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Modeling and Model Predictive Control of the BioPower combined heat and power (CHP) plant

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Abstract

This paper presents a model predictive control (MPC) strategy for BioGrate boiler, compensating the main disturbances caused by variations in fuel quality such as the moisture content of fuel, and variations in fuel flow. The MPC utilizes models, the fuel moisture soft-sensor to estimate water evaporation, and the fuel flow calculations to estimate the thermal decomposition of dry fuel, to handle these variations, the inherent large time constants, and long time delays of the boiler. The MPC strategy is compared with the method currently used in the BioPower 5 CHP plant. Finally, the results are presented, analyzed and discussed.

Keywords: combustion, biomass, fuel quality, MPC, moisture, advanced control

1. Introduction

The utilization of renewable energy sources is increasing due to demand to replace fossil energy sources with more ecological ones. The biomass is one of these renewable energy sources\cite{1,2}. BioGrate burns this fuel with a moisture content as high as 65% \cite{3}. However, a varying moisture content and varying fuel flow of the biomass results in uncertainty about its energy content and complicates operation of BioGrate process.

Kortela and Lautala \cite{4} developed a method in order to estimate how much fuel is burning at the time moment and combustion power based on the flue gas oxygen and the air measurements, and the fuel composition. It was reported that the amplitude and the settling time of the response of the boiler power decreased to about one-third of the original.

Havlena and Findejs \cite{5} employed model-based predictive control strategy to enable dynamical coordination between fuel and air flows. This enabled the boiler to permanently operate with the optimum excess air, and resulted in reduced NO\textsubscript{x} production. Prasad et al. \cite{6} tested the application of a multivariable long-range predictive control (LRPC) with global linear models and local model networks in the simulation of a 200 MW oil-fired drum-boiler thermal plant. They reported extremely small variations of ±0.5 bar, ±1.0°C, and ±1.5°C for steam pressure, steam temperature, and reheat steam temperature, respectively.

Swarnakar et al. \cite{7} presented a scheme for robust stabilization of a boiler, based on linear matrix inequalities (LMIs). The simulation results showed that the proposed control is effective against sudden load changes. However, BioGrate process needs a special consideration in its control strategy development due to its long time delay of min seconds and moisture variations in fuel feed.

Bauer et al. \cite{8} derived a simple model for the grate combustion of biomass based on two mass balances for dry fuel and water. The model was verified by experiments at a pilot scale furnace with a horizontally moving grate. The test results showed that the overall effect of the primary air flow rate on the thermal decomposition of dry fuel is multiplicative. This is also shown in the results of Yang et al. \cite{9} when the air factor is not much larger than stoichiometric air, staying in a typical optimal level from around 1.2 to 1.7. Higher air flows begin to cool the bed, decreasing the propagation rates \cite{10}. In addition, the test results of Bauer et al. \cite{8} showed that the water evaporation rate is mainly independent of the primary air.

Jounela \cite{11} developed a fuel moisture soft sensor that is based on a dynamic model that makes use of combustion power estimates and that makes use of the model of the secondary superheater.

This paper presents a model predictive control (MPC) strategy for a BioGrate boiler. The paper is organized as follows: Section 2 presents The BioPower 5 CHP plant process and its control strategy. Section 3 presents the MPC strategy, and dynamic models, and fuel-moisture soft-sensors of a boiler. The identifications of the models of BioPower 5 CHP plant are presented in Section 4. The simulation results of the MPC strategy are presented in Section 5, followed by the conclusions in Section 6.
2. Description of the process and its control strategy

In the BioPower 5 CHP plant, the heat used for steam generation is obtained by burning solid biomass fuel: bark, sawdust and pellets, which are fed to the steam boiler together with combustion air. As a result, combustion heat and flue gases are generated. The heat is then used in the steam-water circulation process. The fuel is fed onto the center of a grate from below by a stoker screw. The grate is divided into concentric rings with alternate rotating rings and the rings between remaining stationary. Alternate rotating rings are pushed hydraulically clockwise or counterclockwise respectively. This design distributes the fuel evenly over the entire grate with the burning fuel forming an even layer of the required thickness [3].

The water content of the wet fuel in the centre of the grate evaporates rapidly due to the heat of the surrounding burning fuel and thermal radiation from the brick walls. The gasification and visible combustion of the gases and solid carbon take place as the fuel moves to the periphery of the circular grate. Finally, at the edge of the grate, ash falls into a water-filled ash basin underneath the grate [3].

The primary air for combustion, and the recirculation flue gas, are fed from underneath the grate and penetrate the fuel through slots in the concentric rings. Secondary air is fed above the grate directly into the flame. Air distribution is controlled by dampers and speed-controlled fans [3].

Fig. 2 shows the boiler part of the BioPower 5 CHP plant. The essential components of the water-steam circuit are an economizer, a drum, an evaporator and superheaters. Feed water is pumped from a feed water tank to the boiler. First the water is led to the economizer (4) that is heated by flue gases. The temperature of flue gases is decreased by the economizer, and the efficiency of the boiler is improved. From the economizer, heated feed water is led to the drum (5) and along downcomers into the bottom of the evaporator (6) tubes that surround the boiler. From the evaporator tubes the heated water and steam return back to the steam drum, where steam and water are separated. Steam rises to the top of the steam drum and flows to the superheaters (7). Steam heats up further so that it superheats. The superheated high-pressure steam (8) is led to a steam turbine, where electricity is generated.

2.1. Current control strategy of the BioPower plant

The main objective of the BioPower plant is to produce a desired amount of energy by keeping the drum pressure constant. The necessary boiler power is produced by manipulating primary air, secondary air, and stoker speed as illustrated in Fig. 3.

The fuel feed is controlled by manipulating the motor speed of the stoker screw to track the primary air flow measurement. The necessary amount of primary air and secondary air for diverse power levels are specified by air curves. The set point of the secondary air controller is adjusted by the flue gas oxygen controller to provide excess air for combustion and enable the complete combustion of fuel.

3. Model predictive control for the BioPower 5 CHP plant

The improvised MPC strategy over the current control strategy is illustrated in Fig. 4. The proposed strategy utilizes fuel and moisture soft-sensors to estimate the burned fuel and the water evaporation respectively. Subsequently, the combustion power is estimated based on these fuel-moisture soft sensors. As a result, the required amount of combustion power from the boiler can be produced, which is done by manipulating the primary air and the stoker speed. In addition, this combustion power can be accurately predicted.

3.1. MPC for BioGrate boiler

The primary air and the stoker speed are the input variables \((u)\); the fuel moisture content in the fuel feed and the power demand are the measured disturbances \((d)\); and the combustion power and the drum pressure are the controlled variables \((z)\), as illustrated in Fig. 5. The developed MPC utilizes the linear state space system as follows [12]:

\[
\begin{align*}
   x_{k+1} &= Ax_k + Bu_k + Ed_k \\
   z_k &= Cz x_k \\
\end{align*}
\]

(1)

3.2. Regulator

The process is described by linear time invariant (LTI) state space model

\[
   z_k = Cz A^k x_0 + \sum_{j=0}^{k-1} H_{k-j} u_j \\
\]

(2)
where \( H_{k-j} \) are impulse response coefficients. Using the Equation (2), the MPC with input, the input rate of movement, and output constraints is formulated as
Figure 4: Model predictive control (MPC) strategy of BioGrate boiler

Figure 5: Configuration of the boiler model of MPC strategy for BioPower 5 CHP plant

\[ \Gamma_d = \begin{bmatrix} H_{1,d} & 0 & 0 & \cdots & 0 \\ H_{2,d} & H_{1,d} & 0 & \cdots & 0 \\ H_{3,d} & H_{2,d} & H_{1,d} & 0 & \vdots \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ H_{N,d} & H_{N-1,d} & H_{N-2,d} & \cdots & H_{1,d} \end{bmatrix} \]  

For the case \( N = 6 \), the matrices

\[ \Lambda = \begin{bmatrix} -I & I & 0 & 0 & 0 \\ 0 & -I & I & 0 & 0 \\ 0 & 0 & -I & I & 0 \end{bmatrix} \]  

\[ Q_z = \begin{bmatrix} Q_z & 0 & 0 & 0 \\ Q_z & Q_z & 0 & 0 \\ 0 & 0 & \ddots & 0 \\ 0 & 0 & 0 & Q_z \end{bmatrix} \]  

\[ H_S = \begin{bmatrix} 2S & -S & 0 & 0 & 0 \\ -S & 2S & -S & 0 & 0 \\ 0 & -S & 2S & -S & 0 \\ 0 & 0 & -S & 2S & -S \\ 0 & 0 & 0 & -S & 2S \end{bmatrix} \]  

\[ M_{u_{-1}} = \begin{bmatrix} S \\ 0 \\ 0 \end{bmatrix} \]  

\[ Q_z \] are tuned so that drum pressure has more importance than combustion power. \( S \) for primary air and stoker speed can be tuned separately from each other. Then the objective function is expressed as

\[ \psi = \frac{1}{2} \sum_{k=1}^{N} \| z_k - r_k \|^2 + \frac{1}{2} \| \Delta u_k \|^2 \]  

\[ = \frac{1}{2} U' H U + g' U + \rho \]  

where

\[ H = \Gamma' Q_z \Gamma + H_S \]  

\[ g = \Gamma' Q_z \Phi x_0 - \Gamma' Q_z R + M_{u_{-1}} u_{-1} + \Gamma' Q_z \Gamma_d D \]
In addition if the system is augmented with a number of integrating disturbances \( n_\eta \) equal to the number of the measurements \( p (n_\eta = p) \) and if the closed-loop system is stable and constraints are not active at steady state, there is zero offset in controlled variables

### 3.3. Modeling of BioGrate boiler for MPC

An unknown flue flow and the water evaporation rate results in uncertainty in the combustion power. Therefore, the models of the boiler include, model for water evaporation, the model for thermal decomposition of fuel, and the drum model.

#### 3.3.1. The model of water evaporation

The model of water evaporation is [8]

\[
\frac{d m_{w, in}(t)}{dt} = -c_{wev} m_{w, in}(t) \alpha_{wev}(t) + \frac{d m_{w, in}(t - T_d(t))}{dt} [\text{kg/s}] \\
+ \frac{d m_{w, in}(t)}{dt} \left[ \frac{m_{w, in}(t - T_d(t))}{\alpha_{ds, in} m_{ds, in}(t)} \right] [s]
\]

where \( c_{wev} \) is the correction coefficient, \( \alpha_{wev} \) is the coefficient for a dependence on the position of the moving grate, and \( m_{w, in} \) the moisture in the fuel feed (kg/s).

\[
T_d(t) = c_d \left[ \frac{m_{w, in}(t)}{\alpha_{ds, in} m_{ds, in}(t)} \right] [s]
\]

where \( c_d \) is the delay coefficient, \( \alpha_{ds, in} \) is the stoker speed correction coefficient (kg/s/%), and \( m_{ds, in}(t) \) the stoker speed (%).

\[
m_{w, in}(t) = \int_0^t \dot{m}_{w, in}(\tau) d\tau [\text{kg}]
\]

#### 3.3.2. The model of thermal decomposition of dry fuel

The model of thermal decomposition of dry fuel is [8]

\[
\frac{d m_{ds}(t)}{dt} = -c_{thd} m_{ds}(t) \alpha_{thd}(t) \left[ \dot{m}_{pa}(t) + \dot{m}_{pa, 0} \right] + \frac{d m_{ds}(t - T_d(t))}{dt} [\text{kg/s}] \\
+ \frac{d m_{ds}(t)}{dt} \left[ \frac{m_{ds}(t - T_d(t))}{\alpha_{ds, in} m_{ds, in}(t)} \right] [s]
\]

where \( c_{thd} \) is the thermal decomposition rate coefficient, \( \alpha_{thd}(t) \) is the coefficient for a dependence on the position of the moving grate, \( \dot{m}_{pa}(t) \) is the primary air flow rate bias (kg/s), and \( \dot{m}_{pa, 0} \) the primary air flow rate in (kg/s).

\[
m_{ds, in}(t) = \int_0^t \dot{m}_{ds, in}(\tau) d\tau [\text{kg}]
\]

For the linear state space model of Equation (1), the Equation (26) is linearized as

\[
\frac{d m_{ds}(t)}{dt} = -c_{ds} m_{ds}(t) - c_{pa} \dot{m}_{pa}(t) \\
+ \frac{d m_{ds}(t)}{dt} \left[ \frac{m_{ds}(t - T_d(t))}{\alpha_{ds, in} m_{ds, in}(t)} \right] [\text{kg/s}] \\
+ \frac{d m_{ds}(t)}{dt} \left[ \frac{m_{ds}(t - T_d(t))}{\alpha_{ds, in} m_{ds, in}(t)} \right] [s]
\]

where \( c_{ds} \) is the fuel bed height coefficient, and \( c_{pa} \) the primary air flow coefficient.
3.3.3. Drum model

The drum level is kept at a constant level by its controller, and therefore the variations in the steam volume are small. Thus, the drum model is [14]:

\[
\frac{dp}{dt} = \frac{1}{e}(Q - \dot{m}_f(h_w - h_f)) - \dot{m}_s(h_s - h_w)) \tag{29}
\]

\[
e \approx g_w V_w \frac{\partial h_w}{\partial p} + m_t C_p \frac{\partial T_s}{\partial p} \tag{30}
\]

where \( Q \) is the combustion power (MJ/s), \( \dot{m}_f \) is the feed water flow (kg/s), \( h_w \) is the specific enthalpy of the water (MJ/kg), \( h_f \) is the specific enthalpy of the feed water (MJ/kg), \( \dot{m}_s \) is the steam flow rate (kg/s), \( h_s \) is the specific enthalpy of the steam (MJ/kg), \( g_w \) is the specific density of the water (kg/m³), \( V_w \) is the volume of the water (m³), \( m_t \) is the total mass of the metal tubes and the drum (kg), and \( C_p \) is specific heat of the metal (MJ/kg K).

3.3.4. Fuel flow soft-sensor

The elemental composition, and moisture content of a fuel have a strong effect on its heat value. If fuel contains moisture, this evaporates when the fuel is burned, but this decreases its heat value. The effective heat value of a dry fuel is

\[
q_w = 0.348 \cdot w_C + 0.938 \cdot w_H + 0.105 \cdot w_S + 0.063 \cdot w_N - 0.108 \cdot w_O (\text{MJ/kg}) \tag{31}
\]

where \( w_C \) is the carbon in the fuel (%), \( w_S \) is the sulfur in the fuel (%), \( w_N \) is the nitrogen in the fuel (%), and \( w_O \) is the oxygen in the fuel (%). The effective heat value of a wet fuel is obtained using the equation

\[
q_f = q_w \cdot (1 - w/100) - 0.0244 \cdot w (\text{MJ/kg}) \tag{32}
\]

where \( w \) is the moisture content of the wet fuel (%). In order to use Equation (31) and Equation (32), the composition of the fuel has to be known.

Oxygen consumption signals how much fuel is burning at the time moment. This information can be used to calculate the combustion power of the burned fuel. The amount of oxygen needed to burn one kilogram of the fuel is

\[
N_f^O = n_C + 0.5 \cdot n_H + n_S - n_O \tag{33}
\]

where \( n_C \) is the carbon (mol/kg), \( n_H \) is the hydrogen (mol/kg), \( n_S \) is the sulfur (mol/kg), and \( n_O \) is the oxygen (mol/kg). Combustion air includes 3.76 times more nitrogen than oxygen. The flue gas flow to burn one kilogram of fuel is thus

\[
N_f = n_C + n_H + n_S + 3.76 \cdot N_f^O + n_N + n_H2O \tag{34}
\]

where \( n_{H2O} \) is the water (mol/kg). Similarly, the flue gas losses per kilogram of fuel are determined by:

\[
q_f^g = (n_C CO + n_S CSO + (n_{H2O} + n_{H2})C_{H2O} + 3.76 \cdot N_f^O \cdot n_{C} + n_{N} + n_{H2O}) \tag{35}
\]

\[
\dot{m}_{thd}(w) = \frac{0.21 - \frac{n_{Air}}{10}}{N_f^g + \frac{N_{Air}}{100} (N_f^g - 4.76 \cdot N_f^O)} \tag{36}
\]

where \( X_{O2}(t + \tau) \) is the flue gas oxygen content (%), and \( n_{Air} \) the sum of the primary and secondary air flows (total air) (mol/s). The net combustion power for the given thermal decomposition of fuel is

\[
Q = \dot{m}_{thd}(w)(q_f - q_f^g - q_{cr}) (\text{MJ}) \tag{37}
\]

Where as the temperature before the secondary superheater is calculated using:

\[
T_f = (q_f + 0.21(F_{Air}/(22.41 \cdot 10^{-3} \cdot \dot{m}_{thd}(w)))C_{O2} + 0.79(F_{Air}/(22.41 \cdot 10^{-3} \cdot \dot{m}_{thd}(w)))C_{N2})/\]

\[
(n_C CO + n_S CSO + (n_{H2O} + n_{H2})C_{H2O} + 3.76 \cdot N_f^O + n_{C} + n_{N} + n_{H2O}) + 0.21 \cdot N_{ExAir}C_{O2} + 0.79 \cdot N_{ExAir}C_{N2}) (\text{C}) \tag{39}
\]

where the \( N_{ExAir} \) excess air (mol/kg).

3.3.5. Fuel moisture soft-sensor

The fuel moisture soft-sensor assumes that a change in the water evaporation rate affects the enthalpy of the secondary superheater; The effective value of the fuel \( q_{thd} \) changes linearly when the water evaporation rate changes [15]. The water evaporation rate \( w \) is obtained by minimizing

\[
\min J(w) = \sum_{i=0}^{N} |h_2 - \hat{h}_2| \tag{40}
\]

where \( N \) is the prediction horizon, \( h_2 \) is the specific enthalpy after the secondary superheater (MJ/kg), and \( \hat{h}_2 \) is the estimated specific enthalpy after the secondary su
perheater (MJ/kg). The prediction model for the specific enthalpy after the secondary superheater is

$$\frac{d h_2}{dt} = \frac{1}{\varrho V}(Q_t + \dot{m}_1 h_1 - \dot{m}_2 h_2)[MJ/(s \cdot kg)]$$ (41)

where \(\varrho\) is the specific density of the steam (kg/m³), \(V\) is the volume of the steam of the secondary superheater (m³), \(\dot{m}_1\) is the steam flow before the secondary superheater (kg/s), \(h_1\) is the specific enthalpy before the secondary superheater (MJ/kg), and \(\dot{m}_2\) is the steam flow after the secondary superheater (kg/s). The heat transfer from the flue gas to the metal tubes of the secondary superheater in the presence of mixed convection and radiation heat transfer is

$$Q_w = \alpha_w \dot{m}_{fg} 0.65 ((T_{fg} - \alpha_{fo} * T_{fo}) - T_w) + k_w ((T_{fg} - \alpha_{fo} * T_{fo})^2 - T_w^2)[MJ/s]$$ (42)

where \(\alpha_w\) is the convection heat transfer coefficient, \(\alpha_{fo}\) is the correction coefficient, \(T_{fo}\) is the flue gas temperature after the economizer (°C), \(T_w\) is the temperature of the metal tubes of the secondary superheater (°C), and \(k_w\) is the radiation heat transfer coefficient. The temperature of the tube walls of the secondary superheater is

$$\frac{dT_w}{dt} = \frac{1}{m_t C_p}(Q_w - Q_t)[K/s]$$ (43)

where \(m_t\) is the mass of the metal tubes of the secondary superheater (kg), and \(C_p\) is the specific heat capacity of the metal (MJ/kgK). The heat transfer from the metal tubes of the secondary superheater to the steam in the presence of convection heat transfer is

$$Q_t = \alpha_c \dot{m}_{sec} 0.8 (T_w - T)[MJ/s]$$ (44)

where \(\alpha_c\) is the convection heat transfer coefficient.

$$T = (T_1 + T_2)/2[°C]$$ (45)

where \(T_1\) is the steam temperature before the secondary superheater (°C) and \(T_2\) the steam temperature after the secondary superheater (°C).

4. Test results of system identification of model parameters of BioGrate boiler

The identification of models of the water evaporation, the thermal decomposition of dry fuel, and the drum pressure was conducted using the measurements of the BioPower 5 CHP plant. For the fuel feed, the samples were taken every 5 min from fuel dropping from the fuel silo just before the stoker screw and analyzed manually. The Servomex 2500 FT-IR analyzer was used to measure the water evaporation. The flue gas was extracted from the flue gas duct and led into the analyzer. The samples were taken every second. The compression factors for the measurements of the BioPower 5 CHP plant were detected as follows:

$$\Delta(\Delta)_i = \hat{y}_{i+1} - 2\hat{y}_i + \hat{y}_{i-1}$$ (46)

where \(\hat{y}\) is a reconstructed signal and \(h\) is the sampling interval. The index \(i\) ranges from 2 to \(N - 1\), where \(N\) is the number of samples. If the reconstructed data is differenced twice, there will be \(n = N - m\) second differences whose values are zero. Therefore, the compression factor is determined from

$$CF_{est} = \frac{N}{m}$$ (47)

where \(m = N - n\). The compression factor of the measurements are presented in Table 1.

Fig. 6 shows the estimated and measured water evaporation based on the measured data. The model performance is illustrated in Fig. 7. Due to the longer sampling time of 5 minutes of the fuel feed, the estimated values and the measurements are not exactly the same.

<table>
<thead>
<tr>
<th>Measurement</th>
<th>Compression factor (s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pressure</td>
<td>182</td>
</tr>
<tr>
<td>Steam temperature</td>
<td>395</td>
</tr>
<tr>
<td>Steam flow</td>
<td>10</td>
</tr>
<tr>
<td>Feed water pressure</td>
<td>320</td>
</tr>
<tr>
<td>Feed water temperature</td>
<td>5082</td>
</tr>
<tr>
<td>Feed water flow</td>
<td>6</td>
</tr>
<tr>
<td>Primary air flow</td>
<td>4</td>
</tr>
<tr>
<td>Secondary air flow</td>
<td>6</td>
</tr>
<tr>
<td>Flue gas oxygen content</td>
<td>75</td>
</tr>
<tr>
<td>Flue gas moisture content</td>
<td>25</td>
</tr>
<tr>
<td>Stoker speed</td>
<td>367</td>
</tr>
</tbody>
</table>

Fig. 8 shows the estimated and measured thermal decomposition of fuel. The validation of the identified model was performed on another measurement series. The model performance is presented in Fig. 9. The good performance
of the model was due to the constant fuel bed height of grate that affects the thermal decomposition of the fuel.

Fig. 10 shows the estimated and measured drum pressure based on the measured data. The validation of the identified model was performed on another measurement series. The model performance is presented in Fig. 11. The measurement data was compressed. Therefore, the estimated values and the measurements are not exactly the same. The compression factor of the pressure measurement was 3 min as shown in Table 1. However, it was small enough to capture the dynamics for the variable $e$ of the drum model in Equation (29). The inputs, the primary air flow, the secondary air flow, the flue gas oxygen content, and the flue gas moisture content had the small compression factors of 4, 6, 75, 25 sec that were needed to accurately estimate the thermal decomposition of the fuel and the combustion power. Furthermore, the feed water temperature had a large compression factor of 85 min as it doesn’t vary greatly.

Fig. 11: The measured (dashed line) and estimated (solid line) drum pressure, and the model input parameters, combustion power estimation, steam temperature, steam flow, feed water pressure, feed water temperature, and feed water flow in the identification.
5. Test results of the MPC control strategy of BioGrate boiler

The performance of the MPC strategy was compared with the currently used control strategy by using the BioPower 5 CHP plant simulator in a MATLAB simulation environment. The following identified model was used for the simulation:

\[
\begin{align*}
    x_{k+1} &= Ax_k + Bu_k + Ed_k \\
    z_k &= C_x x_k 
\end{align*}
\]  

where

\[
A = \begin{bmatrix} 0.0013 & -0.0028 & 0 & 0 & 0 \\ -0.3900 & 19.3644 & -2.44 & -1 & 0 \\ 0 & 0 & 0 & -1 & 0 \\ 0 & 0 & 0.0020 & -0.0020 & 0 \end{bmatrix} 
\]

\[
B = \begin{bmatrix} 0.0033 & -0.0015 \\ 0 & 0 \\ 0 & 19.3644 \cdot 0.0015 \\ 0 & 0 \\ 0 & 0 \end{bmatrix} 
\]

\[
E = \begin{bmatrix} 0 & 0 \\ 0.0028 & 0 \\ 0 & 0 \\ 0 & 1 \end{bmatrix} 
\]

\[
C = \begin{bmatrix} 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix} 
\]

The first rows of the matrix \(A\) and \(B\) describe the thermal decomposition of the dry fuel. However, no delay was detected in the system identification, which might be caused by the fact that the stoker screw actively pushes the dry fuel. The second rows of the matrix \(A\) and \(E\) describe the water evaporation model. The moisture content is calculated as a percentage from the fuel feed and it is delayed with 1200 time samples. Then it takes 6 min water to evaporate. The integrating disturbance states \(\eta_k\) were 0.047 and 0.072, 4.8975 for the model of thermal decomposition of fuel, the pressure model, and the water evaporation model, respectively, and were determined by calculating the variance of the prediction errors in the system identification. The measurement disturbances \(v_k\) were approximated 1%. Furthermore, the rank of the augmented system was 7. Therefore, the closed-loop system is stable. The input limits were \(u_{1,\text{min}} = 0\), \(u_{1,\text{max}} = 5\), \(\Delta u_{1,\text{min}} = -0.03\), and \(\Delta u_{1,\text{max}} = 0.03\) [kg/s] for the stoker.
speed; \( u_{2,\text{min}} = 0, u_{2,\text{max}} = 8, \Delta u_{2,\text{min}} = -0.03 \), and \( \Delta u_{2,\text{max}} = 0.03\) [kg/s] for the primary air. The output limits were \( y_{1,\text{min}} = 0, y_{1,\text{max}} = 35\) [MW] for the combustion power; and \( y_{2,\text{min}} = 0, y_{2,\text{max}} = 55\) [bar] for the drum pressure. The MPC is tuned with

\[
Q_z = \begin{bmatrix} 0.01 & 0 \\ 0 & 0.1 \end{bmatrix} \quad \text{and} \quad S = \begin{bmatrix} 0.1 & 0 \\ 0 & 0.1 \end{bmatrix}
\]

The fast response is achieved by the combustion power control. However, the inaccuracies are corrected by the pressure control, and therefore, controlling of the pressure has greater the priority.

In the first simulation test, the moisture content of the fuel feed was changed from 55 % to 65 % while the power demand was 17 MW. With the currently used strategy, the power demand was lowered to 14 MW due to the stabilization issues. The settling time of the drum pressure
is only 2 minutes with the MPC control strategy, whereas it was 1.5 hours with the currently used control strategy, as shown in Figs. 12 and 14.

In the developed MPC strategy, the amount of dry fuel in the furnace is kept at the needed level and the fast response is achieved by manipulating the primary air. Due to the linearized model Equation (28), the combustion power could be increased by manipulating only the primary air. Therefore, the change rate of both the fuel flow and primary air have been limited to 0.03 kg/s to realistically simulate the limiting drying rate of fuel.

In the second simulation test, the power demand was changed from 12 MW to 17 MW while the moisture content of the fuel wood was 57%. With the currently used strategy, the maximum power demand was lowered to 16 MW due to the stabilization issues. The settling time of the drum pressure is only 2 minutes with the MPC strategy, whereas it was 1.5 hours with the currently used control strategy, as shown in Figs. 13 and 15. The settling time with the MPC strategy was again mainly limited by the drying rate of the fuel.

The simulation results were used to improve the currently used control strategy of the BioGrate boiler, compensating the main disturbances caused by variations in fuel quality such as the moisture content of fuel, and variations in fuel flow. The performance of the MPC strategy was tested in a simulation environment.

The simulation results showed that the settling time of the drum pressure is 2 minutes with the MPC strategy, whereas it was 1.5 hours with the currently used control strategy. In addition, the settling time with the MPC strategy was mainly limited by the drying rate of the fuel.

The control strategy has been implemented by using MPC. However, the same models and principles can be used to implement the strategy by using classical control and some compensation methods.

6. Conclusions

This paper presented a model predictive control (MPC) strategy for BioGrate boiler, compensating the main disturbances caused by variations in fuel quality such as the moisture content of fuel, and variations in fuel flow. The performance of the MPC strategy was tested in a simulation environment.

The simulation results showed that the settling time of the drum pressure is 2 minutes with the MPC strategy, whereas it was 1.5 hours with the currently used control strategy. In addition, the settling time with the MPC strategy was mainly limited by the drying rate of the fuel.

The control strategy has been implemented by using MPC. However, the same models and principles can be used to implement the strategy by using classical control and some compensation methods.

References


