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FUZZY MODELLING OF CARBON DIOXIDE IN A BURNING PROCESS

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Abstract: Model based observation of carbon dioxide (CO_2) in a burning process is discussed. The described model structure is a combination of fuzzy Takagi-Sugeno (TS) models and operation regime based modelling approach. The selection of local modelling regions and input variables is based on general combustion theory. Recursive stochastic gradient method is employed to model training. Simulations with experimental data are analysed to verify the validity of the discussed combustion observation approach. Performance is further compared to neural and linear models. Results indicate that the presented model has good generalisation properties and it is capable to capture systems behaviour. *Copyright © 2002 IFAC*

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1. INTRODUCTION

Burning in a fuel layer is a series of thermal reactions. The main principles of burning in a small-scale wood combustion process are co-current and counter-current flow. In the former case, fuel feed and combustion gases are both moving into the same direction whereas in the latter case the solid and gaseous streams come across (Koistinen, 1989). Although principles are different, burning stages are similar. Depending on the current state of the process, three main phases can be specified: ignition, burning and charring. The ignition phase includes drying and endothermic part of the wood pyrolysis. In the burning stage, oxidation reactions are dominating. Charring is burning and gasification of the remaining charcoal. It is usual that these phases overlap during combustion (Aho, 1987).

Observation of combustion is essential in order to optimise the wood burning process. It plays an even more important role in small-scale energy production, where the quality of the fuel and burning conditions are continuously changing. The amount of carbon dioxide (CO_2) in combustion gases is one of the main variables that have to be observed. Concentration of CO_2 is usually measured with different types of gas analysers. Unfortunately, present monitoring methods are only designed for large power plants. Thus, the need for alternative methods is evident. One possibility is to model the CO_2 concentration using inferential measurements. This paper describes a fuzzy modelling approach for approximating the CO_2 concentration in a wood burning process.

Modelling of carbon dioxide is a non-linear identification problem. It is difficult to apply linear models with fixed structure to this kind of time variant case. Generalisation capabilities and an adaptive model structure are needed to cope with the changing combustion conditions. In addition, modelling is generally based on measurements, which contain uncertainty and vagueness. For these reasons adaptive, fuzzy logic (Zadeh, 1965) based methods can be considered when defining the structure of the CO_2 -model.

Fuzzy models of different types have been developed for modelling complex systems (Babuska, 1997). The strength of fuzzy modelling is that the prior knowledge can be easily incorporated into a model. On the other hand, performance of the fuzzy model can strongly depend on the level of expert's knowledge. Good modelling results have been reported with a model structure suggested by Takagi and Sugeno (1985). TS-model is relatively simple, with a consequent part that can be represented by linear equations. By using equations in the consequent part, the number of fuzzy rules can be kept quite small in many applications (Johansen, et al., 2000). However, it's not always easy to interpret TS-model when applied to transient operation regimes (Shorten, et al., 1999).

Continuously changing conditions in combustion clearly show the need of the CO_2 model that can adapt itself to different operation regimes. Many local model structures have been proposed for this kind of difficult identification problems. For example in (Chen and Weigand, 1992) and (Feng and Jin, 1993) several neural networks were used in sequence to form a global model. In addition, linear and nonlinear multimodel structures have been introduced together with operation regime based modelling method (Johansen and Foss, 1993; Johansen, 1994). Common features of local and fuzzy modelling are discussed in (Foss and Johansen, 1993).

In this paper the operation regime based modelling method and fuzzy TS-model structure are combined and employed to the modelling task of CO_2. Combination is logical, because TS-model itself contains a set of local models and interpolating technique for models (Babuska, 1997). This can result in a simple structure, yet capable to adapt. In addition, learning methods can be used to estimate the parameters of the TS-model. Theory of the adaptive CO_2 -modelling approach is presented. Motivation for the selected adaptation mechanism is discussed briefly. Simulation results based on measured data from a burning process are analysed and compared with neural network models and linear models.

2. MODELLING APPROACH

2.1 Input Variables of the CO_2-Model

The selection of input variables is based on wood combustion theory. Restrictions caused by small-scale burning environment have to be considered as well. According to combustion theory, temperature is related to the formation of CO_2. It is also simple to measure and measuring devices usually have fast responses. The second variable selected as input for the model is the mass of fuel. Changes in the weight may be used for indicating the progress of burning.

2.2 Adaptation to Operation Conditions

Adaptation to different burning phases is achieved by modelling CO_2 concentration locally at three operation regimes. Progress of burning is described with a proportional value $m_n(t)$ of the fuel weights as

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

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 (Fig. 1). For example, when the current value of $m_n(t)$ is near one, the burning phase according to the fuzzy sets is mostly *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.

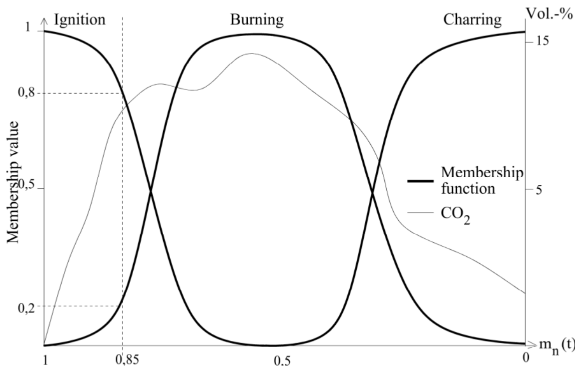

Fig. 1. Examples of membership functions for three burning phases.

2.3 Model Structure

Many techniques have been introduced for the selection of TS-model inputs, for example (Tanaka, et al., 1995; Kim, et al., 1997; Sugeno and Kang, 1988). In this case, the temperature and mass of the fuel are chosen as inputs. These variables are selected on the basis of combustion theory, reasoned to have a partial relationship to the occurrence of carbon dioxide.

In the premise part, two fuzzy sets are defined for the temperature: *low* and *high*. Membership functions of fuzzy sets are in the form of Zadeh's S-function (Driankov, et al., 1996). By using only two membership functions for the temperature, the accuracy of the TS-model may decrease but generalisation capabilities are better. Next, the membership functions of the burning phases are added into premise parts. As the model is now developed for three local regimes with burning phase-membership functions, the adaptation to different burning conditions is achieved. This results in six fuzzy rules with two temperature levels for every burning phase.

The structure of the TS-model consists of fuzzy rules. Membership functions appear in the premise, where as the consequent part contains the linear equation. Fuzzy rules represent linear local input-output relations of the system. TS-type fuzzy rules used for CO_2 modelling are of the following form

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

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 variables 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 temperature and $\hat{y}_i(t)$ is an output of the ith rule. The crisp global output $\hat{y}_k(t)$ of the model can be formed using a simplified method (Tanaka, et al., 1995) as

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

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

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

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

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

where $y_k(t)$ is the real value of CO_2. Error between the real value and model output is minimized by estimating parameters of each rule. This is done by partially differentiating criterion function with respect to consequent parameters of the model (2)

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

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

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

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 currently validated models.

Preliminary there are four a parameters in consequent parts together with four variables: current and past two temperature values with current value of the outlet temperature. Verification values of the CO_2 concentration are needed in order to estimate the parameters of the model. For this, measurements of the gas analyser are used in the criterion function. The data for parameter identification and model validation were obtained from wood combustion experiments described in the following section.

3. EXPERIMENTAL

The burning process under consideration consists of a small fireplace designed for heat production. The furnace of the combustion device is equipped with a grate. Air is supplied into the combustion chamber from two points, which are located at the level of the grate. The amount of combustion air is controlled manually. Temperatures of fuel layer and flue gas were measured with K-type thermoelements. The mass of the fuel was weighted by a load cell connected to the grate. Data from measurement devices were recorded using a computer based data acquisition system. At the same time, a separate infrared gas analyser measured the values of CO_2 in dry flue gas. The sampling period was set to five seconds. Identification data were obtained from one experiment, in which two batches of chopped firewood were burnt sequentially yielding 720 data points. Five randomised experiments were then performed to collect validation data, resulting in total 4885 data points. Number of batches was 15. Fuel batch size was between 1,2 - 2 kilograms of birch and aspen wood. Moisture of the wood was nine percent, except in one batch with moisture content of 30 percent. Recorded values for the model identification are shown in Fig. 2.

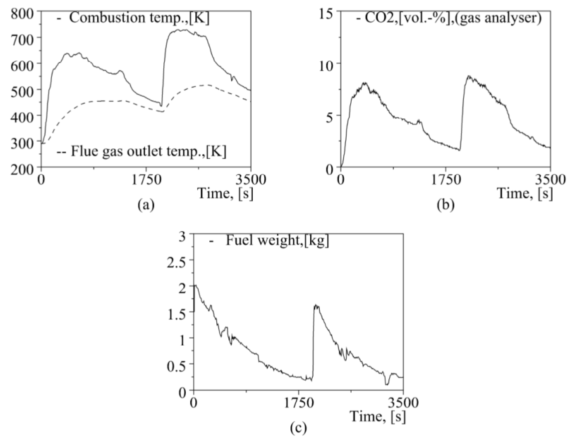

Fig. 2. Identification data set.

The data recorded for model validation was typically similar to Fig. 2. The model structure was programmed to software using HiQ™ script language. Simulations were performed with software that made use of the collected data.

4. MODELLING RESULTS

4.1 Model Identification

Parameters of the models were identified with data set shown in Fig. 2. To achieve a real time modelling capability, time lag of 25 seconds was removed from measured values of CO_2. The lag was caused by drying of flue gas for the analyser. Locations of membership functions *low* and *high* temperature were spaced uniformly between zero and 900 K, the maximum value in the identification data set. In (1) moving average of mass was used, because the measurement of weight was found to be noisy. The time history of temperature values in the consequent part was discovered long enough by using a partial autocorrelation function. Input variables of the model were scaled between zero and one using maximum identification data set values of each variable. Initial values of the consequent parameters were set to 0,1.

Preliminary model identification results showed a moderate deviation between model outputs and measured values. Error was caused by an outlet temperature variable in the consequent part of fuzzy rules. The deviation removed as the outlet temperature was changed to the proportional value of mass (1). After final training, the performance of the identified model was tested with the validation data set.

4.2 Model Performance

In this section an example of model performance is given. Results were obtained through simulations with the validation data set. Outputs of the identified model were compared with the measured values of CO_2 as seen in Fig. 3.

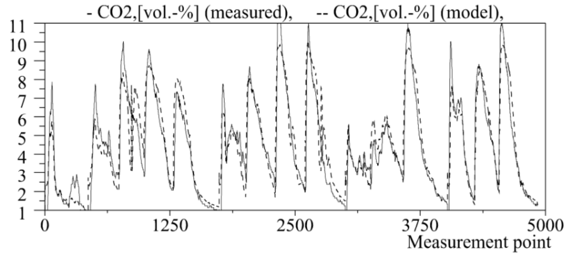

Fig. 3. Validation of the CO_2 -model. Dashed line: model outputs, solid line: measured CO_2 concentration.

Modelling results are satisfactory. Although the validation data set contains many different situations in the burning process compared to identification data set, fuzzy model is quite capable to generalise training data. There are two notable error situations near measurement points 800 and 2700. In these cases, the model performance is deteriorated by the temporary failure of the weight measurements.

Fig. 4 shows an analysis of the modelling error. Time lag has been removed from the CO_2 measurements before the calculation of errors.

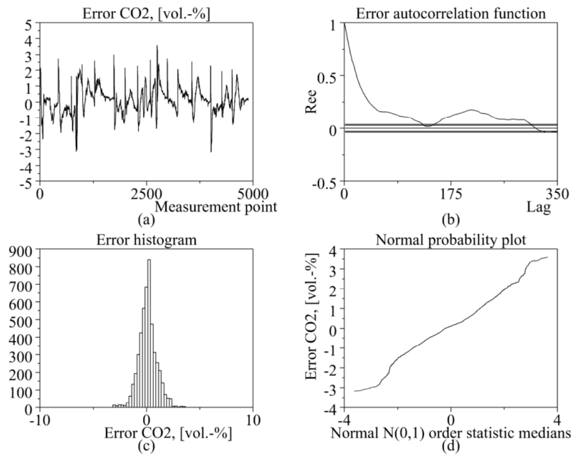

Fig. 4. Modelling error analysis.

Run sequence plot in Fig. 4 a) shows a constant location of errors over the validation data set. Autocorrelation plot of the error is presented in Fig. 4. b). From it can be concluded that randomness assumption of the error holds. Some seasonality in error values occurs in figures, and this is due to the fixed maximum values of the input variables. These values were same as in the model identification. Histogram in Fig. 4 c) and normal probability plot in d) indicate that errors of the model are nearly normally distributed. With normal distribution and randomness assumptions made, sample mean of the error with confidence intervals is 0,11±0,03 vol.-% at confidence level 99 %. Standard deviation of the error is 0,84 vol.-%. Root mean square and mean absolute percentage errors are 0,81 vol.-% and 15 % respectively. Additionally, test results of the presented model were compared with neural and linear models.

5. COMPARISON WITH OTHER MODELS

Comparisons with other models were performed with the same identification and validation data sets obtained from experiments. Neural nets containing one hidden layer were applied to the modelling task. Different combinations of input variables and the amount of hidden nodes were tested in order to maximise the performance of the neural models. Activation function was hyperbolic tangent and hidden nodes included a bias. Backpropagation and conjugate gradient methods were used as learning algorithms. Neural model simulations were run with NNModel -software.

The performance of different neural model structures were first analysed with the identification data set. Measured values of CO_2 were used in the objective function. Best results were obtained with the same input variables as in the consequent part of the presented fuzzy model. Modelling performance with identification data set was accurate at both learning algorithms with five hidden nodes included. For this reason, two trained neural nets using above-mentioned learning algorithms were chosen to model validation. The neural net with backpropagation algorithm was trained in 300 epochs where as the neural net with conjugate gradient method needed 250 epochs to minimise the training error.

At the training phase, both neural nets performed better than the presented fuzzy adaptive model. However, the validation of the models showed opposite results. Especially the backpropagation network was not capable to generalise information from the training data. The neural model trained using conjugate gradient method is more comparable with the modelling results of the fuzzy model. This indicates that the fuzzy model has learnt more local interactions of variables in the burning process.

Different linear model structures were also tested. These included Box-Jenkins model, "black-box" state space model, ARMAX- and ARX-models. Simulations using linear models were performed with MATLAB -identification toolbox. Best results were obtained with the ARMAX-model that included the same input variables as in the preceding models. The training algorithm was an iterative prediction error method. The linear model fails to model the CO_2 concentration after ignitions. Modelled outputs steadily decrease while the real values are usually altering, and error is large at the charring phase.

Performance comparison between models is shown in Table 1. Three error measures were calculated: Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE) and Mean Percentage Error (MPE). Error calculation was based on modelling results with the validation data set.

Table 1. Modelling error comparison, validation data set.

Model / Identification method	RMSE [vol-%]	MAPE [%]	MPE [%]
Neural net, Backpropagation	1,69	36	44
Linear ARMAX-model, Prediction error method	1,22	45	42
Neural net, Conjugate gradient	1,05	21	9
Fuzzy adaptive model, Gradient method	0,81	15	4

Comparison shows that the presented fuzzy model has the lowest modelling error compared to other models. Neural net with conjugate gradient method performed somewhat worse. ARMAX-model and neural model with backpropagation algorithm gave high modelling errors and are not capable to approximate CO_2 concentration with selected measurements.

6. CONCLUSIONS

A fuzzy, adaptive modelling approach for approximating the carbon dioxide concentration of a burning process is presented. The effectiveness of the model is verified through simulations with data obtained from process measurements. The described model structure consists of fuzzy local models on different operation regimes. Fuzzy methodology makes it possible to incorporate a prior knowledge and uncertain information into a model. On the other hand, decomposition of the modelling task provides an adaptation capacity and a way to tackle with non-linearity.

Adaptation mechanism to operation conditions is based on recognition of three different combustion regimes: ignition, burning and charring. These regimes are described by three fuzzy membership functions that are applied to define the validity of local models. For each burning phase, two TS-type fuzzy models are constructed. The selection of model input variables is based on combustion theory and it is an important part of the model development. A gradient method and supervised learning is used for identification of the consequent parameters.

Modelling results showed that the presented model has a good capacity to approximate CO_2 concentration of highly changing burning process. A real-time output was achieved by training the model with undelayed measured values of CO_2. Compared to tested models, the performance of the fuzzy model was superior due to an adaptation mechanism that also enabled a robust and simple structure. Small size of training data and the non-linear process limited performance of other models, while local learning and generalisation capabilities of the presented model compensated for these disturbing factors.

The discussed model has been implemented as a part of the real-time combustion optimisation system. Further development focuses on utilising prediction capabilities of the model as well as synthesis of recursive on-line filtering.

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