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A Case Study on Sensor Fusion for Monitoring Combustion Processes

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Abstract: A model-based quality monitoring method for wood combustion process is discussed. The method consists of a gas sensor signal combined with additional process measurements. In this case, raw signal indicating the presence of Carbon monoxide in flue gas is enriched applying sensor fusion to provide on-line information for control purposes. The presented model is identified and tested with data sets obtained from combustion experiments with a wood fuel. According to simulation results with testing data, the model satisfactory generates similar and undelayed CO concentration values as compared to reference signals of a gas analyser. Further, the presented monitoring method is capable to compensate drift and nonlinearities in the gas sensor response during the combustion tests. These properties could increase the potential usage of such type a gas sensors intended for monitoring combustion quality.

Keywords: Modelling, soft sensor, temperature measurement, wood fuel

1. INTRODUCTION

Quality of a combustion process is determined by emissions and efficiency. In order to maintain optimal process conditions with formation of minimal harmful components, combustion needs to be monitored.

Process conditions may vary remarkably in small-scale combustion units, leading to formation of harmful combustible gases. Carbon monoxide (CO) is one of the typical gaseous component in such conditions. It can be also utilised as an indicator for other combustion products including gaseous hydrocarbons.

Semiconductor gas sensors are one of the most widespread among the measurements of gaseous combustion products. Typical applications include gas leak detectors, low-cost gas analysers and lambda sensors. However, their applications in the real-time combustion monitoring have been rare because of the harsh nature of measuring environment. Semiconductor gas sensors are usually produced applying a reactive metal oxide material that is sensitive to concentration changes of several gas components. This is because of the variation in conductance between electrodes accordingly, making it possible to measure resistance over the semiconductor material layer (Torvela et al., 1989; Petersson and Holmberg, 2005). Often, doping some additional ingredient into a reactive material enhances the properties of the metal oxide. In this way, common characteristics of this type of sensor family like non-linear response, cross-sensitivity and chemical material erosion – drifting in sensor response, can be at least partly compensated (Endres et al. 1995; White and Turner, 1997).

In order to provide instant and reliable information for combustion quality monitoring, response signal of a semiconductor based gas sensor needs to be conditioned and enriched. In CO monitoring, the task is then to minimise cross-sensitivity and sensor drift together with its non-linear response characteristics. In this research, a group of sensor signals is fused to monitor combustion quality in a small-scale heating appliance. The paper presents a model-based method to combine a semiconductor sensor signal with flue gas temperature and fuel weighting signals in small-scale combustion process. Next, the applied methodology related to sensor fusion is discussed. Then, the monitoring results with the data from combustion experiments with solid wood as a fuel are presented. Finally, conclusions originating from the results are given.

2. MODEL-BASED SENSOR FUSION

2.1 Model Inputs

In combustion of solid fuels, flue gas temperature is partly related to the formation of CO. It is also straightforward to measure and related sensors may provide a fast response. The second variable selected as input for the model is the mass of fuel. Changes in the fuel weight may be used for indicating the progress of burning in a fuel layer during batch combustion. The raw signal of a semiconductor sensor is utilised as a third input for the modelling.

Adaptation to different burning phases is achieved by modelling CO concentration locally at three operation regimes. Progress of burning is described here with a proportional value $m_n(t)$ of the fuel weights as

$$m_n(t) = \frac{m_{pa}(t)}{m_{pa}(t_0)} , \quad (1)$$

where $m_{pa}(t)$ is the current mass of the fuel layer and $m_{pa}(t_0)$ is the mass at the start-up. Value of $m_n(t)$ is now used in decomposing the process into separate operation regimes. Local regions are defined by fuzzy sets because of uncertain information in (1). Three burning phases are approximated with fuzzy sets *ignition*, *burning* and *charring*. The membership functions of the presented fuzzy sets apply the current value of $m_n(t)$. The location of functions is permanent, because $m_n(t)$ stays between one and zero. For example, when the current value of $m_n(t)$ is near one, the burning phase according to the fuzzy sets is estimated mostly by *ignition*. At the same time, it is possible that the burning phase belongs a little bit to the fuzzy set *burning*. The membership functions of the burning phase define the validity of the local TS-models for the current operation regime. Local models can be now constructed for these regimes and scheduled using the membership functions. Membership values are acting as weights for the local TS-models. The global model is composed as the sum of weighted local models.

2.2 Structure of the Model

Many successful modelling results have been reported with a fuzzy model structure suggested originally by Takagi and Sugeno (1985). The same modelling approach has been applied formerly also to on-line monitoring of carbon dioxide concentration in flue gases (Ruusunen and Leiviskä, 2004).

The structure of the Takagi-Sugeno (TS) -model consists of fuzzy rules. Membership functions appear in the premise, whereas the consequent part contains the linear equation. Fuzzy rules represent linear local input-output relations of the system. TS-type fuzzy rules applied here for the CO modelling are of the following form

$$\begin{aligned} &\text{RULE}_i: \text{ IF } x_1(t) \text{ is } A_{i1}(x_1(t)) \text{ and } x_2(t) \text{ is } A_{i2}(x_2(t)) \\ &\qquad \text{THEN } \hat{y}_i(t) = \mathbf{a}_i\mathbf{x} + b_i , \end{aligned} \quad (2)$$

where $x_1(t)$ is the value of $m_n(t)$, $x_2(t)$ is the current temperature of the combustion, $\mathbf{a}_i$ and b_i are parameters, $\mathbf{x}$ is the vector of model inputs in the consequent part, $A_{i1}(x_1(t))$ is the membership function of current burning phase, $A_{i2}(x_2(t))$ is the membership function of the flue gas temperature and $\hat{y}_i(t)$ is an output of the ith rule. The output $\hat{y}_k(t)$ of the model can be formed using a simplified method (Tanaka, et al., 1995) as

$$\hat{y}_k(t) = \sum_{i=1}^{6} w_i \hat{y}_i(t) , \quad (3)$$

where w_i is the product of membership values used in the premise part of the ith rule,

$$w_i = \prod_{n=1}^{2} A_{in}(x_n(t)) . \quad (4)$$

For parameter identification of the model, criterion function E_M is defined as follows

$$E_M = \frac{1}{2}\left[y_k(t) - \hat{y}_k(t)\right]^2 , \quad (5)$$

where $y_k(t)$ is the real value of CO concentration. Error between the real value and model output is minimized by estimating the parameters of each rule. This is done by partially differentiating criterion function with respect to consequent parameters of the model (2)

$$\begin{aligned} \frac{\partial E_M}{\partial a_{mi}} &= \frac{\partial E_M}{\partial \hat{y}_k(t)} \cdot \frac{\partial \hat{y}_k(t)}{\partial a_{mi}} = -\left[y_k(t) - \hat{y}_k(t)\right] w_i x_{mi} , \\ \frac{\partial E_M}{\partial b_i} &= \frac{\partial E_M}{\partial \hat{y}_k(t)} \cdot \frac{\partial \hat{y}_k(t)}{\partial b_i} = -\left[y_k(t) - \hat{y}_k(t)\right] w_i , \end{aligned} \quad (6)$$

and after that modifying each parameter recursively using (6) as

$$\begin{aligned} a_{mi}(t) &= a_{mi}(t-1) - \varepsilon \frac{\partial E_M}{\partial a_{mi}} , \\ b_i(t) &= b_i(t-1) - \varepsilon \frac{\partial E_M}{\partial b_i} , \end{aligned} \quad (7)$$

where ε is the learning factor. Subscript m denotes the ordinal number of parameter-input variable pairs in the consequent part. Parameter estimating method (7) is a logical selection for this purpose, because learning now occurs locally, concerning only to currently valid fuzzy rules.

3. EXPERIMENTAL

3.1 Realisation of the Gas Sensor

In this work the gas sensor was based on the thick-film technology. The heating element of the sensor was realised by printing Pt conductors on 96% alumina. The line width of the conductors was 100 µm, the thickness was 5 µm and the total length was about 65 mm. The resistance of the heating element was about 300 ohm.

The conductor layer was fired at peak temperature of 1373 K after which the SnO_2 paste was screen-printed over the conductors. This SnO_2 paste was doped with 100 ppm Sb which decreased the resistivity of the semiconducting layer. The paste was double-printed in order to increase the layer thickness and eliminate any voids in the film. The final thickness of semiconducting layer was 30 µm.

3.2 Set up for Combustion Experiments

The measurement campaign for the wood log combustion, consisting of a batch-fired stove with a 5 kW average heat output was set up. The grate area of the stove was 0.096 m^2 and was installed 0.1 m above the floor of the furnace. The height of the stove was 1.5 metres and the total height of the device approximately two metres.

Combustion air was supplied from two air inlets, located on the level of the grate. Exit temperature of the flue gas was measured using a shielded and ungrounded K-type thermocouple with a wire thickness of 1.5 mm. Actuators for the dampers were installed to enable automatic control. A load cell connected to the grate weighed the fuel mass continuously. A natural draught was present during the measurement campaign. During the tests, sampling frequency of four hertz was in use. Measured signals were saved to a database every five seconds as a mean value of 20 preceding data points. At the same time, an infrared gas analyser was used to measure the concentration of CO in the dry flue gas.

4. RESULTS AND DISCUSSION

4.1 Combustion Experiments

Identification data for the estimation of the model parameters were obtained from one experiment, in which two batches of chopped firewood were burnt. In addition, five combustion experiments were then performed to collect validation data, resulting in total 4885 data points (Ruusunen and Leiviskä, 2004). Total number of burnt fuel batches was 15. Mass of these batches varied between 1.2 – 2 kilograms of birch and aspen wood. Moisture of the wood was nine percent, except in one batch with measured moisture content of 30 percent. As an example, acquired data set for model identification is shown in Figure 1.

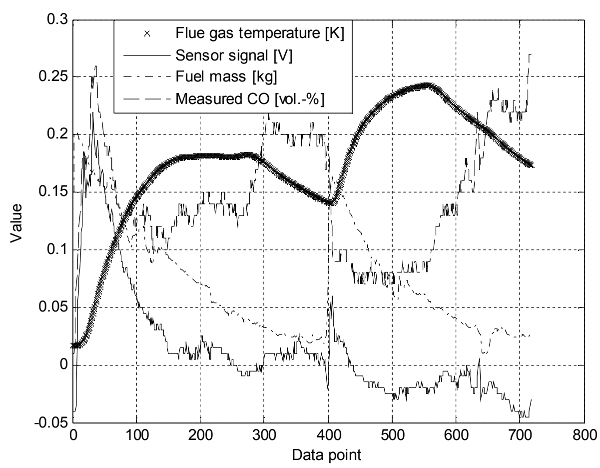

Fig. 1. Acquired data set for parameter estimation.

As seen in Figure 1, the time variant behaviour exhibits in the response of the gas sensor. Also, the flue gas temperature level tends to increase during the test campaign. This is due to the warming of the chimney. Signals in the Figure 1 have been arbitrary scaled to same magnitude for data visualization.

4.2 Simulations With Measured Data

The model parameters (2) were first estimated using measured CO concentrations as a reference signal and by minimising the criterion function (5). For this, identification data set was used.

Model inputs were scaled between zero and one using maximum identification data set values of each variable. Initial values of the model parameters were set to 0.1. The model parameters then typically converged to minimum after 15 iterations.

Based on these results, the model parameters for testing were obtained with learning factor of 0.01 and at 15th iteration. At this point, the minimum value of the error criterion was 0.25.

After identification of the model parameters, validation of the CO monitoring approach was performed with the rest of the data. With the normal distribution and randomness assumptions made, sample mean of the modelling error was 0.01±0.002 percentage by volume at confidence level 99%. Standard deviation of the error was 0.06 percentage by volume. Mean absolute percentage error was 15% respectively. The measured and modelled CO concentration in the flue gas is presented in Figure 2 with validation data set.

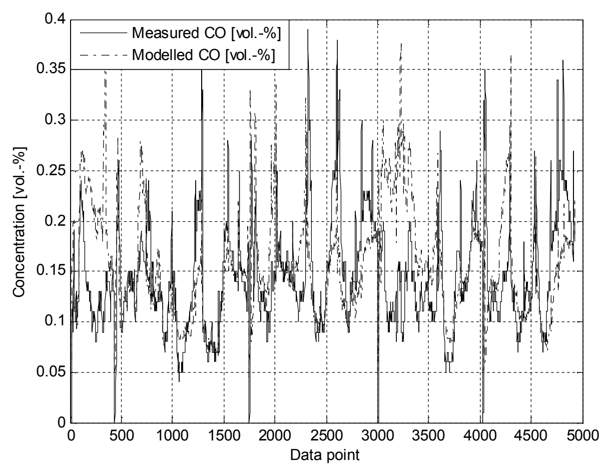

Fig. 2. Measured and modelled CO concentration in flue gas.

It can be noticed from the above Figure 2 that the model output mainly follows the measured CO concentration. Some deviations between the model and the measurement are present due to the noisy fuel weight signal and an abrupt change of fuel moisture content. These issues could be compensated by an additional or different kind of model input combinations. On the other hand, the increase of sensor costs because of this can be major restriction in small-scale heating appliances. Besides, in the followed real-time combustion control tests the presented monitoring approach for CO was successful as a part of the control system.

With the model and the resulting sensor fusion, the time lag of CO measurement (25 second) was removed. This, together with drift compensation of the sensor signal are favourable properties when aiming to minimise gaseous emissions by continuous quality monitoring of combustion processes.

5. CONCLUSIONS

In this case study, fusion of the sensors for monitoring process quality seem to exhibit relevancy when applied with data-based modelling. By using an empirical modelling approach, application family can be transferable. Then, sensor that exhibit nonlinear and drifting response could be easier to apply for mass production with low cost supported by the enriched signal information applying sensor fusion.

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