Data Reconciliation method for improving the performance of MPC control strategy developed for a BioGrate boiler

Palash Sarkar
Aalto University, School of Chemical Technology, P.O. Box 16100, FI-00076 Aalto University, Finland
E-mail: palash.sarkar@aalto.fi

Jukka Kortela
Aalto University, School of Chemical Technology, P.O. Box 16100, FI-00076 Aalto University, Finland
E-mail: jukka.kortela@aalto.fi

Alexandre Boriouchkine
Aalto University, School of Chemical Technology, P.O. Box 16100, FI-00076 Aalto University, Finland
E-mail: alexandre.boriouchkine@aalto.fi

Sirkka-Liisa Jämsä-Jounela
Aalto University, School of Chemical Technology, P.O. Box 16100, FI-00076 Aalto University, Finland
Tel: + 358 50 582 6428, sirkka-liisa.jamsa-jounela@aalto.fi, http://chem.aalto.fi/en/

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ABSTRACT

The primary objective of the Model Predictive Control (MPC) strategy, developed for the BioGrate boiler, is to control the combustion power of the boiler. The combustion power is calculated from the measurements of flue gas oxygen measurements. The flue gas oxygen measurements are however frequently corrupted due to sensor malfunction. As a result, the corrupt measurements adversely affect the performance of the MPC, which subsequently results in economic losses. Thus, the detrimental effect of the corrupt measurements on MPC must be addressed. This paper presents the data reconciliation method for improving the performance of the MPC control strategy through the minimization of power losses caused by the oxygen content sensor fault. The introduction of data reconciliation in the control strategy improves the quality of process measurements which in turn significantly improves MPC performance. The corrupt measurements of flue gas oxygen content was introduced to the MPC. The performance of the MPC with and without the reconciliation algorithm was evaluated and compared, and the test results were analyzed and reported.

1 INTRODUCTION

Environmental concerns such as global warming and the limited availability of fossil fuels have led to an increase in the demand for biomass as a renewable energy source. One promising technology, the BioGrate boiler, utilizes biomass as the raw material for power production. The BioGrate boiler was primarily designed for the combustion of biomass fuel with high moisture content. These boilers are, however, often affected by undesirable power production variations that result in economic losses. Such disturbances arise due to variations in both the moisture content of the biomass fuel and the fuel feeding system, thus complicating the operation of BioGrate boiler. Thus, elimination of power fluctuations is a prime objective of power industries and can be achieved with the introduction of an advanced control strategy such as the Model Predictive Control (MPC).

Kortela and Jämsä-Jounela /2/ developed an MPC control strategy for the BioGrate boiler which utilizes a biomass combustion model and controls combustion power by estimating the moisture content in the fuel and the thermal decomposition of dry fuel. In this control strategy, the combustion power is calculated from the measurements of oxygen content in the flue gas. The flue gas oxygen content is thus a critical process variable in the control strategy of the BioGrate boiler. Therefore it is important to ensure correct oxygen content measurements before they are utilized for control action. This can be achieved by reconciling the measurements with the data reconciliation method that utilizes the state space model of the biomass combustion process.

The aim of this study is to improve the performance of the MPC strategy developed for the BioGrate boiler by introducing a steady-state data reconciliation method into the MPC strategy. The data reconciliation problem is formulated as a weighted least-square optimization problem, with the equations comprising the state-space model as constraints. The weights are defined as the inverse of the variances of variables present in the state-space model. In particular, the weight of the combustion power is set to a relatively small value compared with other variables, as the combustion power is affected by the unreliable flue gas oxygen content measurements. The solution to the optimization problem is a set of reconciled values that are more reliable than the actual measurements.

2 STEADY-STATE DATA RECONCILIATION ALGORITHM

A data reconciliation module was developed at steady state based on the state space model. The system equation is written as the following equality

$$M_h h + M_d d = 0 \quad (1)$$

where $M_h = [A\ B]$, $h = [x\ u]'$, and $M_d = E$. The matrices A, B, and E are the state matrix, the input matrix, and the disturbance matrix respectively. Vector h contains state variables x and manipulated variables u, whereas the vector d includes the unknown disturbances. As suggested by Crowe et al. /1/, the unmeasured variables are eliminated from Equation (1) by multiplying it with the matrix P, selected to satisfy the following equality

$$PM_d = 0 \quad (2)$$

As a result, Equation (1) is transformed to the following

$$PM_h h = 0 \quad (3)$$

The data reconciliation is performed by the least-squares method by minimizing the quadratic objective

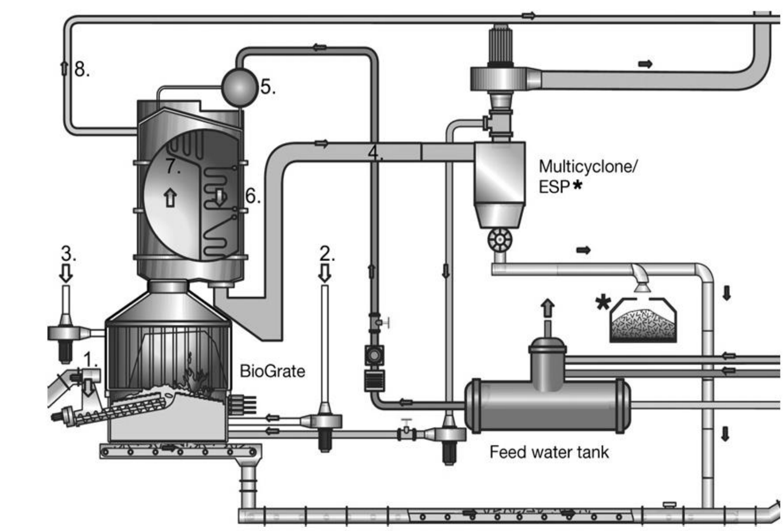
$$\min_h (h_m - h)^T W (h_m - h) \quad (4)$$

in presence of constraints defined by Equation (3). Here h_m represents the vector of the measured state variables and the manipulated variables, and $W \in R^{n \times n}$ is the diagonal matrix with the diagonal elements representing the weights of the corresponding variables. In this paper, the weights are defined as the inverse of the variances of the variables present in the state space. In particular, the weight of the combustion power is set to a relatively small value compared to the other variables, as the combustion power is affected by the unreliable flue gas oxygen content measurement. The solution to the optimization problem given by Equations (3) and (4) can be obtained explicitly using the Lagrange multipliers.

3 PROCESS DESCRIPTION OF THE BIOGRATE BOILER

The BioGrate boiler consists of a conical shaped grate furnace and a steam-water circulation system. The furnace comprises rotating grate rings which are surrounded by heat-insulating walls. Half of the rings rotate in clockwise direction, and the other half in counter-clockwise. This setup ensures uniform distribution of fuel throughout the grate. The fuel is fed from the bottom of the grate where it spreads towards the outer rings and undergoes combustion. The refracting brick walls radiate the heat generated during combustion back to the grate. The furnace is equipped with air register systems for combustion. The primary air flows from the bottom in a direction perpendicular to the fuel feed movement (cross-flow reactor) to ensure efficient mixing of air and fuel. The secondary air flows from the nozzles in the grate-wall to completely combust volatiles present in the over-bed region. This furnace setup ensures highly efficient combustion of biomass and is specially designed for wet fuels with a high moisture content.

The steam-water circulation system absorbs the heat from the furnace and the flue gas to heat water-steam flowing through it by means of natural circulation. The important components of the steam-water circuit system include an economizer, a drum and a evaporator system and two superheaters (primary and secondary). The feedwater is pumped into the economizer where the water absorbs the remaining heat from the flue gas before the flue gas is released into the atmosphere. The heated water is then transferred to the drum and the evaporator system. The evaporator consists of downcomers and risers that are located in the walls of the furnace. It absorbs heat from biomass combustion and produces a mixture of water and steam. The steam separated in the drum is then passed to the two superheaters where it is further heated with the flue gas to form superheated steam. The superheated steam is transferred to the steam turbine to generate electricity. Figure 1 represents the schematic diagram of the BioGrate boiler.



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

Figure 1. The schematic diagram of the BioGrate Boiler.

4 MODEL PREDICTIVE CONTROL WITH DATA RECONCILIATION FOR THE BIOGRATE BOILER

The prime objective of the MPC strategy developed for the BioGrate boiler in Kortela and Jämsä-Jounela /2/ is to produce the desired amount of power for the electricity generator and for the hot water network. The combustion power is controlled by a linear MPC, which is focused on the furnace operations and the steam drum. In addition to the combustion power, the MPC controls the fuel bed height and the drum pressure, which is important to stabilize the furnace operating conditions and to avoid shutdowns. The linear dynamic model is utilized by the MPC:

$$\frac{dx}{dt} = Ax + Bu + Ed \quad (5)$$

$$y = Cx + v \quad (6)$$

with the state vector x including the fuel bed height (x_1), the water content in the furnace (x_2), the combustion power (x_3), the power demand (x_4) and the drum pressure (x_5). The manipulated variable vector u contains the fuel feed flow rate (u_1) and the primary air flow rate (u_2). The measured disturbance d includes the moisture content in the fuel (d_1) and the power demand (d_2). The model outputs y are the fuel bed height (y_1), the combustion power (y_2) and the drum pressure (y_3), whereas v is the measurement noise.

Among the model outputs, the fuel bed height and the drum pressure are directly measured from the process, whereas the combustion power and the moisture content are estimated as it is presented by Equation (7). The key element of the control strategy is the combustion power estimation, which is straightforwardly derived from the energy content of flue gas according to the following equation:

$$\dot{Q}_{comb}(Xo_2, \dot{m}_{air}) = T_{adb} \cdot (C_{n,CO_2} \cdot \dot{n}_{CO_2} + C_{n,O_2} \cdot \dot{n}_{O_2} + C_{n,H_2O} \cdot \dot{n}_{H_2O} + C_{n,N_2} \cdot \dot{n}_{N_2}) - T_{eco} \cdot (C_{n,CO_2} \cdot \dot{n}_{CO_2} + C_{n,O_2} \cdot \dot{n}_{O_2} + C_{n,H_2O} \cdot \dot{n}_{H_2O} + C_{n,N_2} \cdot \dot{n}_{N_2}) \quad (7)$$

where, Q is the combustion power, T_{adb} is the adiabatic temperature of the fuel, $C_{n,i}$ is the molar heat capacity of the i^{th} component of the flue gas and $\dot{n}_i$ is the molar flowrate of the i^{th} component of flue gas. The molar flowrates of each component are calculated from the combustion stoichiometric of the fuel, the air flowrate and the oxygen content in flue gas.

The data reconciliation algorithm is incorporated to the MPC strategy as shown in Figure 2.

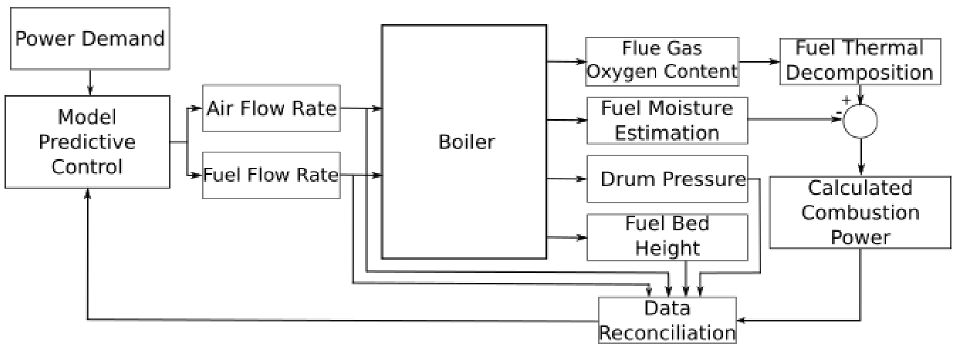


Figure 2. Schematic diagram of the implementation of data reconciliation method into the MPC strategy.

5 RESULTS

The effectiveness of the data reconciliation module to the MPC strategy performance was demonstrated with a case study. The corrupt measurements of combustion power was introduced to the MPC strategy and the MPC performance was analyzed with and without the data reconciliation module. The setpoints for the combustion power, the drum pressure and the fuel bed height were set to 16 MW, 50 bar and 0.5 m respectively in the simulation test. The corrupt measurements of combustion power were introduced to observe the performance of MPC during such circumstances. Figure 3 shows the corrupt measurements of the flue gas oxygen content that occurred on a particular day. The set-point value was set to 3.9%. The measurements were, however, reported to be at 25% between the time period of 2500s and 7500s. Subsequently, the combustion power was affected during this time period. The combustion power values calculated from the corrupt oxygen content measurements were introduced to the simulation at time instant 2500s. Figure 4 shows the effect of corrupt measurements on MPC with and without the data reconciliation method. It was observed that the process was severely affected when the corrupt measurements were introduced and without the data reconciliation method. A sudden drop in the combustion power resulted in a rise in the primary air to compensate for this drop. The disturbance also affected the drum pressure of the boiler.

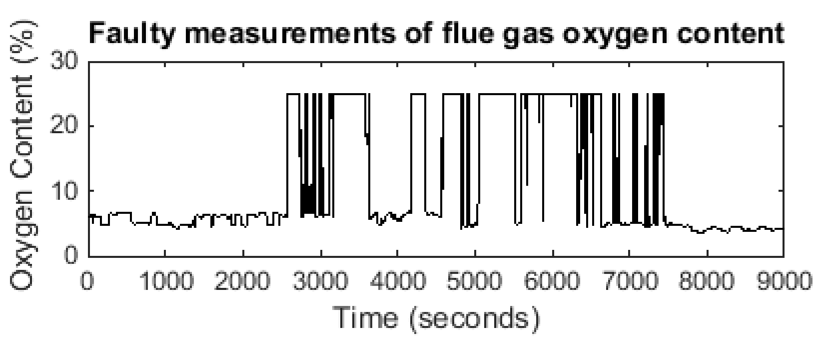


Figure 3. Faulty measurements of flue gas oxygen content sensor

The introduction of the data reconciliation module to the MPC control strategy significantly improved the performance and minimized power loss during the corrupt measurements. The effects of corrupt measurements on the manipulated variables were substantially reduced. In fact, power losses due to sensor malfunction were calculated with the measurements obtained during two consecutive months. It was observed that the introduction of the data reconciliation module significantly reduced the total power losses for the two months as shown in Table 1.

Table 1. Comparison of the MPC control strategy performance with and without the data reconciliation algorithm.

Month	Power Loss (MPC)	Power Loss (MPC + Data Reconciliation)
January	1.1 MW	0.1 MW
February	43.0 MW	6.7 MW

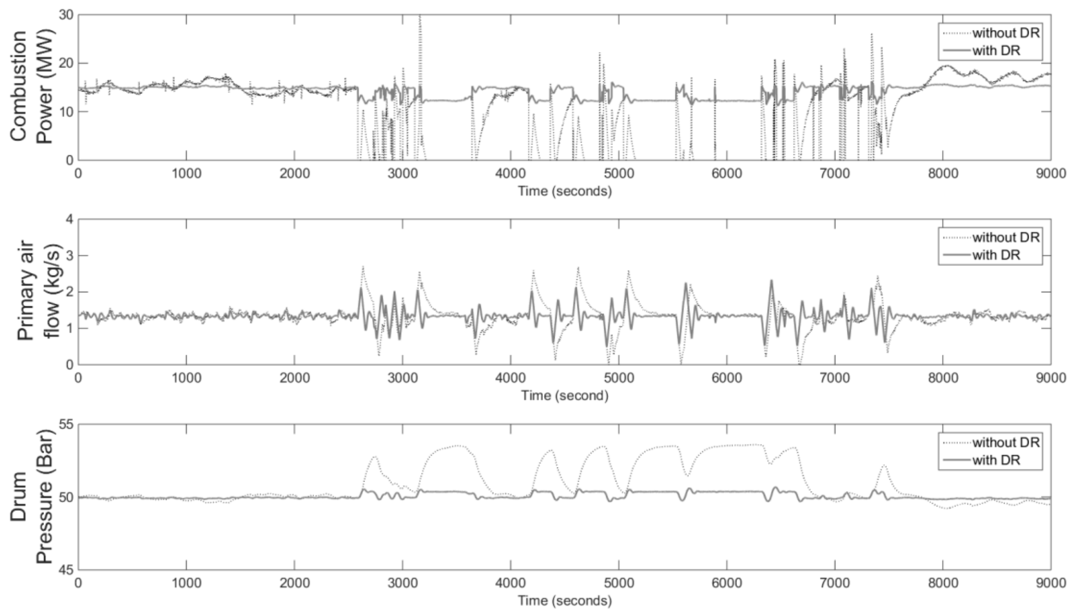


Figure 4. Effect of corrupt measurement on BioGrate boiler without data reconciliation module.

6 CONCLUSIONS

This study proposes a MPC with steady-state data reconciliation for a BioGrate Boiler in order to improve the control performance. The ability of the proposed approach to minimize the effect of the oxygen sensor faults on the MPC performance is demonstrated with a case study.

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