Based on Multi-Sensor Information Fusion Circulating Fluidized Bed Boiler Combustion Process Clustering Control Research

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Abstract

Over the decade, due to the fact that the global energy resources are in deadly shortage, much emphasis is put on the energy consumption in thermal power throughout the world. Following developed is Circulating Fluidized Bed Boiler (CFBB) in recent years, a kind of combustion boiler that can clean and desulfurize the coal efficiently in the combustion process. Circulating Fluidized Bed Boiler (CFBB) is a control object with features of time varying parameters, large delay, and multivariable control tightly coupled. Noticeably, many factors influence the combustion process. This paper designs a three level ART2-BP-BP of data fusion–fusion cluster control system based on methods of multi-sensor information fusion and cluster analysis. It completes data fusion from the data level, the feature level to the decision level. Especially, the concept of Situation Threat Space aiming at the potential threats in CFBB is presented. Results of simulation show that the control system in this paper is feasible and effective, in particular, the control system still has more satisfactory control effect in the case of a variety of sensor failures.

Keywords: Circulating Fluidized Bed Boiler; Multi-Sensor Information Fusion; Clustering Fusion Control; Data Preprocessing; Situation Threat Estimate

1. Introduction

Circulating Fluidized Bed Boiler (CFBB) developed in recent years is a kind of combustion boiler that can clean coal efficiently and desulfurize in the combustion process[1]. It has strong ability to adapt to coal and burns all kinds of high quality coal and low grade coal. Its load change is large ranging from 25% to 110%[2]. It is a technically and economically reasonable method able to solve energy conservation and environmental issues[3]. This method is considered as a major innovation of coal combustion technology by many scholars. Therefore, the world takes efforts to research and develop circulating fluidized bed combustion technology and control technology[4]. United States, Japan, Germany and Canada, the four countries are more advanced in this area[5].

Multi Sensor Information Fusion (MSIF) is information processing, and it coordinates all the sensors information that comes from different sources, different time, different space into an unified feature representation in order to give a complete description of the characteristics of a particular object and environment[6]. MSIF concept first appeared in the late 70s when it did not catch much attention. In military area C3I (command, control, communications and information), MSIF is successfully researched and applied, which attracts great attention of the defense sectors of the western countries. In the mid-80s, it has made considerable progress in the military field. In several major local war of the world, MSIF has shown its strong power, especially in the Gulf War, the role of multinational force C3I systems has attracted the word’s attention[7]. However, the technology of these military research results has been in a closed state. Until the late of 80s in 20th century, research and results have gradually been disclosed publicly[8].

Modern industrial production (such as CFBB combustion process) has integrated, complex, large-scale, continuous characteristics, and it uses a large variety of sensors to monitor and control the production process[9]. In this multi-sensor system, the sensor information in space, time, expression are different. Its credibility degrees of uncertainty are different, and its focus and purpose are also different. So it puts forward new demands for information processing and management. In the traditional approach, processing and handling the information collected by each sensor individually
will not lead to increase workload, but will also cut off all contact information between sensors and lose information characteristics contained in the information through organic combination, which results in a waste of information resources[10]. The integration of MSIF and industrial monitoring control will bring new mechanism for traditional industries, and it is expected to form a new type of industrial monitoring and control system --- cluster fusion control system. To our knowledge, there are no references about clustering fusion control methods applied in combustion process of CFBB[11].

For automatic control problems in CFBB, this paper applies the multi-sensor information fusion in the process of CFBB combustion control. Based on ART-2 and BP neural network, it uses feature level fusion and decision-making fusion to achieve the fusion and classification for collected sensor information, and at last forms an effective control strategy. Simulate the control system by MATLAB, and the simulation results prove that this control system is feasible and effective.

2. The mathematical model and burning control system of the burning process of CFBB

2.1 The mathematical model of the burning process of CFBB

2.1.1 The mathematical model of the process of steam pressure being controlled

When disturbance occurs in the combustion rate and turbine uses hydraulic control system, according to identification situations in site, we can get the mathematical model of steam pressure:

\[ W_p(s) = \frac{(1 - \alpha s)}{(1 + T_p s)} e^{-\tau_p s} \]  

(1)

Through the identification in site, we find that static gain \( K_p \), inertia time constant \( T_p \) and pure delay time \( \tau_p \) are parameters changing with different situations. When boiler duty is changing between 25%~100%, the variation ranges of all parameters above are as follows: \( K_p : 6~10s; \ T_p : 190~300s; \ \tau_p : 160~230s; \ a : 20~30s. \) The steam pressure is essentially the same under a wind disturbance.

2.1.2 The mathematical model of bed temperature

Under the disturbance of coal input, the mathematical model of bed temperature is as follows:

\[ W_\theta(s) = \frac{(1 - b s)}{(1 + T_\theta s)^2} e^{-\tau_\theta s} \]  

(2)

Through the identification in site, we find that \( K_\theta \), \( T_\theta \), \( \tau_\theta \), \( b \) are parameters changing with different situations. When boiler duty is changing between 25%~100%, the variation ranges of all parameters above are as follows: \( K_\theta : 10~20 s; \ T_\theta : 150~300 s; \ \tau_\theta : 40~80 s; \ b : 10~18 s. \)

3. The clustering fusion control system of circulating fluidized bed boiler in the burning process

The burning process of circulating fluidized bed boiler (CFBB) has essential controlled variables such as coal feeding, air feeding, induced draft, and cinder discharging.

The idea and the structure of coal feeding, air feeding, induced draft and cinder discharging control systems are the same. They all use a group of sensors detecting relevant variations which can describe the boiler combustion process condition. Relevant variations of circulating fluidized bed boiler process
condition \( P_X \times X \in \{Q,V,M,F\} \), is respectively concerned about coal feeding, air feeding coal, cinder discharging, induced draft. According to clustering fusion control concept, after the sensor data \( S_X \times X \in \{Q,V,M,F\} \) is clustered, we obtain the corresponding operation categories (furnace condition) \( B_X \times X \in \{Q,V,M,F\} \). For example, for coal capacity control system, in order to get \( B^Q \) which control the capacity of coal, process variables \( P^Q \) can be taken for bed temperature, steam pressure, load, etc. At this time, the sensor group of coal capacity control system can gain sensor data vectors \( S^Q \). In the coal capacity control system, form control output of coal on the basis of furnace condition associated with coal. The coal feeding points in large CFBB are at least two, therefore, the control output of coal is a vector:

\[
U^Q = [u^Q_1, u^Q_2, \ldots, u^Q_n]
\]  

Similarly, the control output of air flow (including the control of primary air flow and secondary), \( U^V \) is also a vector:

\[
U^V = [u^V_1, u^V_2]
\]  

Cinder discharging control output and induced draft output control are also vectors:

\[
U^M = [u^M_1, u^M_2, \ldots, u^M_n]
\]  

\[
U^F = [u^F_1, u^F_2]
\]  

This paper mainly studies design and application of clustering fusion control system, and researches its performance through the actual data. Therefore, it only takes one of the four control systems as an example to undertake the key research. This control system is the coal feeding one, the design methods of the other three control systems are similar.

3.1 Overall structure of circulating fluidized bed boiler coal feeding clustering fusion control system

The change of coal feeding will affect both the boiler steam pressure and bed temperature meanwhile. Using three groups of sensors separately to detect the boiler steam pressure (four points), coal feeding (two points) and oxygen content (one point), the pressure error in material layer (two points) and bed temperature (two points), and the control values is coal feeding. These five tested physical quantities describe respectively the operating condition of the boiled from a side, but each cannot fully describe the operating condition of the furnace. Clustering fusion control system’s task is to make these five physical values fuse so that they can comprehensively describe the furnace condition. According to the hearth furnace conditions, it can adjust the coal feeding to maintain the normal operation of the boiler. The diagram of system structure is shown in Figure 1.
(a) Measurement control charts

(b) Information mapping

Figure 1. CFCS structure of quantity of coal

The system showed in figure 1 adopts a distributed and three levels clustering fusion control system. Among them, the first level uses eleven ART-2 neural network to fuse the sensor signal with time series respectively; the second level uses a BP neural network to fuse of the first level’s fusion results again. Considering the sensor failure, the last level adopts a BP network to achieve decision-level fusion for control strategies again.

3.2 Coal feeding clustering fusion control system design of circulating fluidized bed boiler

3.2.1 The input information space

(1) Sensor Data

Steam pressure \( S_1 = [P_1, P_2, P_3, P_4] \); Oxygen content \( S_2 = [w_{o2}] \); coalfeeder \( S_3 = [M_1, M_2] \); wind chamber static pressure \( S_4 = [H_1, H_2] \); the Main Steam pressure \( S_5 = [T_1, T_2] \); the speed of coal feeder \( n \).

(2) Data preprocessing

In the multi-sensor information fusion system, for the same or different types of sensors distributed in different platform, selecting the observation system are different due to its different place before its observation data fusion. In addition there are different sampling rates of the different sensors. So even the same target is measured, there is a big difference between the measurement data by the different sensors. Therefore, on multi-sensor information fusion, the first thing to do is to unify the time and space reference point of multisensors that come from the different platform, in order to form the unity space-time reference systems of fusion required, and unified measurement unit. This is the data preprocessing.
The combustion process of CFBB belongs to a slow changing process. In the design, each window length takes mode for 90s, and each 5s we sample one time. So for each information source in a pattern window there will be 18 data. After data pretreatment, 5 groups of sensor data participate in 1st level of ART-2 fusion, and their pattern vectors are written separately:

**Steam pressure**

\[
X_1 = \begin{bmatrix}
  x_{11}^{(1)} & x_{11}^{(2)} & \cdots & x_{11}^{(18)} \\
  x_{12}^{(1)} & x_{12}^{(2)} & \cdots & x_{12}^{(18)} \\
  x_{13}^{(1)} & x_{13}^{(2)} & \cdots & x_{13}^{(18)} \\
  x_{14}^{(1)} & x_{14}^{(2)} & \cdots & x_{14}^{(18)} 
\end{bmatrix}^T = \begin{bmatrix}
  p_1^{(1)} & p_1^{(2)} & \cdots & p_1^{(18)} \\
  p_2^{(1)} & p_2^{(2)} & \cdots & p_2^{(18)} \\
  p_3^{(1)} & p_3^{(2)} & \cdots & p_3^{(18)} \\
  p_4^{(1)} & p_4^{(2)} & \cdots & p_4^{(18)} 
\end{bmatrix}^T
\]  

(7)

**Oxygen content**

\[
X_2 = \begin{bmatrix}
  x_{21}^{(1)} & x_{21}^{(2)} & \cdots & x_{21}^{(18)} \\
  x_{22}^{(1)} & x_{22}^{(2)} & \cdots & x_{22}^{(18)} \\
  x_{23}^{(1)} & x_{23}^{(2)} & \cdots & x_{23}^{(18)} \\
  x_{24}^{(1)} & x_{24}^{(2)} & \cdots & x_{24}^{(18)} 
\end{bmatrix}^T = \begin{bmatrix}
  w_1^{(1)} & w_1^{(2)} & \cdots & w_1^{(18)} \\
  w_2^{(1)} & w_2^{(2)} & \cdots & w_2^{(18)} \\
  w_3^{(1)} & w_3^{(2)} & \cdots & w_3^{(18)} \\
  w_4^{(1)} & w_4^{(2)} & \cdots & w_4^{(18)} 
\end{bmatrix}^T
\]  

(8)

**Coal feeding**

\[
X_3 = \begin{bmatrix}
  x_{31}^{(1)} & x_{31}^{(2)} & \cdots & x_{31}^{(18)} \\
  x_{32}^{(1)} & x_{32}^{(2)} & \cdots & x_{32}^{(18)} \\
  x_{33}^{(1)} & x_{33}^{(2)} & \cdots & x_{33}^{(18)} \\
  x_{34}^{(1)} & x_{34}^{(2)} & \cdots & x_{34}^{(18)} 
\end{bmatrix}^T = \begin{bmatrix}
  M_1^{(1)} & M_1^{(2)} & \cdots & M_1^{(18)} \\
  M_2^{(1)} & M_2^{(2)} & \cdots & M_2^{(18)} \\
  M_3^{(1)} & M_3^{(2)} & \cdots & M_3^{(18)} \\
  M_4^{(1)} & M_4^{(2)} & \cdots & M_4^{(18)} 
\end{bmatrix}^T
\]  

(9)

**The pressure error in material layer**

\[
X_4 = \begin{bmatrix}
  x_{41}^{(1)} & x_{41}^{(2)} & \cdots & x_{41}^{(18)} \\
  x_{42}^{(1)} & x_{42}^{(2)} & \cdots & x_{42}^{(18)} \\
  x_{43}^{(1)} & x_{43}^{(2)} & \cdots & x_{43}^{(18)} \\
  x_{44}^{(1)} & x_{44}^{(2)} & \cdots & x_{44}^{(18)} 
\end{bmatrix}^T = \begin{bmatrix}
  H_1^{(1)} & H_1^{(2)} & \cdots & H_1^{(18)} \\
  H_2^{(1)} & H_2^{(2)} & \cdots & H_2^{(18)} \\
  H_3^{(1)} & H_3^{(2)} & \cdots & H_3^{(18)} \\
  H_4^{(1)} & H_4^{(2)} & \cdots & H_4^{(18)} 
\end{bmatrix}^T
\]  

(10)

**Bed temperature**

\[
X_5 = \begin{bmatrix}
  x_{51}^{(1)} & x_{51}^{(2)} & \cdots & x_{51}^{(18)} \\
  x_{52}^{(1)} & x_{52}^{(2)} & \cdots & x_{52}^{(18)} \\
  x_{53}^{(1)} & x_{53}^{(2)} & \cdots & x_{53}^{(18)} \\
  x_{54}^{(1)} & x_{54}^{(2)} & \cdots & x_{54}^{(18)} 
\end{bmatrix}^T = \begin{bmatrix}
  T_1^{(1)} & T_1^{(2)} & \cdots & T_1^{(18)} \\
  T_2^{(1)} & T_2^{(2)} & \cdots & T_2^{(18)} \\
  T_3^{(1)} & T_3^{(2)} & \cdots & T_3^{(18)} \\
  T_4^{(1)} & T_4^{(2)} & \cdots & T_4^{(18)} 
\end{bmatrix}^T
\]  

(11)

**Sensor characteristic information**

Feature information only participates in level 2 of the BP network integration, and it can be expressed as

\[
X_6 = [Z_1, Z_2, Z_3, Z_4, Z_5]
\]  

(12)

**dT and the speed of the coal feeder n**

\[dT\] and \[n\] do not participate in information fusion, and are written together as follows:

\[
X_7 = [dT, n]
\]  

(13)

**The whole system of input information space**

\[
X = [X_1, X_2, X_3, X_4, X_5, X_6, X_7]
\]  

(14)

3.2.2 Clustering fusion space

Clustering fusion space \( C \) is constituted by the mapped \( \Theta \) input information space \( X \),
\[ \Theta : X \rightarrow C \]  
(15)

\[ C = [C_1, C_2, \cdots, C_n] \]  
(16)

\[ \Theta = [\theta_1, \theta_2, \cdots, \theta_n] \]  
(17)

\( n \): Spatial dimension, \( N \): Spatial dimension

According to the specific circumstances of this system, in other word, inputting information space is 5 groups of sensor time series vector \( X_1, X_2, X_3, X_4, X_5 \), which constitute the subspace by 11 ART - 2 network completed mapping \( \Theta \). Now analyze a ART-2 network work, and the rest 10 are similar.

![Figure 2. ART-2 structure in CFBB CFCS](image)

Figure 2 shows the steam pressure sensor data fusion time sequence of ART-2 network diagram.

Vector \( X_{11} \) (a column of \( X_1 \)) in the number of dimensions is 18*1, namely dimension \( K = 18 \), as a result ART-2 network design has 18 input terminals of the network. The remaining related parameters are elected: contrast constants \( a = b = 10 \), Adjusting subsystem constant \( c = 0.1 \), F2 place gain \( d = 0.9 \), Similarity \( \rho = 0.9 \), Filtering threshold \( \theta = 1 / k = 1/18 \), Filtering transformation function

\[ f(x) = \begin{cases} 
0, & 0 \leq x \leq \theta \\
1, & x > \theta 
\end{cases} \]  
(18)

3.2.3 Operation space

Operating space (category space) \( B \) is constituted by clustering fusion space \( C \) after \( \Phi \) alludes.

\[ \Phi : C \rightarrow B \]  
(19)

\[ B = [b_1, b_2, \cdots, b_p] \]  
(20)

\[ \Phi = [\varphi_1, \varphi_2, \cdots, \varphi_p] \]  
(21)

In the study of boiler system, the mapping \( \Phi \) is realized by BP neural network. It also includes the failure information \( X_6 \) besides the input vector \( C \).
In this system, in order to guarantee the study speed, take the BP network three layers, 20 units in hidden layer. The whole BP network structure is 15 x 20 x 6 structure. As is shown in Figure 3.

![BP network of realizing run-space mapping](image)

**Figure 3.** BP network of realizing run-space mapping

### 3.2.4 Control Strategy space

Control strategy space $U$ is constituted by category space $B$ through the mapping $\psi$. In the process, we need to use input information $X$, global database $D$ and the related knowledge of comprehensive knowledge base $K$:

$$\psi : (X, D, K, B) \rightarrow U$$  \hspace{1cm} (22)

$$\psi = \{\varphi_1, \varphi_2, \cdots, \varphi_m\}$$  \hspace{1cm} (23)

$$U = [u_1, u_2, \cdots, u_m]$$  \hspace{1cm} (24)

In type (24) expression, $u_i (i = 1, 2, \cdots, m)$ represents the various control strategy, therefore, $U$ is a multi-mode control vector. In the boiler system studied in this paper, input information which participated in output control are:

$$X = [P \quad P_0 \quad n]^T$$  \hspace{1cm} (25)

In the type, $P$ is steam temperature; $P_0$ steam temperature set value; $n$ is the speed of coal feeder. According to the theory of clustering fusion control, the location (furnace condition) of the running space $B$ and steam pressure control the output size. Clustering fusion control output is the plow speed control values:

$$n(k) = n(k - 1) + \Delta n(k)$$  \hspace{1cm} (26)

### 4. Simulation research on clustering fusion control system in combustion process

As main steam pressure $p$ is an important parameter in boiler combustion process. Therefore, this paper only mentions MATLAB simulation curve of the main steam pressure and the other simulation curves are omitted. In the process of simulation, we adopt conventional PID controller, self-adaptive PID controller, fuzzy controller, fuzzy self-adaptive controller and clustering fusion controller to control the vapor pressure respectively.

Figure 4(a) shows the simulation results of conventional PID controller, self-adaptive PID controller and clustering fusion controller for steam temperature. It can be seen that the conventional
PID controller has relatively dramatic fluctuation for step response, whereas self-adaptive PID controller and clustering fusion controller have relatively weak fluctuation. When steam pressure sensor loses efficacy at 1000s, the conventional PID controller emerges divergent oscillation, and the self-adaptive PID controller emerges undamped oscillation. Whereas, the clustering fusion controller is not subject to interference. The system operates stably and the control effect is good. Figure 4(b) shows the simulation results of fuzzy controller, fuzzy self-adaptive controller and clustering fusion controller for steam temperature. From the simulation results, we can see that fuzzy controller, fuzzy self-adaptive controller and clustering fusion controller have relatively weak fluctuation for step response. When steam pressure sensor fails at 1000s, a linear decline phenomenon emerges in fuzzy controller toward the direction of steam pressure decrease, and divergence oscillation fuzzy self-adaptive controller emerges. The clustering fusion controller, however, is not subject to interference and shows good control effect. Comparing with the five control methods stated above, we obtain Table 1. From Table 1, we can get the conclusion that clustering fusion control processes the advantages of small delay, no overshoot and short transition time.

**Figure 4.** Steam pressure changes under steam pressure sensor failure
Table 1. Comparison of five control methods in steam pressure

<table>
<thead>
<tr>
<th>Function</th>
<th>delay $\tau$</th>
<th>$t_r$</th>
<th>$t_p$</th>
<th>$\sigma_p$</th>
<th>$t_s$</th>
<th>Pressure sensor failure(1000s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>PID</td>
<td>200s</td>
<td>250s</td>
<td>370s</td>
<td>56%</td>
<td>580s</td>
<td>divergence oscillation</td>
</tr>
<tr>
<td>Adaptive PID</td>
<td>200s</td>
<td>300s</td>
<td>380s</td>
<td>5%</td>
<td>500s</td>
<td>undamped oscillation</td>
</tr>
<tr>
<td>Fuzzy control</td>
<td>200s</td>
<td>320s</td>
<td>390s</td>
<td>3%</td>
<td>480s</td>
<td>linearity decline</td>
</tr>
<tr>
<td>Adaptive fuzzy control</td>
<td>200s</td>
<td>310s</td>
<td>360s</td>
<td>2%</td>
<td>440s</td>
<td>divergence oscillation</td>
</tr>
<tr>
<td>Cluster control</td>
<td>200s</td>
<td>460s</td>
<td>--</td>
<td>--</td>
<td>420s</td>
<td>undisturbed</td>
</tr>
</tbody>
</table>

5. Conclusion

Circulating Fluidized bed boiler combustion control of automatic control has been one of the tough issues in the engineering field. This article proposes a cluster control method based on the analysis of dynamic characteristics in circulating fluidized bed boiler burning control. This method is on the basis of information fusion technology and uses neural network algorithm as implementation tool. It fuses and classifies the data sampled by all the sensors, and achieves the corresponding control by judging corresponding policy space of different data. At last control system simulation achieves satisfactory results.

6. References


Acknowledgement

This paper is supported by the National Natural Science Fund of China (60774028) and the National Natural Science Fund of Hebei Province (F2010001318).