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Model predictive control utilizing fuel and moisture soft-sensors for the BioPower 5 combined heat and power (CHP) plant

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Abstract

This paper presents a model predictive control (MPC) strategy for efficient energy production in BioGrate boiler. In addition to compensating for the main disturbances caused by variations in fuel quality such as fuel moisture content, and variations in fuel feed, this strategy models water evaporation, and models and controls the fuel bed height of the grate. Usually, combustion power in a furnace have been estimated by utilizing oxygen consumption. There is however a need for more accurate prediction and control of combustion power, which is greatly affected by the fuel bed height and fuel moisture content. It is shown that water evaporation and thermal decomposition of dry fuel can be estimated by utilizing fuel moisture soft-sensor and oxygen consumption calculations respectively. As a result, the primary air can be adjusted to produce the necessary combustion power, and the power output of the boiler can be accurately predicted. This enables efficient stabilization of plant operations. To verify the model, experiments were performed at a BioPower 5 CHP plant, which utilizes BioGrate combustion technology to enable the use of wet biomass fuels with a moisture content as high as 65%. Then the MPC strategy was compared with the currently used control strategy. Finally, the results are presented, analyzed, and discussed.

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

1. Introduction

The share of biomass in combustion is increasing due to a demand to increase the portion of renewable energy in total energy production. Biomass with a moisture content up to 65% can be burned in BioGrate developed by MW Power. In the BioGrate system, this is achieved by feeding the fuel onto the center of a grate, thus improving water evaporation due to the heat of the surrounding burning fuel and thermal radiation from the brick walls [1]. However, a varying moisture content of the biomass and disturbances in fuel feed results in uncertainty about its energy content and complicates operation of BioGrate process. An important prerequisite in the MPC strategy development for BioGrate has been to develop a biomass combustion model and methods for estimating fuel moisture content, thermal decomposition of fuel, and combustion power, as this system is characterized by the long time delays and large time constants [2].

To improve the current used control strategies it is important to understand how combustion happens in BioGrate. The phenomena should support drying and devolatilization of fresh fuel with a high moisture content.

Several models for biomass combustion have been developed. Saastamoinen et al. [3] studied the effects of air flow rate, fuel moisture content, particle size, bed density, and wood type. The study showed that moisture considerable lowered the speed of the ignition front.

Johansson et al. [4] investigated the effect of using a porous media approximation in modeling fixed bed combustion of wood. They compared the results from the model that uses the approximation with the results from the model, where the internal particle gradients are taken into account. The results show that when the particle size is larger than 2cm, the reaction front is wider when internal particle gradients are considered. Moreover, the approximation can play a greater role when the gas stoichiometry in the reaction front is of importance.

Yang et al. [5] carried out detailed mathematical simulations as well as experiments with a porous model for the combustion of wood chips and the incineration of simulated municipal solid wastes in a bench-top stationary bed. They concluded that ignition time is influenced by both the devolatilization kinetic rate and the moisture level of the fuel: An increase in the moisture level prolongs the ignition time. Moreover, an increase in the fuel moisture level shifts the combustion stoichiometry to a fuel-lean condition. Yang et al. [6] employed mathematical models of a packed bed system to simulate the effects of changes in four different fuel properties on combustion characteristics in terms of combustion rate, combustion stoichiometry

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Nomenclature

M_{u-1}	input weighting vector	N_w	prediction horizon
w_k	zero-mean white-noise disturbance	Q	heat transfer, MJ/s
α	convection heat transfer coefficient	q	heat value, MJ/kg
β	coefficient for a dependence on the position of the moving grate	Q_u	move suppression factor weight matrix
$\dot{m}$	mass flow, kg/s	Q_z	tracking error weight matrix
η_k	integrating disturbance states	R	future target vector
Γ	pulse response matrix	r	target variable
Γ_d	measured disturbance prediction matrix	t_d	time delay, s
$\hat{\eta}$	disturbance estimation	U	input vector
$\hat{h}$	specific enthalpy estimation, MJ/kg	u	manipulated variable
$\hat{x}$	state estimation	V	volume, m ³
Λ	input difference matrix	v_k	zero-mean white-noise disturbance
Q_u	input weighting matrix	w	fuel moisture content, %
Q_z	output weighting matrix	w_i	mass fraction, %
Φ	block Hankel matrix	X	volume, %
ϕ	objective function	x	state
ψ	objective function	Z	output prediction vector
ρ	specific density, kg/m ³	z	controlled variable
ξ_k	zero-mean white-noise disturbance	Subscripts	
A	state matrix of the state space model	1	input
A_d	unit diagonal matrix	2	output
B	input matrix of the state space model	Air	air
B_d	disturbance model	C	carbon
c	correction coefficient	d	disturbance
C_η	zero matrix	ds	dry solid
C_i	specific heat capacity, J/molT	$E Air$	excess air
C_p	specific heat capacity of the metal, MJ/kgK	fg	flue gas
C_z	output matrix of the state space model	fo	economizer
D	disturbance vector	gf	wet fuel
d	disturbance variable	H	hydrogen
E	disturbance matrix of the state space model	in	input
F	volume flow, m ³ /s	mt	metal
h	specific enthalpy, MJ/kg	N	nitrogen
H_i	impulse response coefficient matrix	O	oxygen
I	unit diagonal matrix	S	sulphur
k	radiation heat transfer coefficient	s	steam
L_x	filter gain matrix for the state	td	time delay
L_η	filter gain matrix for the disturbance	thd	thermal decomposition of fuel
m	mass, kg	wev	water evaporation
n_i	moles, mol/kg	wf	dry fuel
N_p	prediction horizon	Superscripts	
		g	gas

etry, flue gas composition, and solid-phase temperature. They showed that the combustion rate is determined by both the fuel particle size and the fuel density: Smaller fuel particle sizes result in higher combustion rates due to increased reaction surface area and enhanced gas-phase mixing in the bed. And even at different primary air levels, the burning rate decreases as biomass material density increases. In [7], Yang et al further investigated especially

the effect of particle size on pinewood combustion in a packed bed. They concluded that both char burnout and fuel devolatilization occur at the same time in a bed of large particles.

Most combustion experiments have been done using a stationary bed and with combustion started on the upper surface of the fuel bed. Thunman and Leckner [8] however studied combustion of wet biofuels in a 31 MW

reciprocating grate furnace. In addition, they performed other experiments in batch-fired pot furnaces. The fuel was forest waste with a moisture content of approximately 50 %. Thunman and Leckner concluded that ignition of wet biofuel has to take place on the surface of the grate, for example, by means of heat conduction through the grate bars. In such a case, heat is generated at the bottom of the bed by char combustion and is transferred along with gas up through the bed, which dries and devolatilizes fresh fuel with a moisture content of up to 70 or 80 %. In the case of a counter-current, which is ignited from the top, such a moisture content would be too high, however, since devolatilization and combustion in a counter-current take place on a narrow front. Thunman and Leckner further compared co-current and counter-current fixed bed combustion of biofuel in [9]. The results show that in a steady state, drying, devolatilization, and char combustion are separated in co-current combustion, whereas the three stages are in closer proximity during the entire counter-current combustion process.

Recently, Ström and Thunman [10] have worked with the development of a robust and computationally efficient particle submodel for use in computational fluid dynamics (CFD) simulations of fixed-bed conversion of biofuels. Based on previous works, Gómez et al. [11] present a bed compaction submodel to account for the local shrinkage of the bed due to the collapse of regions weakened by their combustion, helping in the realistic estimation of the processes involved in packed bed combustion of biomass and point to particle shrinkage.

1.1. State of the art model predictive control of biomass boiler

Based on the insight gained into the basic combustion situation by Bauer et al. [2], they derived a simple model for co-current combustion of biomass based on two mass balances for water and dry fuel. The model was verified by experiments at a pilot scale furnace with a horizontally moving grate. Based on the literature [12][4][13], they suggested 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. [7] when the air factor is not much larger than stoichiometric air, staying at a typical optimal level of about 1.2 to 1.7. Higher air flows begin to cool the bed [14]. In addition, the test results of Bauer et al. [2] showed that the water evaporation rate is mainly independent of the primary air flow. Based on the models, Göller et al. [15][16] implemented a model based control strategy in a commercially available small-scale biomass boiler. Test results showed that the control could always provide the required load whereas the conventional control (PID control based on standard control strategies) could not avoid a feed temperature drop of more than 7 °C. The better control of the residual oxygen and the control of the air ratio led to lower emissions and higher efficiencies. In addition, the control was able to handle the step-wise change of the fuel water content from

Figure 1: BioGrate, showing the stoker screw and the water-filled ash basin underneath the grate

26% to 38% and vice versa without difficulties. Since the developed control requires the knowledge of variables mass of water in the water evaporation zone and the mass of dry fuel in the thermal decomposition zone but only the feed temperature could be measured, the extended Kalman filter was incorporated into the model to estimate the current state of the furnace. Kortela and Jämsä-Jounela have presented a solution for this issue in [17] where these variables are estimated by using fuel and moisture soft-sensors [18]. Simulation studies of Paces et al.[19] presented combined control of combustion load and combustion position in a moving grate biomass furnace. The simulation examples demonstrated that the proposed control scheme effectively decouples combustion load from combustion position. In addition, simulation-based comparisons of Leskens et al. [20] showed that an MPC-based combustion control is capable of delivering improved control performance in comparison to a conventional, multivariable combustion control system when large temporary disturbances are acting. Based on the combustion phenomena in the BioGrate boiler, it is assumed this is co-current combustion. This paper presents a model predictive control (MPC) strategy for BioGrate boiler. The paper is organized as follows: Section 2 presents the BioPower 5 CHP plant process. Section 3 presents the MPC strategy, and models for the fuel

Figure 2: 1. Fuel, 2. Primary air, 3. Secondary air, 4. Economizer, 5. Drum, 6. Evaporator, 7. Superheaters, 8. Superheated steam

bed height and water evaporation are developed. In addition, the calculations to estimate thermal decomposition of dry fuel and fuel moisture soft-sensor for water evaporation are presented. Lastly, the test results are presented in Section 4, followed by the conclusions in Section 5.

Figure 3: Current control strategy of the BioPower 5 CHP plant

2. Description of the process and its control strategy

In the BioPower 5 CHP plant, heat for electricity generation and hot water network is obtained by direct combustion of solid biomass – bark and woodchips – which is fed into the BioGrate together with combustion air (Fig. 1).

Fig. 2 illustrates the boiler of the BioPower 5 CHP plant. The essential components of the boiler are an economizer, an evaporator, a drum, and primary and secondary superheaters. Feed water is pumped into the boiler from a feed water tank. The water is first led into the economizer (4), which is heated by means of flue gases.

From the economizer, the heated feed water is led into 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 into the steam drum, where they are separated. The temperature of steam is raised in primary and secondary superheaters (7) and then the superheated high-pressure steam (8) is led into 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 power 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.

However, the change in the fuel moisture content and the disturbances in the fuel feed are not taken into account in the control strategy, therefore causing oscillation in steam pressure.

3. Model predictive control for the BioPower 5 CHP plant

The investigated MPC strategy over the current control strategy is illustrated in Fig. 4. The proposed strategy utilizes oxygen consumption and fuel moisture soft-sensor to estimate the thermal decomposition of dry fuel and the water evaporation rate respectively. Subsequently, the combustion power is estimated based on these soft-sensors. In addition, the fuel bed height is controlled by utilizing the installed pressure 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 the BioGrate boiler

The MPC manipulates separately both primary air flow rate and stoker speed. The models of the MPC are configured as follows: The primary air flow rate and stoker speed (u) are the manipulated variables; the moisture content in the fuel feed and the steam demand are the measured disturbances (d); and the fuel bed height and the steam pressure are the controlled variables (z), as illustrated in Fig. 5. The MPC utilizes the linear state space system [21]:

$$\begin{aligned} x_{k+1} &= Ax_k + Bu_k + Ed_k \\ z_k &= C_z x_k \end{aligned} \quad (1)$$

where A is the state matrix, B is the input matrix, E is the matrix for the measured disturbances, and C_z the output matrix.

Figure 4: Model predictive control for the BioPower 5 CHP plant

Figure 5: The configuration of the models for the MPC strategy of the BioPower 5 CHP plant

3.2. Regulator

where $\Delta u_k = u_k - u_{k-1}$. The horizon Z , the R , U , and D are formulated as follows:

$$Z = \begin{bmatrix} z_1 \\ z_2 \\ \vdots \\ z_{N_p} \end{bmatrix}, R = \begin{bmatrix} r_1 \\ r_2 \\ \vdots \\ r_{N_p} \end{bmatrix}, U = \begin{bmatrix} u_0 \\ u_1 \\ \vdots \\ u_{N_p-1} \end{bmatrix},$$

$$D = \begin{bmatrix} d_0 \\ d_1 \\ \vdots \\ d_{N_p-1} \end{bmatrix} \quad (4)$$

The system of Equation (1) can be formulated as

$$z_k = C_z A^k x_0 + \sum_{j=0}^{k-1} H_{k-j} u_j \quad (2)$$

where H_{k-j} are impulse response coefficients. Using the Equation (2), the MPC optimization problem with input, the input rate of movement, and output constraints is thus:

$$\begin{aligned} \min \phi &= \frac{1}{2} \sum_{k=1}^{N_p} \|z_k - r_k\|_{Q_z}^2 + \frac{1}{2} \|\Delta u_k\|_{Q_u}^2 \\ s.t. x_{k+1} &= A x_k + B u_k + E d_k, \\ &k = 0, 1, \dots, N_p - 1 \\ z_k &= C_z x_k, k = 0, 1, \dots, N_p \\ u_{\min} &\leq u_k \leq u_{\max}, \\ &k = 0, 1, \dots, N_p - 1 \\ \Delta u_{\min} &\leq \Delta u_k \leq \Delta u_{\max}, \\ &k = 0, 1, \dots, N_p - 1 \\ z_{\min} &\leq z_k \leq z_{\max}, k = 1, 2, \dots, N_p \end{aligned} \quad (3)$$

and the predictions by the Equation (2) are expressed as

$$Z = \Phi x_0 + \Gamma U + \Gamma_d D. \quad (5)$$

Then Φ , Γ , and Γ_d are

$$\Phi = \begin{bmatrix} C_z A \\ C_z A^2 \\ C_z A^3 \\ \vdots \\ C_z A^{N_p} \end{bmatrix}, \quad (6)$$

$$\Gamma = \begin{bmatrix} H_1 & 0 & 0 & \dots & 0 \\ H_2 & H_1 & 0 & \dots & 0 \\ H_3 & H_2 & H_1 & \dots & 0 \\ \vdots & \vdots & \vdots & \dots & \vdots \\ H_{N_p} & H_{N_p-1} & H_{N_p-2} & \dots & H_1 \end{bmatrix}, \quad (7)$$

$$\Gamma_d = \begin{bmatrix} H_{1,d} & 0 & 0 & \dots & 0 \\ H_{2,d} & H_{1,d} & 0 & \dots & 0 \\ H_{3,d} & H_{2,d} & H_{1,d} & & 0 \\ \vdots & \vdots & \vdots & & \vdots \\ H_{N_p,d} & H_{N_p-1,d} & H_{N_p-2,d} & \dots & H_{1,d} \end{bmatrix}. \quad (8)$$

For the case $N_p = 6$, the matrices

$$\Lambda = \begin{bmatrix} -I & I & 0 & 0 & 0 \\ 0 & -I & I & 0 & 0 \\ 0 & 0 & -I & I & 0 \\ 0 & 0 & 0 & -I & I \end{bmatrix}, \quad (9)$$

$$\mathcal{Q}_z = \begin{bmatrix} Q_z & 0 & 0 & 0 \\ Q_z & Q_z & 0 & 0 \\ 0 & 0 & \ddots & 0 \\ 0 & 0 & 0 & Q_z \end{bmatrix}, \quad (10)$$

$$\mathcal{Q}_u = \begin{bmatrix} 2Q_u & -Q_u & 0 & 0 & 0 \\ -Q_u & 2Q_u & -Q_u & 0 & 0 \\ 0 & -Q_u & 2Q_u & -Q_u & 0 \\ 0 & 0 & -Q_u & 2Q_u & -Q_u \\ 0 & 0 & 0 & -Q_u & 2Q_u \end{bmatrix}, \quad (11)$$

and

$$M_{u-1} = - \begin{bmatrix} S \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix}. \quad (12)$$

Q_z are tuned for the fuel bed height and the drum pressure. Q_u for primary air and stoker speed, can be tuned separately from each other. Then the objective function is expressed as

$$\begin{aligned} \psi &= \frac{1}{2} \sum_{k=1}^{N_p} \|z_k - r_k\|_{Q_z}^2 + \frac{1}{2} \|\Delta u_k\|_{Q_u}^2 \\ &= \frac{1}{2} U' H U + g' U + \rho \end{aligned} \quad (13)$$

where

$$H = \Gamma' Q_z \Gamma + Q_u \quad (14)$$

$$g = \Gamma' Q_z \Phi x_0 - \Gamma' Q_z R + M_{u-1} u_{-1} + \Gamma' Q_z \Gamma_d D \quad (15)$$

The MPC optimization problem of Equation (3) can be solved as a solution of the following convex quadratic pro-

gram

$$\begin{aligned} \min_U \psi &= \frac{1}{2} U' H U + g' U \\ U_{\min} &\leq U \leq U_{\max} \\ \Delta U_{\min} &\leq \Delta U \leq \Delta U_{\max} \\ \bar{Z}_{\min} &\leq \Gamma U \leq \bar{Z}_{\max} \end{aligned} \quad (16)$$

where

$$\bar{Z}_{\min} = Z_{\min} - \Phi x_o - \Gamma_d D \quad (17)$$

$$\bar{Z}_{\max} = Z_{\max} - \Phi x_o - \Gamma_d D \quad (18)$$

In order to achieve offset-free performance, the system of Equation (1) is augmented with integrating disturbance matrices [22]. The designed system uses an input disturbance model where $B_d = B$, A_d has only ones in diagonal, and C_d has only zeros.

$$\begin{bmatrix} x_{k+1} \\ \eta_{k+1} \end{bmatrix} = \begin{bmatrix} A & B_d \\ 0 & A_d \end{bmatrix} \begin{bmatrix} x_k \\ \eta_k \end{bmatrix} + \begin{bmatrix} B \\ 0 \end{bmatrix} u_k + \begin{bmatrix} E \\ 0 \end{bmatrix} d_k + \begin{bmatrix} w_k \\ \xi_k \end{bmatrix} \quad (19)$$

$$y_k = [C \quad C_\eta] \begin{bmatrix} x_k \\ \eta_k \end{bmatrix} + v_k \quad (20)$$

The w_k and v_k are white noise disturbances with zero mean. Thus, the disturbances and the states of the system are estimated as follows:

$$\begin{bmatrix} \hat{x}_{k|k} \\ \hat{\eta}_{k|k} \end{bmatrix} = \begin{bmatrix} \hat{x}_{k|k-1} \\ \hat{\eta}_{k|k-1} \end{bmatrix} + \begin{bmatrix} L_x \\ L_\eta \end{bmatrix} (y_k - C \hat{x}_{k|k-1} - C_\eta \hat{\eta}_{k|k-1}) \quad (21)$$

and the state predictions of the augmented system of Equation (19) are obtained by

$$\begin{bmatrix} \hat{x}_{k+1|k} \\ \hat{\eta}_{k+1|k} \end{bmatrix} = \begin{bmatrix} A & B_d \\ 0 & A_d \end{bmatrix} \begin{bmatrix} \hat{x}_{k|k} \\ \hat{\eta}_{k|k} \end{bmatrix} + \begin{bmatrix} B \\ 0 \end{bmatrix} u_k + \begin{bmatrix} E \\ 0 \end{bmatrix} d_k \quad (22)$$

3.3. Modeling of BioGrate combustion

An unknown fuel moisture content and flue flow variations result in uncertainty in a combustion power. Therefore, the models for the water evaporation and for the fuel bed height are developed for BioGrate combustion.

3.3.1. The model of water evaporation

Most of the water evaporates in region marked "moist fuel", as shown in Fig. 6. The energy for the water evaporation is mainly provided by the combustion of char near the surface of the grate. However, in BioGrate, the water in the centre of the grate also evaporates rapidly due

to the heat of thermal radiation from the brick walls. The model of the water evaporation rate is [2]:

$$\frac{dm_w(t)}{dt} = -c_{wev}m_w(t)\beta_{wev}(t) + \frac{dc_{w,in}m_{w,in}(t-t_d(t))}{dt} [\text{kg/s}] \quad (23)$$

where $m_w(t)$ is the mass of the water in the evaporation zone (kg), c_{wev} is the correction coefficient, β_{wev} is the coefficient for a dependence on the position of the moving grate, $c_{w,in}$ is the correction coefficient, and $m_{w,in}$ the moisture in the fuel feed (kg/s).

$$t_d(t) = c_{td} \frac{m_w(t)}{m_{ds,in}(t)} [\text{s}] \quad (24)$$

where c_{td} is the delay coefficient, and $m_{ds,in}(t)$ is the dry biomass flow rate (kg/s). The fuel feeder (stoker screw) in the BioGrate is volume feeder and thus the actual flow rate can vary highly although the biomass feed is kept constant.

$$m_{w,in}(t) = \int_0^t \dot{m}_{w,in}(\tau) d\tau [\text{kg}] \quad (25)$$

3.3.2. The fuel bed height model

In co-current combustion, devolatilization and char combustion take place in different regions, as shown in Fig. 6. First, the primary air enters the heat source. Then, the heat is transferred inside the bed. Next, the gas leaves the char combustion region and devolatilizes the fuel. Finally, the gas leaves the devolatilization zone and dries the fuel. In a steady state, combustion, drying, devolatilization, and char zoned are separated from each other [9]. It is therefore correct to use only one zone for modelling the thermal decomposition of the fuel. Thus, the amount of dry biomass m_{ds} in the thermal decomposition zone is

$$\frac{dm_{ds}(t)}{dt} = -\dot{m}_{thd}(t) + \frac{dc_{ds,in}m_{ds,in}(t-T_d(t))}{dt} [\text{kg/s}] \quad (26)$$

$$m_{ds,in}(t) = \int_0^t \dot{m}_{ds,in}(\tau) d\tau [\text{kg}] \quad (27)$$

where $\dot{m}_{thd}(t)$ is the thermal decomposition rate of the fuel (kg/s), and $c_{ds,in}$ is the correction coefficient. In [2], the effect of the primary air flow rate on the thermal decomposition of the fuel is multiplicative. However, in contrast to the model presented in [2], the following model for the thermal decomposition rate $\dot{m}_{thd}$ is proposed:

$$\dot{m}_{thd} = c_{thd} \cdot \dot{m}_{pa} - c_{ds} \cdot m_{ds} [\text{kg/s}] \quad (28)$$

where c_{thd} is the thermal decomposition rate coefficient, c_{ds} the fuel bed height coefficient, and m_{ds} dry biomass (kg). The fuel bed height (m) is calculated by utilizing installed pressure sensors and the density of the biomass.

The fuel bed height coefficient c_{ds} describes how a large bed height decreases the thermal decomposition rate of the fuel. Moreover, with a constant fuel bed height, the thermal decomposition increases linearly as the primary air flow rate increases.

3.4. Fuel quality

An elemental composition, quality, and moisture content of a fuel have a strong effect on its heat value. All biomass fuels contain carbon (C), hydrogen (H), oxygen (O), and nitrogen (N). In addition, biomass contain substances from soil, such as water, minerals, rock materials, and sulfur (S). The evaporation of water found in fuel requires heat, and therefore decreases the heat value of the fuel. The effective heat value of a wet fuel is thus [23]

$$q_{gf} = q_{wf} \cdot (1 - w/100) - 0.0244 \cdot w [\text{MJ/kg}] \quad (29)$$

where w is the moisture content of the wet fuel (%).

Figure 6: Thermal decomposition of fuel

Figure 7: Pressure sensors of the grate

$$q_{wf} = 0.348 \cdot w_C + 0.938 \cdot w_H + 0.105 \cdot w_S + 0.063 \cdot w_N - 0.108 \cdot w_O [\text{MJ/kg}] \quad (30)$$

Figure 8: The model output variable, fuel bed pressure, and the model input variables, stoker speed and primary air in the identification.

Figure 9: The model output variable, fuel bed pressure, and the model input variables, stoker speed and primary air in the validation.

where C_i is mass fraction of the component (%). In order to use Equation (29) and Equation (30), the composition of the fuel has to be known.

3.4.1. Soft-sensor of thermal decomposition of dry fuel

Oxygen consumption is used as a measure of heat generation in a plant's furnace [24]. By summing up the oxygen needed for different components and subtracting the amount of oxygen in the fuel, the theoretical amount of oxygen needed to burn one kilogram of fuel is

$$n_{O_2}^g = n_C + 0.5 \cdot n_{H_2} + n_S - n_{O_2} [\text{mol/kg}] \quad (31)$$

where n_i is the moles (mol/kg). The theoretical flue gas flow is thus

$$n_{fg} = n_C + n_{H_2} + n_S + 3.76 \cdot n_{O_2}^g + n_{N_2} + n_{H_2O} [\text{mol/kg}] \quad (32)$$

where the value $(3.76 \cdot n_{O_2}^g)$ is the nitrogen that comes with the combustion air. There is no direct measurement for the thermal decomposition of the fuel in Equation (28). However, it can be calculated indirectly by utilizing flue gas oxygen and total air measurements. The thermal decomposition rate for the wet fuel is calculated as follows

[18]

$$\dot{m}_{gf} = \frac{(0.21 - \frac{X_{O_2}}{100})n_{Air}}{n_{O_2}^g + \frac{X_{O_2}}{100}(n_{fg} - 4.76 \cdot n_{O_2}^g)} [\text{kg/s}] \quad (33)$$

where $X_{O_2}(t)$ is the flue gas oxygen content (%), and n_{Air} the sum of the primary and secondary air flows (mol/s). For the dry fuel, the calculations can be done similarly.

Figure 10: Thermal decomposition rates for different primary air values with the fuel bed pressures (from thinnest to thickest line) 10-12 mbar, 15-17 mbar, 50-52 mbar, 70-72 mbar, 80-82 mbar, 85-87 mbar, 90-92 mbar, 95-97 mbar, 98-100 mbar, and 100-102 mbar,

Figure 11: MPC strategy: Reactions of fuel bed height, dry fuel flow, and moisture in the fuel to a change in the moisture content of fuel flow

3.4.2. Fuel moisture soft-sensor

The fuel moisture soft-sensor estimates the water evaporation rate which affects the enthalpy of the secondary superheater [25] through the flue gas flow $\dot{m}_{fg}$ and the flue gas temperature T_{fg} . Therefore, the water evapora-

tion rate w is obtained by minimizing

$$\min J(w) = \sum_{i=0}^{N_w} |h_2 - \hat{h}_2| \quad (34)$$

where N_w is the prediction horizon, h_2 is the measured output enthalpy of the secondary superheater (MJ/kg), and $\hat{h}_2$ is the estimated output enthalpy of the secondary superheater (MJ/kg). The prediction model for the enthalpy of the secondary superheater is

$$\frac{dh_2}{dt} = \frac{1}{\rho V} (Q_s + \dot{m}_1 h_1 - \dot{m}_2 h_2) [\text{MJ}/(\text{s} \cdot \text{kg})] \quad (35)$$

where ρ is the specific density of the steam of the secondary superheater (kg/m^3), V is the volume of the secondary superheater (m^3), $\dot{m}_1$ 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

$$Q_{fg} = \alpha_{fg} \dot{m}_{fg}^{0.65} ((T_{fg} - c_{fo} * T_{fo}) - T_{mt}) + k_{fg} ((T_{fg} - c_{fo} * T_{fo})^4 - T_{mt}^4) [\text{MJ}/\text{s}] \quad (36)$$

where α_{fg} is the convection heat transfer coefficient, c_{fo} is the correction coefficient, T_{fo} is the flue gas temperature after the economizer ($^{\circ}\text{C}$), T_{mt} is the temperature of the metal tubes of the secondary superheater ($^{\circ}\text{C}$), and k_{fg} is the radiation heat transfer coefficient. Flue gas flow for fuel flow in Equation 33 is

$$\dot{m}_{fg} = F_{Air} + \dot{m}_{gf} (n_{fg} - 4.76 \cdot n_{O_2}^g) \cdot 22.41 \cdot 10^{-3} [\text{m}^3/\text{s}] \quad (37)$$

where F_{Air} is the sum of the primary and secondary air flows (m^3/s). The flue gas temperature for fuel flow is

$$T_{fg} = (q_{gf} + 0.21(F_{Air}/(22.41 \cdot 10^{-3} \cdot \dot{m}_{gf}))C_{O_2} + 0.79(F_{Air}/(22.41 \cdot 10^{-3} \cdot \dot{m}_{gf}))C_{N_2}) / (n_C C_{CO_2} + n_S C_{SO_2} + (n_{H_2O} + n_{H_2})C_{H_2O} + (3.76 \cdot n_{O_2}^g + n_{N_2})C_{N_2} + 0.21 \cdot n_{EAir} C_{CO_2} + 0.79 \cdot n_{EAir} C_{N_2}) [^{\circ}\text{C}] \quad (38)$$

where C_i is the specific heat capacity of the component i ($\text{J}/\text{mol}\cdot\text{T}$), and the n_{EAir} excess air (mol/kg). The temperature for the tube walls of the secondary superheater is

$$\frac{dT_{mt}}{dt} = \frac{1}{m_{mt} C_p} (Q_{fg} - Q_s) [\text{K}/\text{s}] \quad (39)$$

where m_{mt} is the mass of the metal tubes of the secondary superheater (kg), and C_p is the specific heat of the metal

Figure 12: MPC strategy: Reactions of Drum Pressure, dry fuel flow, combustion power, and primary air flow to a change in the moisture content of fuel flow

Figure 13: The current control strategy: Reactions of total air flow, fuel flow, and pressure to a change in the moisture content of fuel flow

(MJ/kgK). The heat transfer from the metal tubes of the secondary superheater to the steam in the presence of convection heat transfer is

$$Q_s = \alpha_c \dot{m}_2^{0.8} (T_{mt} - T) [\text{MJ/s}] \quad (40)$$

where α_c is the convection heat transfer coefficient.

$$T = (T_1 + T_2)/2 [^\circ\text{C}] \quad (41)$$

where T_1 is the steam temperature before the secondary superheater ($^\circ\text{C}$) and T_2 the steam temperature after the

secondary superheater ($^\circ\text{C}$).

4. Test results

4.1. System identification of the dry fuel content's model

The system identification of the models of the fuel bed height and the thermal decomposition of the dry fuel was conducted using the measurements of the BioPower 5 CHP plant. The aim of the system identification was to determine the coefficients c_{ds} and c_{thd} . The fuels used were spruce bark with a moisture content of 54% and composition (51.5% carbon, 6.2% hydrogen, less than 0.3% nitro-

Figure 14: MPC strategy: Reactions of fuel bed height, dry fuel flow, and moisture in the fuel to a change in electricity & hot water demand

Figure 15: MPC strategy: Reactions of Drum Pressure, dry fuel flow, combustion power, and primary air flow to a change in electricity & hot water demand

gen, 0.2% sulfur, and 2.8% ash) and dry spruce woodchips with a moisture content of 20% and composition (51.0% carbon, 6.0% hydrogen, less than 0.2% nitrogen, less than 0.2% sulfur, and 0.5% ash). The both fuels had a same dry fuel effective heat capacity of 18.9 MJ/kg. In addition, 7 pressure sensors have been installed in the rings 1, 3, 5, 7, 9, 11, and 13, as illustrated in Fig. 7, to measure the fuel bed height pressure. The samples were recorded in 1 second interval.

Fig. 8 shows the estimated and measured fuel bed height pressure and the inputs, total air flow, and stoker speed based on the measurements. The validation of the identi-

fied model was performed on another measurement series. The performance of the fuel bed height model for the validation data is shown in Fig. 9. The identified model also works well using the validation data series. The thermal decomposition rate for different primary air flow rates and different fuel bed heights are shown in Fig. 10. The thermal decomposition of the dry fuel was calculated according to Equation (33). The results show that an increase in fuel bed height requires an increase in primary air flow to maintain the same thermal decomposition rate. In addition, the amount of needed primary air grows almost linearly, showing the behavior as presented in Equation (28).

Figure 16: The current control strategy: Reactions of total air flow, fuel flow, and pressure to a change in electricity & hot water demand

As both fuel bed height and the thermal decomposition of the dry fuel models were depended of the same dry biomass variable m_{ds} , iteration was needed to determine the coefficients c_{ds} and c_{thd} for the overall combustion model.

4.2. Test results of the MPC strategy for BioGrate boiler

The MPC strategy was compared with the currently used control strategy in a MATLAB programming environment. The model parameters for the water evaporation were $c_{wev} = 0.0028$, $c_{w,in} = 0.0028$ and $\beta_{wev} \simeq 1$, and the model parameters for the thermal decomposition of the dry fuel were $c_{thd} = 0.0015$, $c_{ds} = 0.0013$ and $c_{ds,in} = 0.0033$. The excess air of 4% was used and the primary air and secondary air ratio was chosen according to the model of the thermal decomposition of the dry fuel. Temperatures for the primary air feed and secondary air feed were 25°C .

The input limits were $u_{1,min} = 0$, $u_{1,max} = 5$, $\Delta u_{1,min} = -0.03$, and $\Delta u_{1,max} = 0.03$ [kg/s] for the stoker speed; $u_{2,min} = 0$, $u_{2,max} = 8$, $\Delta u_{2,min} = -0.03$, and $\Delta u_{2,max} = 0.03$ [kg/s] for the primary air. The output limits were $y_{1,min} = 0$, $y_{1,max} = 1$ [m] for the fuel height; and $y_{2,min} = 0$, $y_{2,max} = 55$ [bar] for the drum pressure. The MPC is tuned with

$$Q_z = \begin{bmatrix} 0.1 & 0 \\ 0 & 0.1 \end{bmatrix} \quad \text{and} \quad S = \begin{bmatrix} 0.1 & 0 \\ 0 & 0.1 \end{bmatrix} \quad \text{In the first}$$

simulation test, the moisture content in the fuel feed was changed from 54% to 65% while the steam demand was 14 MW. The settling time in the response of the current control strategy was about 2h, whereas there is no disturbance in the drum pressure when using the MPC strategy, as show in Figs. 11-13. The MPC strategy utilizes the water evaporation model and gradually increases the primary air flow rate, preventing disturbances in the drum pressure.

In the second simulation test, the steam demand was changed from 12 MW to 16 MW while the moisture content in the fuel feed was kept at 57%. With the current control strategy, the change in steam demand caused again strong oscillations. With the MPC strategy, the settling time of the drum pressure is only 2 minutes, as show in Figs. 13-16. The error of the target pressure compared with the measured pressure is due to the feed-forward compensation from the steam flow in the current control strategy.

The reason for the fast settling time of 2 minutes in the response of the developed MPC strategy is that fuel bed is used as a buffer instead of directly connecting primary air flow rate to the stoker speed. This fast response is then achieved by manipulating the primary air flow rate while keeping the fuel bed height at a desired level. The response for the MPC about actual combustion power is achieved by utilizing fuel moisture soft-sensor and oxygen consumption calculations for water evaporation and thermal decomposition of dry fuel respectively.

5. Conclusions

This paper presented a model predictive control (MPC) strategy for efficient energy production in a BioGrate boiler. In addition to compensating for the main disturbances caused by variations in fuel quality such as fuel moisture content, and variations in fuel feed, this strategy modeled water evaporation, and modeled and controlled the fuel bed height of the grate.

The system identification of the models of the fuel bed height and the thermal decomposition of the dry fuel was conducted using the measurements of the BioPower 5 CHP plant. The results clearly show that an increase in fuel bed

height requires an increase in primary air flow to maintain the same thermal decomposition rate.

The MPC strategy for the BioGrate boiler was tested in a controlled simulation environment. The fast settling time in the response of the developed MPC strategy was achieved by regulating the primary air while keeping the fuel bed height at a desired level. In comparison, the settling time in the response of the currently used control strategy was 2 h.

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