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On the Flexible Operation of Supercritical Circulating Fluidized Bed: Burning Carbon Based Decentralized Active Disturbance Rejection Control

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Abstract: Supercritical circulating fluidized bed (CFB) is one of the prominent clean coal technologies owing to the advantages of high efficiency, fuel flexibility, and low cost of emission control. The fast and flexible load-tracking performance of the supercritical CFB boiler-turbine unit presents a promising prospect in facilitating the sustainability of the power systems. However, features such as large inertia, strong nonlinearity, and multivariable coupling make it a challenging task to harmonize the boiler's slow dynamics with the turbine's fast dynamics. To improve the operational flexibility of the supercritical CFB unit, a burning carbon based decentralized active disturbance rejection control is proposed. Since burning carbon in the furnace responds faster than throttle steam pressure when the fuel flow rate changes, it is utilized to compensate the dynamics of the corresponding loop. The parameters of the controllers are tuned by optimizing the weighted integrated absolute error index of each loop via genetic algorithm. Simulations of the proposed method on a 600 MW supercritical CFB unit verify the merits of load following and disturbance rejection in terms of less settling time and overshoot.

Keywords: supercritical circulating fluidized bed; boiler-turbine unit; active disturbance rejection control; burning carbon; genetic algorithm

1. Introduction

Circulating fluidized bed (CFB) technology has demonstrated its ability to efficiently utilize a wide variety of fuels, including high sulfur coal to coal gangue and coal slurries [1]. Taking coal-water slurries containing petrochemicals fuels for example, through experiments and calculations the advantages are much lower anthropogenic emissions and ash residue, low cost of the components, positive economic performance indicators of storage, transportation, and combustion, as well as higher fire and explosion safety [2,3]. It is believed that a combination with supercritical steam cycle to increase the efficiency of energy conversion is one of the futures of CFB combustion technology [4]. The first 600 MW supercritical CFB boiler demonstration project was put into commercial operation in 2013 [5]. By the end of 2017, more than eighty-two supercritical CFB boilers were in operation or under construction in China [6].

As Lyu pointed out [4], in the demonstration the control of the 600 MW supercritical CFB boiler was the heart of the matter. Some factors attribute to the difficulties of the coordinated control of the unit:

1. Higher requirement for operational flexibility. With increasing intermittent renewable energy integrated in the grid, thermal power plants are required to operate in a wider range [7]. Supercritical CFB boilers can regulate their load from 30% to 100%, which extends 20% more in the low load region compared with pulverized coal-fired boilers [8]. However, the considerable quantities of bed materials in furnace result in large inertia of the CFB boiler. In addition, dynamics of the boiler vary at different operation conditions, leading to strong nonlinearity. Both of these factors make it hard to design controllers of coordinated control system (CCS) to harmonize the boiler's slow dynamics with the turbine's fast dynamics so as to follow the command from grid promptly.
2. Capability to reject disturbance in fuel. Since the CFB boiler works with a variety of fuels, the variability of fuel brings in disturbance for the unit operation. In addition, the amounts of fuel that enter the boiler sometimes fluctuate due to mechanical reasons. Consequently, it is necessary to design advanced controllers so as to suppress the influence of disturbance from fuel.
3. Complex dynamics of the supercritical CFB unit. Besides the thermal inertia, strong nonlinearity, and time delay of supercritical CFB unit, multivariable coupling has a significant impact on the controller design [9]. The adjustments of manipulated variables would cause changes in all controlled variables. Furthermore, the unit would become more complicated when the bed temperature of the CFB boiler is taken into consideration [10].

As can be anticipated, a well-designed control system of the supercritical CFB unit can yield potential environmental and economic benefits.

Much of the literature has paid particular attention to this problem. Among them, investigation of the dynamic characteristic and mechanism-based modeling for supercritical CFB boilers lays the groundwork. Prior knowledge about subcritical CFB boilers is essential to the modeling research. Majanne and Köykkä presented a dynamic model which consisted of the air-flue gas and the water-steam systems [11]. The model was based on the first principles mass, energy, and momentum balances and experimental correlations about reaction kinetics and heat transfer, and was finally tested against measured process data. Furthermore, a mechanism-based control model in the form of transfer functions for the CCS of the subcritical coal-fired 300 MW CFB unit was established based on the dynamic characteristics in [12]. The research has been extended to the supercritical CFB unit. In [13] a hybrid dynamic model was developed to characterize the main physical and chemical processes in a supercritical CFB boiler. Steady-state verification was made to evaluate the accuracy of the model while step responses of different manipulate variables were tested. Through some reasonable simplification, a nonlinear control model of supercritical CFB unit was established in [14], and the parameters of the system model were identified by steady-state derivation, function fitting, and optimization algorithm. The correctness of the model structure and validity of the identification method were verified by operation data of a 600 MW supercritical CFB unit in service.

Based on the derived dynamic model of CFB unit, a variety of control methods are adopted for the coordinated control purpose. The proportional-integral-derivative (PID) control is the most widely used control strategy in real control engineering. Hultgren and Hao et al. analyzed the relative gain and designed a decentralized PID control structure for the CFB unit [15,16]. The controllers in [16] were devised based on desired dynamic equation (DDE) while an heuristic algorithm was used to optimize the PID controllers for the CFB unit in [17]. In [18], dynamic feedforward was employed to improve the performance of PID controllers. on basis of decentralized PI control, two disturbance observers (DOBs) were designed to estimate and compensate the effect of coupling in the CFB unit [19]. However, higher requirements are imposed for the supercritical CFB unit which the conventional decentralized PID control can hardly satisfy. Some advanced control methods have been discussed, such as fuzzy control [20–22], neural network based control [23,24], etc. Although good performances were observed in simulations, these methods could seldom be used in the real CFB power plant due to the restrictions in the distributed control system.

Due to the ability to deal with uncertainty, active disturbance rejection control (ADRC) has received increased attention across a number of disciplines in recent years, such as gasoline engines [25], proton exchange membrane fuel cell [26], electromechanical actuator [27], pendulum cart system [28], piezo-driven positioning stage [29], flight control [30], and so on. The basic principle of ADRC is the estimation and actively compensation via extended state observer (ESO). The stability analysis of ADRC and the convergence of ESO have been studied by many researchers [31,32]. ADRC has also been employed for the process control of CFB unit, such as the superheated steam temperature control [33], primary air control [34], secondary air control [35], combustion system control [36], and control of boiler-turbine unit [37]. However, none of them have taken control problems of supercritical CFB unit into consideration. The increase in inertia aggravates the difficulty of the supercritical CFB unit. Recent studies show that combination of burning carbon in the furnace of CFB with heat signal can improve the control performance [9]. To make use of the burning carbon, Gao et al. added the rate of heat released in combustion of burning carbon as the feedforward signal on basis of decentralized PI controllers. However, detailed analysis of the control structure should be undertaken.

The primary aim of this research is to provide reasonably consistent evidence of an association between burning carbon and operation performance and to explore the enhancement of the operation performance of the supercritical CFB unit, making the following contributions:

- Burning carbon is integrated into the control framework to accelerate the load following;
- The disturbance rejection performance is improved via the design of decentralized ADRC controllers;
- Genetic algorithm (GA) is employed to tune the parameters of the ADRC controllers.

The remaining part of the paper proceeds as follows: Section 2 introduces the 600 MW supercritical CFB boiler-turbine unit and analyzes its dynamics. In Section 3, the decentralized ADRC framework is proposed for the supercritical CFB unit, in which burning carbon information is utilized. In order to achieve satisfying performance, GA is used to tune the controllers for both traditional decentralized controllers and the proposed method in Section 4. In Section 5, simulation results are given to verify the merits of the proposed method. Finally, some conclusions are drawn in Section 6.

2. Performance Analysis of Supercritical Circulating Fluidized Bed Boiler-Turbine Unit Model

Gao et al. investigated the dynamics of supercritical CFB unit and established the nonlinear model for control purposes [14]. The model represented the behavior of the boiler-turbine unit in the 600 MW supercritical CFB power plant located at Baima, China, and was validated by its operation data.

Simplified working process of the supercritical CFB boiler-turbine unit is illustrated in Figure 1. The essential working principle of the boiler-turbine unit is energy conversion. The chemical energy stored in coal is transformed into steam thermal energy by the boiler, then it is transformed into rotational mechanical energy by the turbine, and finally it is transformed into electric energy by the turbogenerator.

In the derived model, the manipulate variables are the fuel flow rate command u_B (u_1, kg/s), feedwater flow rate D_{fw} (u_2, kg/s), and turbine throttle valve opening u_t (u_3, %); the controlled variables are the throttle steam pressure P_{st} (y_1, MPa), separator steam enthalpy h_m (y_2, kJ/kg), and active electric power generated by the turbogenerator N_e (y_3, MW), respectively. Some typical operating conditions are shown in Table 1.

Table 1. Typical steady-state operation conditions of the supercritical circulating fluidized bed (CFB) unit.

	y_1 (MPa)	y_2 (kJ/kg)	y_3 (MW)	u_1 (kg/s)	u_2 (kg/s)	u_3 (%)
High (100%)	23.93	2609.53	600	32.79	485.98	91.51
Medium (70%)	19.30	2669.29	420	24.54	335.60	79.40
Low (40%)	12.53	2804.35	240	15.28	184.10	69.91

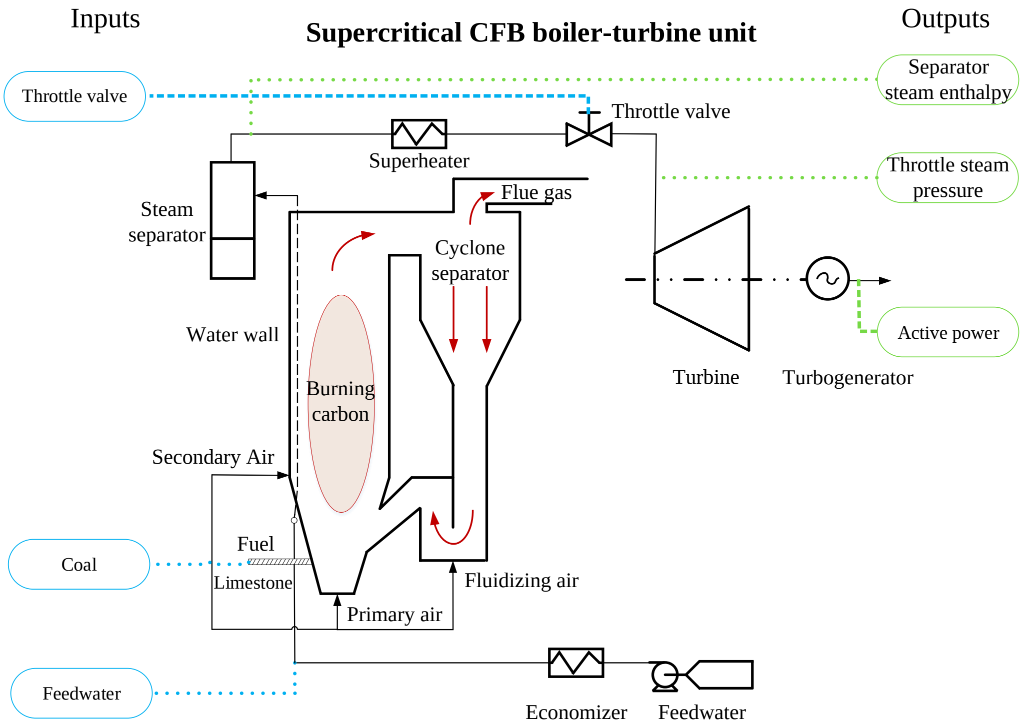
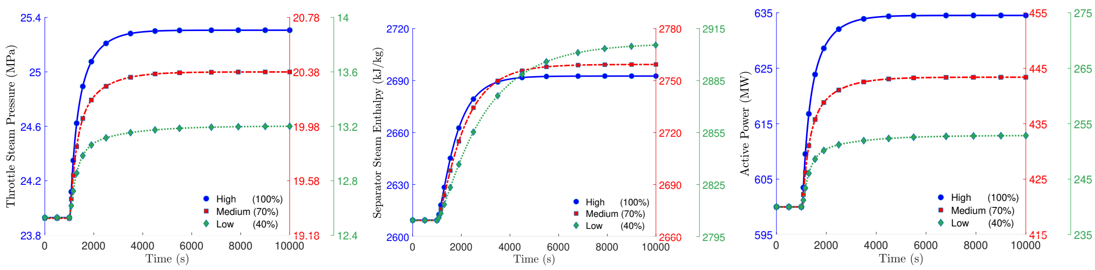


Figure 1. Simplified diagram of a supercritical circulating fluidized bed (CFB) boiler-turbine unit.

Since the purpose of modeling is to design and test advanced control algorithms suited for the supercritical CFB boiler-turbine unit, many simplifications are made during the modeling, however, for the most important variables of the unit, the model can capture both the steady-state and dynamic properties of the unit well thus is very suited for controller design and test.

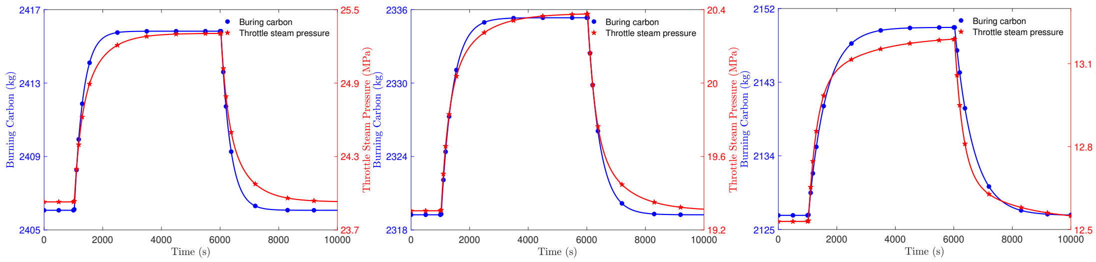
Large inertial, nonlinear, and strong multivariable coupling behavior of the unit can be clearly indicated through step response tests. Taking u_B for example, Figure 2 shows the step response at typical operation conditions. The evidence from this test suggests that unit takes more than 4000 s to reach steady-state when an increase in fuel command u_B is occurred. Meanwhile, it is also of interest to note u_B has an effect on all the outputs. Multivariable coupling should be taken into consideration when the control system is designed. Furthermore, the unit exhibits signs of nonlinearity since the amplitudes and time constants at different operation conditions are quite different from each other.



(**a**) Throttle steam pressure (**b**) Separator steam enthalpy (**c**) Active power

Figure 2. Outputs of a supercritical CFB unit when u_B increases by 5%.

We also investigate the character of burning carbon when the unit changes its load, as shown in Figure 3. Researchers have discussed the model of burning carbon in CFB unit [14,38]. Here we follow the model proposed in [14] because it can reflect the change tendency and is simple enough to satisfy the fast calculation requirement in real-time operation. Figure 3 indicates that burning carbon in the furnace is strongly related to the operation condition of the unit. Once the fuel flow command changes, the burning carbon varies accordingly. The second major finding is that burning carbon will reach the steady-state earlier than the throttle steam pressure when the fuel flow rate changes. This fact motivates us to make use of the burning carbon information to design the control system for the unit.



(**a**) High load (100%) (**b**) Medium load (70%) (**c**) Low load (40%)

Figure 3. Performance of burning carbon in a supercritical CFB unit when u_B increases by 5% at 1000 s and decreases by 5% at 6000 s.

3. Burning Carbon Based Decentralized Active Disturbance Rejection Control of a Supercritical CFB Unit

As mentioned previously, large inertial and unknown disturbances are the two main problems in the operation of the supercritical CFB boiler-turbine unit, therefore we propose a burning carbon based decentralized ADRC method to deal with both issues simultaneously.

3.1. Linear Active Disturbance Rejection Control

Without loss of generality, a class of nonlinear plant can be depicted by the following equation:

$$y^{(n)} = bu + f\left(y^{(n-1)}, y^{(n-2)}, \cdots, y\right) + d \tag{1}$$

where y is the measurable system output, u is the measurable control input, d is the unknown external disturbance, $f(\cdot)$ is the unknown internal (state-dependent and potentially nonlinear) dynamics of the process, and b is the unknown input scaling factor.

In order to design the input signal to make the output track the desired reference regardless of the unmodeled/unknown disturbance, the above system can be firstly augmented using a virtually extended state:

$$\begin{cases} y^{(n)} = b_0 u + \sigma \\ \dot{\sigma} = h \end{cases} \tag{2}$$

where b_0 is the approximation of b, σ represents the lumped disturbance including the unmodeled dynamics and external disturbance [32]:

$$\sigma = f(\cdot) + d + (b - b_0)\, u \tag{3}$$

It is assumed that σ is differentiable.

If the lumped disturbance is regarded as one dimensional state, we can define $x = [x_1, \cdots, x_n, x_{n+1}]^T = \left[y, y^{(1)}, \cdots, y^{(n)}, \sigma\right]^T$. So plant (2) can be described in the state space representation as

$$\begin{cases} \dot{x} = Ax + Bu + E\sigma \\ y = Cx \end{cases} \tag{4}$$

where

$$A = \begin{bmatrix} 0 & 1 & 0 & \cdots & 0 \\ 0 & 0 & 1 & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \cdots & 1 \\ 0 & 0 & 0 & \cdots & 0 \end{bmatrix}_{(n+1)\times(n+1)}$$

$$B = \begin{bmatrix} 0 \\ \vdots \\ 0 \\ b_0 \\ 0 \end{bmatrix}_{(n+1)\times 1}, \quad E = \begin{bmatrix} 0 \\ \vdots \\ 0 \\ 0 \\ 1 \end{bmatrix}_{(n+1)\times 1}$$

$$C = \begin{bmatrix} 1 & 0 & \cdots & 0 \end{bmatrix}_{1\times(n+1)}$$

For the extended system model (4), $(n+1)$-th order extended state observer (ESO) is designed to estimate the unknown lumped disturbance σ [39]:

$$\begin{cases} \dot{z} = Az + Bu + L(y - \hat{y}) \\ \hat{y} = Cz \end{cases} \tag{5}$$

where $z = [z_1, \cdots, z_n, z_{n+1}]^T = [\hat{x}_1, \cdots, \hat{x}_n, \hat{\sigma}]^T$ is the estimate of state x, $L = [\beta_1, \cdots, \beta_{n+1}]^T$ is the observer gain. If the gains $\beta_1, \cdots, \beta_{n+1}$ are chosen properly, the lumped disturbance σ can be estimated as well as the states x.

Then, the control law is designed as

$$u = \frac{-z_{n+1} + u_0}{b_0} \tag{6}$$

where u_0 is to be determined to meet the specific type of application. Since the estimate of the extended state z_{n+1} approximates the lumped disturbance σ, i.e., $z_{n+1} \approx \sigma$, when combining control law (6) with the plant (4) we get

$$y^{(n)} \approx u_0 \tag{7}$$

which reduces the uncertain plant (4) to a cascade form of integrators. The canonical form of cascade of integrators makes the system trivial to govern due to inherent robustness against any perturbation in the system [40,41]. One should notice that the plant is still under the influence of uncertainties, however, the impact on output is removed [40].

The derived model (7) can be effectively controlled by state feedback law [42]:

$$u_0 = k_1(r - z_1) + k_2(\dot{r} - z_2) + \cdots + k_n(r^{(n-1)} - z_n) \tag{8}$$

where r is the desired reference.

For convenience in industrial applications, the 1st and 2nd order linear ADRC are commonly used [33]. Taking the 1st order ADRC for example, it can be reduced from the general form (5), (6), and (8) to the following:

$$\begin{cases} \dot{z}_1 = z_2 + b_0 u + \beta_1(y - z_1) \\ \dot{z}_2 = \beta_2(y - z_1) \end{cases} \tag{9}$$

$$u = \frac{u_0 - z_2}{b_0} \tag{10}$$

$$u_0 = k_p(r - y) \tag{11}$$

Thus, for the 1st order ADRC we have four parameters to be determined, namely k_p, b_0, β_1, and β_2. Once the ADRC is well tuned, the system output can track the reference while overcoming the uncertainties. The structure of the 1st order ADRC is illustrated by Figure 4, where G_p denotes the transfer function of the controlled plant.

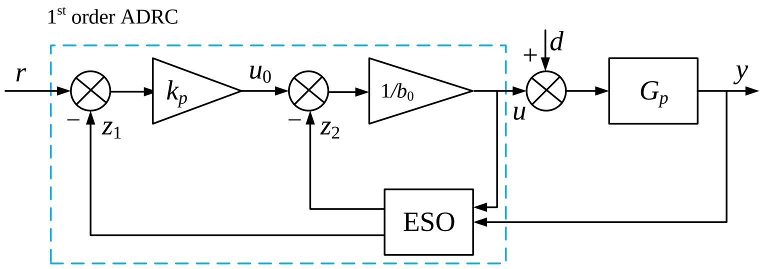


Figure 4. Structure of 1st order active disturbance rejection control.

3.2. Burning Carbon Based Decentralized ADRC for Supercritical CFB Boiler-Turbine Unit

Decentralized control is widely used in the industry process due to its simplicity. Instead of decentralized PID control, we propose the decentralized ADRC control for the supercritical CFB unit to improve the capability to follow load command in large-scale and enhance the capacity to unknown fuel variation. Figure 5 shows the designed control structure.

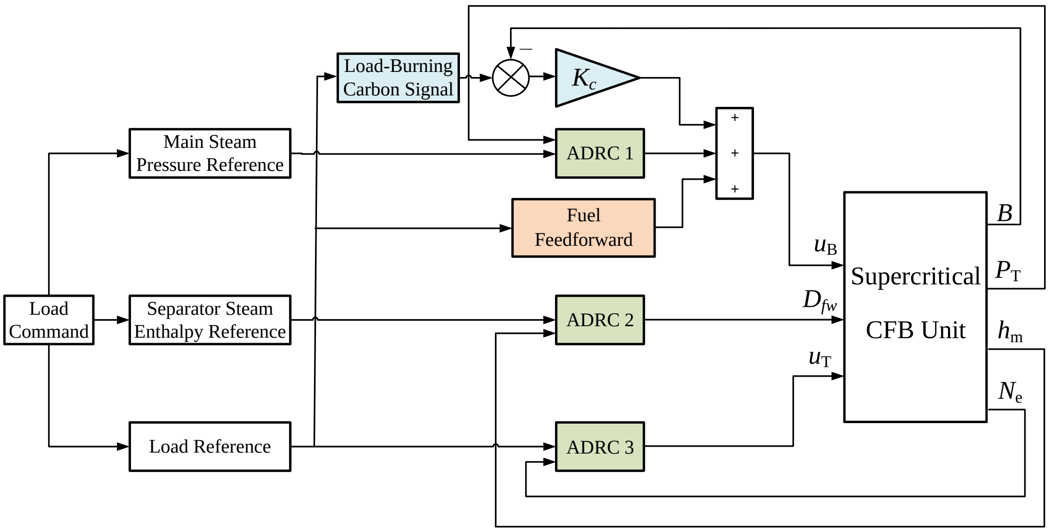


Figure 5. Structure of the burning carbon based decentralized active disturbance rejection control (ADRC) for a supercritical CFB unit.

In the proposed control structure, three ADRC controllers are devised for the individual loops. The ADRC controllers can not only alleviate the coupling of different loops, but also enhance the disturbance rejection performance. Fuel feedforward is included in this structure so that the output power can track the load command promptly. It is noted that we design the dynamic compensation for the fuel-main steam pressure loop based on the load-burning carbon signal. In the following, control of fuel-main steam pressure loop is analyzed. Its structure is shown in Figure 6.

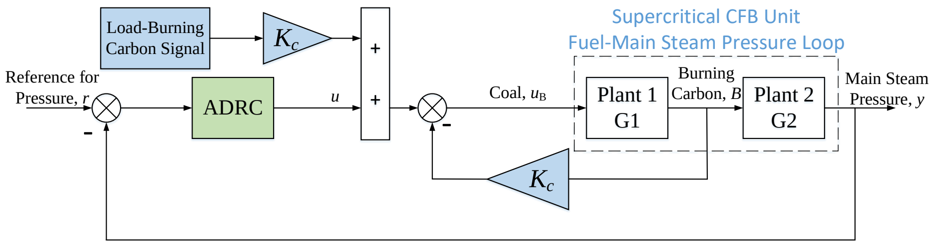


Figure 6. Control structure of fuel-main steam pressure loop based on load-burning carbon signal.

To illustrate the effectiveness of the dynamic compensation, the transfer function from coal to burning carbon is identified and used for analysis. The identified model $G_1 = \frac{K}{Ts+1}e^{-\tau s}$ at 100% and 40% operation conditions are:

$$\begin{aligned} G_{1(100)} &= \frac{6.0567}{306.1587s+1}e^{-28s} \\ G_{1(40)} &= \frac{29.6893}{591.5113s+1}e^{-28s} \end{aligned} \tag{12}$$

The dynamics of G_1 varies considerably at different operation conditions, including the gain coefficient and time constant. The large time constant in G_1 indicates the huge inertial in CFB boiler, especially when it is at low load operation condition. In addition, since $\frac{\tau}{T+\tau} < 0.08$ the effect of time delay can be ignored when we analyze the control structure. The load-burning carbon signal is precalculated based on past operation data.

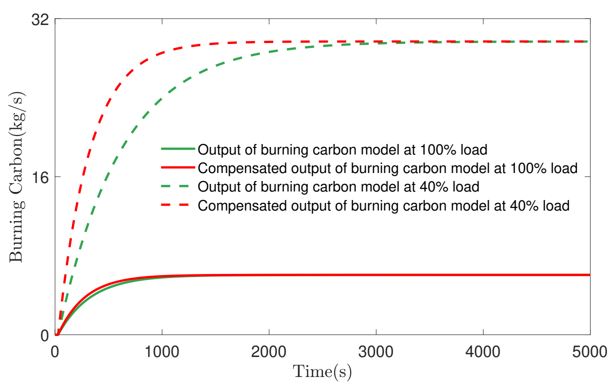
The equivalent transfer function from ADRC's output to burning carbon in (12) is

$$B'(s) \approx \frac{K\left(K_cK+1\right)}{Ts+K_cK+1}u \tag{13}$$

Compared with the original transfer function from burning carbon to ADRC's output,

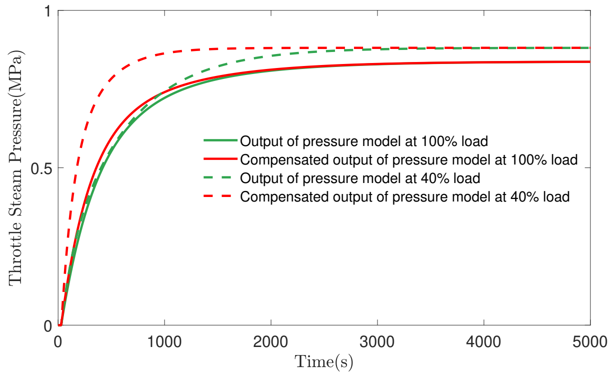
$$B(s) = \frac{K}{Ts+1}u \tag{14}$$

The pole is shifted left from $-\frac{1}{T}$ to $-\frac{K_cK+1}{T}$ when $K_c > 0$. Also, both (13) and (14) have the same static gain K. Thus, the compensated burning carbon could be accelerated. Figure 7 shows the unit step response of the compensated burning carbon and throttle steam pressure model at different loads, in which $K_c = 0.03$. It can be found that dynamics at low load is more compensated.



(**a**) Unit step response of the compensated burning carbon

Figure 7. *Cont.*



(**b**) Unit step response of the compensated throttle steam pressure

Figure 7. Unit step response of the compensated burning carbon and throttle steam pressure model at different loads.

The load-burning carbon signal is constructed according to the steady-state values of burning carbon at different operation conditions in advance. Based on the compensated fuel-main steam pressure loop, we design the decentralized ADRC controllers for the multi-input-multi-output (MIMO) supercritical CFB unit.

4. Tuning of ADRC Controllers

The performance of the ADRC controller is greatly affected by parameters b_0 in (10), k_p in (11), and β_1, β_2 in (9). Therefore, there are overall twelve parameters for the decentralized controllers to be optimized.

Genetic algorithm is a global search method that mimics the process of natural selection. It is one of the most well-known heuristic optimization methods, and has been used in various research areas [43]. In this research, the parameters in the decentralized ADRC controllers are optimized by GA.

To evaluate the control performance, the integrated absolute error (IAE) index is used,

$$\mathrm{IAE} = \int_0^T |e(t)|dt \tag{15}$$

where $e(t)$ is the tracking error of the controlled variable. IAE tends to produce responses with less sustained oscillation. For the MIMO CFB unit, there are three controllers to be optimized. To obtain the trade-off between different loops, the fitness function for GA is defined as the weighted sum of each IAE,

$$J = \sum_{i=1}^{3} \omega_i \cdot \mathrm{IAE}_i \tag{16}$$

where i denotes the i-th loop in CFB unit.

The optimization flowchart can be depicted as Figure 8.

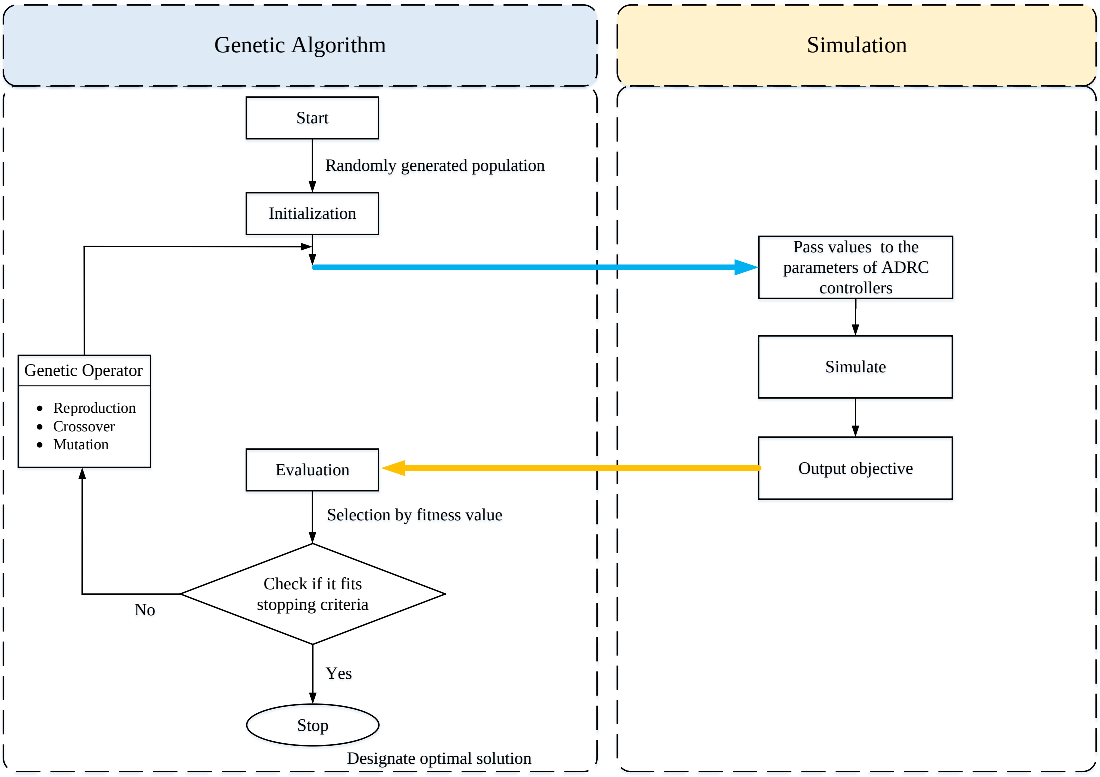


Figure 8. Flowchart of genetic algorithm based ADRC controller.

5. Simulations

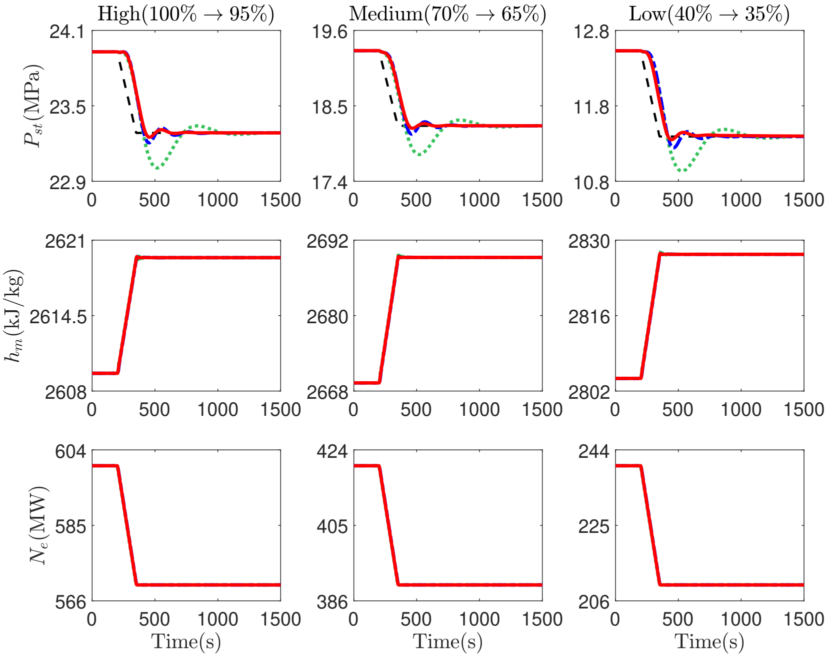
In this section, the proposed burning carbon based decentralized ADRC is employed to control the supercritical CFB unit. Simulations under different scenarios, i.e., load tracking at different operation conditions and disturbance rejection, are performed to test the proposed method.

The simulation configuration of the burning carbon based decentralized ADRC of supercritical CFB unit is shown in Figure 5. The nonlinear dynamic model developed in [14] functions as the real plant since its dynamics has been tested by operation data. The fuel feedforward plays an important role in the boiler-turbine unit control. We design this feedforward signal based on the history steady-state data of the supercritical CFB unit so that it corresponds to the target load. The load-burning carbon signal is constructed based on the steady-state values of burning carbon at different operation conditions. The compensated gain K_c equals 0.03. As analyzed in Section 3.2, the introduced burning carbon can compensate the dynamics of the fuel-main steam pressure loop. The distributed ADRC controllers has been devised according to Equations (9) to (11). The parameters of the ADRC controllers are tuned by GA, the procedures of which are depicted in Section 4. The settings of GA are such that population size is chosen as 100, generation is 50, crossover fraction is 0.6, and individuals that are guaranteed to survive to the next generation are 10.

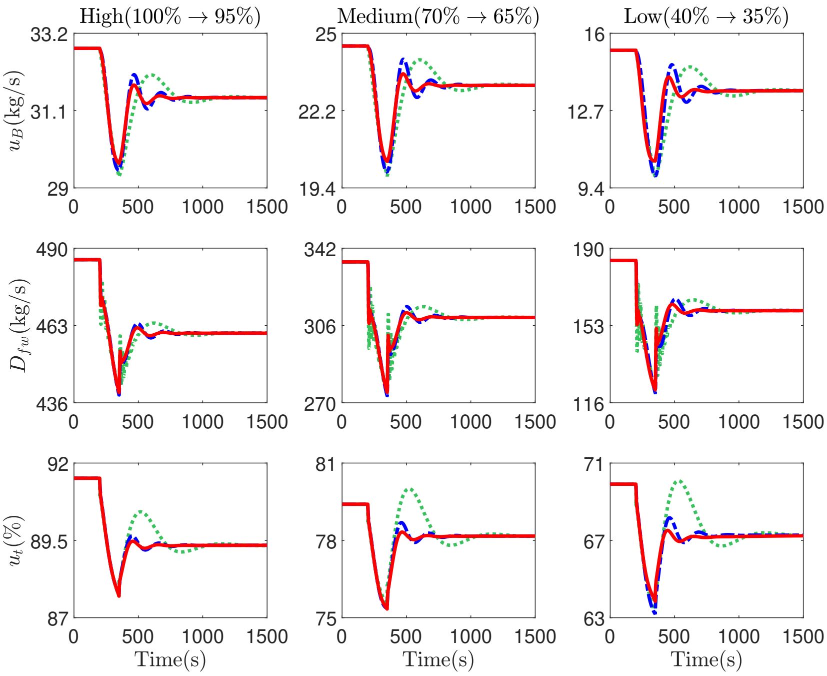
The proposed method is compared with two others, namely decentralized PI [16] and decentralized ADRC [37]. Both of them have the same fuel feedforward used in the proposed method. In addition, the controllers in these two methods are separately tuned by GA with the same settings. The differences in performance are expected to be found among the above three methods.

5.1. Load Tracking

The first case is designed to test the wide range load following performance of the controllers. The unit is assumed to decrease and increase at the rate of 2%/MCR/min at high (100%)/medium (70%)/low (40%) operation conditions, respectively. The results are shown in Figures 9 and 10.

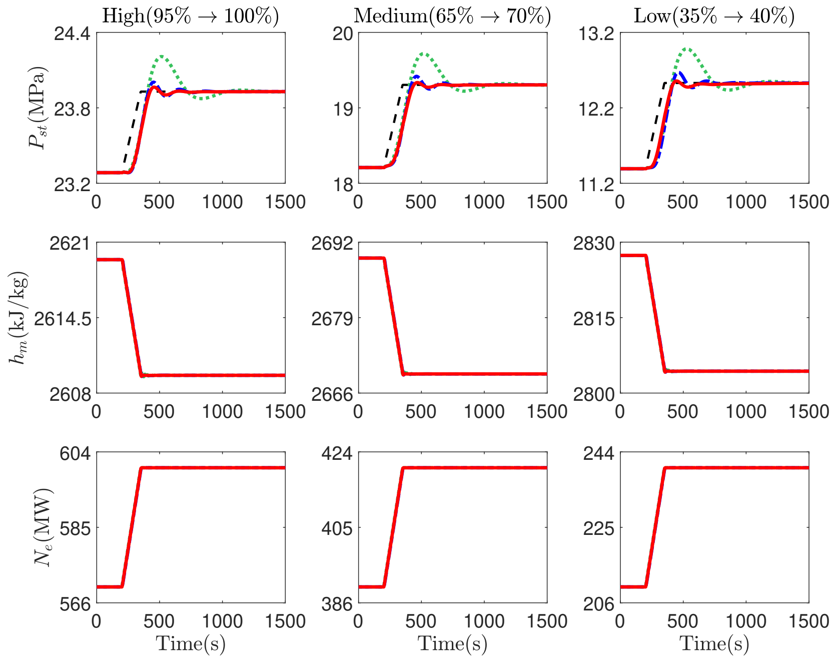


(**a**) Controlled variables (solid line: burning carbon based decentralized ADRC, dash-dotted line: decentralized ADRC, dotted line: decentralized PI, dashed line: reference).

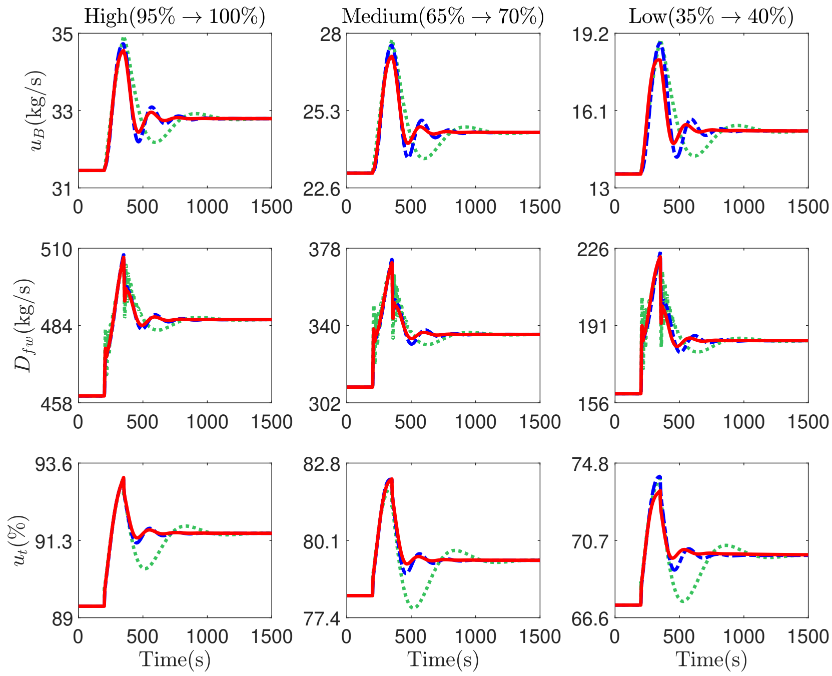


(**b**) Manipulated variables (solid line: burning carbon based decentralized ADRC, dash-dotted line: decentralized ADRC, dotted line: decentralized PI).

Figure 9. Load following performance of supercritical CFB unit at typical conditions (load decrease).



(**a**) Controlled variables (solid line: burning carbon based decentralized ADRC, dash-dotted line: decentralized ADRC, dotted line: decentralized PI, dashed line: reference).



(**b**) Manipulated variables (solid line: burning carbon based decentralized ADRC, dash-dotted line: decentralized ADRC, dotted line: decentralized PI).

Figure 10. Load following performance of supercritical CFB unit at typical conditions (load increase).

The simulation results indicate that all three decentralized control methods can regulate the supercritical CFB unit and make the unit follow the command from grid. When the controllers are well tuned, both the output power N_e and separator steam enthalpy h_m can closely track the references. The major difference is the control performance in throttle steam pressure P_{st}, and the transient response criteria are listed in Tables 2 and 3.

Table 2. Transient response criteria of throttle steam pressure for the supercritical CFB unit at typical conditions (load decrease).

	Decentralized PI			**Decentralized ADRC**			**Burning Carbon Based Decentralized ADRC**		
	High	**Medium**	**Low**	**High**	**Medium**	**Low**	**High**	**Medium**	**Low**
Overshoot (%)	1.20	2.30	4.02	0.23	0.55	1.14	0.28	0.84	0.62
Settling time (s)	793.4	798.8	829.0	487.4	492.6	508.7	397.1	397.1	405.3

Table 3. Transient response criteria of throttle steam pressure for the supercritical CFB unit at typical conditions (load increase).

	Decentralized PI			**Decentralized ADRC**			**Burning Carbon Based Decentralized ADRC**		
	High	**Medium**	**Low**	**High**	**Medium**	**Low**	**High**	**Medium**	**Low**
Overshoot (%)	1.16	2.15	3.62	0.20	0.49	0.98	0.25	0.80	0.50
Settling time (s)	789.3	794.7	823.8	484.1	488.7	504.6	398.9	396.0	404.3

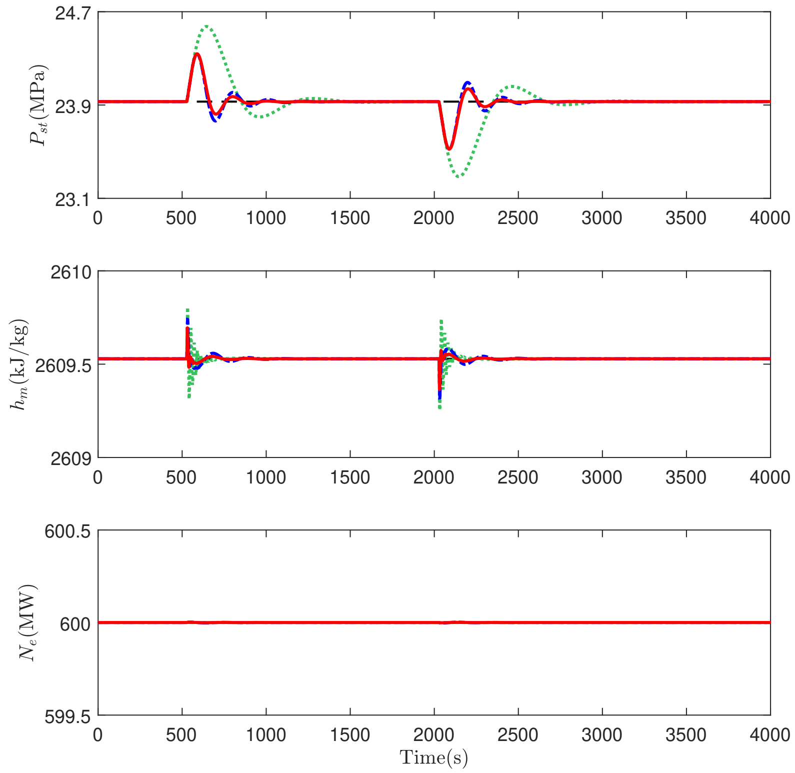
Decentralized PI control [16] with fuel feedforward is widely used in the real power plant. However, it takes the longest time for the throttle steam pressure to reach the steady-state. On the contrary, decentralized ADRC control [37] with fuel feedforward provides notable improvement. Since the coupling between the loops is regarded as disturbance and compensated by ADRC, its settling time is shortened while the overshoot is reduced.

The settling time of throttle steam pressure can be further improved under the proposed burning carbon based decentralized ADRC. As analyzed in Section 3.2, the burning carbon based compensated method ameliorates the dynamics of fuel-main steam pressure loop. The devised ADRC controller can result in a faster tracking performance. According to Tables 2 and 3, the settling time is about 50% less than that of decentralized PI method [16], and about 19% less than that of decentralized ADRC method [37]. In addition, it can be observed that the improvements of settling time at low load region is larger than that at high/medium load region. This is due to the fact that dynamics at low load are more compensated, as shown in Figure 7.

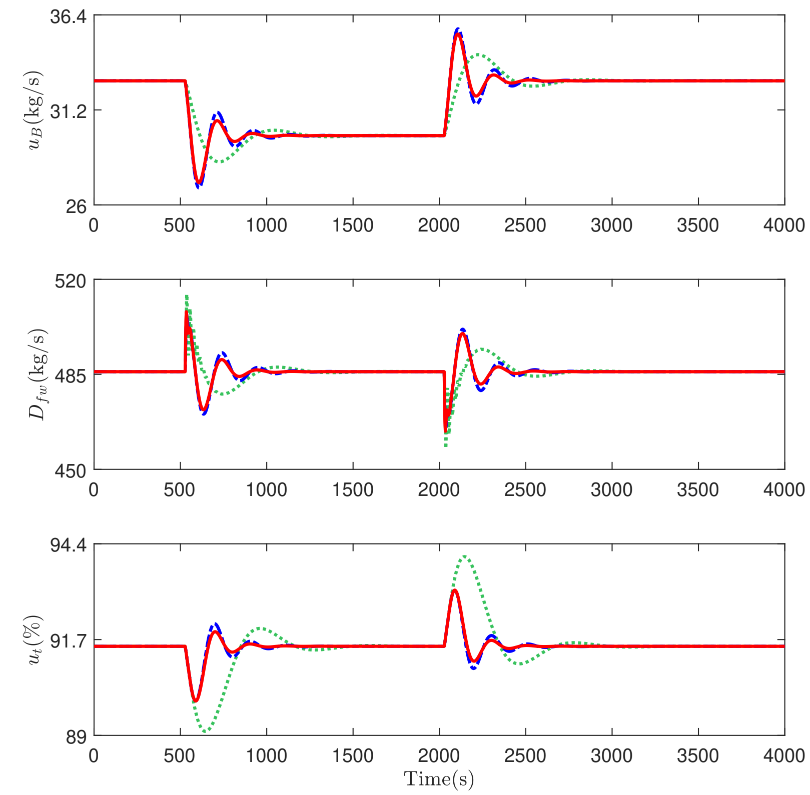
5.2. Disturbance Rejection

To further verity the disturbance rejection performance, a significant unknown step-type disturbance in fuel is considered in this case. This disturbance is common in coal-fired power plants because of the variability of coal. The unit is assumed to operate at 100% condition, and at $t = 500$ s the step-type disturbance $d = 3$ kg/s is acted on u_B, at $t = 2000$ s the step-type disturbance $d = -3$ kg/s is acted on u_B. The controllers are the same with those optimized in last case. The results are shown in Figure 11.

The results show that all these methods can remove the impact of the fuel disturbance, especially on the throttle steam pressure. However, decentralized PI [16] provides the slowest response because the integral action works on the bias between the output and the reference. Both decentralized ADRC [37] and the proposed burning carbon based decentralized ADRC method use the ESO to estimate the lumped disturbance and reject it according the principle of ADRC. Thus, the disturbance rejection is prompt and effective. The proposed burning carbon based decentralized ADRC is lightly better in terms of less settling time and overshoot.



(**a**) Controlled variables (solid line: burning carbon based decentralized ADRC, dash-dotted line: decentralized ADRC, dotted line: decentralized PI, dashed line: reference).



(**b**) Manipulated variables (solid line: burning carbon based decentralized ADRC, dash-dotted line: decentralized ADRC, dotted line: decentralized PI).

Figure 11. Disturbance rejection of the supercritical CFB unit under unknown fuel variation.

6. Conclusions

To achieve a sustainable future for renewable energy and integrate more renewable energy into the power grid, increasing the operational flexibility of supercritical power plants plays a crucial role in power systems.

The coordinated control system of the supercritical CFB unit is designed to harmonize the boiler's slow dynamics with the turbine's fast dynamics so as to meet the power grid's demand and maintain the parameters of the unit within the safe range. Since the burning carbon circulates in the boiler and releases the energy gradually, it can affect the change of the heat provided by the boiler and the impact of fuel variation on unit load. To this end, we make use of the burning carbon information to compensate the dynamics of the fuel-throttle pressure loop and reduce the regulating time.

In this research, we propose the burning carbon based decentralized ADRC for the operation of the supercritical CFB unit. The dynamics of the supercritical CFB unit, including the controlled variables and burning carbon in furnace, are analyzed on the basis of step response. One interesting finding is that burning carbon responds faster than the throttle steam pressure when the fuel flow rate changes. We utilize the burning carbon information to design the decentralized ADRC to reduce the influence of the large inertia of the supercritical CFB unit. A genetic algorithm is employed to optimize the controllers of the multivariable unit using a weighted integrated absolute error index. Through simulations of the supercritical CFB unit, it is demonstrated that the proposed method can notably reduce the settling time and maintain the disturbance rejection capability. These advantages benefit from the capacity of the well-tuned active disturbance rejection controllers and the utilization of burning carbon information. Consequently, a particular attention should be paid to the fast calculation of the burning carbon, as well as the steady-state values.

Applying the proposed method to the realistic supercritical CFB unit will be our future interest. Some practical issues should be taken into consideration, e.g., the implementation of the proposed method in the distributed control system of the power plant, and the tracing and undisturbed switching logic between controllers.

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Abbreviations

The following abbreviations are used in this manuscript:

ADRC	Active Disturbance Rejection Control
CFB	Circulating Fluidized Bed
CCS	Coordinated Control System
DDE	Desired Dynamic Equation
DOB	Disturbance Observer
ESO	Extended State Observer
GA	Genetic Algorithm
IAE	Integrated Absolute Error
MIMO	Multi-Input-Multi-Output
PID	Proportional-Integral-Derivative

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