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Real-time moisture content monitoring of solid biomass in grate combustion

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Abstract: A novel method for real-time moisture level monitoring of the solid biomass fuel in grate combustion is presented. The measurement principle is based on temperature sensor information from both flame and a fuel bed. Based on the combustion theory and data analysis, selected features have been extracted from the fused sensor information and estimate of the fuel quality is then made continuously with calculated features. The monitoring approach has been tested in a 300 kW stoker combustion unit intended for decentralized heat production, over a wide range of different process conditions and wood fuel moistures, giving satisfactory accuracy for control purposes. The availability of moisture information made possible to adjust primary/secondary air ratio, leading to reduction of emissions and excess air. Based on the results, the method has capability to give new possibilities for cost effective control and more energy efficient use of solid biomass as a fuel in small-scale energy production.

1. INTRODUCTION

Solid fuel moisture content variations are among the main disturbances in the biomass combustion based energy production. Especially in the small combustion units, thermal output typically less than 1 MW, the fuel range nowadays increasingly covers solid biomass with large quality and moisture fluctuations. From the monitoring and control point of view, small boilers in this scale exhibit problems due to the absence of real-time moisture content measurements. This means that changes in fuel calorific value has to be accounted for as unknown disturbances, resulting non-optimal process behaviour with higher emissions and lower total efficiency.

For this reason, on-line information about the fuel moisture in small boilers would favour the optimisation and stabilisation of the process leading to maximisation of energy efficiency. This paper describes an indirect, combustion temperature-based monitoring procedure for on-line and in-situ estimation of fuel moisture content in woodchips.

Several modern techniques for determination of on-line woodchips moisture content have been reviewed in (Nyström & Dahlquist, 2004). In the covered measurement principles, fuel moisture is measured either in a fuel flow or a fuel bulk where the sample has to be specifically representative of the bulk. Six methods have been reviewed in the study: dual x-ray measurements, near infrared spectroscopy (NIR), indirect method based on flue gas water content measurement, microwaves, radio frequents (RF), and nuclear magnetic resonance (NMR). For continuous fuel flow measurement, NIR-method could be favourable with a multivariate calibration, see also (Jensen *et al.*, 2006). However, invest costs and practical implementation issues (inhomogeneous fuel flow and bed height, frozen fuel, calibration needs, delays) are strongly affecting the applicability of these methods in small-scale.

A method for on-line compensation of inhomogeneous fuel quality in fluidised bed combustion has been reported for example in (Mononen & Mikkonen, 1999). In this extensively studied strategy, fluctuations in fuel calorific value are compensated in feedforward manner by estimating the combustion power using total airflow and flue gas oxygen measurements. The main assumption for applicability of the method is a fast burning fuel type, minimising the estimation delay. This is not a case in a grate-fired boilers using solid biomass as a fuel boilers, because of a slowly burning fuel bed.

Another fuel quality compensation strategy in (Karppanen, 2000) is based on oxygen measurement and fuzzy logic. In this case, variations in calorific value are estimated monitoring the changes in flue gas oxygen levels. A fuzzy rulebase was developed to produce a correction term to the estimated and fixed heat value of the waste fuel. Maximum correction range reported was ±15 % change in the heat value. The corrected heat value of the fuel was then used as an input for a main control concept.

Fuel quality monitoring concepts based on energy and mass balances are reported for example in (Joronen, 2003) and (Kessel van *et al.*, 2004). These monitoring approaches, however, require a lot of measurements and instrumentation including calculation power in order to be applicable in practice to small-scale combustion units.

Available fuel moisture monitoring methods exhibit common features that are not well suited to small-scale combustion processes, namely costly measurement principle and lack of robustness due to inhomogeneous fuel quality. Typically, water in the fuel is measured either from the bulk sample or on-line from the conveyer, before the combustion chamber. These methods can then have either too large delay for disturbance compensation of the moisture changes, or noisy measurement environment. In this paper, an alternative

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method for approximating moisture content in the woodchips is presented to overcome above mentioned measurement issues. The method is based on the assumption that flame temperature changes are at least partially related to changes in fuel moisture levels. The temperature measurements are made solely inside the combustion chamber. It then enables in principle continuous and undelayed monitoring of moisture content. This in turn, is crucial for successful compensation of firing rate and continuous optimisation of primary/secondary air feed ratio, together with fuel quality control.

In the following sections, the indirect measurement procedure for estimation of moisture content in wood fuel based on combustion temperature sensor fusion and data analysis is briefly discussed. Finally in section 5, some concluding remarks are pointed out.

2. THE MONITORING APPROACH

2.1 Theoretical basis

Theoretical flame temperature, namely the maximum adiabatic temperature in combustion, is depended on amount of excess air and fuel moisture content (Fig.1), see for example (Yang *et al.*, 2004).

As depicted in the figure, the growing amount of excess air lowers the maximum achievable flame temperature, together with higher moisture content when burning wood as a fuel. This is because both excess air and evaporated water are binding part of the heat produced during the exothermic combustion stages (Wahlroos, 1980).

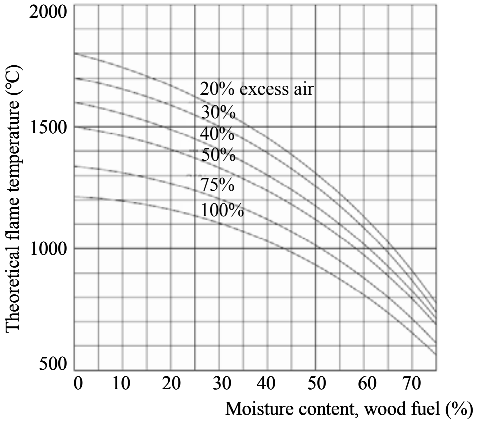

Fig. 1. Theoretical flame temperatures as a function of moisture content and excess air, wood as a fuel. (Wahlroos, 1980)

However, in a real combustion processes the straightforward determination only the maximum flame temperature can be impractical because of non-adiabatic processes and strongly changing process conditions. On the other hand, fusing the information collected from multiple temperature sensors can lead to success especially in small-scale combustion, as in model-based monitoring of carbon monoxide, CO_2, (Ruusunen & Leiviskä, 2004).

2.2 Data analysis procedure

Three targets were set for designing the monitoring concept: on-line applicability, robustness and generalisation requirement for model transferability. Straightforward configuration property is needed in small, but numerous different process environments. On the other hand, real-time and robust moisture information is essential to achieve fast disturbance compensation and fuel quality control.

According to preceding section, combustion chamber temperature measurements were chosen to data analysis in order to find the most valuable indicators for determination of changes in fuel moisture content. A general view of variables included to analysis, their connections, and direction of analysis is presented in (Fig. 2).

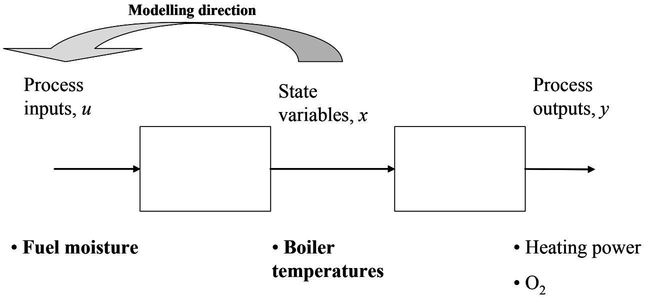

Fig. 2. Data analysis direction and process variable connections.

The general framework of the monitoring concept consists of variable selection, feature extraction and model identification. For selecting the variables, the search criterion (1) was formed in order to find the most sensitive sensors for detection of moisture changes, namely mean relative temperature change:

$$\frac{1}{k}\sum_{i=1}^{k}\frac{T_{ni,ml}}{T_{ni,mh}}, \tag{1}$$

where $T_{ni,ml}$ is value of temperature sensor number n, at low fuel moisture, ml. Accordingly, $T_{ni,mh}$ is the value of the same sensor at high moisture content in the fuel during the combustion. The summed values are divided by the number of samples, k. In the selection of variables using (1), at least two moisture level data sets are needed to find out the mean maximum difference between temperature values of the same sensor.

A data mining algorithm was developed for feature extraction with the selected temperatures. It consists of testing feature prototypes according to search criterion (2). In order to have comparable criterion for calculated variables with different scales, standardised variance of the feature variables was utilised. Prototypes here are variables that may be subject to transformations or calculations with other variables, such as *x-y, z-xy, log(z),* and *x/z*. All together 57 prototypes were formed with three variables, with and without normalisation of temperature values. This way the calculated variable transformations and their combinations can be tested automatically. Search criterion (2) for feature extraction is

$$\frac{\mathrm{var}\left(\sum_{i=1}^{k} \frac{feature_{ni,ml}}{feature_{ni,mh}}\right)}{E\left(\sum_{i=1}^{k} \frac{feature_{ni,ml}}{feature_{ni,mh}}\right)^2}, \qquad (2)$$

where $feature_{ni}$ is the value of nth feature prototype. Other preferred properties for features in this case are monotonically increasing values respect to moisture level increase to help with the modelling task, number of sensors needed, and degree of mutual independency for model inputs if used with other features.

The data analysis proceeds as follows: first, data sets for two fuel moisture levels are collected from combustion experiments. These include values of every available temperature sensors in a boiler. Then, a small set, 10 data points from both data is chosen for example during 1000 epochs randomly according to uniform distribution. This stage is similar to k-fold cross validation procedure. For every sensor at every epoch, mean values of temperature changes are calculated using (1). The largest mean values indicate the most relevant sensors for moisture monitoring. The procedure aims with the re-sampling towards robust identification of relevant sensors straight from the raw measurement values. In this case, the mean value is utilised as a filter to reduce effect of measurement noise. Feature extraction with the selected temperature sensor values has the similar procedure, utilising the values formed from the prototypes, and using (2) as a search criterion.

3. EXPERIMENTAL SET-UP

For the combustion tests, an experimental campaign was set up. The process consisted of a commercial 300kW stoker-fired boiler, fuel silo, fuel feeding screw, heat exchanger, and instrumentation needed to monitor and control the system (Fig. 3).

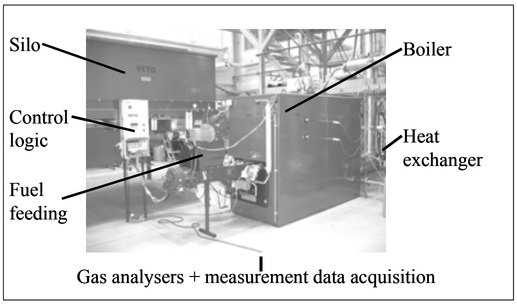

Fig. 3. Combustion process and experimental set-up.

Birch chips were first used as a fuel at two moisture levels, 9% and 39% when collecting data for model identification. Operating range of the boiler was varied between 30%-100% of the nominal output during the planned experiments. All together there were 40 measurement points in the process. In addition to gas analyser measurements (CO2, O2, CO, NOx, OGC), the boiler was equipped with a lambda sensor. Data from experiments was acquired continuously with sample rate of 10 seconds. The on-line tests consisted of five days combustion campaign, where mixed species of woodchips were used as a fuel. The process was both in open and closed loop control during the test runs. The heat output level was varied between 60% - 100% at on-line tests.

Moisture range in the fuel silo batch varied in between three percentage units around the target moisture level set. The accuracy of the reference bulk sample moisture measurement was 2%. Reference measurement was based on the mass weighing of the sample before and after the drying in the oven.

The data analysis and on-line algorithms for modelling were programmed with MATLAB® software. OPC-interface was used to connect the combustion process and data acquisition software (Fig.3).

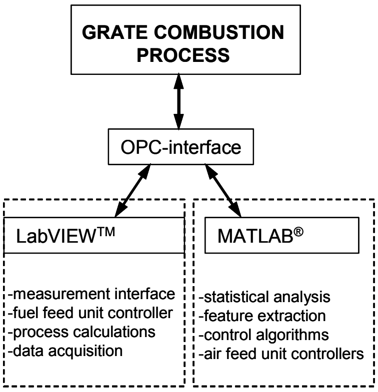

Fig. 3. Software: connections and focus during test runs.

4. RESULTS AND DISCUSSION

4.1 Data analysis and model calibration

The data analysis for finding the most representative temperatures and features was made with data collected earlier from the combustion process described in Section 3. Using (1), the data was re-sampled 5000 epochs, choosing randomly 20 samples each time. The results of the variable selection (Fig. 4) are in the form of box-plot, describing the distributions of values resulting from (1).

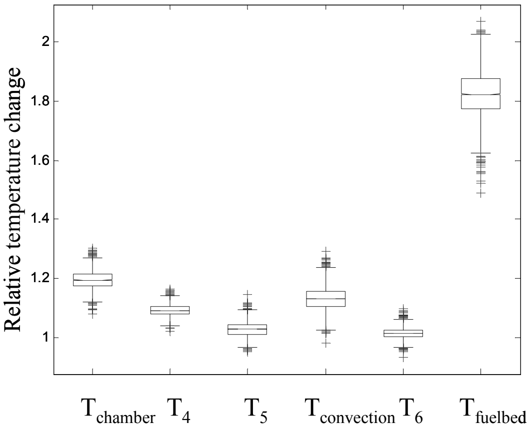

Fig. 4. Results of variable selection.

It can be seen that temperature of the fuel-bed has the most significant difference in the mean values when using dry and wet fuel in changing operating conditions. The result indicates almost two times higher temperatures when using dry fuel (Fig. 4). Other two selected measurements for feature extraction were temperatures in lower combustion chamber and convection canal.

The selected variables are in this case almost mutually independent (Fig. 5), although there are two clusters seen depending on the heat output level (200 or 270 kW). Also, dependencies with process outputs were tested with no indication of significant interactions.

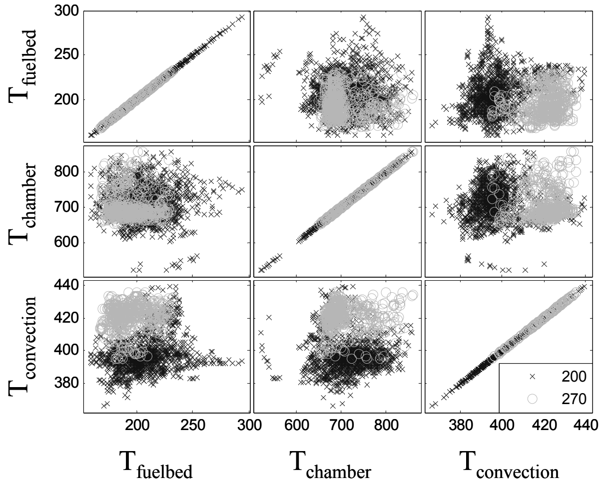

Fig. 5. Interactions of the selected variables, two heat output levels.

The three chosen measurements were not sensitive enough to monitoring task of the moisture levels by utilising raw values of the sensors. For this reason, sensor combinations and calculated values were considered.

Feature extraction indicated the calculated variable (3) as a potential input for model according to search criteria stated in Section 2.2,

$$x = \ln(T_{fuelbed}) \cdot \ln(T_{chamber}) , \quad (3)$$

where x is the input for calibration model of the fuel moisture. The model (4) with feature x and was identified utilising linear model structure and regression as follows:

$$moisture_{fuel} = -4.9x + 42.5 , \quad (4)$$

where $moisture_{fuel}$ is the estimated value of moisture content in the woodchips as percents. The identified calibration model (4) was then applied to on-line tests.

4.2 On-line tests

Mean values with 95% confidence intervals of the variable (3) during the on-line combustion tests are presented in (Fig. 6). The figure shows that real-time value of the feature x varied between 40 and 34. Also, the moisture dependency of the variable is almost monotonically decreasing. However, at moisture level 17%, the value is not separable from the level 34%. This is mainly because these different fuel batches were partially mixed in silo during the combustion tests.

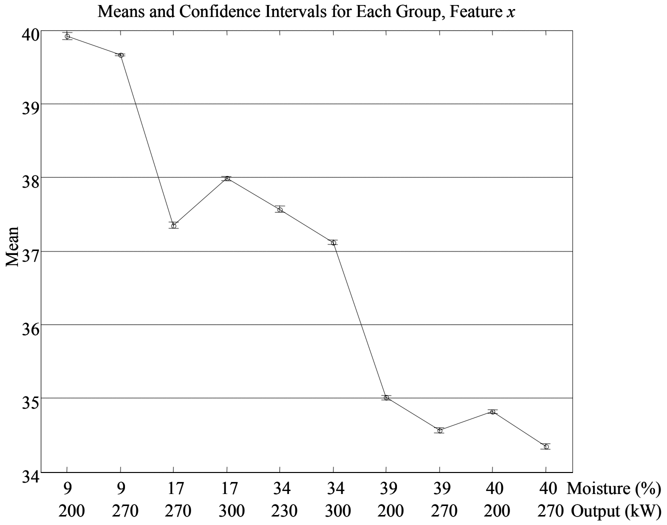

Fig. 6. Mean values of feature x with 95% confidence intervals, as a function of fuel moisture and heat output level.

On-line estimation (4) of absolute fuel moisture content was carried out during the combustion tests (Fig. 7). It can be seen that the calibration model satisfactory stays within the range of reference measurements and moisture variations in fuel silo. During the day two, the model has overestimated the moisture level showing values around 14% as the reference measurement indicates 9% fuel moisture.

The dotted line shows the moisture variation range of measured fuel bulk samples taken from the silo during test periods. It is clearly seen that the mixed fuel batch of 17% and 34% at third day is estimated to be about 25% that is actually the mean value resulting from such a mixing.

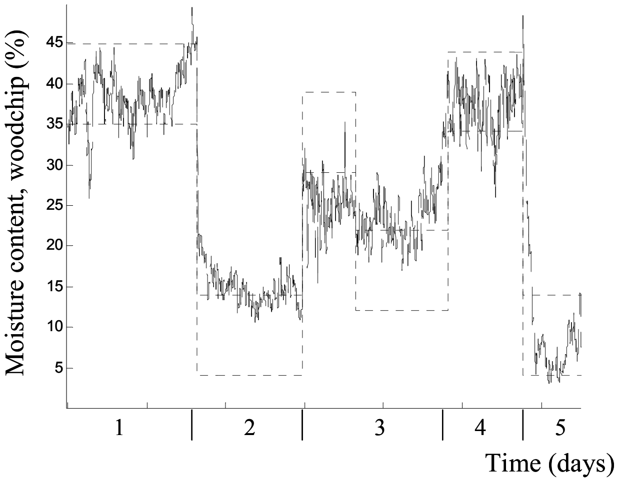

Fig. 7. On-line estimation results of fuel moisture content 9 – 40 %. Dotted line: moisture range in silo, reference measurement. Dashed line: estimated moisture in combustion chamber.

The estimated fuel moisture content (4) was utilised to set-point control of primary and secondary air feed ratio. In grate combustion, the ratio is determined mainly by the moisture content of the fuel. Primary air is needed relatively more as the fuel moisture content increases. Since in the small-scale combustion units fuel moisture is not measured, at least in real-time, air feed ratio typically has a constant value.

The case example illustrates the effect of on-line moisture estimation (4) information compared to the same control strategy with constant primary/secondary air ratio, 40%/60%. Here, constant ratio of 0.55 was adapted to 0.25 utilising the information from the moisture content model. In this case, the model output was between 10-25% moisture content. The result after adaptation of air feed ratio shows that total efficiency of the boiler has increased from 88% to 90% and its variation reduced remarkably (Fig. 8).

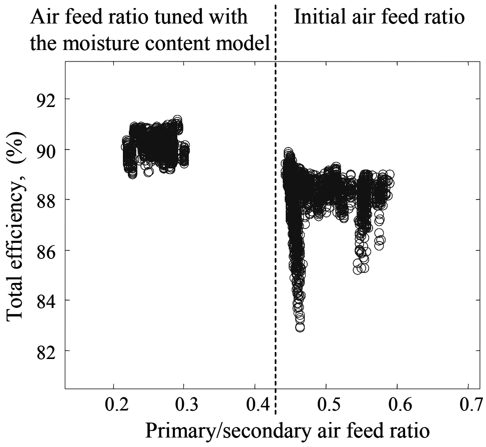

Fig. 8. Set-point change in air feed ratio according to on-line estimated moisture content.

5. CONCLUSION

On-line, indirect method for moisture content determination of wood fuel in small-scale grate combustion is presented. The approximation is based on the information of two temperature sensor in the combustion chamber. The relevant sensors were identified with the measurement data. The first sensor was positioned above the grate, the second inside the fuel layer. Data analysis was applied to collected data for extracting calculated variables that are dependent on moisture levels. Regression was then used for linear calibration model identification to scale selected features into absolute moisture content values.

Results show that wood fuel moisture has strong impact on combustion temperatures. Especially temperature in the fuel-bed seems to be a robust indicator for the moisture changes. Product of the two logarithm transformed temperature measurements is a potential feature for robust moisture identification. On-line tests showed that the method has fast response and good accuracy for control purposes.

The method was utilised to set-point control of primary/secondary air feed ratio to demonstrate importance of moisture information. The test results showed increase in total efficiency with simple adjustment of the ratio, compared to constant value. This affects directly to the energy efficiency of the process, in terms of minimised excess air and reduced emissions. Although these findings imply the robustness of the method, care should be taken in positioning of the temperature sensors and when the combustion environment changes.

Thus, the presented method seem to suit for on-line determination of wood fuel moisture content according to results. Other uses for this kind of indirect method could be utilisation to firing rate compensation in the form of lower heating value estimation. Also, the fuel quality control is an important issue in small-scale power plants, where solid biomass can be from many different sources. The future research will focus on multivariate modelling and connecting the method to on-line compensation of biomass heating value fluctuations in grate combustion.

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