Enhanced decentralized PI control for fluidized bed combustor via advanced disturbance observer

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A B S T R A C T
Motivation of this paper is to propose an engineering friendly control strategy to handle the various difficulties in fluidized bed combustor (FBC). The control objectives of FBC and the difficulties arisen from nonlinear dynamics, frequent disturbances and strong coupling are first formulated. The capability of the disturbance observer (DOB) to handle the nonlinearity and disturbances is analyzed and the decoupling effect of DOB is revealed in terms of equivalent transfer function. For the power loop, a robust loop shaping design method is proposed to balance the performance and robustness of DOB. For the temperature loop, the DOB filter is designed based on H∞ optimization. Abilities of DOB are confirmed by numerical simulations. A water tank experiment is designed to show the simplicity of implementing DOB in an industrial Distributed Control System. Finally, a global simulation on the FBC process demonstrates that, compared with the conventional PI scheme, the DOB-enhanced PI strategy achieves overall improvement and can even be comparable with the complex Model Predictive Control in some aspects.

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1. Introduction

Fluidized bed combustor (FBC) boilers have been developed increasingly in recent decades as an advanced clean coal technology (Ozdemir, Hepbasli, & Eskin, 2010). It facilitates burning of a wide variety of fuels with high combustion efficiency, especially for low-grade coal. The FBC was developed to strive for a combustion condition, under which the pollutant emissions can be reduced significantly without a chemical scrubber. The burning temperature of such technology is within the range of 750–950 °C, exactly out of the range where nitrogen oxides form so that the amount of NOx emission is just 1/3–1/4 of that in a conventional pulverized coal plant. Thus, bed temperature regulation, along with strong capacity of load tracking, is critical to reduce pollutant emissions.

However, essentially, the FBC can be described as a typical multivariable system with almost all the difficulties found in process control, i.e., nonlinearities, strong couplings, various internal and external disturbances, non-minimum phase (NMP), and time delay. These difficulties result in enormous hardships on controller design. The conventional decentralized proportional-integral (PI) control scheme is thus powerless in achieving satisfactory performance under such extreme circumstances. Many researchers (Aygun, Demirel, & Cernat, 2012; Hadavand, Jalali, & Famouri, 2008; Leimbach, 2012; Ćojbašić, Nikolić, Ćirić, & Ćojbašić, 2011; Sun, Pan, & Shen, 2013; Zhang, Feng, Lu, & Xiang, 2008) have worked on various advanced control schemes for FBC processes to accommodate some of the difficulties. Aygun and Demirel proposed a particle swarm optimization (PSO) algorithm to optimize the proportional-integral-derivative (PID) controllers for the bed temperature (Aygun et al., 2012). An H∞ control algorithm based on linear matrix inequalities (LMI) was also proposed in Hadavand et al., (2008) to improve the performance of the bed temperature. However, strong interactions between power and bed temperature were not considered. Intelligent control strategies (Leimbach, 2012; Ćojbašić et al., 2011) were also introduced to facilitate the reference tracking of FBC boiler. But, there are few relevant literatures taking into an explicit consideration of the NMP characteristics in the FBC system. Model predictive control (MPC), which is widely recognized as a powerful strategy in handling decoupling, reference tracking and time delays, also received considerable attention in the FBC control (Sun et al., 2013; Zhang et al., 2008). However, the conventional or improved MPCs are usually subject to a great deal of calculation, which makes it not feasible for the contemporary Distributed Control System (DCS) in power plant. Compared with the
conventional PI controller, MPC usually requires an additional computer, such as high-performance Programmable Automation Controller (PAC), to calculate the control signals and then communicate with DCS. Inevitably, it brings more hardware uncertainties into the system, which is unacceptable for practitioners because they always consider the long-term reliability as their primary concern.

The long-term running of FBC boiler is also subject to various disturbances, such as variations in the calorific value of feed coal, changing moisture content of the primary air, and slagging or erosion on the water wall. These disturbances, together with plant perturbations under different working conditions, deteriorate the performance of the FBC process. Although previous researches mainly focused on the reference tracking issue, they paid little attention to the disturbance rejection.

As is well known, the basic PID controller, actually in most cases PI controller, is still dominant in power generation for its simplicity and ease of use (Xue, Li, & Gao, 2010). This paper attempts to accommodate all the aforementioned control difficulties within the framework of conventional decentralized PI scheme with the assistance of the disturbance observer (DOB) (Umeno & Hori, 1991). While PI controllers are responsible for the zero-offset reference tracking, the other control difficulties are expected to be handled by the DOB, whose enhancement role is embodied as:

- The quasi feed-forward compensator which can estimate the disturbances and then reject it actively;
- The plant re-shaper which can recover the nonlinear plant as the nominal linear model in the wide operating range;
- The dynamic decoupler which requires lower modeling accuracy than conventional methods.

With the advantages above, the DOB approaches have been widely utilized in many practical applications (see Chen, Yang, Li, and Li (2009), Li, Qiu, Ji, Zhu, and Li (2011), Liu Chen, and Andrews (2012) and references therein). In a traditional explanation of the DOB’s decoupling ability, interaction is assumed as a part of the total disturbance, which should be observed by DOB and then rejected. This paper will clarify the decoupling ability by bridging DOB to the well-known inverted decoupling structure. Considering the slow dynamics, time delay and NMP feature of the FBC boiler, the standard DOB is modified to achieve an improved performance. A water tank experiment is carried out to test the realizability of the proposed strategy in the DCS.

The feature that makes the proposed method distinct from other advanced algorithms is attributed to the engineeringfriendliness. The proposed strategy needs negligible amount of computation and is completely compatible with already existing control systems. The DOB can be embedded into the DCS in a bumpless manner without the necessity of retuning the PI parameters. The remainder of the paper is organized as follows: the control difficulties in the FBC system are formulated in Section 2. Section 3 analyzes the capability of DOB in dealing with the disturbances, nonlinearity and coupling as well as the time delay and NMP characteristics. In Section 4, a numerical simulation and experimental test is given to confirm the effectiveness and implementability of DOB. A comparative simulation of the FBC application is carried out in Section 5 and conclusions are drawn in Section 6.

2. Problem formulation

2.1. Overview of fluidized Bed combustion technology

Fluidized bed suspends coal particles on continuous updraft of primary air during the combustion process, which leads to an intensive mixing of solid fuel and gas. The turbulent condition, similar to a bubbling fluid, leads to a higher efficiency for the chemical reactions and heat transfer. The schematic of a FBC boiler is shown in Fig. 1. A mixture of inert/sorbent bed material and solid fuel is fluidized by the primary air entering from below. Secondary air is injected above the fuel bed to ensure complete gas burning out. However the total amount of air should be limited due to economic efficiency. The heat released in combustion is captured by heat exchangers to convert the circulating water to the steam.

2.2. Control objectives

The past two decades has witnessed a rapid development of the renewable energy generation. However the intermittent characteristics of the sustainable source make it more challenging to maintain power grid stability. The conventional fossil fuel generation should thus bear more responsibility in the primary frequency regulation of power grid. In light of this background, the control objectives of FBC boiler is listed below in a descending order of importance:

I. The thermal power output of the boiler should track the reference load commanded by the turbine.
II. The bed temperature should be adjusted correspondingly to a reasonable value.
III. The power output and the bed temperature should be as insensitive as possible to the furnace disturbances.

The first requirement is set for the real-time balance of the power grid or microgrid and the second for the environmental and economic purposes. Although the temperature range between 750 °C and 950 °C can prevent the formation of NOx, a particular value is usually preferred for the combustion efficiency. Now the third requirement is attracting considerable attention in engineering practice but less from the academic community. Without proper treatment, the variation of the coal quality, i.e., the heat value perturbation, may make the boiler outputs deviate from the desired value significantly.

![Fig. 1. A schematic of a typical fluidized bed combustor.](image-url)
2.3. Dynamic model of FBC boiler

Zhou, Flament, and Gauthier (2004) set up an elaborate model of FBC to describe the complex turbulent characteristics based on the 2-D Navier–Stokes equations. However, the equations are expected to be solved by the numerical method of large eddy simulation (LES), whose computational complexity makes it inappropriate for a control simulation platform. Due to the turbulent characteristics of the FBC furnace, the plug flow model is also not applicable. Ikonen and Kortela (1994) proposed a simple dynamic bubbling FBC model by separating the whole furnace as two interconnected regions, bed and freeboard. By assuming each region as a continuous stirred-tank reactor (CSTR), the balance equations were built based on the first law of thermodynamics. This simple model was validated by a 30 MW pilot coal combustor region from 19 MW to 28 MW, covering the normal operating range of the FBC boiler. To achieve a balance between fidelity and simplicity, the model was slightly modified as follows (Ikonen & Najim, 2001; Sun, Dong, Li, & Zhang, 2014):

Dynamics of fuel inventory, \( W_C \) [kg]:

\[
\frac{dW_C(t)}{dt} = (1 - V)Q_C(t) - Q_B(t)
\]

(1)

Dynamics of bed oxygen content \( C_F \) [N m\(^3\)/N m\(^3\)]:

\[
\frac{dC_F(t)}{dt} = \frac{1}{V_B}[C_F(t)F_1(t) - Q_B(t)X_C - C_F(t)F_1(t)]
\]

(2)

Dynamics of freeboard oxygen content, \( C_F \) [N m\(^3\)/N m\(^3\)]:

\[
\frac{dC_F(t)}{dt} = \frac{1}{V_F}[C_F(t)F_1(t) + C_F(t)V_C(t)X_Y - C_F(t)F_1(t) + F_2(t)]
\]

(3)

Dynamics of bed temperature, \( T_B \) [K]:

\[
\frac{dT_B(t)}{dt} = \frac{1}{C_JW_I} \left\{ H_C Q_B(t) + c_F F_1(t)T_1 - a_B A_B [T_B(t) - T_B] - C_F(t)T_B(t) \right\}
\]

(4)

Dynamics of freeboard temperature, \( T_F \) [K]:

\[
\frac{dT_F(t)}{dt} = \frac{1}{C_JF_F} \left\{ H_C V_C Q(t) - a_B A_B [T_F(t) - T_N] + c_F F_1(t)T_B(t) + c_F F_2(t)T_2(t) + c_L F_1(t)F_2(t) \right\}
\]

(5)

Dynamics of thermal power, \( P \) [MW]:

\[
\frac{dP(t)}{dt} = \frac{1}{\tau_{\text{mix}}} [P_C(t) - P(t)]
\]

(6)

where the combustion rate in bed, \( Q_B \) [kg/s], is \( Q_B(t) = W_C(t)C_F(t)/(\tau_C C_I) \), and the combustion power, \( P_C \) [MW], is

\[
P_C(t) = 10^{-6}[H_C Q_B(t) + H_Y V_C Q(t)].
\]

The parameter settings can be found in Appendix.

According to the control objectives, manipulated inputs are determined as fuel feed \( Q_C \) [kg/s] (denoted as \( u_1 \)) and primary air flow \( F_1 \) [N m\(^3\)/s] (denoted as \( u_2 \)). Controlled variables are accordingly determined as output power \( P \) [MW] (denoted as \( y_1 \)) and bed temperature \( T_B \) [K] (denoted as \( y_2 \)). Freeboard oxygen content, \( C_F \), which can easily be controlled by secondary air, is relatively independent. It is found that delay is negligible for air flow, but 20 s delay is necessary for fuel transport. Hereby a standard nonlinear model for control can be derived from (1)–(6) as:

\[
\begin{align*}
\dot{x} &= f(x, u) \\
y &= h(x)
\end{align*}
\]

(7)

where, \( x = [W_C \ C_B \ C_F \ T_B \ F_1 \ y] \) and \( u = [Q_C(t - 20) \ F_1]^T \). Some representative operating conditions are shown in Table 1.

<table>
<thead>
<tr>
<th>Operating condition</th>
<th>( Q_C ) [kg/s]</th>
<th>( F_1 ) [N m(^3)/s]</th>
<th>( P_C ) [MW]</th>
<th>( T_B ) [K]</th>
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<td>20.25</td>
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<td>22.04</td>
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<td>3.69</td>
<td>24.31</td>
<td>1049</td>
</tr>
<tr>
<td>5</td>
<td>3.12</td>
<td>3.73</td>
<td>25.34</td>
<td>1070</td>
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<td>3.43</td>
<td>3.82</td>
<td>27.81</td>
<td>1123</td>
</tr>
</tbody>
</table>

2.4. Control difficulties

In this section, the difficulties for FBC control will be analyzed in detail. The first one obviously originates from the time delay in the fuel feed loop which will strictly limit the closed-loop bandwidth (Aström & Hagglund, 2006).

To further illustrate the difficulties, the model (7) is linearized around operating condition 4:}

\[
\begin{bmatrix}
Y_1(s) \\
Y_2(s)
\end{bmatrix} =
\begin{bmatrix}
G_{11}(s) & G_{12}(s) \\
G_{21}(s) & G_{22}(s)
\end{bmatrix}
\begin{bmatrix}
U_1(s) \\
U_2(s)
\end{bmatrix}
\]

(8)

An obvious distinction caused by nonlinearity can be seen in the step-input responses of the original and locally linearized model, are shown in Fig. 2. The strong coupling is also evident. The fuel feed \( u_1 \) can significantly affect the power and the temperature simultaneously. Although the primary air \( u_2 \) only influences the static value of the temperature, it may help release the thermal storage in the bed and result in a power peak. The action of primary air could raise the output power rapidly by releasing bed heat storage at the very start while causing no effects at the end.

To quantitatively measure the nonlinearity of the system and provide guidance for reference setting, the gap metric for multi-variable system (Tan, Marquez, Chen, & Liu, 2005) is used, which is defined as

\[
\delta_N = \sup_{L_N} \| \delta_{\text{lin}}(L_N) \|
\]

(9)

where, \( L_N \) is the nominal linear model of the nonlinear system \( N \), and \( L_N \) is the linearization of \( N \) at an operating point \( r_0 \). The gap metric \( \delta \) in (9) is defined as:

\[
\delta(P_1, P_2) = \max (\delta(P_1, P_2), \delta(P_2, P_1))
\]

(10)

where \( \delta(P_1, P_2) \) and \( \delta(P_2, P_1) \) are the directed gaps. When two linear systems are represented by normalized coprime factorizations as \( P_1 = N_1 M_1^{-1} \) and \( P_2 = N_2 M_2^{-1} \), the directed gap \( \delta(P_1, P_2) \) can be computed by

\[
\delta(P_1, P_2) = \inf_{Q, \xi} \| M_1 - N_1 Q \|_{\infty}
\]

(11)

It follows that the closer the distance to 1, the stronger is the nonlinearity of the system. In this paper, the intermediate operating condition 4 is chosen as the nominal model for controller design. Fig. 3 shows the gap metric between the nominal model and linearized models at other operating conditions around it. Note that the nominal condition 4 is in the center of the varied range. It is obviously seen that the nonlinearity increases with the distance deviating from the nominal model. The resulting worst-case gap metric \( \delta_N \) is 0.91, which represents a quite strong nonlinearity of the FBC system.

The valley existing in Fig. 3 shows that the nonlinearity measure can be somewhat attenuated by increasing or decreasing the fuel feed and primary air simultaneously. This intuitive phenomenon happens to agree with the reference settings of
temperature and power for optimal combustion efficiency. Since the nonlinearity measures of operating conditions below and above '4' are approximately symmetric, the simulation will be carried out from condition '4'–'8' gradually in Section 5.

In addition to time delay, nonlinearity and strong coupling, another difficulty is raised by the non-minimum phase (NMP) characteristics, which is shown visually via the inverse response of the bed temperature [see Fig. 2(b)]. A set of field data from a 300 MW circulating fluidized bed boiler in north China also confirms the inverse response of the bed temperature, shown in Fig. 4. The theoretical difficulty of the NMP control is attributed to its additional phase lag (Zhao, Sun, Li, & Gao, 2014). However here a nice physical interpretation can be made. In the initial period of the step response of the primary air, the suddenly injected air will help blow out the pulverized coal stacked in the bed and then burn out to release the heat, therefore, the bed temperature increases rapidly. However, since the storage is non-sustainable and more heat is brought away by the air, the bed temperature will eventually decrease in the steady state.

3. Analysis and advanced design of disturbance observer

This section attempts to demonstrate the ability of disturbance observer to accommodate the difficulties discussed above.

3.1. Disturbance observer

The general disturbance observer (DOB) is presented in Fig. 5. Its capabilities in dealing with external disturbances, modeling uncertainties, time delay and NMP was analyzed detailed in (Sun, Li, & Lee, 2015). Signals $c(s)$, $u(s)$, $y(s)$ and $n(s)$ are the controller output, the manipulated variable, the controlled variable and the sensor noise, respectively. The process is decomposed into a
minimum phase function, $P_m(s)$, and a non-reversible function, $P_l(s)$, which may contain time delay and NMP elements with unity gain. The linear transfer function $P_{m}(s)$ is the nominal model of $P_m(s)$. Here the process nonlinearity is treated as modeling uncertainty beyond $P_m(s)$. The low-pass filter $Q(s)$ with unity gain is used to ensure the properness of DOB.

In the model matching case, $\hat{P}_m(s) = P_m(s)$, the DOB is transparent to the outer controller (i.e., it does not affect the dynamics from $c(s)$ to $y(s)$). Based on Mayson’s rule, the closed-loop transfer function from the disturbance $d$ to its estimation $\hat{d}$ is derived as:

$$D(s) = \frac{\hat{d}(s)}{d(s)} = \frac{Q(s)P_l(s)}{1 - Q(s)P_l(s)} = \frac{Q(s)P_l(s)}{1}$$. \hfill (12)

Since $Q(s)P_l(s)$ is of unity gain, the disturbance observer can provide a reasonable estimation of the real disturbance.

For analysis on the modeling uncertainty, an equivalent form of Fig. 5 is derived in Fig. 6. The transfer function from $c(s)$ to $y(s)$ can be easily calculated as:

$$G_{cy}(s) = \frac{P_m(s)P_l(s)}{(1 - \alpha(s))P_m(s) + \alpha(s)P_l(s)}$$. \hfill (13)

where, the weighting factor $\alpha(s) = Q(s)P_l(s)$ determines the normalization performance of DOB. If $\alpha(s)$ can be shaped to equal to zero in the frequency range of interest, the new equivalent plant $G_{cy}(s)$ can be recovered as the nominal model $P_m(s)P_l(s)$.

### 3.3 Decoupling ability

In addition to the abilities above, the decoupling effect of DOB has also been observed in many applications (Chen et al., 2009; Sun et al., 2015). It is, however, not clear that why, how and in what condition the decoupling ability exists. Here, the two-input two-output (TITO) minimum phase process is taken as an example, as shown in Fig. 7(a). Both loops are compensated by a disturbance observer, where $\hat{g}_{11}$ and $\hat{g}_{22}$ are the nominal models of $g_{11}$ and $g_{22}$, respectively.

As shown in Fig. 7(b), the output signal $y_{11}(s)$ is divided into two parts $y_{11}(s)$ and $y_{12}(s)$, which are assumed to be sent to DOB separately. It is interesting to see that the resulting $u_{11}$ happens to be an inner loop enhanced by DOB, whose transfer function at low frequencies can be approximated as:

$$G_{u_{11}y_{11}}(s) = \frac{\hat{g}_{11}(s)}{Q(s)[\hat{g}_{11}(s) - \hat{g}_{11}(s)]\hat{g}_{11}(s)} \approx \hat{g}_{11}(s)$$. \hfill (14)

The final equivalent block diagram is thus obtained in Fig. 7(c), which is identical to the classical dynamic decoupling method, namely inverted decoupling (Wade, 1997). If there are model uncertainties in the process, the DOB-based approach will possess robustness advantages because the diagonal elements of the process are normalized as the model and non-diagonal elements are not required in the DOB scheme. Actually it is the poor robustness that limits the implementation of inverted decoupling in industry (Garduno-Ramirez & Lee, 2005). In the presence of time delay or NMP in the process, the decoupling ability of DOB will degrade but still remains partly. The disturbance observer can at least work as a static decoupler because $P_l(s)$ is of unity gain.

### 3.3. The DOB design for time-delay processes

The conventional Q filter of DOB was usually chosen as below:

$$Q(s) = \frac{1}{(1 + Ts)^n}$$ \hfill (15)

For motion control or other processes with fast dynamics, the order $n$ was tuned to obtain a proper observer and the time constant $T$ was usually determined by a desired bandwidth. However for the fuel-thermal power loop ($G_{11}$) with time-delay and slow dynamics, such a design may produce a quite sluggish response though the time constant is chosen sufficiently small. The reason is that, as shown in (12), the disturbance can only be observed after the time delay and then the compensation has to go through the slow process. To this end, a lead-lag module is introduced to accelerate the response of disturbance rejection by artificially creating an overshoot in disturbance estimation. That is, the Q filter is designed as:

$$Q(s) = \frac{1 + j\omega T_f s}{(1 + j\omega T_f s)(1 + j\omega T_1 s)}$$. \hfill (16)

Tuning of $T_f$ is determined by the expected settling time of the overshoot. A larger $\omega$ may lead to a quicker response but it also results in smaller robustness stability margin. For a given process, i.e., $G_{11}$, tuning of $\omega$ is thus a loop-shaping problem and a trade-off between the performance and the robustness. Based on the structure shown in Fig. 6, assuming $P_l(s) = e^{-\tau s}$ and $P_m(s) = \tilde{P}_m(s)$, the open-loop transfer function of the DOB enhanced process is:

$$G_{L}(s) = \frac{Q(s)e^{-\tau s}}{1 - Q(s)e^{-\tau s}}$$. \hfill (17)

The closed-loop robustness can be evaluated on $G_{L}(s)$ in terms of two popular robustness indices, i.e., sensitivity index $M_s$ and complementary sensitivity index $M_c$, defined as follows:

$$M_s = \max_{\omega} \frac{1}{1 + G_L(\omega)w}$$ \hfill (18)

$$M_c = \max_{\omega} \frac{G_L(\omega)w}{1 + G_L(\omega)w}$$ \hfill (19)

As recommended in Åström and Hågglund (2006), the robustness constraints on the DOB loop are chosen as: $M_s = 1.8$ and $M_c = 1.4$, which may be satisfied by shaping the Nyquist plot of $G_L$ outside the contour of each robustness index. Under settling time chosen as $T_f = 100$, the largest $\omega$ can be determined as 1.3 by drawing a cluster of the Nyquist plots, shown in Fig. 8.

### 3.4 $H_{\infty}$ optimization for the NMP–DOB filter

For the NMP process, it is possible to obtain an analytic solution to the optimal filter. Referring to Fig. 5, the non-minimum phase part was constructed as a transfer function that has unity gain.
magnitude and a right-half plane zero $1/a$,

$$P_i(s) = \frac{1 - as}{1 + as}$$  \hspace{1cm} (20)

Based on (12), the estimation error of the disturbance is accordingly calculated as:

$$\epsilon(s) = (1 - Q_i(s)P_i(s))d(s)$$  \hspace{1cm} (21)

As the right-half plane zero cannot be canceled by the filter, (21) implies that the estimation of disturbance should also endure an initial inverse response, which would inevitably deteriorate the disturbance rejection performance. To balance the initial inverse response and the subsequent tracking speed, an $H_\infty$ optimization problem is formulated

$$\min \quad ||[1 - Q(s)]P(s)d(s)||_\infty$$  \hspace{1cm} (22)

Fig. 7. Schematic of the equivalent transformation. (a) Conventional decentralized feedback based on DOB. (b) Decomposition of DOB in terms of outputs. (c) Equivalent form of inverted decoupling.
The minimization in (22) will suppress the inverse response while pursuing a fast tracking ability. Prior to solving this problem, a fundamental theorem (Solomentsev, 2001) of complex variables should be introduced:

\[ \sup_{|s| = a} |1 - Q(s)P(s)\hat{d}(s)| \geq |1 - Q(s)P(s)d(s)|_{z = 1/a} = |\epsilon(s)|_{z = 1/a} \]

By letting \( \epsilon(s) \equiv a \), it is possible to obtain the following unique optimal solution:

\[ Q_{\text{opt}}(s) = \frac{1 - a/d(s)}{P(s)} = 1 + as \]

Note that the optimal \( Q_{\text{opt}}(s) \) is improper. A low-pass filter must be introduced to make the DOB implementable. Thus a suboptimal filter can be obtained as:

\[ Q(s) = \frac{1 + as}{(1 + T_2s)^p} \]

It is shown that the proposed filter has a zero, which is different from the conventional form.

### 4. Disturbance rejection abilities and implementation in DCS

All the control difficulties in the FBC system are identified in Section 2, which are expected to be handled under the framework of the disturbance observer (DOB), as analyzed in Section 3. In this section, simulations are carried out to demonstrate the abilities point by point. At last, a water tank experiment is designed to show the most important virtue of DOB: realizability in DCS.

#### 4.1. Disturbance rejection

The disturbance observer in Section 3.3 is applied in the nominal linear model \( G(31) \) of the power loop of FBC. Assuming a step load disturbance is added at \( t = 1000 \) s, the performance of disturbance rejection is shown in Fig. 9. It can be found that the output can be dragged back faster to steady state with the improved DOB.

The disturbance observer in Section 3.4 is applied in the nominal linear model \( G(22) \) of the temperature loop of FBC. The improvement is validated via a simulation by adding a step disturbance at \( t = 1000 \) s, as shown in Fig. 10. Compared with the conventional filter, the suboptimal design gives a faster convergence rate but with the same magnitude of inverse response and more smooth control action. Note that there are no PI controllers in these two examples, and the disturbance is rejected only by DOB.
4.2. Performance recovery

The power loop of FBC is chosen to validate the performance recovery ability of DOB. Step responses (from \(c\) to \(y\) in Fig. 5) under different operating conditions are shown in Fig. 11. It is easy to see that the step responses under the different working conditions are shaped almost the same due to the compensation effect of DOB.

4.3. Decoupling

A simple minimum phase TITO plant is constructed to clearly show the decoupling ability analyzed in Section 3.2,

\[
G(s) = \begin{bmatrix}
\frac{2}{1+2s} & \frac{12}{1+12s} \\
\frac{1.5}{1+1.5s} & \frac{3}{1+3s}
\end{bmatrix}
\]  (26)

The control system is configured in the form of Fig. 7(a). Each PI controller is tuned by the pole placement method (Åström & Hagglund, 2006). The simulation results for the decentralized PI with and without DOB are shown in Fig. 12. Obviously, the DOB-PI scheme can obtain a very good decoupling performance.

4.4. An experimental realization in DCS

In this section, the realization of the DOB-enhanced PI strategy is tested in a water tank system, as shown in Fig. 13. The controlled variable is the water level and the control input is the pump rotor speed. The experimental results of PI controller without and with DOB compensation are shown in Fig. 14. Obviously, the DOB-PI control system works very well and the resulting performance is much less sensitive to the operating condition compared with the conventional PI control system.

5. Application to the nonlinear FBC boiler

The abilities of DOB have been confirmed in the simple linear cases in Section 4. In this section, the simulation will be carried out by applying the DOB enhanced PI control strategy on the nonlinear FBC model, as shown in Fig. 15, where, \(G_{11m}\) and \(G_{22m}\) are the minimum parts of \(G_{11}\) and \(G_{22}\), respectively, and \(G_{0}\) is the non-minimum phase part of \(G_{22}\).

The performance under the DOB-enhanced decentralized PI scheme will be compared with and without DOB compensation. To further demonstrate that the proposed strategy can rival the complex MPC, a set of parameters of state space MPC were tuned.
Three control strategies are all designed based on the nominal transfer function (8) and then applied in the nonlinear model (7). In industry, the PI controllers are usually designed independently according to the diagonal elements of transfer function matrix. In this paper, the PI controllers are optimized based on heuristic optimization algorithm (Li, Gao, Xue, & Lu, 2007; Lee & El-Sharkawi, 2008) to achieve a minimum integral absolute error (IAE). The parameters of DOB were already determined in Section 4. All the parameters are summarized in Table 2.

5.1. Set-point tracking in wide-range operating conditions

The tracking simulation is carried out by shifting both setpoints of power and temperature from the steady state ‘4’ to ‘5’→ ‘6’→ ‘7’→ ‘8’ in Table 1. The responses of controlled variables and manipulated variables are shown in Fig. 16. Obviously, the DOB-enhanced PI control achieved more robust performance than the multi-loop PI control. The decentralized PI control without DOB performs well near the nominal condition but tends to oscillate significantly when the operating condition is far away from the nominal point. The tracking performance under DOB-PI has much fewer fluctuations under different operating conditions, indicating the performance recovery ability against nonlinearity.

Now the point is turned to the comparison between the DOB-PI and the state space MPC. The temperature performance of MPC is somewhat better than that of DOB-PI. And around the nominal condition ‘4’, the MPC, widely acknowledged as the advanced multivariable control algorithm, yields perfect performance of reference tracking and decoupling. However, the varying working conditions caused significant degradation of the MPC performance in power loop. The load tracking performance around 27.5 MW condition tends to oscillate severely. As introduced in Section 1, the oscillation of output power will pose significant risks on the power grid safety. What is worse, there exists a steady-state offset due to the model mismatch (see the inset in Fig. 16(a)), which is also definitely unacceptable for the power plant operation. Granted, these deficiencies may be overcome by augmenting the state-space representation with a disturbance model (Maeder, Borrelli, & Morari 2009) or in the scheme of data-driven MPC (Wu, Shen, Li, & Lee, 2013), stochastic MPC (Cannon, Cheng, Kouvaritakis, & Raković, 2012) or fuzzy MPC (Wu, Shen, Li, & Lee, 2014), but all these improved methods would lead to additional computation cost and make the system even more complex, which is definitely not preferable for practitioners.
5.2. Disturbance rejection

The frequent disturbances in FBC system, such as variations of heat value of feed coal, moisture content of primary air and erosion of water wall, may deteriorate the performance of feedback control system significantly. In this part, the simulation is carried out by assuming the step disturbances imposed on the input port of feed coal and primary air at $t = 20$ min and $t = 150$ min, respectively. The closed-loop response curves of the output power and bed temperature are shown in Fig. 17.

Another simulation is carried out by adding the sinusoidal external disturbances in the output ports. The corresponding response curves are shown in Fig. 17. The dynamic behaviors of output power indicate that DOB-based decentralized PI control achieved overwhelming superiority over other methods in the power loop. Similar to the previous phenomenon, DOB-based strategy did not perform as well as MPC in the temperature loop. The reason can be attributed to the NMP characteristic existing in the loop. Even with the suboptimal disturbance estimation, the initial inverse estimation of disturbance is still unavoidable, which will of course degrade the performance of disturbance rejection. However, as discussed in the previous section, it is not a wise decision to choose the MPC controller in this loop due to the inconvenient configuration. If simplicity is of primary concern, it is highly suggested to select the DOB-PI structure to achieve a balance between the performance and ease of use.

5.3. Discussion

The DOB-enhanced decentralized PI control can achieve superior performances to the conventional decentralized control in most cases. Nonlinear plant can be compensated as linear nominal model, in particular in steady state and low-frequency region; coupling can be attenuated significantly; internal and external disturbances can be rejected in a timely manner.

Even though the control accuracy of the temperature loop is not as good as MPC, it may be argued that the resulting temperature can also be guaranteed within the safe region to avoid NOX formation. In terms of the practical implementation, only the lead–lag components, which can be easily found in the library of the current mainstream DCS, is needed to configure the DOB module.

Another distinctive feature of the method that should be argued is the compatibility with the already running PI controllers and convenience for tuning. The tuning of DOB can be completed without incorporating the signal of disturbance estimation to the feedback loop. Only after confirming the stability and reasonability of the estimation, the signal may be fed back to the closed-loop. If
the designed control system is not satisfactory, the DOB can be quickly switched off. Since the conventional PI controllers can still operate independently, the system can work safely in the whole procedure of DOB configuration, tuning, and implementation.

6. Conclusions

In this paper, the control difficulties arising from the nonlinearity, coupling, time delay and non-minimum phase of fluidized bed combustor are formulated at first. Later analyzed are the abilities of disturbance observer in accommodating those difficulties. The linear simulation and experiment confirm these abilities as well as the realizability. Compared with the conventional decentralized PI and multivariable MPC schemes, simulation results show that the proposed strategy can achieve a reasonably good performance, especially in the power loop. The simplicity and ease of implementation demonstrate the promising prospect in practical application.

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Appendix. Parameters for the FBC model

<table>
<thead>
<tr>
<th>Bed:</th>
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<tbody>
<tr>
<td>Bed material specific</td>
<td>Heat $c_i = 800$ [J/kg K]</td>
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<tr>
<td>Bed inert material</td>
<td>Volume $V_B = 25,000$ [kg]</td>
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<tr>
<td>Heat transfer coefficient</td>
<td>$\alpha_B = 210$ [W/m² K]</td>
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<tr>
<td>Heat exchange surface</td>
<td>$A_B = 26.8$ [m²]</td>
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<tr>
<td>Cooling water temperature</td>
<td>$T_{BI} = 573$ [K]</td>
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</table>

<table>
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<tr>
<th>Freeboard:</th>
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<tr>
<td>Volume</td>
<td>$V = 128.1$ [m³]</td>
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<tr>
<td>Heat transfer coefficient</td>
<td>$\alpha_F = 210$ [W/m² K]</td>
</tr>
<tr>
<td>Heat exchange surface</td>
<td>$A_F = 130.7$ [m²]</td>
</tr>
<tr>
<td>Cooling water temperature</td>
<td>$T_{FI} = 573$ [K]</td>
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</table>

<table>
<thead>
<tr>
<th>Air flows:</th>
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</tr>
</thead>
<tbody>
<tr>
<td>Primary air $O_2$ content</td>
<td>$C_1 = 0.21$ [N m³/m³]</td>
</tr>
<tr>
<td>Primary air specific heat</td>
<td>$c_1 = 1305$ [J/m³ K]</td>
</tr>
<tr>
<td>Primary air temperature</td>
<td>$T_1 = 328$ [K]</td>
</tr>
<tr>
<td>Secondary air $O_2$ content</td>
<td>$C_2 = 0.21$ [N m³/N m³]</td>
</tr>
<tr>
<td>Secondary air specific heat</td>
<td>$c_2 = 1305$ [J/m³ K]</td>
</tr>
<tr>
<td>Secondary air temperature</td>
<td>$T_2 = 328$ [K]</td>
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<tr>
<td>Flue gas specific heat</td>
<td>$c_2 = 1305$ [J/m³ K]</td>
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<table>
<thead>
<tr>
<th>Fuel feed:</th>
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<tbody>
<tr>
<td>$O_2$ consumed in combustion</td>
<td>$X_C = 1.886$ [N m³/kg]</td>
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<tr>
<td>Heat value of char</td>
<td>$H_C = 30 \times 10^6$ [J/kg]</td>
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<tr>
<td>Mean combustion rate</td>
<td>$\tau_c = 50$ [s]</td>
</tr>
<tr>
<td>Fraction of volatiles</td>
<td>$V = 0.75$ [kg/kg]</td>
</tr>
<tr>
<td>$O_2$ consumed in combustion</td>
<td>$X_V = 1.225$ [N m³/kg]</td>
</tr>
<tr>
<td>Heat value of volatiles</td>
<td>$H_V = 50 \times 10^6$ [J/kg]</td>
</tr>
</tbody>
</table>

References


