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Simultaneous state and fuel property estimation in biomass boilers - theory and practice ⋆

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Abstract: A key factor for the further distribution of biomass boilers in modern energy systems is the capability of changing the applied feedstock during normal plant operation. This is only possible with the application of advanced control strategies that utilize knowledge about the state variables and varying fuel properties. However, neither the state variables nor the fuel properties are measurable during plant operation and, thus, need to be estimated. This contribution presents a method for the simultaneous real-time estimation of the state variables and the fuel properties in fixed-bed biomass boilers which is a novel approach in the field of biomass boilers. The method bases on an Extended Kalman Filter using a nonlinear dynamic model and measurement data from the combustion process. The estimated variables are the masses of dry fuel and water in the fuel bed as well as the fuel's bulk density, water content, chemical composition and lower heating value. The proposed method is easy to implement and requires moderate computational effort which increases the potential of its application at actual biomass boilers. The proposed method is verified with simulation studies and by test runs performed at a representative small-scale fixed-bed biomass boiler. The estimation results show a good agreement with the actual values, demonstrating that the proposed method is capable of accurately estimating the biomass boiler's state variables and simultaneously its fuel properties. For this reason, the presented method is a key technology to ensure the further distribution of biomass boilers in modern energy systems.

Keywords: Renewable energy systems, Biomass combustion, Biomass fuels, System state estimation, Parameter estimation, Kalman filters

1. INTRODUCTION

Biomass combustion plays a central role in the supply of heat and electricity from renewable energy technologies. Unlike volatile renewable energy technologies such as solar thermal plants or wind turbines, energy systems based on biomass combustion are capable of providing a consistent and stable thermal or electric output. Simultaneously, they offer a high degree of flexibility as their power output can be adjusted according to the load demand. However, there is an increasing number of applications for conventional biomass feedstocks apart from combustion such as processes for the conversion of biomass into chemicals, e.g. (Alamia et al., 2017). This results in conventional biomass feedstocks becoming more expensive. Hence, a key element in the further distribution of biomass boilers is their capability of utilizing new and alternative biomass feedstocks. This includes cheaper feedstocks that typically exhibit a lower fuel quality and locally available, special feedstocks with strongly varying fuel properties. Especially the capability of performing fuel changes during the normal plant operation without any noticeable influence on the biomass boiler's output variables is essential for their further distribution. This is only possible with the application of advanced control strategies that utilize knowledge about the changing fuel properties. Most advanced control strategies also require knowledge of the controlled system's state variables. As neither the state variables nor the fuel properties are typically measurable during plant operation, their determination by other means is necessary. For this reason, this contribution presents a method for the simultaneous real-time estimation of state variables and fuel properties in fixed-bed biomass boilers. This is the first method capable of simultaneously estimating these variables for fixed-bed biomass boilers. The application of the presented method enables the compensation of the effects of fuel changes during the plant operation and, as a result, supports the further distribution of biomass boilers.

The focus lies on combustion processes in fixed-bed biomass boilers with air staging, which represents a widely used combustion technology. Such boilers can be consid-

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ered as a nonlinear, coupled, multi-variable system with parameters depending on the fuel properties. State-of-the-art linear control strategies are not capable of compensating the effects of changing and fluctuating fuel properties sufficiently well. Control strategies based on a mathematical model of the combustion process can potentially directly utilize the knowledge of changing fuel properties and compensate their effects. The state variables used by the model-based control strategies found in literature, e.g. (Gölles et al., 2014), are the mass of water and dry fuel on the fuel bed. The fuel properties considered in the mathematical models used by these control strategies are he chemical composition of the dry fuel as well as the fuel's bulk density, water content and lower heating value. Although all these fuel properties are considered in the mathematical models, they are typically assumed to be constant and known. A variation of the fuel properties leads to a model error which has to be compensated by these control strategies. In order to avoid this model error, methods for the real-time estimation of the fuel properties have been proposed in literature. A method for the estimation of fuel properties based on mass and substance balances was suggested by (vanKessel et al., 2004) for waste incineration plants which can also be applied at biomass boilers. However, it only estimates the fuel's water content, chemical composition and lower heating value but neither the bulk density nor the state variables needed by model-based controllers when high fuel-flexibility should be achieved. (Kortela et al., 2013) developed a method for the estimation of the fuel's moisture content in biomass boilers based on mass and energy balances. Other fuel properties as well as the state variables are not determined by this method. (Gölles et al., 2011) and (Gölles et al., 2014) as well as (Seeber et al., 2014) and (Zemann et al., 2014) applied Extended Kalman Filters to estimate the state variables in biomass boilers that do not directly determine the fuel properties. A method estimating both, the state variables and the fuel properties is not available in literature. For this reason, the objective of this work is the development of a method for the simultaneous real-time estimation of a fixed-bed biomass boiler's state variables, specifically the mass of water and dry fuel in the fuel bed and the properties of the supplied fuel, in particular the bulk density, the water content, the chemical composition and, thus, the lower heating value.

Most of the estimation methods explained above utilize a combination of mass-, substance- and energy balances to determine the fuel properties or state variables. Each of these balance equations introduces additional mathematical models, simplifying assumptions and the necessity for more measurement variables, increasing the complexity and computational effort of the estimation method. In order to minimize the computational effort and measurement variables needed by the proposed method, it should be limited to the utilization of the least amount of balance equations necessary. As especially energy balances require a multitude of accurately measured variables and mathematical models, the presented estimation method is limited to the utilization of mass- and substance balance equations. This reduces the effort necessary for the implementation of the estimation method increasing the potential of its application at actual biomass boilers.

To achieve the objective, a mathematical model for the considered biomass boilers is derived from partial models available in literature. This is explained in section 2 where also the calculation of the lower heating value is discussed. The observability of the resulting model, which is essential for the viability of the application of a state estimator, is also shown in that section. The derived model is used in an Extended Kalman Filter (EKF) in section 3 to estimate the biomass boiler's state variables and the fuel properties. In that section, also simulation studies are conducted to show the EKF's basic functionality and to investigate the influence of measurement errors and model parameter errors on the estimation results. Finally, in the same section, the EKF is verified with measurement data from test runs performed at a representative biomass boiler. A conclusion and outlook is given in section 4.

2. PROCESS DESCRIPTION AND MATHEMATICAL MODEL

This section describes the derivation of a state-space model that can be used in state observers such as an EKF to estimate the state variables and the fuel properties. In section 2.1, the combustion process is first described and then divided into sub-processes to simplify modeling. For each sub-process a mathematical model is formulated in sections 2.2, 2.3 and 2.4 respectively. Then, the calculation of the lower heating value is explained in section 2.5. Subsequently, a state-space representation is derived from these models for the use in a state observer in section 2.6 and its observability shown in section 2.7.

2.1 Process Description and Segmentation

In fixed-bed biomass boilers with air staging (schematically illustrated in Fig. 1) the wet biomass fuel is fed to a fuel bed through a fuel feed such as a screw feeder or a stoker feeder. In the fuel bed, a substoichiometric combustion takes place driven by the supplied primary air. This consists of the evaporation of water in the biomass and the thermal decomposition of the dry fuel. The resulting mass flow of incompletely combusted flue gas is mixed with the supplied secondary air and enters the secondary combustion zone, where it is completely combusted. To simplify the modeling, the entire combustion process is divided into less complex sub-processes as proposed in (Gölles et al., 2012). The process is divided into the fuel feed, the fuel bed and the secondary combustion zone. For each of these sub-processes, a separate mathematical model is formulated in the following sections.

2.2 Fuel Feed

The mathematical model of the fuel feed describes the correlation between the fuel feed's input variable and the resulting mass flow of wet fuel $\dot{m}_{\mathrm{fuel}}$ supplied to the fuel bed. A typically used screw feeder operated in pulsed mode, with the pulse frequency f_{FF}, can be described by

$$\dot{m}_{fuel} = b_{fuel} k_{FF} f_{FF}. \tag{1}$$

The pulse frequency f_{FF} is the screw feeder's input variable and is, thus, known. The variable k_{FF} is a model parameter. Data from test runs performed with different

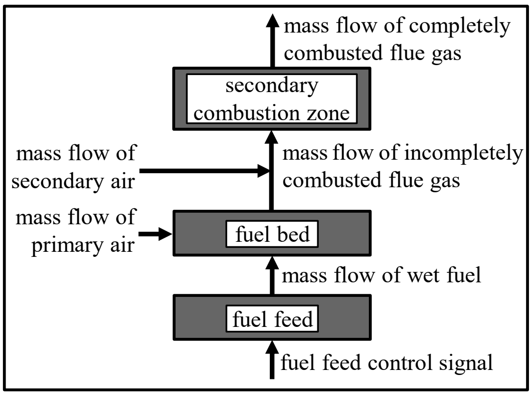

Fig. 1. Combustion process in fixed-bed biomass boilers.

types of biomass fuels suggest that k_{FF} can be assumed to be constant and independent of the fuel used. It can be determined with little effort in test runs where the fuel properties are known. For this reason, it is assumed to be a known variable. The fuel's bulk density b_{fuel} is unknown and changes with different fuels which is why it needs to be estimated. In the remainder of this contribution it is assumed that the biomass boiler is equipped with such a screw feeder. This is not a limitation since a stoker feeder can be modeled similarly (Zemann et al., 2014).

2.3 Fuel Bed

The mathematical model of the fuel bed describes the evaporation of water and the thermal decomposition of dry fuel in the fuel bed. It consists of two ordinary differential equations adapted from (Bauer et al., 2010):

$$dm_W/dt = -c_W\, m_W + w_{H_2O}\, \dot m_{fuel} \tag{2}$$

$$\begin{aligned} dm_{DS}/dt = &-c_{DS,1}\, m_{DS}\, (\dot m_{PA} + c_{DS,2}) \\ &+ (1 - w_{H_2O})\, \dot m_{fuel} \end{aligned} \tag{3}$$

The state variables are the masses of water m_{W} and dry fuel m_{DS} in the fuel bed. One input variable is the mass flow of wet fuel from the fuel feed $\dot m_{\mathrm{fuel}}$ (see section 2.2). The other input variable is the mass flow of primary air $\dot m_{\mathrm{PA}}$ which, for the purpose of parameter and state estimation, has to be measured. The model parameters are the mass fraction of water in the wet fuel entering the fuel bed ('water content') $w_{\mathrm{H_2O}}$ as well as the coefficients c_{W}, $c_{\mathrm{DS,1}}$ and $c_{\mathrm{DS,2}}$. Data from test runs performed with different types of biomass fuels suggest that c_{W}, $c_{\mathrm{DS,1}}$ and $c_{\mathrm{DS,2}}$ can be assumed to be constant and independent of the fuel used. They can be determined in test runs where the fuel properties are known. For this reason, these coefficients are assumed to be known. The fuel's water content $w_{\mathrm{H_2O}}$ is unknown and can change with the fuel used which is why it needs to be estimated.

2.4 Secondary Combustion Zone

The mathematical model describing the complete combustion of the incompletely combusted flue gas with the secondary air provides the output variables of the biomass boiler which are the molar flow of oxygen $\dot n_{\mathrm{O_2}}$ and water $\dot n_{\mathrm{H_2O}}$ in the completely combusted flue gas as well as the mass flow of thermally decomposed wet fuel $\dot m_{\mathrm{WF}}$. It bases on a common combustion calculation, e.g. (Moran et al., 2006), under the assumptions of a complete combustion and that the dry fuel entirely consists of hydrogen, carbon and oxygen, neglecting all other components such as nitrogen and especially ash. The sum of the respective mass fractions of hydrogen w_{H}, carbon w_{C} and oxygen w_{O} in the dry fuel equals to one:

$$w_H + w_C + w_O = 1 \tag{4}$$

This is a valid assumption for most biomass feedstocks since the weight fractions of the remaining components are typically smaller than 1 wt.%. Some special biomass feedstocks such as mint straw or palm kernels (Vassilev et al., 2010) exhibit higher nitrogen or ash contents. In these cases, an adaption of (4) is necessary. Based on the examination of different representative fuels (see Table 1) and following the suggestion in (vanKessel et al., 2004) the fraction $w_{\mathrm{H}}/w_{\mathrm{C}}$ is assumed to be constant and independent of the fuel used:

$$\alpha := w_H/w_C = 0.129 \tag{5}$$

This simplification reduces the number of unknown fuel properties in the model. The choice in (5) results in a deviation in the ratio α of less than 5% in the fuels examined in Table 1 which is assumed to be sufficiently small for practical applications. The influence of this assumption on the estimation results is investigated in simulation studies in section 3.3.

Table 1. Typical composition of different biomass feedstocks.

Fuel	w_C	w_H	α
-	(kg/kg)	(kg/kg)	-
Spruce[1)]	0.502	0.063	0.125
Straw[1)]	0.449	0.056	0.125
Corncob[2)]	0.477	0.059	0.124
VFGD[3)]	0.531	0.071	0.135

[1)] (Sommersacher et al., 2013), [2)] (Kelz et al., 2017),
[3)] (vanKessel et al., 2004) Using (4) and (5) in a common combustion calculation, e.g. (Moran et al., 2006), the output variables can be calculated as

$$\dot n_{O_2} = \beta_1(w_C)\, c_{DS,1}\, m_{DS}\, (\dot m_{PA} + c_{DS,2}) \tag{6}$$

$$\begin{aligned} \dot n_{H_2O} = &\, c_W\, m_W/M_{H_2O} + \beta_2(w_C)\, c_{DS,1}\, m_{DS} \\ &(\dot m_{PA} + c_{DS,2}) \end{aligned} \tag{7}$$

$$\dot m_{WF} = c_W\, m_W + c_{DS,1}\, m_{DS}\, (\dot m_{PA} + c_{DS,2}) \tag{8}$$

with

$$\beta_1(w_C) = (\gamma_1 - 3/M_C - 3\alpha/(2M_H))\, w_C + \gamma_2, \tag{9}$$

$$\beta_2(w_C) = w_C\, \alpha/(2M_H) \tag{10}$$

and

$$\begin{aligned} M_{DS} &= M_O - \frac{(1/3)w_C + 15\alpha w_C}{1/M_O + (1/4)w_C/M_C + (15/16)\alpha w_C/M_H} \\ &= \frac{1}{\gamma_1 w_C + \gamma_2}. \end{aligned} \tag{11}$$

These equations contain the molar masses of hydrogen M_{H}, carbon M_{C}, oxygen M_{O} and water $M_{\mathrm{H_2O}}$ as well as the positive constants γ_1 and γ_2. The unknown mass fraction of carbon in the fuel w_C depends on the fuel used and, thus, needs to be estimated. All other parameters are either known physical constants or model parameters already assumed to be known and independent of the fuel used. These output variables can not be measured directly. However, they can be calculated from the mass flows of primary air $\dot{m}_{PA}$, secondary air $\dot{m}_{SA}$ and completely combusted flue gas $\dot{m}_{FG}$ as well as the oxygen content x_{O_2} and the water content x_{H_2O} of the flue gas. These are either typically measured variables or can be measured with moderate effort for the estimation of the state variables and fuel properties. The output variables can be calculated with these measured variables using the equations

$$\begin{aligned}\dot{n}_{O_2} &= 2x_{O_2}\dot{m}_{FG}/M_{FG}\\ &\quad -2(w_{air,O_2}/(2M_O))(\dot{m}_{PA}+\dot{m}_{SA}) \quad (12)\\ \dot{n}_{H_2O} &= x_{H_2O}\dot{m}_{FG}/M_{FG}\\ &\quad -(w_{air,H_2O}/M_{H_2O})(\dot{m}_{PA}+\dot{m}_{SA}) \quad (13)\\ \dot{m}_{WF} &= \dot{m}_{FG}-(\dot{m}_{PA}+\dot{m}_{SA}) \quad (14)\end{aligned}$$

with the typically sufficiently well known mass fractions of water w_{air,H_2O} and oxygen w_{air,O_2} of the wet air as well as the molar mass of the flue gas M_{FG}. The molar mass M_{FG} can be calculated using available measurement data in a common combustion calculation. This requires an assumption about the unknown mass fraction of carbon in the fuel w_C. Even a significant variation of w_C of 100% results in a deviation in M_{FG} of less than 12% for typically observed combustion conditions. For this reason, the influence of w_C on M_{FG} is considered negligibly small for practical applications. Thus, it is sufficient to assume that $w_C = 0.49$ kg/kg when calculating M_{FG} which is the mean value for the mass fractions w_C displayed in Table 1. $\dot{m}_{FG}$ excludes the mass flows of any recirculated flue gas.

2.5 Lower Heating Value

The lower heating value is a fuel property that changes with the used fuel. It determines the heat released during complete combustion of the fuel which can potentially be used in a subsequent process. This makes the lower heating value an important parameter for the evaluation and the model-based control of biomass boilers. Using a common approximation formula (Gaur et al., 1998) and incorporating assumption (4), it can be calculated by

$$\begin{aligned}LHV =&(1-w_{H_2O})(45.25w_C+128.17\alpha w_C-10.34)1e6\\ &-(w_{H_2O}+(1-w_{H_2O})\alpha w_C M_{H_2O}/(2M_H))\Delta h_v\end{aligned} \quad (15)$$

with Δh_v being the enthalpy of evaporation of water. This equation contains the unknown fuel properties w_{H_2O} and w_C as well as known molar masses. For this reason, an estimation of these unknown fuel properties enables the calculation of the lower heating value.

2.6 State-Space Representation

Combining (1) to (11) and changing the variable names to a more generalized nomenclature leads to the state-space representation of the model which is subsequently used in the estimator. The fuel properties to be estimated (w_{H_2O}, b_{fuel} and w_C) are considered by random walk models as state variables. Table 2 shows the state variables

Table 2. State variables, input variables and output variables of the state-space model with their corresponding physical quantities.

variable	physical quantity	variable	physical quantity
x_1	m_W	u_1	f_{FF}
x_2	m_{DS}	u_2	$\dot{m}_{PA}$
x_3	w_{H_2O}	y_1	$\dot{n}_{O_2}$
x_4	b_{fuel}	y_2	$\dot{n}_{H_2O}$
x_5	w_C	y_3	$\dot{m}_{WF}$

x_i, input variables u_j and output variables y_l and their corresponding physical quantities. The resulting state-space model is

$$\begin{aligned}dx_1/dt &= -c_1x_1+c_2x_3x_4u_1\\ dx_2/dt &= -c_3x_2(u_2+c_4)+c_2(1-x_3)x_4u_1\\ dx_3/dt &= 0\\ dx_4/dt &= 0\\ dx_5/dt &= 0\end{aligned} \quad (16)$$

$$\begin{aligned}y_1 &= c_3\,(u_2+c_4)\,x_2\,\beta_1(x_5)\\ y_2 &= c_1\,c_5\,x_1+c_3\,(u_2+c_4)\,x_2\,\beta_2(x_5)\\ y_3 &= c_1x_1+c_3(u_2+c_4)x_2.\end{aligned} \quad (17)$$

The constant coefficients c_1 to c_5 are all real-valued, positive and known. The overall model is a time-continuous, nonlinear (affine-input), multi-variable system of 5th order with three manipulated variables and three output variables

$$\frac{d\boldsymbol{x}}{dt} = \boldsymbol{f}(\boldsymbol{x},\boldsymbol{u}); \quad \boldsymbol{y} = \boldsymbol{h}(\boldsymbol{x},\boldsymbol{u}) \quad (18)$$

with the state vector $\boldsymbol{x}$, the input vector $\boldsymbol{u}$ and the output vector $\boldsymbol{y}$.

2.7 Observability Analysis

According to (Kou et al., 1973) a nonlinear system as described by (18) is said to be completely observable on the time interval $[t_0, t]$ if there exists a value of $k \in \mathbb{N}$ such that the matrix equation

$$\begin{pmatrix}\boldsymbol{y}(t_0)\\ \dot{\boldsymbol{y}}(t_0)\\ \vdots\\ \boldsymbol{y}^{(k-1)}(t_0)\end{pmatrix} = \underbrace{\begin{pmatrix}\boldsymbol{h}(\boldsymbol{x}(t))\big|_{t=t_0}\\ \frac{\partial}{\partial t}\boldsymbol{h}(\boldsymbol{x}(t))\big|_{t=t_0}\\ \vdots\\ \frac{\partial^{(k-1)}}{\partial t^{(k-1)}}\boldsymbol{h}(\boldsymbol{x}(t))\big|_{t=t_0}\end{pmatrix}}_{\hat{\boldsymbol{h}}} \quad (19)$$

has a unique solution for the initial state $\boldsymbol{x}_0 := \boldsymbol{x}(t_0)$. The corresponding vector $\hat{\boldsymbol{h}}$ for the state-space model (16) and (17) reads as

$$\hat{\boldsymbol{h}} = \begin{pmatrix} a_1x_{2,0}\beta_1\\ a_2x_{1,0}+a_1x_{2,0}\beta_2\\ a_3x_{1,0}+a_1x_{2,0}\\ a_5x_{2,0}\beta_1+a_6x_{4,0}\beta_1+a_6x_{3,0}x_{4,0}\beta_1\\ a_4x_{1,0}+a_5x_{2,0}\beta_2+a_6x_{4,0}\beta_2+a_7x_{3,0}x_{4,0}\beta_2\\ a_8x_{1,0}+a_5x_{2,0}+a_6x_{4,0}+a_9x_{3,0}x_{4,0}\end{pmatrix} \quad (20)$$

with

$$\beta_1 = \beta_1(x_{5,0}), \quad \beta_2 = \beta_2(x_{5,0}) \quad (21)$$

and

$$a_1 = c_3(u_2\big|_{t=t_0} + c_4) \tag{22}$$
$$a_2 = c_1 c_5 \tag{23}$$
$$a_3 = c_1 \tag{24}$$
$$a_4 = -c_1^2 c_5 \tag{25}$$
$$a_5 = c_3 \dot{u}_2\big|_{t=t_0} - c_3^2(u_2\big|_{t=t_0} + c_4)^2 \tag{26}$$
$$a_6 = c_2 c_3 u_1\big|_{t=t_0}(u_2\big|_{t=t_0} + c_4) \tag{27}$$
$$a_7 = c_1 c_2 c_5 u_1\big|_{t=t_0} - c_2 c_3 u_1\big|_{t=t_0}(u_2\big|_{t=t_0} + c_4) \tag{28}$$
$$a_8 = -c_1^2 \tag{29}$$
$$a_9 = c_1 c_2 u_1\big|_{t=t_0} - c_2 c_3 u_1\big|_{t=t_0}(u_2\big|_{t=t_0} + c_4). \tag{30}$$

The system of equations using $\hat{\boldsymbol{h}}$ calculated in (20) does have a unique solution for the initial state variables $x_{1,0}$ to $x_{5,0}$ if the initial values for the input variable $u_1\big|_{t=t_0}$ is positive and the initial value for the input variable $u_2\big|_{t=t_0}$ is non-negative. As these input variables represent mass flows, they are always greater than zero when a combustion takes place. Thus, the state-space model (16) and (17) is observable.

3. ESTIMATION APPROACH AND VERIFICATION

3.1 Extended Kalman Filter

An Extended Kalman Filter is chosen for the simultaneous estimation of the state variables and fuel properties as it is a well established method with moderate computational costs. The recursive algorithm applied for calculating the estimated state vector $\hat{\boldsymbol{x}}_{\mathrm{k|k}}$ and the covariance matrix $\boldsymbol{P}_{\mathrm{k|k}}$ is, e.g. (Grewal et al., 2001),

Prediction

$$\begin{aligned} \hat{\boldsymbol{x}}_{k|k-1} &= \hat{\boldsymbol{x}}_{k-1|k-1} + T_S \boldsymbol{f}(\hat{\boldsymbol{x}}_{k-1|k-1}, \boldsymbol{u}_k) \\ \boldsymbol{P}_{k|k-1} &= \boldsymbol{A}_k^T \boldsymbol{P}_{k-1|k-1} \boldsymbol{A}_k + \boldsymbol{Q}_k \end{aligned} \tag{31}$$

Correction

$$\begin{aligned} \boldsymbol{S}_k &= \boldsymbol{H}_k^T \boldsymbol{P}_{k|k-1} \boldsymbol{H}_k + R_k \\ \boldsymbol{K}_k &= \boldsymbol{P}_{k|k-1} \boldsymbol{H}_k \boldsymbol{S}_k^{-1} \\ \hat{\boldsymbol{x}}_{k|k} &= \hat{\boldsymbol{x}}_{k|k-1} + \boldsymbol{K}_k\big(y_k - h(\hat{\boldsymbol{x}}_{k|k-1}, \boldsymbol{u}_k)\big) \\ \boldsymbol{P}_{k|k} &= (\boldsymbol{I} - \boldsymbol{K}_k \boldsymbol{H^T}_k) \boldsymbol{P}_{k|k-1} \end{aligned} \tag{32}$$

with the sampling time t_{s}, the system gradient matrix $\boldsymbol{F}_{\mathrm{k}}$, the constant covariance matrix of the process noise $\boldsymbol{Q}$ and the constant covariance matrix of the observation noise $\boldsymbol{R}$. The system gradient matrix $\boldsymbol{F}_{\mathrm{k}}$ and the measurement matrix $\boldsymbol{H}_{\mathrm{k}}$ are defined as

$$\boldsymbol{F}_k = \frac{\partial \boldsymbol{f}}{\partial \boldsymbol{x}}\Big|_{\hat{\boldsymbol{x}}_{k-1|k-1}, \boldsymbol{u}_k} \text{ and } \boldsymbol{H}_k = \frac{\partial \boldsymbol{h}}{\partial \boldsymbol{x}}\Big|_{\hat{\boldsymbol{x}}_{k|k-1}}. \tag{33}$$

In biomass boilers, the time constants of (16) are typically in the range of some minutes. For this reason, the sampling time is chosen as $t_{\mathrm{s}} = 1$ s to guarantee stable behavior of the EKF's Euler-discretization for all combustion conditions. The covariance matrix of the process noise $\boldsymbol{Q}$ is a diagonal matrix with constant coefficients that are empirically chosen, through trial and error, to provide a sufficiently fast estimation of the state variables and fuel properties.

3.2 Simulation Results - Basic Functionality

Simulation studies are performed to verify the estimation method. The model parameters are chosen to simulate a representative small-scale biomass boiler with a nominal capacity of 50 kW ($k_{\mathrm{FF}} = 6.58\mathrm{e}{-5}$, $c_{\mathrm{W}} = 2\mathrm{e}{-2}$, $c_{\mathrm{DS,1}} = 4\mathrm{e}{-1}$ and $c_{\mathrm{DS,2}} = 1\mathrm{e}{-3}$). The simulation is performed with a constant simulation step-size of $t_{\mathrm{S,sim}} = 0.1$ s. Fuel changes as well as changes in the operating conditions of the biomass boiler are simulated. In order to demonstrate the basic functionality of the estimation scheme no modeling error, measurement error or noise is considered in the simulation. The influence of these errors is investigated separately in section 3.3. The fuel initially used has the properties $b_{\mathrm{fuel}} = 650$ kg/m^3, $w_{\mathrm{H_2O}} = 10$ wt.% and $w_{\mathrm{C}} = 0.48$ kg/kg. At minute 30 the fuel properties are changed to $b_{\mathrm{fuel}} = 421$ kg/m^3, $w_{\mathrm{H_2O}} = 45$ wt.%, $w_{\mathrm{C}} = 0.3$ kg/kg and at minute 60 the fuel properties are changed to $b_{\mathrm{fuel}} = 550$ kg/m^3, $w_{\mathrm{H_2O}} = 30$ wt.%, $w_{\mathrm{C}} = 0.6$ kg/kg. The hydrogen content w_{H} of all fuels is chosen to exhibit a ratio $\alpha = 0.129$, which is also used in the estimator. In summary, all assumptions made in section 2 are fully met. During the entire simulation, the fuel feed has a constant input signal, resulting in the fuel mass flow varying with the fuel's bulk density. The mass flows of primary and secondary air are adjusted simultaneously with the fuel change to keep the operating conditions representative. Additionally to these changes of the fuel properties the mass flow of primary air is changed at minutes 15, 45 and 75 to alter the mass of dry fuel on the fuel bed while the fuel properties are unaltered.

Fig. 2 shows the actual and estimated fuel properties. For all fuels and operating conditions, the fuel properties can be estimated accurately in steady state. While quick fuel changes are not detected instantaneously the estimated value approaches the actual value asymptotically. During this time, the estimated fuel properties differ from the actual ones, which results in the estimated state variables slightly deviating from the actual values (shown in Fig. 3). For constant fuel properties, the state variables and the lower heating value calculated using (15) and shown in Fig. 4 can be estimated accurately. A change in the operating conditions as a result of a changing mass flow of primary air (minutes 15, 45 and 75) does not affect the estimated fuel properties.

These results clearly demonstrate that the proposed estimation method is capable of simultaneously estimating the state variables and fuel properties in fixed-bed biomass boilers. The influence of measurement errors and model parameter errors on the estimation results are investigated in the following section.

3.3 Simulation Results - Influence of Measurement Errors and Model Parameter Errors

Measurement errors as well as errors in the model parameters typically lead to an inaccurate estimation of the state variables when using state estimators. For this reason the EKF's behavior needs to be investigated for cases when model parameters as well as measurement values exhibit errors. This section investigates the EKF's behavior for these errors in simulation studies. The same model parameters for the biomass boiler as in section 3.2 are chosen and

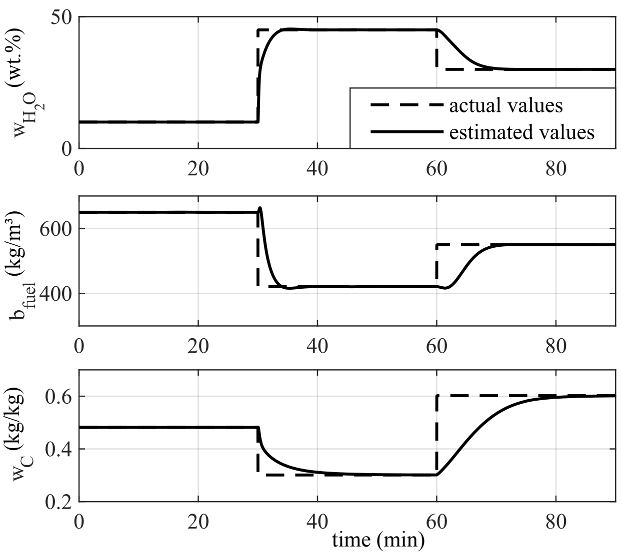

Fig. 2. Simulation results: estimated fuel properties.

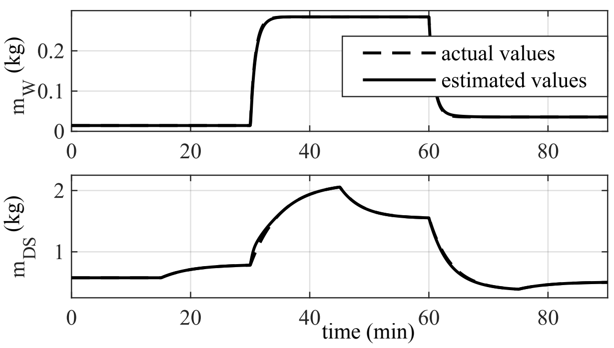

Fig. 3. Simulation results: estimated state variables.

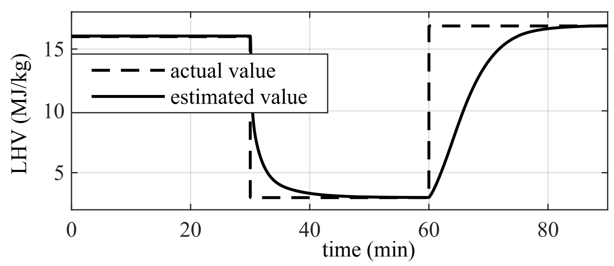

Fig. 4. Simulation results: estimated lower heating value.

the simulation is again performed with a constant simulation step-size of $t_{\mathrm{S,sim}} = 0.1$ s. The fuel properties used are $b_{\mathrm{fuel}} = 650$ kg/m^3, $w_{\mathrm{H_2O}} = 10$ wt.% and $w_{\mathrm{C}} = 0.48$ kg/kg and $\alpha = 0.129$. All input variables are kept constant for the entire simulation. Three particular cases are investigated which represent the most relevant errors to be expected in biomass boilers.

In case 1 the influence of the simplification (5), i.e. $\alpha = 0.129 = const.$, on the estimation results is investigated. This is a deliberately chosen model parameter error introduced for the sake of simplifying the state and parameter estimation. It is a known source of error and introduces inaccuracies to the EKF even when no measurement errors occur. In the simulation, the value for α used in the EKF is changed at minute 40 by $\Delta\alpha = 0.005$ while the actual value remains the same. This matches the difference between the standard value defined in (5) and the value valid for corncob (see Table 1). At minute 60 this error is reverted to $\Delta\alpha = 0$.

In case 2 the influence of a measurement error of $\dot{m}_{\mathrm{SA}}$ is investigated. The measurements of air mass flows frequently exhibit errors in biomass boilers for example due to insufficient inlet or outlet distances for the measurement devices. For this reason, this case represents a typical source of error to be expected in biomass boilers. Additionally, a measurement error in $\dot{m}_{\mathrm{SA}}$ has the same effect as the occurrence of leakage air, i.e. non-measurable air mass flows entering the secondary combustion zone through cracks and openings of the biomass boiler. At minute 60 a measurement error $\Delta\dot{m}_{\mathrm{SA}} = 4.77$kg/h (+10% of the actual value) and reverted at minute 80. This is considered a large error for the secondary air mass flow.

In case 3 the influence of a measurement error of $\dot{m}_{\mathrm{FG}}$ is investigated. This mass flow is particularly difficult to measure due to frequently occurring fouling of the measurement devices. At minute 100 a measurement error $\Delta\dot{m}_{\mathrm{FG}} = 9.49$ kg/h (+10% of the actual value) and reverted at minute 120 which is considered a large error for this mass flow.

An overview over these errors is given on Table 3 with the time the error being introduced 'start time' and the time the error being reverted 'end time'.

Table 3. Measurement errors and model parameter errors introduced to the simulation.

case	variable	error	start time	end time
case 1	$\Delta\alpha$	0.005	minute 20	minute 40
case 2	$\Delta\dot{m}_{SA}$	+10%	minute 60	minute 80
case 3	$\Delta\dot{m}_{FG}$	+10%	minute 100	minute 120

Fig. 5 and Fig. 6 show the actual and estimated fuel properties and state variables respectively while Fig. 7 shows the lower heating value calculated using (15). The results indicate that case 1, i.e. the simplification (5), only marginally influences the estimation results. Even a comparatively large error of α results in small errors in the estimated fuel properties and state variables. Case 2 as well as case 3 show that large measurement errors of the mass flows, i.e. secondary air and completely combusted flue gas respectively, lead to significant errors in the estimation results. However, despite these significant measurement errors the estimation method (EKF) still exhibits stable behavior. After the errors are reverted, all estimated values approach the actual values asymptotically. This demonstrates that a sufficiently accurate measurement of these mass flows is required. In cases where no accurate mass flow measurements are available energy balance equations with additional measurement data can lead to an improvement of the estimation accuracy and is, therefore, recommended.

3.4 Results with Measurement Data

The estimation method is verified using measurement data from test runs at a small-scale biomass boiler with a nominal capacity of 50 kW. The model parameters for this

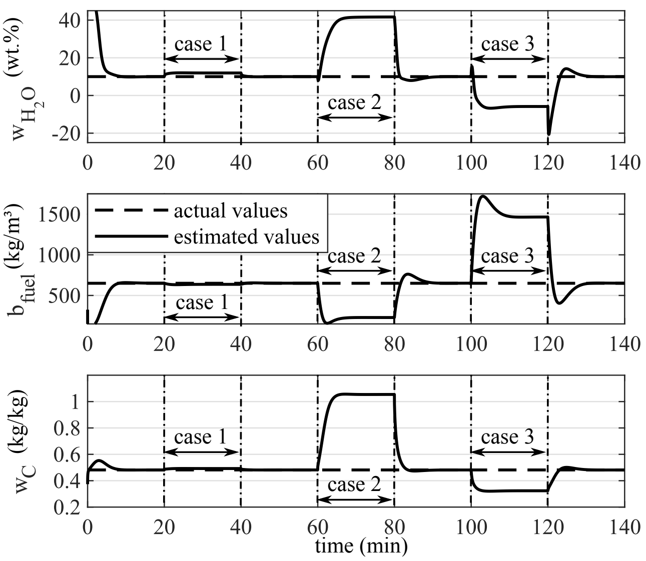

Fig. 5. Influence of errors: estimated fuel properties.

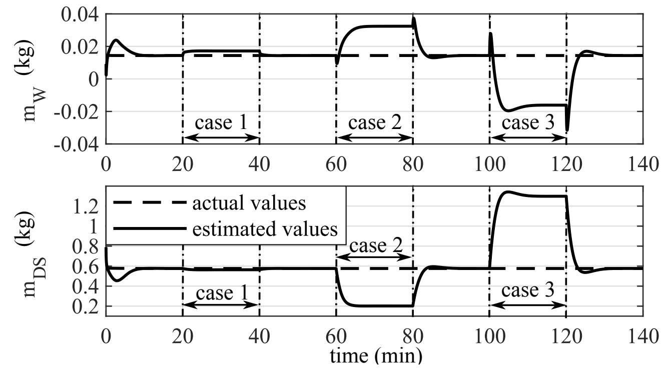

Fig. 6. Influence of errors: estimated state variables.

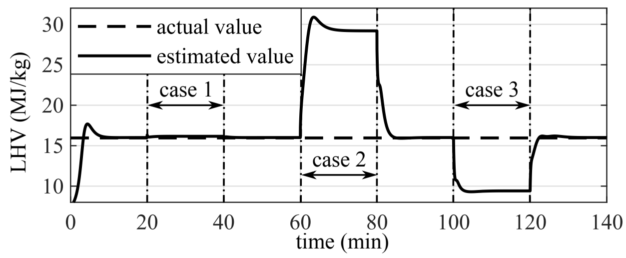

Fig. 7. Influence of errors: estimated lower heating value.

boiler are the same as used for the simulation in section 3.2. The sampling time for the data acquisition is chosen as $t_{\mathrm{S,acq}} = 1$ s. The boiler is operated at different loads and with corncob grits as a fuel (average fuel properties determined a-posteriori: $b_{fuel} = 480$ kg/m^3, $w_{\mathrm{H_2O}} = 12$ wt.%, $w_{\mathrm{C}} = 0.477$ kg/kg). The actual value for the average ratio is $\alpha = 0.124$, while the value used in the estimator is $\alpha = 0.129$.

Fig. 8 shows the estimated and the actual fuel properties. While the fuel's carbon content w_{C} and hydrogen content w_{H} as well as its bulk density b_{fuel} can be estimated correctly, the estimated water content $w_{\mathrm{H_2O}}$ exhibits a noticeable error of up to 58%. This is assumed to be a result of the combined measurement errors in the mass flows of completely combusted flue gas and air which is in accordance with simulation results shown in section 3.3. Fig. 9 shows the estimated state variables. As they cannot be measured in real boilers, no comparison between actual and estimated value can be given. Fig. 10 shows the lower heating value calculated from the estimated fuel properties using (15). The mean value of the calculated lower heating value of 16.03 MJ/kg is higher than the value determined a-posteriori of 15.15 MJ/kg. The fluctuations in all estimated variables are a result of stochastic fluctuations in the combustion process that are not considered in the model. In order to reduce the fluctuations in the estimated variables, a suitable choice of the EKF parameters is necessary. However, a stronger damping of the fluctuations will lead to lower estimation speed in the case of quick fuel changes. These results demonstrate that the presented estimation method is capable of simultaneously estimating the fuel properties and state variables in fixed-bed biomass boilers.

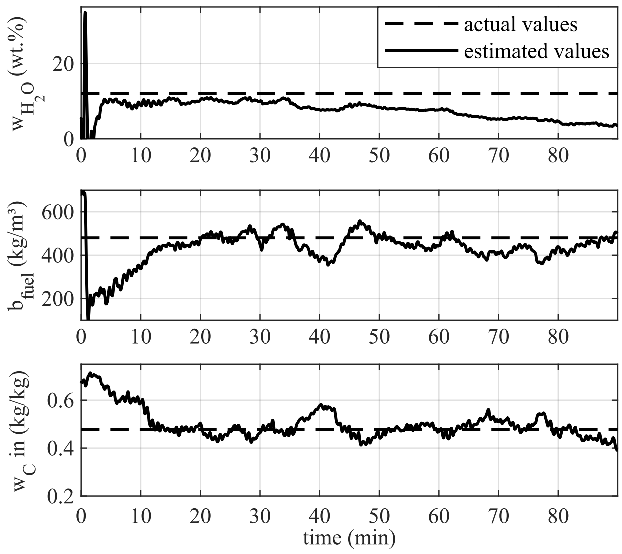

Fig. 8. Validation results: estimated fuel properties.

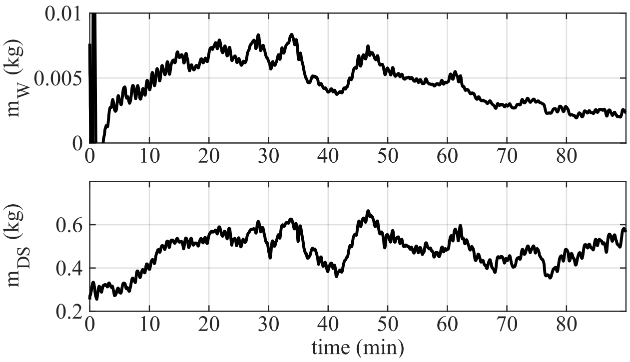

Fig. 9. Validation results: estimated state variables.

4. CONCLUSIONS AND OUTLOOK

The result of the work presented is a method for the simultaneous estimation of the non-measurable state variables and fuel properties in fixed-bed biomass boilers with air staging. This is the first discussion of such a method for the application at biomass boilers.

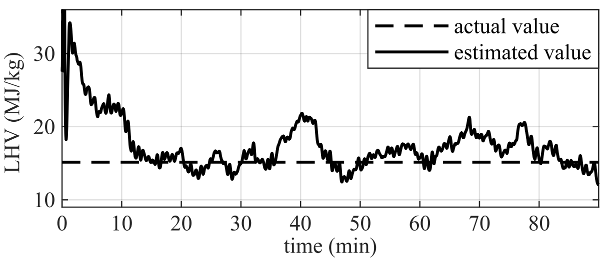

Fig. 10. Validation results: estimated lower heating value.

The presented method is limited to the utilization of mass- and substance balances which leads to a low implementation effort. It can be implemented at all fixed-bed biomass boilers with the necessary instrumentation. In addition to the typically available residual oxygen content of the flue gas, the method requires the measurement of the mass flows of air and flue gas as well as the water content of the fully combusted flue gas which are typically not available at biomass boilers. Due to the costs associated with retrofitting the necessary instrumentation, this method is mostly relevant for medium-scale biomass boilers.

As with other state estimators, measurement errors or errors in the model parameters lead to a deviation of the estimation results from their actual value at steady state. The investigated errors in the model parameters showed only a small influence on the estimation results. However, measurement errors for the mass flows of secondary air and fully combusted flue gas have a bigger influence on the estimation results. In cases where significant measurement errors for these mass flows are expected, the use of energy balance equations with additional measurement data can lead to an improvement of the estimation accuracy and is therefore recommended. However, this is not deemed necessary for the application at biomass boilers with accurate measurements for the mass flows. Further improvements could be achieved through the application of robust state estimation methods instead of the EKF utilizing a-priori knowledge of the uncertainties of the measured variables.

The application of this estimation methods in combination with model-based control strategies is expected to especially improve the biomass boiler's operational behavior during fuel changes. This enables a fully automated operation of biomass boilers even when the fuel quality varies strongly. As a result, the plant operator's effort necessary for ensuring a smooth operation of the biomass boiler during a fuel change is significantly decreased. Thus, the utilization of new and alternative biomass feedstocks is made more viable by the application of the proposed estimation method. For this reason, the presented estimation method is a key technology to ensure the further distribution of biomass boilers in modern energy systems.

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