Modeling of a Grate-Firing Biomass Furnace for Real-Time Application

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ABSTRACT
A dynamic model of a grate-firing biomass furnace for real-time applications like model predictive control is presented. Power generation by renewable energy resources is becoming increasingly important and the related technologies call for suitable simulation models. The model presented here is based on the analytical equations for solids and gaseous components at the grate, which is divided into five sections with different combustion stages. The freeboard is modeled as a single volume. The parameters of the analytical model parts are adapted by particle swarm optimisation, and a grey-box model for oxygen and a black-box model for steam generation are also included. To facilitate real-time implementation the resulting model is linearised and reduced to 17 states. Validation results with measured process data demonstrate the excellent performance of the model.

Keywords: Biomass Furnace, Grate-Firing, Modeling, Real-Time Model

1. INTRODUCTION
Biomass is of great significance in the field of renewable energy. Most countries in the world showed their willingness to reduce emission of CO$_2$ and other greenhouse gases at the latest UN Climate Change Conference in Cancun 2010 [1]. This indicates that renewables such as biomass will gain more and more importance in power production.

Grate firing is a state-of-the-art technique that is currently used in biomass combustion for heat and power production. Present-day grate-fired boilers are usually well designed and sufficiently equipped with monitoring systems. However, usage of modern control strategies for biomass combustion is still not very widespread.

The objective of this paper is to provide a mathematical model for a model based controller that is sufficiently detailed but as simple as possible. Yin et al. [2] review the most common approaches to modelling biomass furnaces. All approaches utilise either very complex CFD simulations [3, 4, 5, 6] or very detailed particle size and species modeling, e.g. the work of Swithenbank et al. [7, 8, 9]. Thunman and Leckner [10] concentrate on a different combustion behaviour - co-current with ignition at the bottom of the bed - which is not suitable for this study. Bauer et al. [11] present a very simple mathematical model of grate combustion in a pilot plant. However, their model lacks the influence of multiple primary air zones and varying grate velocities in e.g. large scale biomass furnaces.

In this study a dynamic biomass furnace model is developed for control purposes. The manipulated variables, disturbance variables and controlled variables of the future model predictive controller are shown in figure 2. The biomass furnace model comprises physical and experimental modeling. The physical modeling can be split into two parts (section 3, figure 3): modeling of biomass conversion in the fuel bed on the grate and modeling of mixing, combustion and pollutant formation in the freeboard. On the contrary, the use of experimental data allows a good parameter adaption for the physical model and an adjustment of the modeled O$_2$ concentration in the flue gas through an additional all-pass, see section 4. The steam mass flow is completely identified by simulated and measured data, because the steam circuit is not part of the physical model. Validation results can be seen in section 5. The resulting models are numerically linearised and converted into one state-space system, see section 6. Although this model has been reduced from 46 to 17 states, its performance is not compromised.

2. PROCESS DESCRIPTION
Modern grate-fired boilers consist generally of four key elements: a fuel feeding system, a grate assembly, an intelligent air supply system (primary and secondary air) and an ash discharge system. For the heat production a steam generator with either natural or forced circulation is chosen. Optionally, a steam turbine can be added for power production.

Figure 1 sketches the main combustion processes in grate-fired boilers. Biomass is fed onto the air-cooled or water-cooled grate. Thermal conversion of biomass in the fuel
The grate and modeling of burnout in the freeboard. Both parts are described by non-stationary balance and energy equations. The biomass bed on the grate can be viewed as a reacting gas-solid stirred tank cascade, which includes one gas phase and one solid phase in every zone, \( i = 1, 2, \ldots, 5 \). The gas phase represents the void space in the fuel bed only for heat exchange and heat transportation. For that modeling approach the species transport equations in the gas phase are not necessary and therefore omitted. Whereas the solid phase has 4 components, \( j = \text{moisture}, \text{volatile matter}, \text{fixed carbon}, \text{and inert ash} \) which are transported from zone to zone. In the freeboard there is only one burnout zone where the main gas reactions take place. Here, the species transport equations are also neglected, but the \( \text{O}_2 \) concentration which is important for the controller is calculated separately by a common stoichiometrical approach.

For such an air-solid system, the general non-stationary balance and energy equations for modeling can be summarised as follows.

**Mass balance: solid phase**

The non-stationary mass balance equation for the solid phase in each zone is

\[
\frac{dm_{j,i}}{dt} = \dot{m}_{j,i-1} - \dot{m}_{j,i} - r_{j,i}
\]

where \( \dot{m}_{j,i} \) and \( r_{j,i} \) represent the mass flow of the solid phase (i.e., moisture, volatile matter, fixed carbon, inert ash) [kg/s], and the conversion rate from solid to gases due to evaporation, devolatilisation, and char burning [kg/s] for the \( j \)-th components, respectively.

The process rate equations for this combustion mechanism can be written as a linearised Arrhenius equation

\[
r_{j,i} = k_n \cdot m_{j,i} + k_{T,n} \cdot (T_{s,i} - T_{g,i})
\]

where \( k_n \) and \( k_{T,n} \) represent the reaction rate [1/s] and corrected proportional factor [kg/(s K)] for the \( n \)-th combustion mechanism (drying, pyrolysis, and char burning), re-
respectively. $T_{g,i}$ and $T_{s,i}$ represent the solid phase temperature [K] and gas phase temperature [K].

The fuel feed of the $j$-th component into the first zone $\dot{m}_{j,0}$ [kg/s] is equivalent to a percentage $k_j$ [%] of the whole biomass input feed $\dot{m}_{input}$ [kg/s], see eqn. 3.

$$\dot{m}_{j,0} = k_j \cdot \dot{m}_{input}$$  (3)

The mass flow of the solid phase in each zone depends on the grate velocity $v_{g,i}$ [strokes/s] and its proportional factor $k_v$ [1/strokes], see eqn. 4.

$$\dot{m}_{g,i} = v_{g,i} \cdot k_v \cdot m_{j,i}$$  (4)

Energy balance: solid phase

The non-stationary energy equation for the solid phase in each zone can be expressed as

$$c_{p,s} \cdot \dot{m}_{s,i} \cdot \frac{dT_{s,i}}{dt} = \dot{Q}_{s,i-1} - \dot{Q}_{s,i} - k_{sg} \cdot (T_{s,i} - T_{g,i}) + \Delta H_{r,i}$$  (5)

where $c_{p,s}$, $\dot{m}_{s,i}$, $\dot{Q}_{s,i}$, $k_{sg}$ and $\Delta H_{r,i}$ represent the specific heat of the solid phase [J/(kg K)], sum of all mass components in the solid phase in one zone [kg] (eqn. 6), heat flow of the solid phase [W], gas-solid heat transfer coefficient [W/K], and heat of reaction in solid phase [W] (including the heat loss due to moisture evaporation and heat generation due to char oxidation, see eqn. 7), respectively. In eqn. 7 $h_{r,i}$ represents the reaction enthalpy of the solid phase mass components [J/kg] and $\bar{r}_{sg,i}$ is the sum of all conversion rates in one zone [kg/s], see eqn. 6. In this modeling framework the radiation heat source is neglected for simplification.

$$\dot{m}_{s,i} = \sum_j m_{j,i} \quad \text{and} \quad \bar{r}_{sg,i} = \sum_j r_{j,i}$$  (6)

$$\Delta H_{r,i} = h_{r,i} \cdot \bar{r}_{sg,i}$$  (7)

Mass balance: gas phase

The mass balance equation for the gas phase in each zone is

$$\frac{d\dot{m}_{g,i}}{dt} = \dot{m}_{PA,i} + \dot{m}_{Rezi,i} + \bar{r}_{sg,i} - \dot{m}_g$$  (8)

where $\dot{m}_{g,i}$, $\dot{m}_{PA,i}$ and $\dot{m}_{Rezi,i}$ represent the mass flow of the gas phase [kg/s] (i.e., void space in fuel bed), mass flow of the primary air supply [kg/s], and mass flow of the recirculated gas below grate [kg/s], respectively.

Energy balance: gas phase

Similar to the energy equation for the solid phase, the energy equation for the gas phase in each zone can be expressed as

$$c_{p,g} \cdot \dot{m}_{g,i} \cdot \frac{dT_{g,i}}{dt} = \dot{Q}_{PA,i} + \dot{Q}_{Rezi,i} - \dot{Q}_{g,i} + k_{sg} \cdot (T_{s,i} - T_{g,i})$$  (9)

where $c_{p,g}$, $\dot{Q}_{PA,i}$, $\dot{Q}_{Rezi,i}$ and $\dot{Q}_{g,i}$ represent the specific heat of the gas phase [J/(kg K)], heat flow of the primary air supply [W], heat flow of the recirculated gas below grate [W], and heat flow of the gas phase [W], respectively. In this case the heat of reaction in the gas phase is neglected. It is assumed that the whole gas reaction takes place in the flue gas phase whereas only heat exchange occurs between solid and gas phase and heat transportation between gas and flue gas phase.

Mass balance: flue gas phase

The mass balance equation for the flue gas phase is

$$\frac{d\dot{m}_f}{dt} = \dot{m}_{SA} + \dot{m}_{EA,i} + \dot{m}_{Rezi,SA} + \dot{m}_g - \dot{m}_f$$  (10)

where $\dot{m}_f$, $\dot{m}_{SA,i}$, $\dot{m}_{EA,i}$, $\dot{m}_{Rezi,SA}$ and $\dot{m}_g$ represent mass flow of the flue gas phase [kg/s] (i.e., burnout zone in the freeboard), mass flow of the secondary air supply [kg/s], optional mass flow of the excess air [kg/s], mass flow of the recirculated gas in the freeboard [kg/s], and sum of all mass flows in the gas phase [kg/s] (eqn. 11), respectively.

$$\dot{m}_g = \sum_i \dot{m}_{g,i}$$  (11)

Energy balance: flue gas phase

The energy equation for the flue gas phase can be expressed as

$$c_{p,f} \cdot \dot{m}_f \cdot \frac{dT_f}{dt} = \dot{Q}_{SA} + \dot{Q}_{Rezi,SA} + \dot{Q}_{EA} + \dot{Q}_g - \dot{Q}_f + \dot{Q}_w + \Delta H_R$$  (12)

where $c_{p,f}$, $T_f$, $\dot{Q}_{SA}$, $\dot{Q}_{Rezi,SA}$, $\dot{Q}_{EA}$, $\dot{Q}_g$, $\dot{Q}_f$, $\dot{Q}_w$ and $\Delta H_R$ represent the specific heat of the flue phase [J/(kg K)], temperature of the flue gas phase [K], heat flow of the secondary air supply [W], heat flow of the recirculated gas in the freeboard [W], heat flow of the optional excess air [W], sum of all heat flows in the gas phase [W] (eqn. 13), heat flow of the flue gas phase [W], heat exchange between flue gas phase and chamber wall [W], and heat of reaction in flue gas phase [W] (including all gas reactions, see eqn. 14), respectively. In eqn. 14 $h_R$ represents a fixed reaction enthalpy of the whole flue gas phase at ideal combustion conditions [J/kg], whereas the feed-back term $k_{O2} \cdot \Delta O2$ illustrates the deviation from the ideal conditions. $k_{O2}$ is a corrected feed-back gain [J/kg] and $\Delta O2$ represents the difference between the known input and the modeled output $O2$ concentration [vol%], see next subsection.

$$\dot{Q}_g = \sum_i \dot{Q}_{g,i}$$  (13)

$$\Delta H_R = (h_R - k_{O2} \cdot \Delta O2) \cdot \dot{m}_f$$  (14)
Combustion calculation: \( O_2 \) concentration

The combustion calculation is a common stoichiometrical approach to determine the \( O_2 \) concentration [vol\%] in the flue gas phase \([12]\)

\[
\frac{dO_2}{dt} = \left( \lambda - 1 \right) \cdot 0.21 \cdot \frac{Air_{min} \cdot 100}{V_f} - O_2 \tag{15}
\]

where \( Air_{min}, V_f, \) and \( \lambda \) represent the minimum required air supply for complete combustion at ideal conditions [Nm\(^3\)/kg], wet flue gas volume related to the biomass input feed [Nm\(^3\)/kg], and correlation between the real air supply \( Air \) (see eqn. 16) and \( Air_{min} [-] \), respectively.

\[
Air = \frac{\hat{V}_{PA} + \hat{V}_{SA} + \hat{V}_{EA}}{\sum m_{s,i}} \tag{16}
\]

In eqn. 16 \( \hat{V}_{PA}, \hat{V}_{SA}, \) and \( \hat{V}_{EA} \) represent the volume flows of primary, secondary and excess air supply [Nm\(^3\)/s]. Since this equation is just a stationary relation and no further interactions between \( O_2 \) and biomass particles are modeled, an experimental model adaption for the \( O_2 \) concentration has been carried out, see section 4.

4. EXPERIMENTAL MODELING

Experimental modeling is used for parameter adaption, improving physical models or identifying black-box models. In this case the use of experimental data and the particle swarm optimisation algorithm allow a good parameter adaption. The \( O_2 \) concentration is adjusted by an additional all-pass which is experimentally determined. This yields a new grey-box model of the \( O_2 \) concentration. Since the steam circuit is not part of the physical model, a linear black-box model for the steam mass flow \( \dot{m}_{steam} \) is identified by simulated and measured data.

Parameter adaption

In the course of the model validation the different parameters and coefficients of the mass and energy balances have to be adjusted. Because of equation simplification not all parameters can be found in literature. Therefore, a computational optimisation method for parameter adaption has been chosen.

Particle swarm optimisation (PSO) is a population based stochastic optimisation algorithm that is initialised with a population of random solutions and searches for optima by updating generations. The detailed algorithm and PSO tuning parameters can be found in \([13]\). Furthermore, the number of particles in the swarm, the number of iterations and a cost function have to be defined. In this case, a population number of 40 was chosen. The number of iterations depends on the amount of optimising parameters and therefore varies between 50 and 100. The PSO algorithm optimises the defined cost function, i.e. quadratic deviation between modeled and measured data is minimised.

Grey-box model: \( O_2 \) concentration

An experimental model adaption for the \( O_2 \) concentration in the flue gas has been carried out. Because of aforementioned simplifications neither gas reaction kinetics nor further interactions between \( O_2 \) and biomass particles are modeled. This calls for adjustment of the dynamic behaviour of the modeled \( O_2 \) concentration. The stationary solution remains unchanged.

Experimental data show that if primary air supply is increased, the system initially reacts with decreasing \( O_2 \) concentration in the flue gas. After reaching quasi-static conditions, the measured \( O_2 \) concentration is equivalent to the modeled stationary solution. This indicates that the interactions between \( O_2 \) molecules and biomass particles rise momentarily. This phenomenon can be accounted for by an additional all-pass which has been experimentally determined, see eqn. 17. So the new estimated volume flow \( \hat{V}_{PA} \) replaces the old one \( V_{PA} \) in eqn. 16.

\[
\hat{V}_{PA} = V_{PA} \cdot \frac{T_1 s^2 - T_2 s + 1}{T_1 s^2 + T_2 s + 1} \tag{17}
\]

Black-box model: steam mass flow

Since the steam circuit is not part of the physical model, a linear black-box model for the steam mass flow \( \dot{m}_{steam} \) is identified by simulated and measured data. The inputs for this model are the modeled flue gas temperature \( T_f \), and measured attemperator mass flow \( \dot{m}_{AT} \), whereas the steam mass flow represents the output.

The so-called \( n4sid \) algorithm has been chosen to identify the desired model structure. It estimates a state-space model using a subspace method. Detailed information about the algorithm can be found in \([14, 15]\). Moreover, the \( n4sid \) algorithm is supported by the Matlab System Identification Toolbox, see \([16]\). The following state-space model in discrete-time form with 4 states has been identified.

\[
x(k + 1) = Ax(k) + Bu(k) \\
y(k) = Cx(k) + Du(k) \tag{18}
\]

where \( x, y \) and \( u \) represent the (4×1)-state vector, (1×1)-output vector, and (3×1)-input vector. Whereas \( A, B, C \) and \( D \) represent the (4×4)-state matrix, (4×3)-input matrix, (1×4)-output matrix, and feedforward matrix equal to zero.

5. VALIDATION RESULTS

In order to validate the physical model against experimental data and to identify the black-box model, measurements were taken at a Bertschenergy grate-firing biomass furnace plant. This plant has a maximum steam output of 30 t/h and the biomass used there contains blends of natural wood waste and agricultural waste.
In the next paragraph the validation results are discussed. Two open-loop measurement series are presented, i.e., changes of two manipulated variables are shown. The secondary air supply - which influences fast process dynamics - and the biomass feed input - which influences slow process dynamics - were changed, respectively, whereas all other manipulated variables remained constant. The step responses of the O\textsubscript{2} concentration and the steam mass flow \(\dot{m}_{\text{steam}}\) in figure 4 and 5 are related to the actual operating point (OP). Therefore only delta (\(\Delta\)) values are given.

Figure 4 shows the comparison of simulated and measured O\textsubscript{2} concentration and steam mass flow \(\dot{m}_{\text{steam}}\). The secondary air supply was increased by 40\% at \(t=0\) and was decreased by 40\% again at \(t=22\) min. Although a mix of measurement and process noise can be seen, especially in the first diagram, the modeled step responses follow the measured data well. Process noise is mainly caused by the unsteady combustion of the used biomass.

Figure 5 shows the comparison of simulated and measured O\textsubscript{2} concentration and steam mass flow \(\dot{m}_{\text{steam}}\). Secondary air supply was increased by 40\% at \(t=0\) and was decreased by 40\% again at \(t=22\) min. Although a mix of measurement and process noise can be seen, especially in the first diagram, the modeled step responses follow the measured data well. Process noise is mainly caused by the unsteady combustion of the used biomass.

6. LINEARISATION AND MODEL REDUCTION

In order to facilitate a real-time implementation and a linear state-space predictive controller the model is linearised and reduced to 17 states by a balanced truncation.

The physical and experimental models are numerically linearised in a typical operating point of the biomass furnace plant and converted into one state-space system with 46 states, 6 inputs and 3 outputs, see figure 2.

This state-space system is then reduced to 17 states by a balanced truncation. This method simply discards the states associated with small Hankel singular values. After plotting the Hankel singular values, it can be observed that the states 18 to 46 have only small Hankel singular values (< 1\%) and are therefore eliminated. To point out the right decision of an adequate approximation order, figure 6 illustrates the comparison of the non-linear and reduced linear model. It shows the step responses of the O\textsubscript{2} concentration and the steam mass flow \(\dot{m}_{\text{steam}}\) after a unit step of primary air supply. A minimal deviation in the stationary solution can be seen between the step responses of the non-linear and reduced linear model which is insignificant.

Figure 6: Comparison of non-linear and reduced linear model: step responses of O\textsubscript{2} concentration and steam mass flow \(\dot{m}_{\text{steam}}\) after a unit step of primary air supply
A model of a grate-firing biomass furnace has been presented which is designed for the use in real-time applications like model predictive control (MPC). The model combines analytical equations for the combustion on the travelling grate and in the freeboard, a grey-box model for oxygen concentration in the exhaust gases, and a black-box model for steam generation in the heat recovery boiler. The different stages of combustion along the travelling grate are modelled by separate zones, which are described by individual sets of equations. Non-stationary mass and energy balances together with phenomenological relations are utilised to describe the dynamics of those zones. The complete model consists of 46 states, which are mainly masses and temperatures of reactants, the oxygen concentration in the exhaust gas, and the states of the black-box model. Validation results show that the model accurately captures dynamic as well as stationary characteristics of the process. Aside from process and measurement noise of the measured data an excellent agreement can be found.

In order to facilitate a real-time implementation the model is linearised and reduced to 17 states by a balanced truncation. A comparison with the nonlinear full-order model shows almost identical performance. The resulting linear model is therefore well suited for implementation in a process control system.

Future work will be focused on the design and implementation of an MPC controller for the biomass furnace. This control scheme is especially promising since it explicitly incorporates the numerous process constraints in the design phase.

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