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Optimization of Thermal Efficiency and Unburned Carbon in Fly Ash of Coal-Fired Utility Boiler via Grey Wolf Optimizer Algorithm

YIDING ZHAO[1], QINGHE WU[1], HENG LI[3], SHUHUA MA[1], PING HE[2,3], JUN ZHAO[4], AND YANGMIN LI[5], (Senior Member, IEEE)

[1]School of Control Engineering, Northeastern University at Qinhuangdao, Qinhuangdao 066004, China
[2]School of Intelligent Systems Science and Engineering, Jinan University (Zhuhai Campus), Zhuhai 519070, China
[3]Department of Building and Real Estate, The Hong Kong Polytechnic University, Hong Kong
[4]Department of Automation, Sichuan University of Science and Engineering, Zigong 644004, China
[5]Department of Industrial and Systems Engineering, The Hong Kong Polytechnic University, Hong Kong

Corresponding author: Ping He (pinghecn@qq.com)

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ABSTRACT This paper focuses on improving thermal efficiency and reducing unburned carbon in fly ash by optimizing operating parameters via a novel high-efficient swarm intelligence optimization algorithm (grey wolf optimizer algorithm, GWO) for coal-fired boiler. Mathematical models for thermal efficiency and unburned carbon in fly ash of the discussed boiler are established by artificial neural network (ANN). Based on the ANN models, the grey wolf optimizer algorithm is used to obtain higher thermal efficiency and lower unburned carbon by optimizing the operating parameters. Meanwhile, the comparisons between GWO and particle swarm optimization (PSO) and genetic algorithm (GA) show that GWO has superior performance to GA and PSO regarding the boiler combustion optimization. The proposed method can accurately optimize the boiler combustion performance, and its validity and feasibility have been experimentally validated. Additionally, a run of optimization takes a less time period, which is suitable for the real-time optimization.

INDEX TERMS Coal-fired utility boiler, grey wolf optimizer, thermal efficiency, unburned carbon in fly ash.

I. INTRODUCTION

Motivation: In the recent years, the coal-fired utility boilers face the dual requirements of reducing operating costs, energy saving. And efficient combustion optimization technology has attracted increasing attention in related fields. In the "National Guideline on Medium and Long-term Program for Science and Technology Development", the State Council of China pointed out that energy saving is a top priority. In order to significantly improve the efficiency in the use of energy, overcoming technological snag is an urgent problem to solve. As the biggest coal consumer in the world, electricity generation by coal-fired power plants in China represents over 75% of the national production [1]. It is necessary to improve thermal efficiency and reduce unburned carbon in fly ash so as to use coal in a highly utilization and economically viable way. The thermal efficiency called here denotes the utilization of coal heat of boiler, which could also represent boiler combustion conditions. As one of the main economic index, the level of unburned carbon also reflects the

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safety and reliability of boiler equipment. The purpose of this paper is to propose a method for simultaneously optimizing thermal efficiency and unburned carbon of coal-fired utility boiler in a shorter period of time.

Brief Summary of Prior Literature: Over the past decade, a good many research studies on combustion optimization have been published in order to improve thermal efficiency and reduce unburned carbon in fly ash for utility boilers. So many methods can be applied to optimize thermal efficiency and unburned carbon in fly ash, such as optimizing operating parameters of boilers [2]–[5], optimization of excess air [6], over-fire air arrangement [7], the retrofit of boiler [8], improve load adaptability of boiler with an efficient control scheme [9], and coordinated control strategy of energy balance [10], etc. All of them, the method of optimizing the operating parameters of boilers [11]–[22] is better. Because it takes less time and cost than other methods and is easier to implement. Generally speaking, the method of optimizing operating parameters for the coal-fired boiler has two steps. Firstly, the model of boiler combustion process should be established, and then operating parameters of boiler combustion would be optimized by appropriate algorithms based on previously established model. The relevant researches on operating parameters optimization are referred in this paper. Artificial neural networks (ANN) was used to model coal combustion process and boiler combustion process was optimized by genetic algorithm (GA) [11], [12]. The prediction and optimization of nitrogen oxides emission for large capacity pulverized coal fired boilers were investigated applying ANN and GA [13]. Genetic algorithm (GA) was applied to improve the performance of coal rate prediction model of coal-fired utility boiler trained by support vector regression (SVR) [14]. Based on the boiler combustion model trained by support vector regression, multi-objective optimization of boiler combustion performance was achieved by cellular genetic algorithm [15]. Considering the quality improvement of optimization results, the operating parameters in coal-fired utility boiler were optimized by three different algorithms and simulated annealing genetic algorithm (SAGA) showed a superior optimization performance [16]. The relationship between operating parameters and NOx emission was studied with extreme learning machine, which showed that it had a stronger generalization ability, and harmony search was also proved to be more powerful in optimizing operating parameters [17]. Particle swarm optimization (PSO) was applied to optimize the air distribution scheme to reach best combustion based on the boiler combustion prediction model [18]. The mathematical models of boiler combustion were trained by support vector regression, the optimization results of ant colony optimization (ACO) showed that ACO can optimize boiler combustion effectively [19]. The approach to obtain the optimal NOx emission and thermal efficiency was discussed by optimizing secondary air and overfire air [20]. The secondary and tertiary air flow rate of conventional pulverised-coal-fired boilers were optimized in order to minimize the NOx emissions, CO concentration and unburned carbon [21]. In the modeling process of thermal efficiency and nitrogen oxides emissions in an ultra supercritical boiler, computational fluid dynamics (CFD) simulation data was added to improve the accuracy of ANN model, and then GA was employed to search for the best damper openings of secondary air to optimize boiler combustion [22]. The optimization performace in aforementioned works [2]–[5], [11]–[22] show that thermal efficiency has been effectively improved. But the optimization results of unburned carbon often exceed 3%, which are harmful to the environment and waste energy. And the optimization time is more than 1 minute, or even more than 2 minutes, which is not conducive to optimize the boiler combustion process online. So how to reduce optimization running time and reduce unburned carbon by suitable algorithm is a key problem during the optimization process.

Recently, metaheuristics algorithms have become very popular in many fields [23], such as grey wolf optimizer (GWO) [24]–[26], whale optimization algorithm (WOA) [27], coyote optimization algorithm (COA) [28], salp swarm algorithm [29], and new optimization approaches based on modeling the nonlinear physics processes [30]. The grey wolf optimizer is derived from the hierarchy mechanism and predator behavior of grey wolf populations in nature. GWO is easy to tune and is suitable for online optimization. The GWO algorithm has been used in real optimization projects, such as training the models of macromolecules release from poly-lactide-co-glycolide (PLGA) [31], feature selection for pharmaceutical tabletting processes [32], power system economic dispatch [33]–[35], load frequency controller parameter optimization [36], [37], and image segmentation [38], etc. A method based on combination of grey wolf optimizer and antlion optimization was used to select a representative set of features for machine learning, and the results show superior performance [39]. The yarn tenacity is related to many process parameters, so grey wolf optimization and neural network were proposed to train the prediction model [40]. The grey wolf optimizer was applied to optimize the prediction model for bottom hole pressure of vertical wells that trained by ANN and the optimized prediction model is highly accurate [41]. GWO algorithm was proved to have superior accuracy in carbon dioxide emissions estimating and renewable energies generation [42]. It is proved that the optimization performance and convergence speed of GWO are superior to other methods.

Contribution of This Paper: Motivated by the aforementioned discussions, a method of combining ANN and GWO scheme is proposed to optimize the boiler combustion process online, as shown in Figure 1. The best air distribution scheme is searched by GWO algorithm so that the boiler would operate in a high thermal efficiency under the given limit of unburned carbon in fly ash. Then, the closed-loop control of utility boiler could straight adjust the air distribution scheme to optimize boiler combustion process. The main difficulty of this paper is meeting the requirements of simple operation flow, easy operation by staff, and short optimization time.

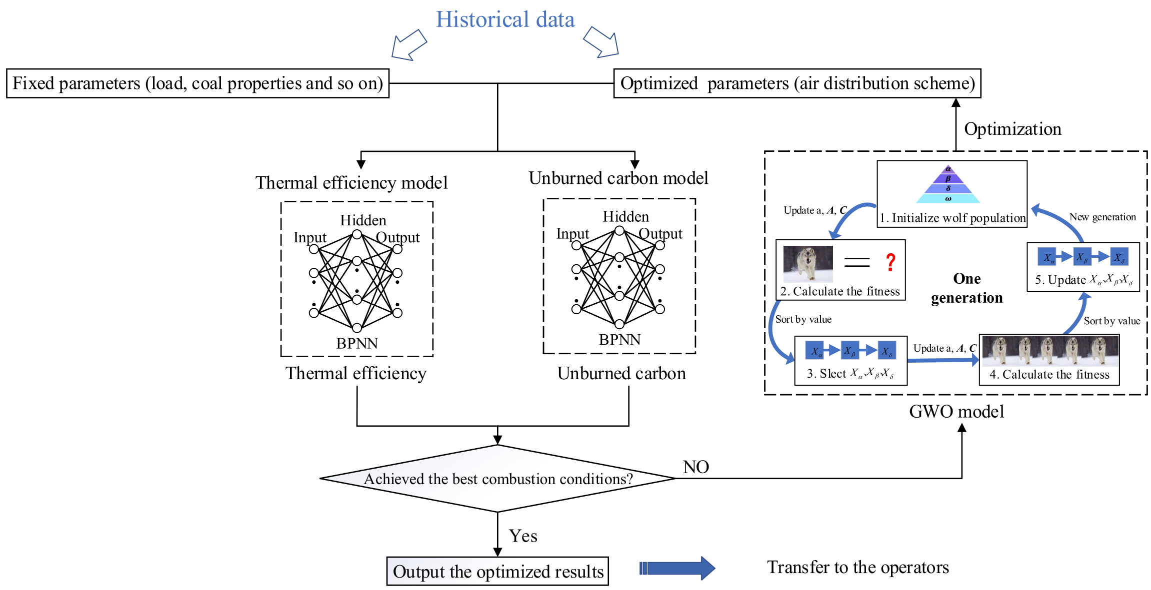

FIGURE 1. Flowchart of the proposed ANN-GWO method.

The main contributions of this paper focus on the following two aspects.

- GWO is applied to search the best operating parameters in utility coal-fire boiler. Compared with other methods, GWO algorithm greatly improves the boiler optimization performance and shortens the optimization time by more than half.
- The population size of GWO algorithm is the only parameter to be set by users, which is simple operation flow and easy operation by staff.

Organization: The rest of this paper is organized as follows. In Section II, the ANN models of thermal efficiency and unburned carbon in fly ash are established, and GWO optimization model is built. In Section III, GWO optimization results of every case, the comparisons between the ANN-GWO method and other boiler optimization methods are studied. In Section IV, we obtain the final conclusions.

Notation: Let t be the number of iterations. $\boldsymbol{X}(t+1)$ is the next grey wolf individual position vector. $\boldsymbol{a}$ is the convergence factor. F_{fit} is the fitness of individual. η_g denotes the thermal efficiency. A_{ar} is the ash content as received (%). M_{ar} is the moisture content as received (%). $Q^{ar}_{net,p}$ is the net heat value as received at constant pressure (kJ/kg). V_{ar} is the volatile content as received (%).

II. METHODOLOGY

A. ANN MODELS

Artificial neural network (ANN) can be used to predict the boiler combustion process. It can establish an exact mathematical model of a highly nonlinear process. Back-propagation neural network (BPNN) trains multilayer perceptrons through propagation algorithm, and it is one of the most widely used ANN models in the related field. In this part, a BP neural network is built to obtain mathematical model of boiler combustion process. A large amount of historical operating data from utility boiler can be obtained through DCS and these data can be used as ANN models training samples [11], [12], [22]. We select 50 groups from these data to train the ANN model, and select 10 sets of data to test the ANN model. Training samples are divided into two categories. One category is fixed parameters that are constant during the boiler combustion optimization, such as load, coal quality and excess air. Another category is the parameters to be optimized, such as 6 damper opening positions that are referred to as air distribution scheme. And referring to engineering practice, the load of the plant, the coal properties (A_{ar}, M_{ar}, $Q^{ar}_{net,p}$, V_{ar}), excess air, 6 damper opening positions totally 12 variables are the ANN models input parameters. Thermal efficiency and unburned carbon in fly ash representing boiler combustion performance are the output parameters of ANN models. Considering the operating conditions of utility boiler and accuracy of the model, the ANN models have a hidden layer with 23 neurons. Figure 2 is the structure of the ANN models.

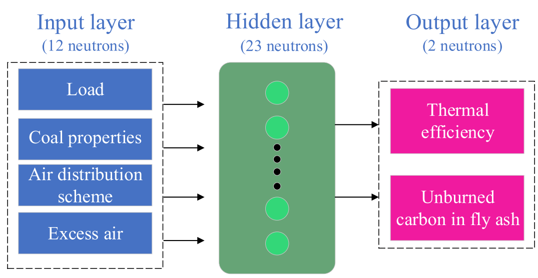

FIGURE 2. The ANN models structure of utility boiler combustion process.

The BP neural network models of thermal efficiency and unburned carbon in fly ash are simulated in MATLAB. Specifically, the training function is TRAINBR, the transfer function is TANSIG, the performance function is MSE, the adaptive learning function is LEARNGDM.

B. GREY WOLF OPTIMIZER (GWO)

The GWO algorithm is a heuristic algorithm for mimicking the hierarchy mechanism and hunting pattern of the natural grey wolf population [24]. The GWO algorithm has strong robustness, and it starts with a set of search agents, also known as solutions. The adaptive values of parameters $\boldsymbol{A}$, $\boldsymbol{C}$ and $\boldsymbol{a}$ guarantee the GWO to obtain the optimal solution. The coefficient vector $\boldsymbol{A}$ with random value is used to diverge the search agent from the victim. Component $\boldsymbol{C}$ determines the random weights to search for the prey in the search space. The explorations of $\boldsymbol{A}$ and $\boldsymbol{C}$ permit GWO to search the area globally. In the simulation process, grey wolves are defined as four types (based on the objective function values). The best would be alpha (α), the second best would be beta (β), the third best would be delta (δ), and the rest would be the omega (ω) group. The hunting positions of grey wolves are influenced by the first three search agent (α, β and δ) obtained so far and the next generation or new grey wolf positions can be gained as:

$$\boldsymbol{X}(t+1) = \frac{\boldsymbol{X}_{\alpha}(t+1) + \boldsymbol{X}_{\beta}(t+1) + \boldsymbol{X}_{\delta}(t+1)}{3} \tag{1}$$

where $\boldsymbol{X}(t+1)$ is the next grey wolf individual position vector, $\boldsymbol{X}_{\alpha}(t+1)$, $\boldsymbol{X}_{\beta}(t+1)$ and $\boldsymbol{X}_{\delta}(t+1)$ are the first three best grey wolf individual position vectors, respectively. The specific process of the GWO algorithm can be seen in Ref. [24].

According to boiler combustion performance experiment study, the air distribution scheme has influence on the thermal efficiency and unburned carbon in fly ash. In addition, adjusting the air distribution scheme is the best boiler combustion optimization control strategy for the coal-fired utility boiler. Thus, the air distribution scheme is optimized by GWO to achieve higher thermal efficiency and lower unburned carbon. And the fitness of individual is obtained by the ANN models of thermal efficiency and unburned carbon. The fitness function is set as follow:

$$F_{fit} = \exp(-\frac{0.01}{\eta_g}) \tag{2}$$

where F_{fit} is the fitness of individual, and η_g is the thermal efficiency of individual. In addition, if an individual's unburned carbon exceeds 3%, the fitness of individual will be set to 0.01 so that this individual will be eliminated in the next generation. Usually in the actual plant operation, the damper opening positions of air distribution scheme has an adjustable range. Considering the operational routines and security, the adjustable range for air distribution is 70-100%. When the algorithm reaches the maximum number of iterations, or a satisfactory objective function value has been obtained, the algorithm ends. Figure 3 is the flowchart of the GWO process.

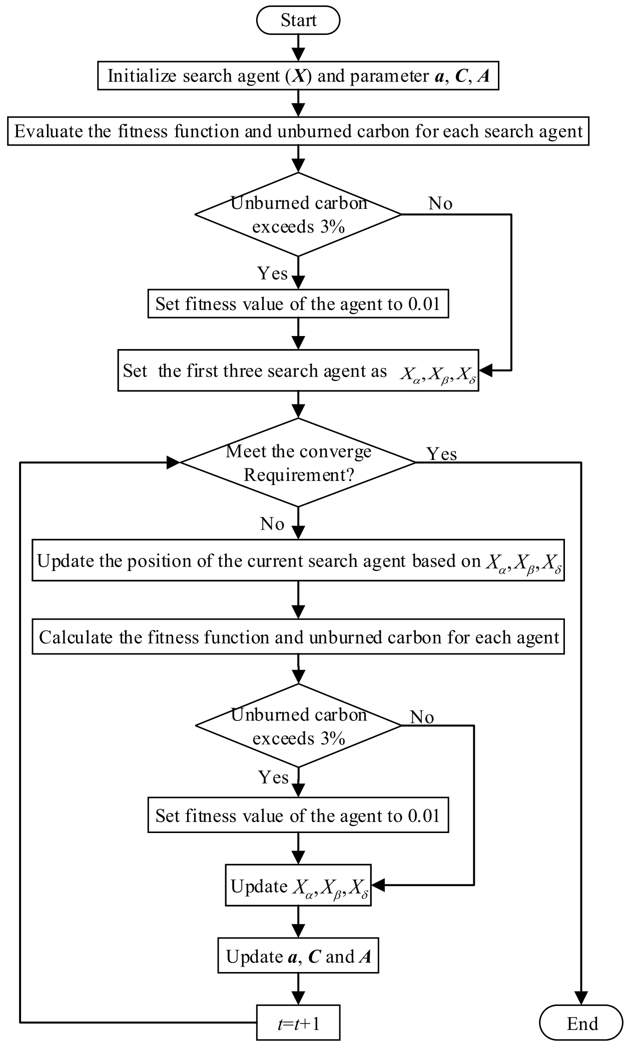

FIGURE 3. The process block diagram of the GWO.

III. RESULTS AND DISCUSSION

This section summarizes and analyzes the optimization results obtained by the proposed ANN-GWO method on boiler combustion optimization. Several quantitative measures are used to analyze the results obtained by the ANN-GWO method. The first and second metrics are used to show the accuracy of ANN models. The third metrics indicates the repeatability of the optimization results. The fourth, fifth and sixth metrics are the average, best and worst optimization results of thermal efficiency and unburned carbon. The seventh metrics is used to evaluate the significant difference between these optimization algorithms. The last metrics is used to assess whether the method is suitable for online optimization.

1 Average absolute percent error (AARD%): It measures the average percent error of ANN models in predicting boiler performance. It is the average of all independent predicting results error, and its mathematically

expressed as follow:

$$AARD\% = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{P_i - M_i}{M_i}\right| \times 100 \tag{3}$$

where P_i is the predicted boiler performance by ANN model, and M_i is the measured data in the practical process.

2 Correlation factor (R^2): It is the metrics that reflects the accuracy of the ANN models prediction. Its mathematically expressed as follow:

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(M_i - \bar{P}_m)^2}{\sum_{i=1}^{N}(P_i - \bar{P}_m)^2} \tag{4}$$

where $\bar{P}_m$ is the average of the boiler performance data.

3 Standard deviation (std): It is used to indicate the repeatability of the optimization results. It is calculated over all independent optimization results obtained by optimizer in plenty of individual runs.

4 Mean fitness: It is the average of all independent optimization results in plenty of individual runs by optimizer.

5 Maximum fitness: It is the best optimization result of all independent optimization results in plenty of individual runs by optimizer.

6 Minimum fitness: It is the worst optimization result of all independent optimization results in plenty of individual runs by optimizer.

7 T-test: It evaluates the significant difference between these optimization algorithms, as follow:

$$t = \frac{\bar{x} - \mu_0}{S/\sqrt{n}} \tag{5}$$

where μ_0 is the average value of the t-distribution and $\frac{S}{\sqrt{n}}$ is the std value of algorithm.

8 Average running time: It is the average running time for optimization algorithm in plenty of independent runs.

A. MODELING RESULTS OF ANN

As mentioned above, there are two ANN models developed to predict the thermal efficiency and unburned carbon in fly ash. The two ANN models are trained with the same input parameters. The setting parameters of ANN are given in Section II-A. The configurations of ANN models are 12 × 23 × 2 (an input layer containing 12 input parameters, a hidden layer with 23 neutrons and an output layer with 2 output parameters which are thermal efficiency and unburned carbon in fly ash), as shown in Figure 2. In order to verify the accuracy of the build ANN models, the results of model statistical errors are shown in Table 1. In terms of thermal efficiency and unburned carbon in fly ash, the comparison results of measured data and predicted data are shown in Figure 4 and Figure 5. The analysis and comparison results show that there is a strong correlation between the measured and predicted data of thermal efficiency and unburned carbon, either training or testing data. The fitting errors of thermal efficiency and unburned carbon are shown in Figure 6. Overall, these prove that ANN models have perfect accuracy and robustness. Therefore, the ANN model is an effective method to predict thermal efficiency and unburned carbon of utility boiler.

TABLE 1. The results of ANN prediction models.

		AADR(%)	R^2
Thermal efficiency	training data	0.16%	0.9914
	testing data	0.14%	0.9856
Unburned carbon in fly ash	training data	2.36%	0.9801
	testing data	2.17%	0.9823

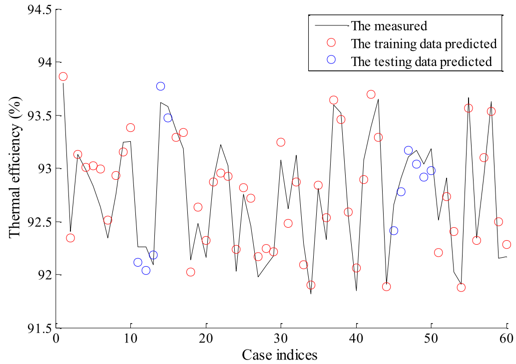

FIGURE 4. The fitting results of thermal efficiency.

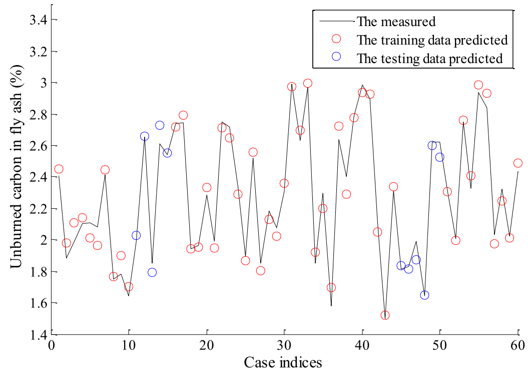

FIGURE 5. The fitting results of unburned carbon in fly ash.

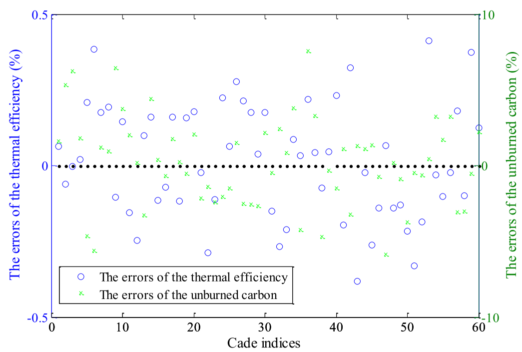

FIGURE 6. Fitting errors of thermal efficiency and unburned carbon.

Algorithm 1 The searching process of GWO

Initialize the grey wolf population $\boldsymbol{X}$
Initialize $\boldsymbol{a}$, A and $\boldsymbol{C}$
Calculate the fitness of each grey wolf individual
Calculate unburned carbon of each grey wolf individual
if the unburned carbon of grey wolf individual exceeds 3% **then**
    the fitness of grey wolf individual will be set to 0.01
end if
Set the best grey wolf individual as $\boldsymbol{X}_\alpha$;
Set the second best grey wolf individual as $\boldsymbol{X}_\beta$;
Set the third best grey wolf individual as $\boldsymbol{X}_\delta$;
while $t <$ Maximum number of iterations **do**
    for each search grey wolf individual **do**
        Update the position of the current grey wolf individual by equation (1);
    end for
    Calculate the fitness of each grey wolf individual
    Calculate unburned carbon of each grey wolf individual
    if the unburned carbon of grey wolf individual exceeds 3% **then**
        the fitness of grey wolf individual will be set to 0.01
    end if
    Update $\boldsymbol{X}_\alpha$, $\boldsymbol{X}_\beta$ and $\boldsymbol{X}_\delta$
    Update $\boldsymbol{a}$, $\boldsymbol{A}$ and $\boldsymbol{C}$
    $t = t + 1$
end while
return $\boldsymbol{X}_\alpha$

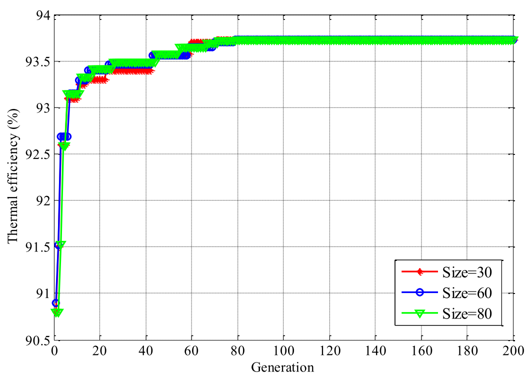

FIGURE 7. The effect of the population size on optimization results.

TABLE 2. The setting parameters of three algorithms.

Algorithm	Parameters	Value/setting
GA [11]	Population size	80
	Crossover's probability	0.8
	Mutation's probability	0.2
	Max number of generation	200
PSO [18]	Size of the Swarm	80
	Max number of iteration	200
	C1	2.05
	C2	2.05
	Convergence factor of PSO: χ	0.729
GWO	Number of wolves	80
	Max number of iteration	200

B. OPTIMIZATION RESULTS OF GWO

After the ANN models are established, the GWO algorithm is used to optimize the thermal efficiency while ensuring that the unburned carbon is within the allowable limit. To ensure that unburned carbon is within limit, if the unburned carbon of an individual exceeds 3%, we delete the individual by setting the fitness value to 0.01. The pseudo code of the GWO algorithm searching for the best air distribution scheme is presented in Algorithm 1.

A major advantage of the ANN-GWO approach is its easy tune, because there are limited number of parameters to be adjusted in GWO algorithm simulation process. The population size is the only parameter to be set by users. One case with thermal efficiency of 91.8% and unburned carbon in fly ash of 3.88% is chosen for optimization. To compare the effect of population size, three different population sizes are studied, and Figure 7 is the optimization process of GWO with different population sizes. The results clearly show that the performance of the ANN-GWO approach is less relied on the population size, which would make it easier for users to select the appropriate parameters.

In order to further demonstrate the effect of optimization, 20 sets of historical operating data are randomly selected to be optimized. The maximum iteration number of GWO algorithm is set as 200, the population size is set as 80. Based on the optimization results (as shown in Figure 8), the minimum thermal efficiency is improved by 0.14% and the maximum is improved by 0.78%. 90% of the samples

TABLE 3. The comparison results between three different algorithms.

Operating conditions	Before optimiztion	GWO	PSO [18]	GA [11]
Unburned carbon in fly ash	3.88%	1.52% (60.8%↓)	1.64% (57.7%↓)	1.95% (49.7%↓)
Thermal efficiency	91.8%	93.73% (2.11%↑)	93.67% (2.03%↑)	93.63% (1.99%↑)

TABLE 4. Stability results analysis of three algorithms.

Operating conditions		GWO	PSO [18]	GA [11]
Thermal efficiency (91.8%)	Minimum fitness	93.66%	92.96%	92.85%
	Mean fitness	93.72%	93.32%	93.24%
	Maximum fitness	93.78%	93.68%	93.63%
	std	0.0350	0.2170	0.1927
Unburned carbon in fly ash (3.88%)	Minimum fitness	1.5%	1.63%	1.92%
	Mean fitness	1.53%	1.68%	2.15%
	Maximum fitness	1.56%	1.72%	2.38%
	std	0.0180	0.0188	0.1310

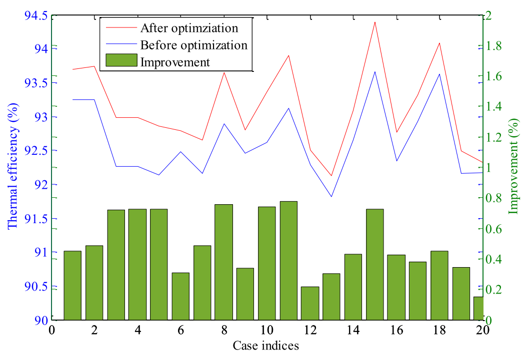

FIGURE 8. Optimization results of different operating conditions.

show an increase in thermal efficiency of more than 0.3% and the mean improvement rate is 0.5%, which significantly confirm the GWO algorithm effectiveness.

C. COMPARISON WITH OTHER EXISTING APPROACHES

The proposed GWO approach is compared with GA approach [11] and PSO approach [18]. To ensure the fairness of comparison, the control parameters of GWO, PSO and GA need to be carefully set. The setting parameters of the three algorithms are showed in Table 2.

The purpose of Section III-C is to verify the improvement of the GWO algorithm in improving thermal efficiency and reducing unburned carbon in fly ash. Therefore, we choose one case with thermal efficiency of 91.8% and unburned carbon of 3.88% to study the performance comparison between the proposed ANN-GWO approach and other existing approaches. Besides the above settings parameters, the three algorithms optimize the same operating parameters based on the same ANN models, and the initial input data of three algorithms are also the same. Moreover, all simulation experiments are done on the same laptop (2.6GHz, 4GB RAM). The optimization results of three algorithms are given in Table 3. The three optimizing processes are shown

TABLE 5. Significant measures for GWO against other optimizers.

Optimizer_1	Optimizer_2	p-value of T-test	Comment
PSO	GWO	0.006	significant
GA	GWO	0	significant

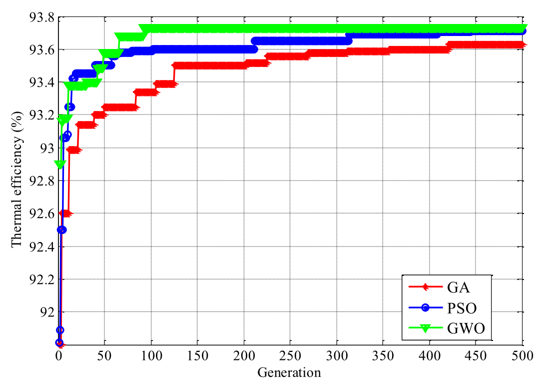

FIGURE 9. Optimization processes of three algorithms.

in Figure 9. These results clearly show that the GWO algorithm is superior to the PSO and GA algorithms. By comparing the thermal efficiency (91.8%), the optimization results obtained by GA, PSO and GWO approaches are 93.63% (1.99% improvement), 93.67% (2.03% improvement) and 93.73% (2.11% improvement), respectively. It is clearly that GWO algorithm achieves a great improvement in optimization quality. Meanwhile, in the early evolution of the GWO algorithm, the thermal efficiency rises significantly and then converges in approximately 100 generations. Compared with other two algorithms which converge in 300 and 450 generations respectively, the GWO algorithm converges faster and is more suitable for online optimization.

It is clear that GWO outperforms PSO and GA, which verifies the capability of GWO to search the operating parameters for optimal boiler combustion performance and the capability of improving the running time. Compared with these

TABLE 6. Optimization results of three algorithms.

	GWO		PSO		GA	
	Thermal efficiency	Unburned carbon in fly ash	Thermal efficiency	Unburned carbon in fly ash	Thermal efficiency	Unburned carbon in fly ash
1	93.76%	1.52%	93.11%	1.69%	93.15%	2.34%
2	93.70%	1.52%	93.06%	1.66%	93.09%	1.95%
3	93.75%	1.54%	93.22%	1.72%	93.04%	2.18%
4	93.69%	1.55%	93.04%	1.70%	93.01%	2.26%
5	93.68%	1.56%	93.34%	1.71%	93.29%	1.97%
6	93.72%	1.52%	93.02%	1.66%	93.58%	2.10%
7	93.75%	1.54%	93.06%	1.64%	93.51%	2.06%
8	93.77%	1.53%	93.38%	1.67%	93.07%	2.26%
9	93.69%	1.55%	93.57%	1.63%	93.28%	2.33%
10	93.71%	1.55%	93.42%	1.64%	93.38%	2.29%
11	93.69%	1.51%	93.49%	1.71%	92.99%	2.13%
12	93.71%	1.53%	93.30%	1.67%	93.20%	1.94%
13	93.75%	1.55%	93.58%	1.69%	93.43%	2.01%
14	93.66%	1.51%	93.33%	1.70%	93.43%	2.06%
15	93.77%	1.54%	93.51%	1.68%	93.09%	2.29%
16	93.75%	1.53%	93.50%	1.71%	93.59%	2.07%
17	93.70%	1.56%	93.32%	1.66%	93.09%	2.31%
18	93.69%	1.56%	93.55%	1.64%	93.63%	2.16%
19	93.67%	1.52%	93.11%	1.72%	93.51%	2.06%
20	93.71%	1.54%	93.43%	1.64%	93.08%	2.27%
21	93.70%	1.55%	93.28%	1.65%	93.48%	1.92%
22	93.71%	1.54%	93.45%	1.67%	93.09%	2.26%
23	93.68%	1.52%	93.03%	1.72%	93.48%	2.30%
24	93.76%	1.51%	93.67%	1.65%	93.57%	1.95%
25	93.67%	1.55%	93.19%	1.67%	93.18%	2.26%
26	93.71%	1.51%	93.44%	1.63%	93.02%	1.94%
27	93.75%	1.51%	93.27%	1.71%	93.12%	2.08%
28	93.76%	1.55%	93.25%	1.66%	93.19%	2.34%
29	93.74%	1.53%	93.19%	1.71%	92.89%	2.27%
30	93.68%	1.51%	93.34%	1.66%	92.94%	2.07%
31	93.75%	1.54%	93.28%	1.65%	93.60%	2.32%
32	93.74%	1.51%	93.32%	1.72%	93.60%	2.24%
33	93.69%	1.56%	93.51%	1.70%	93.57%	2.38%
34	93.70%	1.52%	93.21%	1.71%	93.16%	2.28%
35	93.72%	1.53%	93.29%	1.67%	93.03%	2.30%
36	93.75%	1.51%	93.49%	1.64%	93.28%	1.97%
37	93.77%	1.55%	93.22%	1.69%	93.60%	2.33%
38	93.76%	1.52%	93.42%	1.71%	93.39%	2.17%
39	93.66%	1.52%	93.21%	1.68%	93.52%	2.37%
40	93.72%	1.52%	93.33%	1.70%	93.11%	2.18%
41	93.74%	1.53%	93.48%	1.64%	93.50%	1.97%
42	93.67%	1.51%	93.03%	1.66%	93.28%	2.16%
43	93.76%	1.55%	92.99%	1.72%	93.29%	2.31%
44	93.68%	1.54%	93.18%	1.70%	93.46%	2.00%
45	93.76%	1.53%	93.11%	1.68%	93.14%	1.94%
46	93.69%	1.56%	93.56%	1.69%	93.42%	1.98%
47	93.70%	1.56%	93.23%	1.70%	93.01%	2.15%
48	93.66%	1.54%	93.23%	1.72%	93.22%	2.05%
49	93.77%	1.54%	93.36%	1.69%	93.49%	2.26%
50	93.78%	1.50%	93.48%	1.70%	93.37%	1.93%
51	93.73%	1.55%	93.49%	1.71%	92.96%	2.04%
52	93.76%	1.50%	93.10%	1.63%	92.91%	2.23%
53	93.70%	1.55%	93.47%	1.68%	93.27%	2.25%
54	93.68%	1.51%	93.21%	1.68%	93.05%	2.07%
55	93.74%	1.50%	93.59%	1.71%	93.16%	2.23%
56	93.78%	1.51%	93.28%	1.66%	93.07%	2.36%
57	93.69%	1.53%	93.64%	1.71%	92.93%	1.93%
58	93.75%	1.50%	93.38%	1.67%	93.42%	2.30%
59	93.74%	1.52%	93.64%	1.69%	93.28%	1.92%
60	93.76%	1.55%	93.52%	1.66%	93.34%	2.25%
61	93.66%	1.51%	93.42%	1.63%	93.31%	2.13%
62	93.75%	1.52%	93.07%	1.67%	93.56%	2.14%
63	93.76%	1.52%	93.41%	1.67%	92.98%	2.10%
64	93.72%	1.52%	93.12%	1.68%	93.39%	2.27%
65	93.73%	1.54%	93.33%	1.64%	93.42%	2.11%
66	93.70%	1.52%	93.42%	1.68%	93.45%	2.24%
67	93.71%	1.52%	93.40%	1.67%	92.85%	1.97%
68	93.72%	1.50%	93.22%	1.66%	93.15%	2.37%
69	93.73%	1.55%	93.57%	1.63%	93.14%	2.38%
70	93.67%	1.51%	93.62%	1.69%	93.07%	2.35%

TABLE 6. ***(Continued).*** **Optimization results of three algorithms.**

	GWO		PSO		GA	
	Thermal efficiency	Unburned carbon in fly ash	Thermal efficiency	Unburned carbon in fly ash	Thermal efficiency	Unburned carbon in fly ash
71	93.78%	1.53%	93.03%	1.66%	93.39%	2.03%
72	93.77%	1.55%	92.96%	1.68%	93.44%	2.32%
73	93.67%	1.54%	93.37%	1.64%	93.21%	2.05%
74	93.75%	1.56%	93.17%	1.64%	92.85%	2.21%
75	93.75%	1.50%	93.49%	1.72%	93.38%	1.98%
76	93.71%	1.51%	93.06%	1.70%	93.30%	1.96%
77	93.69%	1.56%	93.31%	1.70%	93.14%	2.13%
78	93.75%	1.54%	93.22%	1.71%	93.10%	2.32%
79	93.68%	1.50%	93.63%	1.71%	93.02%	2.01%
80	93.72%	1.51%	93.03%	1.65%	93.24%	2.25%
81	93.67%	1.50%	93.21%	1.67%	93.10%	2.02%
82	93.76%	1.53%	93.19%	1.70%	92.89%	2.38%
83	93.68%	1.52%	92.96%	1.71%	93.23%	1.97%
84	93.70%	1.55%	93.61%	1.67%	93.59%	1.97%
85	93.77%	1.55%	93.67%	1.66%	93.13%	1.92%
86	93.67%	1.51%	93.20%	1.71%	93.44%	1.93%
87	93.75%	1.56%	93.38%	1.66%	93.38%	2.24%
88	93.68%	1.55%	93.29%	1.66%	93.00%	2.05%
89	93.70%	1.56%	93.25%	1.63%	92.99%	2.22%
90	93.72%	1.51%	93.08%	1.64%	92.91%	2.12%
91	93.71%	1.56%	93.44%	1.64%	93.63%	2.04%
92	93.74%	1.52%	93.49%	1.68%	93.28%	2.35%
93	93.67%	1.53%	93.01%	1.63%	93.29%	2.18%
94	93.78%	1.52%	93.16%	1.64%	93.11%	2.31%
95	93.76%	1.54%	93.46%	1.65%	93.04%	2.03%
96	93.74%	1.52%	92.98%	1.71%	93.06%	1.97%
97	93.67%	1.52%	93.45%	1.69%	93.19%	2.06%
98	93.72%	1.55%	93.46%	1.72%	93.40%	2.37%
99	93.72%	1.52%	93.10%	1.64%	92.87%	2.23%
100	93.74%	1.52%	92.99%	1.64%	92.94%	2.12%

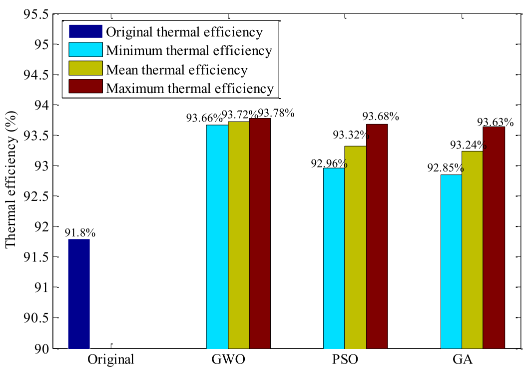

FIGURE 10. Thermal efficiency optimization results.

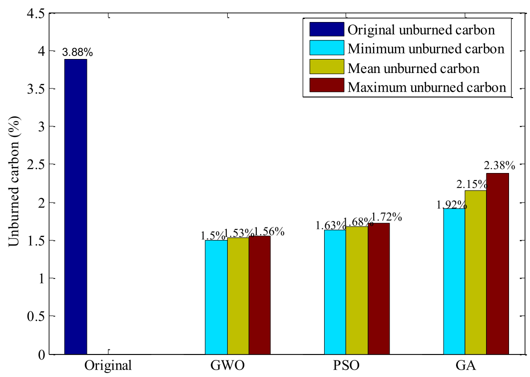

FIGURE 11. Unburned carbon in fly ash optimization results.

methods, GWO algorithm has the advantages as follows: firstly, the conveying mechanism and information sharing capability of GWO is super. Secondly, it gets the optimal solution based on random function and first three solutions, and it converges quickly by jumping from local optimal to global optimal. Finally, the principle of GWO algorithm is simple, and it is easy to tune and implement.

To further verify the optimization performance of the GWO algorithm, the three algorithms are repeated 100 times according to the previous settings to optimize the case of thermal efficiency of 91.8% and unburned carbon of 3.88%. The optimization results are shown in Table 6 and Table 6 (Continued). Minimum fitness, mean fitness, maximum fitness, and standard deviation values obtained by three algorithms are shown in Figure 10, Figure 11 and Table 4. It is shown that all of the three algorithms can improve thermal efficiency efficiently. However, the mean boiler combustion optimization results of GWO are better than these of PSO and GA. The minimum optimization results of GWO are close to the maximum optimization results. Furthermore, Table 4 shows that the std value of GWO is smaller than the ones obtained by PSO and GA, which verify the capability of GWO to search for the best or near-optimal solutions. The optimization results clearly indicate that GWO could provide

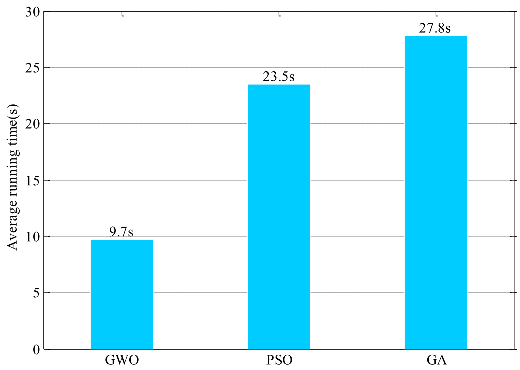

FIGURE 12. Average running time of three algorithms.

superior and more stable solutions than PSO and GA. And the average running times of three algorithms are shown in Figure 12. The direct comparisons between GWO and other two algorithms clearly show that a run of GWO method requires a less period time, which will facilitate online boiler combustion optimization. Hence, GWO might be a better alternative method to optimize boiler combustion online.

Significance tests can be used to confirm whether there is a significant statistical difference between two algorithms. The p-values of T-test for all the three algorithms are shown in Table 5. In order to verify the performance of GWO, Table 5 only shows the comparisons of other algorithms with GWO. It is clear that the optimization performance obtained by GWO is significantly superior compared to PSO (0.006) and GA (0).

Additionally, the results also show that GWO can control unburned carbon in fly ash. In particular, the unburned carbon in fly ash has an allowable limit, so as long as unburned carbon is within 3%, the results are considered acceptable. It can also set optimization objectives as multi-objective optimization.

IV. CONCLUSIONS

This paper proposes an ANN-GWO approach for optimizing the thermal efficiency and unburned carbon in fly ash of coal-fired utility boiler. ANN is applied to establish mathematical models of thermal efficiency and unburned carbon in fly ash. Both of the models show considerable accuracy for predicting thermal efficiency and unburned carbon. After that, GWO algorithm is used to optimize air distribution for the coal-fired utility boiler to improve thermal efficiency and reduce unburned carbon. The optimization results of test cases by GWO confirmed the effectiveness of the GWO algorithm. Furthermore, the performance of GWO is further discussed by comparing its optimization results with the PSO and GA approaches. It is showed that GWO can improve thermal efficiency to a higher level and provide more stable solutions. Meanwhile, GWO algorithm optimization requires a shorter time period for a run, which is suitable for the online application. The results of this paper enhance the performance on boiler combustion optimization and reduce optimization running time. For future work, changes in the coal properties and some extreme operating conditions should be considered to reduce the errors in experimental performance.

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YIDING ZHAO was born in Shulan, Jilin, China, in 1962. He received the B.S. degree in mechanical manufacturing process and equipment and the M.S. degree in mechanical engineering from the Xi'an Jiaotong University, Xi'an, Shaanxi, in 1983 and 1990, respectively.

He is currently an Associate Professor with the School of Control Engineering, Northeastern University at Qinhuangdao, Qinhuangdao, Hebei, China. He has edited and published many universal teaching materials, such as *"Automatic Control System"* and *"Software Engineering Foundation"*. His research interests include automatic control of industrial processes, embedded measurement, and control technology. He is also a member of the automation professional teaching team of Hebei.

QINGHE WU was born in Dalian, Liaoning, China, in 1995. He received the B.S. degree in automation from Northeastern University, Shenyang, China, in 2013.

He is currently a Graduate Student with the School of Control Engineering, Northeastern University at Qinhuangdao, Qinhuangdao, Hebei, China. His research interests include automatic control of industrial processes, process monitoring, and diagnostics and optimization control.

HENG LI was born in Hunan, China, in 1963. He received the B.S. and M.S. degrees in civil engineering from Tongji University, in 1984 and 1987, respectively, and the Ph.D. degree in architectural science from the University of Sydney, Australia, in 1993.

From 1993 to 1995, he was a Lecturer with James Cook University. From 1996 to 1997, he was a Senior Lecture with the Civil Engineering Department, Monash University. Since 1997, he has been gradually promoted from an Associate Professor to his current position: the Chair Professor of construction informatics with The Hong Kong Polytechnic University. He is the author of two books and more than 400 articles. His research interests include building information modeling, robotics, functional materials, and the Internet of Things. Dr. Li was a recipient of National Award from Chinese Ministry of Education, in 2015, and Gold Prize of Geneva Innovation 2019. He is also a Reviews Editor of *Automation in Construction*.

SHUHUA MA was born in Changli, Qinhuangdao, Hebei, China, in 1967. She received the B.S. degree in automation of production process from the Beijing Institute of Chemical Technology, Beijing, in 1989, and the M.S. degree in measurement technology and instrumentation from Yanshan University, Qinhuangdao, in 1998.

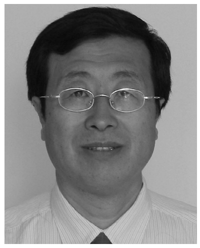
From 1989 to 1993, she was an Assistant Engineer with Qinhua Pharmaceutical Factory. From 1993 to 2001, she was a Lecturer with the Department of Control Engineering, Northeast University at Qinhuangdao, Hebei. Since 2002, she has been an Associate Professor with the School of Control Engineering, Northeastern University at Qinhuangdao. She is the author of three books and more than 15 articles. Her research interests include intelligent control systems and microcontroller-based control system design. She completed many engineering projects in industry, such as process control system for the glass plant and environment monitor project.

PING HE was born in Huilongya, Nanchong, Sichuan, China, in November 1990. He received the B.S. degree in automation from the Sichuan University of Science and Engineering, Zigong, Sichuan, China, in June 2012, the M.S. degree in control science and engineering from Northeastern University, Shenyang, Liaoning, China, in July 2014 and the Ph.D. degree in electromechanical engineering from the Universidade de Macau, Taipa, Macao, in June 2017.

From December 2015 to November 2018, he was an Adjunct Associate Professor with the Department of Automation, Sichuan University of Science and Engineering. From August 2017 to August 2019, he was a Postdoctoral Research Fellow with the Emerging Technologies Institute, The University of Hong Kong, and Smart Construction Laboratory, The Hong Kong Polytechnic University. Since December 2018, he has been a Full Professor with the School of Intelligent Systems Science and Engineering, Jinan University (Zhuhai Campus), Zhuhai, Guangdong, China. He is the author of one book, and more than 40 articles. His research interests include sensor networks, complex networks, multi-agent systems, artificial intelligence, control theory, and control engineering. Dr. He is also a Reviewer Member for *Mathematical Reviews* of American Mathematical Society. He was a recipient of the Liaoning Province of China Master's Thesis Award for Excellence, in March 2015, and the IEEE Robotics & Automation Society Finalist of Best Paper Award, in July 2018. He is also an Associate Editor of *Automatika*.

JUN ZHAO was born in Korla, Xinjiang, China, in October 1984. He received the B.S. degree in optics and the M.S. degree in control science and engineering from the Southwest University of Science and Technology, Mianyang, Sichuan, China, in July 2007 and June 2011, respectively, and the Ph.D. degree in control science and engineering from the Harbin Institute of Technology, Harbin, Heilongjiang, China, in June 2017.

Since July 2017, he has been an Assistant Professor with the Artificial Intelligence Key Laboratory of Sichuan, Department of Automation, Sichuan University of Science and Engineering, Zigong, Sichuan, China. He is the author of five articles. His research interests include networked control systems, multi-agent systems, artificial intelligence, control theory, and control engineering.



YANGMIN LI received the B.S. and M.S. degrees in mechanical engineering from Jilin University, Changchun, China, in 1985 and 1988, respectively, and the Ph.D. degree in mechanical engineering from Tianjin University, Tianjin, China, in 1994.

He started his academic career, in 1994; he was a Lecturer of Mechatronics Department, South China University of Technology, Guangzhou, China. He was a Fellow with the International Institute for Software Technology of the United Nations University (UNU/IIST), from May to November 1996; a Visiting Scholar with the University of Cincinnati, in 1996; a Postdoctoral Research Associate with Purdue University, W. Lafayette, USA, in 1997. He was an Assistant Professor, from 1997 to 2001, an Associate Professor, from 2001 to 2007, a Full Professor, from 2007 to 2016, all with the University of Macau. He is currently a Full Professor with the Department of Industrial and Systems Engineering, The Hong Kong Polytechnic University, Hong Kong. He has authored and coauthored 419 scientific papers in journals and conferences. His research interests include micro/nanomanipulation, compliant mechanism, precision engineering, robotics, and multibody dynamics and control. He is also an Associate Editor of the IEEE TRANSACTIONS ON AUTOMATION SCIENCE AND ENGINEERING, *Mechatronics*, IEEE ACCESS, and the *International Journal of Control, Automation, and Systems*.