation (6) after rearranging:

$$q_3 = \lambda \alpha_{py} \frac{\mu - V_{O_2}}{\omega} \quad \% \tag{6}$$

3) Heat loss due to unburned carbon

Heat loss due to unburned carbon consists of three parts including heat loss due to coal slag, heat loss due to leakage of coal and heat loss due to fly ash. In this paper, the research object is the pulverized coal furnace, which does not have leakage of coal. For the running boiler, we analyze weight percentage of combustible material in coal slag and fly ash, $C_{hz}(\%)$ and $C_{fh}(\%)$. Therefore, heat loss due to unburned carbon can be calculated by Equation (7) (Wu, 2006):

$$q_4 = \frac{BA_{ar}}{Q_r}\left(\frac{a_{hz}C_{hz}}{100-C_{hz}} + \frac{a_{fh}C_{fh}}{100-C_{fh}}\right) \quad \% \tag{7}$$

Where B is the calorific value of combustible material, A_{ar} is ash content of as received basis in fuel, Q_r is gross calorific value of as received basis.

a_{hz}, a_{fh} respectively represent the percentage of coal slag content and fly ash content in total amount of fuel ash. In addition, we get the following equation from gray balance (Wu, 2006):

$$a_{hz} + a_{fh} = 1 \tag{8}$$

In this paper, $a_{hz} = 0.1$, so we can know $a_{fh} = 0.9$.

4) Heat loss due to radiation

Heat loss due to radiation has little change when the load of boiler changes. As a matter of fact, the relative value of Heat loss due to radiation is inversely proportional to boiler load (Sun, 2008). The commonly used calculation equation is:

$$q_5 = -\frac{hX}{100X_0} + d \quad \% \tag{9}$$

Where $h = 0.33$, $d = 0.495$, X_0 is rated load of boiler unit, X is current load of boiler unit.

5) Heat loss due to sensible heat in slag

There is heat loss due to sensible heat in slag because the temperature of coal slag and transudatory coal exhausted by boiler is usually above $600 \sim 800^{\circ}C$. In this paper, the research object is the pulverized coal furnace, which does not have transudatory coal. So Heat loss due to sensible heat in slag can be calculated by Equation (10) (Wu, 2006):

$$q_6 = a_{hz}\frac{100}{100-C_{hz}}(c\vartheta)_{hz}\frac{A_{ar}}{Q_r} \tag{10}$$

Where, $(c\vartheta)_{hz}$ is enthalpy of coal slag.

2.1.3 Model of the Optimization of Boiler Efficiency

Power station uses Equation (1) to compute boiler efficiency based on anti-balanced method. Substituting Equation (2), Equation (6), Equation (7), Equation (9) and Equation (10) into Equation (1), we can get boiler efficiency function:

$$\begin{aligned}\eta_{gl} = 100 - [(m+n\alpha_{py})(1-\frac{q_4}{100})\frac{\theta_{py}-t_{amb}}{100} + \lambda\alpha_{py}\frac{\mu - V_{O_2}}{\omega} \\ + \frac{BA_{ar}}{Q_r}(\frac{a_{hz}C_{hz}}{100-C_{hz}} + \frac{a_{fh}C_{fh}}{100-C_{fh}}) + (-\frac{hX}{100X_0} + d) \\ + a_{hz}\frac{100}{100-C_{hz}}(c\vartheta)_{hz}\frac{A_{ar}}{Q_r}] \quad \%\end{aligned} \tag{11}$$

We fit the relationship between enthalpy of coal slag $(c\vartheta)_{hz}$ and exhausted gas temperature θ_{py} based on the data from relevant literature (Wu, 2006), so that we get Equation (12):

$$(c\vartheta)_{hz} = 0.0002887\theta_{py}^{\ 2} + 0.6851\theta_{py} + 26.76 \tag{12}$$

Taking the boiler whose rated load is $300MW$ for an example, we can get the value of some parameters:

α_{py}=1.205 , $t_{amb} = 20(^{\circ}C)$, $X_0 = 300(MW)$, $A_{ar} = 14.70(\%)$, $B = 32866(KJ/kg)$, $C_{hz} = 2(\%)$, $Q_r = 25020$(KJ/ kg) . Then we can know that boiler efficiency η_{gl} changes as $(c\vartheta)_{hz}$, C_{fh} , V_{O_2} and X change. Making these four parameters as independent variables, boiler efficiency function can be expressed as Equation (13):

$$\eta_{gl} = f(\theta_{py}, C_{fh}, V_{O_2}, X) \tag{13}$$

After determining the range of variables when boiler is running, the optimization model of boiler efficiency is set up:

$$\begin{aligned} & Max \quad \eta_{gl} = f(\theta_{py}, C_{fh}, V_{O_2}, X) \\ & s.t. \quad 120 \le \theta_{py} \le 140 \\ & \qquad 5 \le C_{fh} \le 7 \\ & \qquad 4 \le V_{O_2} \le 6 \\ & \qquad 200 \le X \le 300 \end{aligned} \tag{14}$$

2.2 The Optimization of Boiler Efficiency based on ABC Algorithm

Based on the optimization model of boiler efficiency, we use ABC algorithm and set appropriate parameters of ABC algorithm to optimize boiler efficiency. When it comes to the optimization of boiler efficiency, GA is unstable during the process of the optimization and easy to fall into local optimal solution. However, ABC algorithm has quick global convergence speed and stable optimization process. In addition, the optimization result of ABC algorithm is better than that of GA.

2.2.1 Brief Introduction of ABC Algorithm

ABC algorithm is proposed according to the intelligent foraging behavior of bees and is used to optimize multidimensional function and multimodal function. Compared with the traditional searching algorithm, ABC algorithm has the advantages of quick convergence, less parameters, easy implementing and simple calculation. In addition, it is much less likely to fall into local optimization (Shen, 2012).

In the algorithm, artificial bees consist of three types of bees: employed bees, onlooker bees and scout bees. Among the bees, the amount of employed bees is equal to the amount of onlooker bees, being half of the colony amount. Additionally one employed bee only corresponds to one food source, that is to say, the amount of employed bees is equal to the amount of food sources. When an employed bee gives up the food, it translates into a scout bee. As we know, different types of bees have different duty. Employed bees collect nectar having been found and convey the information about food to onlooker bees which are near honeycomb. While onlooker bees wait in dance area and select food sources according to the information about food. And scout bees search for new food sources in the space nearby spontaneously and randomly.

At the beginning of searching for food sources, scout bees search environment to find food. After having found food, scout bees translate into employed bees and collect nectar. At the same time, employed bees carry nectar back to honeycomb, after which they can return to the place where they find food sources or convey food information to onlooker bees by dancing in dance area. If food source has been thoroughly mined, corresponding employed bees translate into scout bees and continue to search for new food sources in the space nearby randomly. As for Onlooker bees, they waiting in honeycomb select food sources with high fitness according to dance. The higher the frequency of dance is, the better the food source is. In ABC algorithm, food source location represents feasible solutions of optimization question, and nectar amount of food source represents quality (fitness) of corresponding solution.

2.2.2 Algorithm Design and Implementation

In the optimization model of boiler efficiency based on ABC algorithm, one food source represents a feasible solution of decision variables including $(c\vartheta)_{hz}$, C_{fh} , V_{O_2} and X , and information of food sources represent the value of variables. Nectar amount of food sources represents the corresponding value of objective function, which is boiler efficiency in this paper. Additionally, search scope of bee colony represents the range of decision variations: $120 \le \theta_{py} \le 140$, $5 \le C_{fh} \le 7$, $4 \le V_{O_2} \le 6$, $200 \le X \le 300$.

The parameters of ABC algorithm is setting as the following: dimensionality $dim = 4$, population amount $ColonySize$=10 , food source amount $sn = 5$, the controlling parameter of the abandon of food sources $limit = 20$, maximum cycling frequency $MaxCycles = 200$.

Therefore, the implementation steps of ABC algorithm are shown as the following (Jia, 2013):

Step1 Algorithm is initialized, and scout bees generate initial solutions x_{ij} by Equation(15):

$$x_{ij} = x_j^{\min} + rand(0,1)(x_j^{\max} - x_j^{\min}) \tag{15}$$

Where $i = 1,2,\cdots,sn, j = 1,2,\cdots,dim$, sn is the amount of food sources(the initial solutions), dim is the dimension of the solution. After the initial solutions are generated, their fitness are calculated.

When the cycling starts again, the continuous frequency of non-improvement of x_i, $trial_i$, is initialized to 0. During the searching, the cycling won't stop until it has reached the maximum cycling frequency $MaxCycles$, or has been beyond the allowable error.

Step2 Employed bees search for new food by Equation (16):

$$\upsilon_{ij} = x_{ij} + \phi_{ij}(x_{ij} - x_{kj}) \tag{16}$$

Where j is an integer generated randomly within $[1, dim]$, k is another integer not equal to i which generates within $[1, sn]$, ϕ_{ij} is a random number within $[-1,1]$.

When search finishes, new solution will be compared with the previous one and the solution with higher fitness is selected out based on Greedy Algorithm.

Step3 Onlooker bees select food sources according to probability calculated by Equation (17):

$$p_i = \frac{fitness_i}{\sum_{i=1}^{sn} fitness_i} \tag{17}$$

Where $fitness_i$ is the fitness of a food source and $\sum_{i=1}^{sn} fitness_i$ is the sum of fitness of all food sources.

Step4 Determine whether there is a food source to give up. If $trial_i$ is greater than a given controlling parameter $limit$, the food source has run out. Therefore, the employed bee gives up the corresponding solution and translates into a scout bee to search for new solution.

Step5 Determine whether algorithm should end. First the number of iterations is increased, $Cycle = Cycle + 1$. Then if $Cycle > MaxCycles$, algorithm ends and output the best solution. Otherwise, return to ***Step2*** to continue the loop.

2.2.3 Result Analysis of ABC Algorithm

Taking boiler efficiency function as optimization objective, we use ABC algorithm to optimize the boiler efficiency and get the optimal boiler efficiency which is 96.19%. The optimal decision variables are shown Table 1:

Table 1. The optimal solution of ABC algorithm

Decision variable	θ_{py}	O_2	C_{fh}	X
Optimal value	120	7	4	300

Iteration results during the optimization process of ABC algorithm are shown in Figure 1:

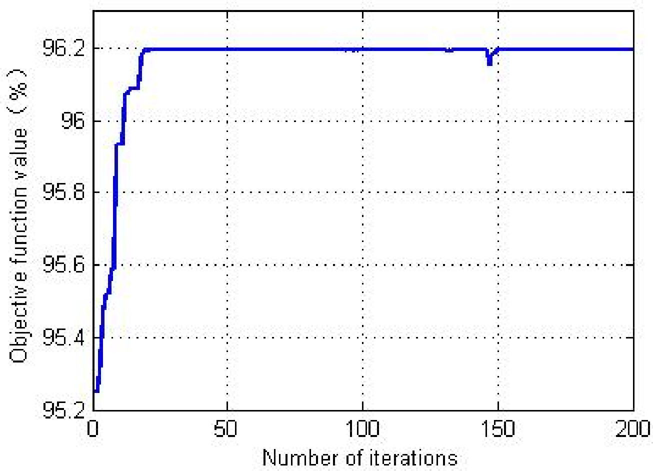

Figure 1. The optimization process of ABC algorithm

From Figure 1, we can draw a conclusion that ABC algorithm has quick global convergence speed. After about 20 times of iterations, the global optimal value is got and the following iteration results remain near the global optimal value. In brief, the whole optimization process is considerably stable.

In order to verify the validity of ABC algorithm, we make the algorithm run 20 times independently and average their results. Meanwhile 3 indicators are defined to describe the performance of ABC algorithm: *mean*, the average of the optimal value of 20 times of running; *std*, the standard deviation of the optimal values of 20 times of running; *max*, the global optimal value of all running. Where *mean* represents the gathered degree of the optimization, *std* represents the stability during the optimization process, and *max* represents the ability to avoid local optimal value.

The optimization process of the global optimal value of 20 times of running is shown in Figure 2:

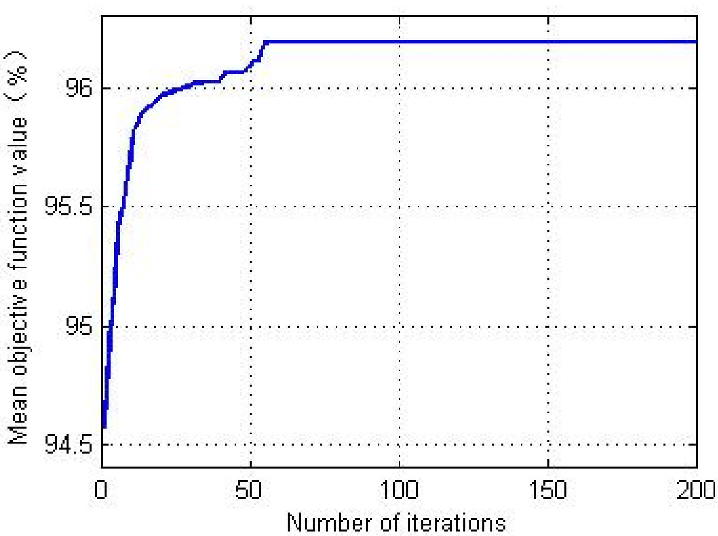

Figure 2. The optimization process of 20 times of running

From Figure 2, we can know ABC algorithm gets the global optimal solution after about 60 times of iterations, which indicates the average convergence speed of 20 tiems of running is quick. In the latter period of the algorithm, the average of optimal value after each of iteration is steadily near the global optimal value, further indicating the stability of ABC algorithm in the optimization of boiler efficiency.

Indicators to describe the algorithm based on the results of 20 times of running are shown by Table 2:

Table 2. The Indicators of the performance of ABC algorithm

Index	*mean*	*std*	*max*
Value	96.19%	2.92e-14	96.19%

From Table 2, we know that *mean*, the average of the optimal values of 20 times of running, is the same as *max*, the global optimal value. Additionally the optimization results gathered near the global optimal value, which indicates the high gathered degree of the optimization based on ABC algorithm. And the standard deviation of the optimal values of 20 times of running is very close to zero, indicating the stable optimization process as well as the small difference among the optimization results. Therefore the performance of ABC algorithm is excellent.

2.2.4 Comparison between ABC Algorithm and GA

We use GA to optimize the boiler efficiency, setting population mutation probability as 0.05, setting crossover probability as 0.9, and making the number of iterations 200. After the running of the algorithm, we get the optimal boiler efficiency which is 95.93%. Then we compare ABC algorithm with GA.

Table 3. The comparison of optimal solution between ABC algorithm and GA

	θ_{py}	O_2	C_{fh}	X	η_{gl}
ABC	120	7	4	300	96.19%
GA	122.87	6.99	4.61	236.61	95.93%

As Table 3 shows, the optimization result of ABC algorithm is better than that of GA. Moreover, we compare the optimization process of the two kinds of algorithm, which is shown in Figure 3:

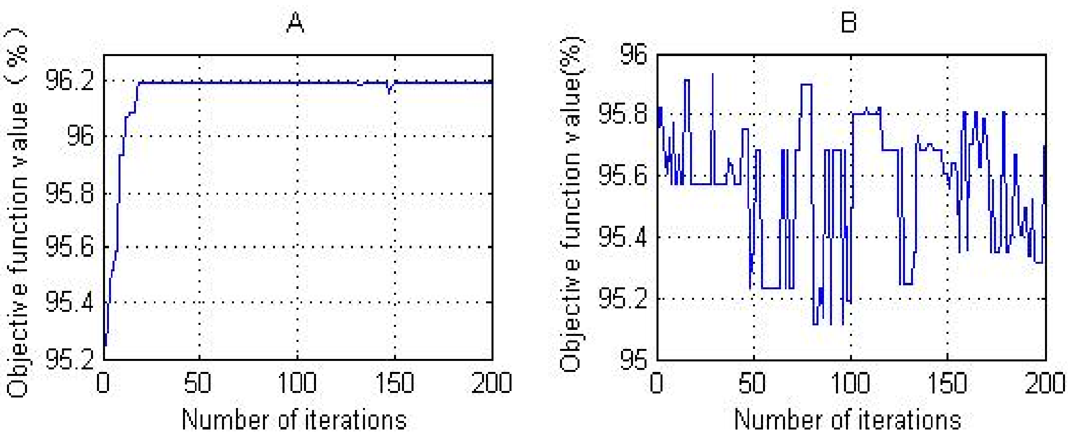

Figure 3. The comparison of the optimization process between ABC algorithm and GA

Where, Figure A is the optimization process of ABC algorithm while Figure B is the optimization process of GA. As Figure A shows, we get the global optimal value after 20 times of iterations, and the latter optimization results maintain near the global optimal value; From Figure B, we know the local optimal value is got after about 30 times of iterations. However, the latter optimization solution is poor and the optimization process of GA is unstable. Comparing the two figures, we can draw a conclusion that ABC algorithm is faster and more efficient. Meanwhile Figure 3 indicates that ABC algorithm has quick global convergence speed and stable optimization process. Therefore in the field of the optimization of the boiler efficiency, ABC algorithm is better than GA.

3. Conclusion

Boiler is a complex system, whose combustion efficiency is of great significance for sustainable development of energy and economy. However, this paper has shown ABC algorithm, implementing optimization based on dynamic interaction between bees and environment, is an ideal method for boiler efficiency optimization.

In this paper, we first set up the optimization model of boiler efficiency on basis of research on heat loss of running boiler, then we used quick-convergence ABC algorithm to optimize the boiler efficiency. The research proved that this method can obtain satisfactory results. In addition, introducing ABC algorithm to optimize the boiler efficiency can make the optimization of the boiler efficiency more efficient and faster. It also has practical significance to use ABC algorithm creatively in the field of the optimization of boiler efficiency. Finally, we compared the optimization result of ABC algorithm with that of GA. The comparison reflected the superior performance of ABC algorithm and highlighted the superiority of ABC algorithm in the field of the optimization of boiler efficiency.

ABC algorithm is a type of swarm intelligence optimization algorithm, having promising prospects. The research and development of ABC algorithm will gradually deepen because of its practicability and superiority in the field of the optimization of boiler efficiency, so that more actual problems can be solved.

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