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Influence of fuel properties on the performance of the feed forward model predictive control (FF MPC) for biomass boilers

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ABSTRACT

The growing share of renewable energy sources drives the need for increased flexibility in the energy systems. The flexibility provision from thermal plants is limited by the boiler's thermal inertia as a bottleneck. Advanced controllers, such as model predictive control (MPC), have been identified as potential flexibility enablers. Fuel properties are crucial input for controllers. This work investigated the feasibility of using the properties obtained online by using near infrared spectroscopy based soft sensor to further improve the control performance. The performance of the existing proportional integral (PI) controller is compared with those of 2 feed forward (FF) MPC controllers. Both FF MPCs have significant improvement compared to PI controller and the FF MPC based on the full elemental composition shows the best performance due to more complete fuel information. There is a potential for revenues improvement with advanced control up to 1050 euros for one operation day.

Keywords: biomass fuel, model predictive control, feed forward, near infrared spectroscopy, soft sensor, dynamic model

NOMENCLATURE

Abbreviations	
AE	absolute error
BFB	bubbling fluidized bed
CHP	combined heat and power plant
FF	feed forward
HHV	higher heating value
IAE	integral of the absolute error
LHV	lower heating value
MIMO	multiple input multiple output
MPC	model predictive control
PI	proportional integral
RES	renewable energy sources

1. INTRODUCTION

The growing climate change concerns have motivated a strong push towards decarbonizing the power generation sector with a higher share of renewable energy sources (RES). To keep the balance for power supply, improved flexibility is required from the energy systems, which is considered as the ability of a power system to respond to changes in supply and demand, based on [1]. Combined heat and power plants (CHPs) attract increasing attention to provide flexibility, since they can switch the generation of power and heat. The flexibility provided by the CHPs is limited by the operation of the boiler, which is the bottleneck for load change, due to its high thermal inertia. Improved transient operation of the boiler will improve the output of the whole CHP plant. Within biomass boiler, the variations within the fuel composition are major disturbances for the boiler operation. Application of advanced controllers such as MPC can provide more effective control for the boiler. Advanced controllers have been identified as potential flexibility enablers [2].

Boilers are complex multiple inputs multiple outputs (MIMO) systems, for which conventional proportional integral (PI) controllers have limited performance. The crucial uncertainty in the operation of a biomass boiler comes from the fuel properties, especially the fuel moisture content [3]. It has been proved that feed forward (FF) signal based on a soft sensor that can analyze the boiler characteristics in real time can contribute to better control performance [4]. Therefore, in order to further improve the control system, it is of

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importance to measure the fuel property and include it as input signal.

Research work on novel control systems has shown potential for application in biomass boilers. Within large scale boilers, FF MPC benefits have been analyzed in [5], where FF MPC has shown superior performance compared to PI. Kortela and Jämsä-Jounela [6] developed MPC for biomass grate boiler, based on soft sensor which estimates water evaporation from the fuel. The controller had shorter settling time compared to the PI reference controller. Seeber et al. [7] and Schörghuber et al. [8] showed internal model and reference shaping model based control for a 180 kW grate water boiler. No assessment of the influence of the fuel properties was provided. Most of the controller works have been applied towards small size boiler systems.

To the best of knowledge there is no known work on the fuel properties influence on the control of the thermal load within the boiler. The aim of this work is to study the influence of fuel properties on the controller performance for a bubbling fluidized bed (BFB) boiler. For that purpose, 3 controllers are used – the existing PI controller without any fuel info, FF MPC with fuel moisture content signal (FF MPC 1) and FF MPC with full fuel elemental composition signal (FF MPC 2).

2. METHODOLOGY

2.1 BFB biomass boiler dynamic model

The analyzed BFB biomass boiler, with the regions of interest is shown in Fig. 1. The boiler model and the controllers for this work are based on [5]. Only the key equations for the boiler model and the developed controllers parameters are listed in this section. The heat transferred in heat exchangers (water wall, SH and economizer) is calculated by using Eq. 1:

$$Q = A \cdot U \cdot \Delta T \;\; [MW] \; (1)$$

where: Q is heat, A is surface area of heat exchangers, U is overall heat transfer coefficient (contains conduction, convection and radiation in the waterwall), and ΔT is the temperature difference, which can be calculated by Eq. 2.

$$\Delta T = \frac{(T_{h1} - T_{c2}) - (T_{h2} - T_{c1})}{\ln\left(\dfrac{T_{h1} - T_{c2}}{T_{h2} - T_{c1}}\right)} \; [\,K\,] \; (2)$$

In Eq.3 heat balance and temperature change over time is calculated for each control volume:

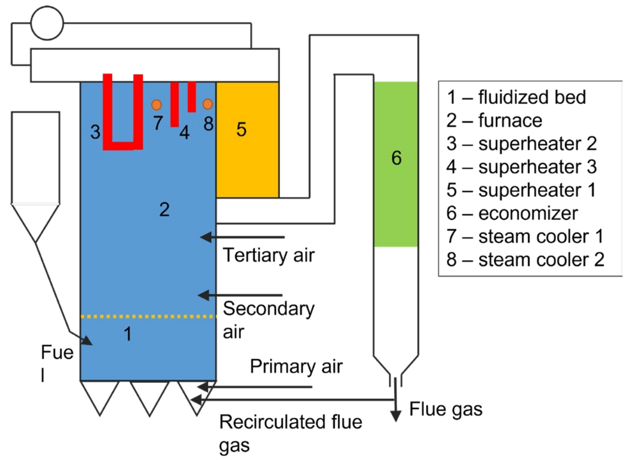

Fig. 1 BFB biomass boiler layout

$$\frac{dT}{dt} = \frac{Q_{balance}}{HE_{capacity}} = \frac{Q_{in} - Q_{out}}{c_p \cdot M} = \frac{Q_{in} - Q_{out}}{c_p \cdot (\rho \cdot V)} \left[\frac{K}{s}\right] \; (3)$$

where: T is temperature, Cp is specific heat capacity, M is mass accumulation, ρ is density and V is volume. Subscripts h and c indicate hot and cold fluid in heat exchanger, *in* and *out* for the incoming and outgoing stream in a control volume, respectively. Enthalpy, specific heat capacity and specific volume for the steam are calculated based on polynomial functions [9].

Elemental composition is used to calculate the heating values of fuel with empirical formulas. Higher heating value (HHV) and lower heating value (LHV) for the fuel are calculated by Eq. 4 and 5, as per [10]:

$$HHV = 0.3491 \cdot X_C + 1.1783 \cdot X_H + 0.1005 \cdot X_S - 0.0151 \cdot X_N - 0.1034 \cdot X_O - 0.021 \cdot X_{ash} \left[\frac{MJ}{kg}\right] (4)$$

$$LHV = HHV \cdot \left(1 - \frac{w}{100}\right) - 2.444 \cdot \frac{w}{100} - 2.444 \cdot \frac{h}{100} \cdot 8.936 \cdot \left(1 - \frac{w}{100}\right) \left[\frac{MJ}{kg}\right] \; (5)$$

For the combustion model, LHV value on wet basis of the fuel is used. The thermal efficiency of combustion is assumed as 95%. Heat released during combustion is calculated by Eq. 6:

$$Q_{combustion} = LHV_{fuel} \cdot mf_{fuel} \cdot 0.95 \; (6)$$

where mf_{fuel} is the mass flow rate of the fuel.

The thermal load of the boiler is calculated as the heat absorbed in water preheaters (economizers), evaporators (water wall) and superheaters, by Eq. 7:

$$Q_{boiler} = Q_{economizer} + Q_{evaporation} + Q_{superheating} \; [MW_{th}] \; (7)$$

Table 1 PI controller parameters values

Manipulated variable	Controlled variable	Proportional K_c (-)	Integral τ_I (s)
Fuel mass flow	Boiler thermal load	0.63	400
Feedwater mass flow	Final steam temperature	-0.3	1500
Total air mass flow	O2 content in flue gas	45	300
Recirculated flue gas flow	Fluidized bed temperature	-0.46	900

Each component of Eq.7 is calculated by solving Eq. 1-3 for the relevant regions. PI control loops for water sprays injection in the attemperators are also implemented in the model.

2.2 *Controllers for the boiler*

FF MPC is developed based on identified linearized state space model of 4th order, which is identified from the validated dynamic model of the boiler. The state space model is identified with the "n4sid" function in Matlab. The MPC controller function, which is also known as objective or target function is shown in Eq.8, based on [11]:

$$J = W_j^{e_y} S_{e_y}(k)^2 + W_j^{MV} S_{MV}(k)^2 + W_j^{\Delta MV} S_{\Delta MV}(k)^2 \quad (8)$$

where: S_{e_y} includes the error between outputs and setpoints, S_{MV} is the vector of manipulated variables and $S_{\Delta MV}$ is the vector of the manipulated variables rate of change, *Wj* are weights, and *k* is time step. Each term in the equation represents the weights allocation on the output values, the inputs, and inputs rate of change. The manipulated and controlled variables, together with the tuned values for each PI control loop are shown in Table 3. Detailed description for the development of the controllers is provided in [5]. In this work, FF MPC with 2 different FF signals are used. FF MPC 1 uses FF signal based only on the knowledge of the fuel moisture content. FF MPC 2 is based on whole elemental fuel composition knowledge.

2.3 *Fuel samples characteristics*

As input for the fuel properties, lab data with 50 biomass fuel samples analyzed with NIRS is used. C, H, N, ash, moisture and HHV are read from the NIRS sensor, O is calculated by subtracting the remaining elements from 100 (wt.%). LHV is calculated by Eq. 5. The properties of the fuel data are summarized in Table 2.

2.4 *Key performance indicators*

The controllers are assessed based on 2 key performance indicators (KPIs).

Absolute error (AE) shows the deviation between the setpoint and the measured value for the controlled parameters:

$$AE = |y - x| \quad (11)$$

where y is the setpoint and x is the measured value for that parameter. The integral error is a commonly used metric for control performance analysis. Here it is calculated as an integral of the absolute error (IAE) by Eq. 12:

$$IAE = \int_0^\infty |e(t)| dt \qquad (12)$$

3. RESULTS

The controllers are assessed on their ability to control the thermal load of the boiler during one

Table 2 Biomass fuel properties – NIRS lab analysis

Parameter	Minimum value	Maximum value	Average	Delta (Max-Min)
Carbon (C)	48.91	50.85	49.86	1.94
Hydrogen (H)	5.89	7.01	6.27	1.12
Nitrogen (N)	0.10	0.48	0.27	0.38
Oxygen (O)*	36.92	44.2	40.97	7.28
Ash	0.93	4.74	2.63	3.81
Moisture	38.32	68.26	53.13	29.94
HHV	19.45	22.58	21.04	3.13
LHV*	4.79	10.96	7.91	6.17

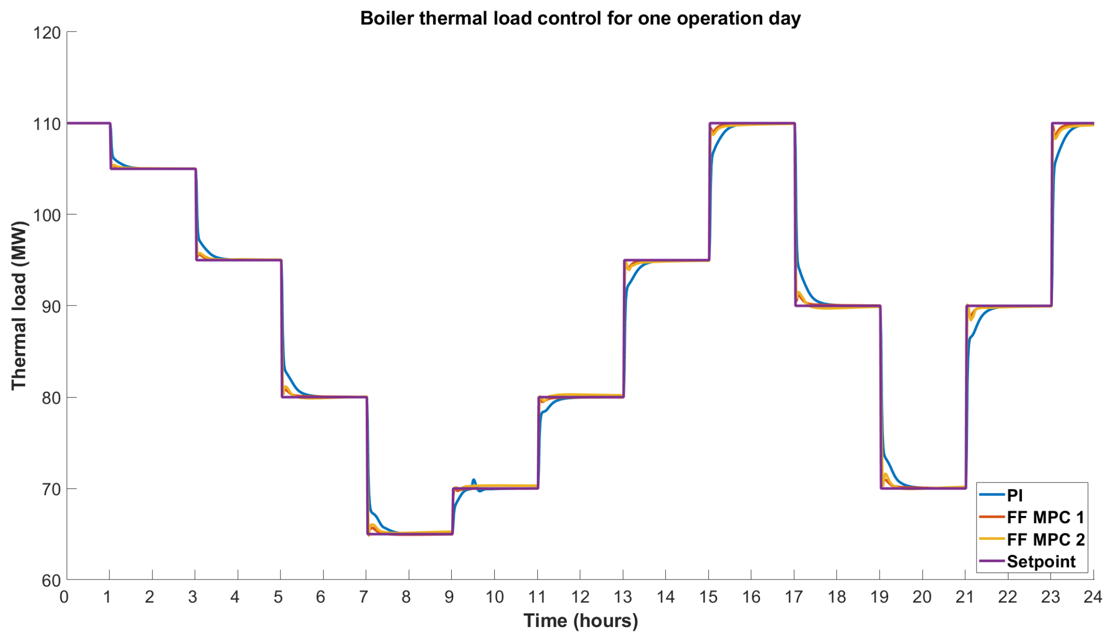

Fig. 2 Controllers performance for one operation day

operation day. The thermal load is ramped up and down with rates of ± 5, 10, 15 and 20 MWth, which are common changes in the boiler operation. For each operation hour different fuel characteristics is used, selected randomly from the fuel samples lab data shown in section 2.3. The boiler load control is shown in Fig. 2.

Both FF MPCs show superior performance compared to the existing PI control as expected. FF MPC 2 (full elemental composition) shows slightly better performance compared to FF MPC 1 (fuel moisture content only). This can be attributed to the more complete information about the fuel characteristics with the full elemental composition obtained by the new FF signal. The results for the KPIs are summarized in Table 3.

To analyze the benefits of the improved control, assessment of potential improvements in the revenues are analyzed. The effect of improved control on revenues can be assessed based on the difference in the thermal output. At each results interval (1min), the difference between boiler thermal output and the setpoint is calculated, and then summed for the whole simulation period (1 day). The periods when there is lower thermal output than the setpoint are counted here as lost revenues. The quantity of thermal output that is converted to power is calculated by multiplying by the α

Table 3 KPIs values

	KPI			
Controlled variable	Controller	**Max absolute error**	**Mean absolute error**	**IAE**
Final steam temperature (C)	PI	33.75	3.87	5573.48
	FF MPC 1	12.83	0.56	813.99
	FF MPC 2	12.37	0.42	602.82
Boiler thermal load (MWth)	PI	17.19	0.73	1051.07
	FF MPC 1	8.75	0.18	266.56
	FF MPC 2	7.99	0.15	214.45
Fluidized bed temperature (C)	PI	22.88	3.19	4593.02
	FF MPC 1	3.35	0.50	717.62
	FF MPC 2	3.18	0.30	428.15
Oxygen content in flue gas (wt%.)	PI	0.26	0.01	16.62
	FF MPC 1	0.61	0.07	95.39
	FF MPC 2	0.65	0.06	86.85

Table 4 - Assessment of impact on revenues

Controller	Thermal output deviation (MW min)	Conversion to MWh	Electricity estimation * 0.31	Cost, with 500 euros/MWh
PI	506.1	8.4	2.6	1300
FF MPC 1	120.6	2	0.6	300
FF MPC 2	96	1.6	0.5	250

factor of the CHP plant, or power to heat ratio (0.31 assumed for the analyzed plant). Given the strong volatility in the electricity price in the last year, assessment is made for a high price of 500 euros/MWh. The obtained results are summarized in Table 4.

4. CONCLUSIONS

In this work 3 controllers for BFB biomass boiler thermal load control were compared – PI, FF MPC based on fuel moisture content (FF MPC 1) and based on full fuel elemental composition (FF MPC 2). Both FF MPC show significantly better performance compared to PI. FF MPC 2 shows improvement compared to FF MPC 1 which can be attributed to the better fuel knowledge.

The lower deviation from the specified thermal load can yield better revenues profile for the advanced controller. For the simulated day of operation, the revenues can be improved up to 1050 euros. In addition to this, the absolute errors reported for the final steam temperature and the fluidized bed are smaller, which can allow to raise the values for their setpoints and improve the boiler efficiency.

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DECLARATION OF INTEREST STATEMENT

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. All authors read and approved the final manuscript.

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