Protected Supervised Control in Bioenergetic Devices

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Abstract: Current European Union environmental policy aims at larger utilization of renewable energy sources. This paper describes the targets of renewable energy policy in the Czech Republic. However, when operating bioenergetic devices we can be tackled by problems of a hidden increase in harmful emissions This increase is caused by gradual loss of the proper function of the control variable sensor. As will be shown, if the control variable sensor produces biased data, then there is a danger that undesirable harmful emissions, above all emissions of CO and NO_x, will increase and will remain unrecognized. This paper will show how a supervised control can improve the ecological operation of a device. As a specific example of a technical solution, experimental Verner biomass boiler equipped with an oxygen sensor is used.
Key-Words: biomass combustion, supervised control, malfunction detection, control variable sensor discredibility

1 Renewable energy sources and current policy

Current policy of the European Union – and favours of the Czech Republic – supposes increased utilization of renewable energy sources. In European conditions, biomass is one of the most perspective renewable energy sources. In the Czech Republic, biomass has a dominant position among renewable energy sources, and it will definitely become even more important, particularly due to the commitment to cover 8 % of total energy consumption by renewable energy sources by 2010. In 2005, the total percentage of energy produced from renewable energy sources in the Czech Republic was 4 %, of which biomass represented nearly 80 %. This is shown in Table 1. No newer data is yet available.

It will be necessary to increase the share of renewable energy sources in primary energy sources, by a huge amount –by almost 99 PJ more than in 2004 (assuming constant annual consumption). With current technology, such an increase can best be achieved by increasing the use of biomass as a direct energy source.

Biomass as a fuel for combustion has many advantages. It is a readily available renewable fuel, which can be directly used without any difficult treatment. A variety of different biomass materials can be used near where it grows, with very few additional costs for treatment and transportation. On the other hand, biomass has some features that are not encountered with traditional fossil fuels, e.g. coal. Biomass cannot be sorted into groups by properties, as coal can – each plant is unique. This means that the properties of a biofuel can vary within certain species of plant. Furthermore, the composition of a plant depends on the place where it originates. In the case of biofuels, originating from agriculture, fertilization and other farming techniques that influence the properties of the fuel have an impact. It is obvious that the term “biofuel” does not refer to a specific type of fuel. Unfortunately, there is still no standard that would exactly specify the properties of biological materials for use as fuels.

The term “biomass” does not refer only to wooden materials, as it is usually interpreted. The potential for using wood cannot be increased greatly – the available wooden material is widely used and there is almost nothing left over for increased of energy utilization. However, there are other materials that have so far been used only for food production, e.g. grain. These materials, or residues from their treatment, can provide interesting amounts of energy that are currently often wasted. Another interesting group comprises is called energetic plants – plants that are especially grown for energetic purposes.

2 Hidden Increase in Harmful Emissions in Bioenergetic Devices

When operating bioenergetics devices, we can encounter hidden inaccuracy of the control loop operation. This control loop inaccuracy arises due to

Table 1 Current proportion of employed renewable energy sources used in the Czech Republic

Type of Renewable Energy Sources (RES)	Total energy produced from RES [GJ]	Share of primary energy sources [%]	Share of RES [%]
Biomass – households	37 078 678	1,94	48,66
Biomass – industry, others	24 040 367	1,26	31,55
Hydropower	8 567 676	0,45	11,24
Solid household waste – biodegradable fraction	2 346 380	0,12	3,08
Industrial waste – biodegradable fraction	990 107	0,05	1,30
Biogas	2 335 388	0,12	3,06
Liquid bio fuels	117 570	0,01	0,15
Heat pumps	545 000	0,03	0,72
Thermal solar energy (water collectors)	103 000	0,01	0,14
Windmills	77 191	0,00	0,10
Solar electricity (photovolatics)	1 418	0,00	0,00
Total	76 202 775	3,99	100,00

so-called discredibility of the controlled variable sensor. The notion of sensor discredibility means that the sensor is still functioning, but its properties have changed (or they have been changing gradually), and thus the sensor has started to provide biased data. The problem of sensor discredibility detection is generally not of great importance. If the side effects on the controlled process are negligible, they need not be taken into account. However, in the case of bioenergetic devices the side effects can involve an increase in harmful and penalized emissions of CO, CO_2, NO_x.

To avoid undesirable side effects, either hardware or software can be used for sensor discredibility detection. Hardware discredibility detection is usually achieved by adding another redundant sensor. This may be a costly solution. The cheapest solution is offered via the software. This is what we are investigating, and we are presenting our finding here. Generally, the aim of our study is to extend the function of a standard controller so that it will be able, in additional to its normal control function, to discover impreciseness in the control loop operation.

The problem of control variable sensor discredibility detection is demonstrated on the Verner A25 pilot experimental power boiler (Fig. 1), which is available in the CTU labs.

The Verner A25 is an automated boiler for heat water production with electrical ignition. All kinds of biomass pellets can be used as fuel. According to the manufacturer, the nominal power output for wood is 25 kW and for grain pellets 18 kW. A specific feature of the boiler is that the combustion chamber has a trapezoidal cross-section and it is equipped with a moving steel grate. The primary combustion air passes through the grate from below and the secondary air is injected through holes in both sides above the grate. The air is fed into the boiler by air fan that is controlled (together with the fuel feeder) by the controller unit. The unit controls the operation of the boiler, e.g. rate of feeding, amount of air or movement of the grate, and allows manual changes in the operation settings. Fuel is fed from the storage bin into the combustion chamber by a screw feeder. The feeder is connected to the rear wall of the combustion chamber above the grate in such a way that the fuel falls onto the grate. The fuel starts to burn on the rear side of the chamber and is moved by the grate to the front side, still burning. The ashbin is placed below the grate. The fine ash particles fall into the ashbin

Fig. 1 The Verner A25 boiler – installation in the CTU labs

through the grate, and the rest of the ash (and any unburned material) is moved into the bin by the grate on its front edge. The flue gases leaving the chamber pass through the heat exchangers to the chimney. The boiler is connected to the partially closed water cycle that is driven by a water pump. Two connections are made in the water cycle – the pipe delivering cold water is connected at the lowest point of the cycle before the entrance into the boiler, and at the top of the cycle there is a connection that removes excess hot water. There are also points for temperature measurements and a sampling point for flue gas analysis in the exhaust tube.

Fig. 3 shows the scheme of the boiler, and demonstrates the problem of control variable sensor discredibility. The temperature control loop maintains the water temperature at the desired value by adjusting the fuel supply; and the oxygen control loop maintains the air factor (fuel - air ratio) α at its desired value (in an attempt to produce minimal gaseous emissions and steady fuel combustion).

The influence of the changes in the oxygen sensor properties on the control process is depicted in Fig. 2. When the oxygen sensor starts to provide biased data the oxygen control loop reacts to incorrect information about the fuel/air ratio by removing (seemingly) the control error [5]. The main loop of the heating water temperature control appears to work properly, because it returns the control error back to zero. The desired temperature value can be achieved at the cost of increasing the fuel supply, because the oxygen control loop has changed the combustion air delivery. Therefore environmental impacts will occur, but they will remain unrecognized.

In the quest to produce minimal gaseous emissions and to maintain the steady fuel combustion, it is necessary to control the air factor (air excess) α, at its desired value [3]. The flow rate of the air

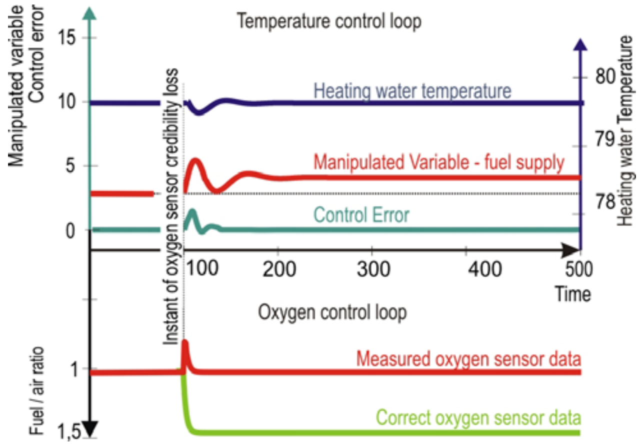

Fig. 2 Impacts of changes in the control variable sensor changes on the development of control loop signals

supplied to the combustion chamber is manipulated by a valve and by the controller, in an attempt to keep the proportion of oxygen in the flue gases at the desired value. The topical value of air factor α in the running combustion process is acquired via oxygen concentration measurement in the flue gases at the flue gas exhaust.

Fig. 4 shows that if the air factor is between α_{min} and α_{max}, then the emissions of CO and NO_x will not exceed the maximum acceptable level. However, the problem is that oxygen probes are vulnerable to faults [10]. If the oxygen probe starts to provide biased information about the oxygen content in the flue gases, the emissions of CO and NO_x will be excessive, and penalties can be incurred for undesirable environmental impacts. Thus it is essential to avoid any unrecognized increase in emissions, particularly of CO and NO_x, with the use of oxygen sensor discredibility detection.

In addition to emissions of CO and NO_x there are also carbon dioxide CO_2 emissions. CO_2 is one of the final combustion products of fuels containing carbon

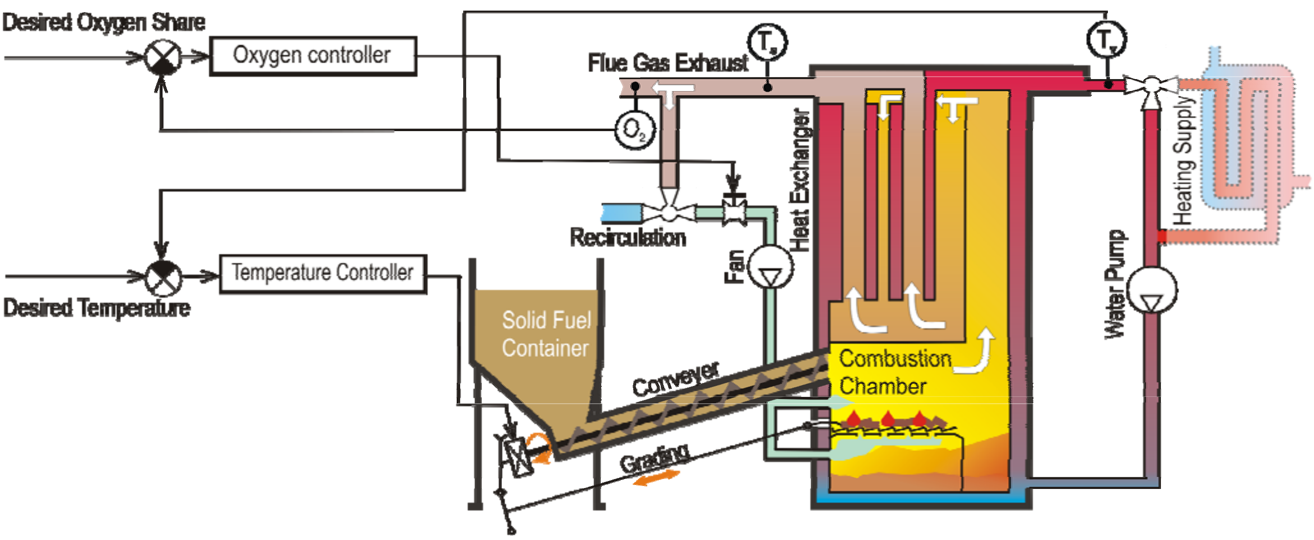

Fig. 3 Experimental power boiler for biomass combustion

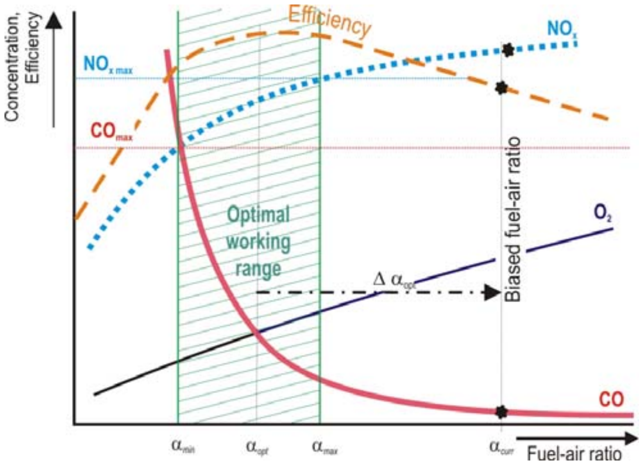

Fig. 4 Optimal operating range in dependence on the fuel – air ratio

(including all kinds of biomass). In the case of complete combustion, the CO_2 concentration in the flue gas is proportional to the amount of burned fuel. An advantage of biomass combustion is that it is almost CO_2 neutral. Plants consume the CO_2 released by the combustion for their growth. The real emissions of CO_2 in biomass combustion come from harvesting, treatment and transportation of the fuel, etc. Emissions of carbon dioxide are a matter of current interest – CO_2 is one of the main intensifiers of the so-called "greenhouse effect". Current search in combustion therefore focuses on low CO_2 emissions and CO_2 capture technologies. The share of CO_2 in intensification of the greenhouse effect is estimated at almost 60 %. It is followed by methane (17 %) and chlorinated and fluorinated hydrocarbons (12 %) [1], [2].

3 Engineering Model of the Boiler

Fig. 5 depicts a block scheme of the described boiler. It is based on principles used in the past [11] in engineering modelling of thermo energy devices, with imaginary separation and idealisation of the physical phenomena. Such models make it possible to carry out simulation on various levels of complexity using own library blocks and information from records of real data measurements.

4 Oxygen sensor discredibility detection

To avoid undesirable side effects resulting from controlled variable sensor discredibility, we have suggested a software tool which is able to detect changes at their source. However, before any implementation of the proposed model-based control variable sensor discredibility detection method it was necessary to test its proper function on a simulated example.

The general requirement for successful application of the proposed method is to design a so called objective function. In terms of sensor

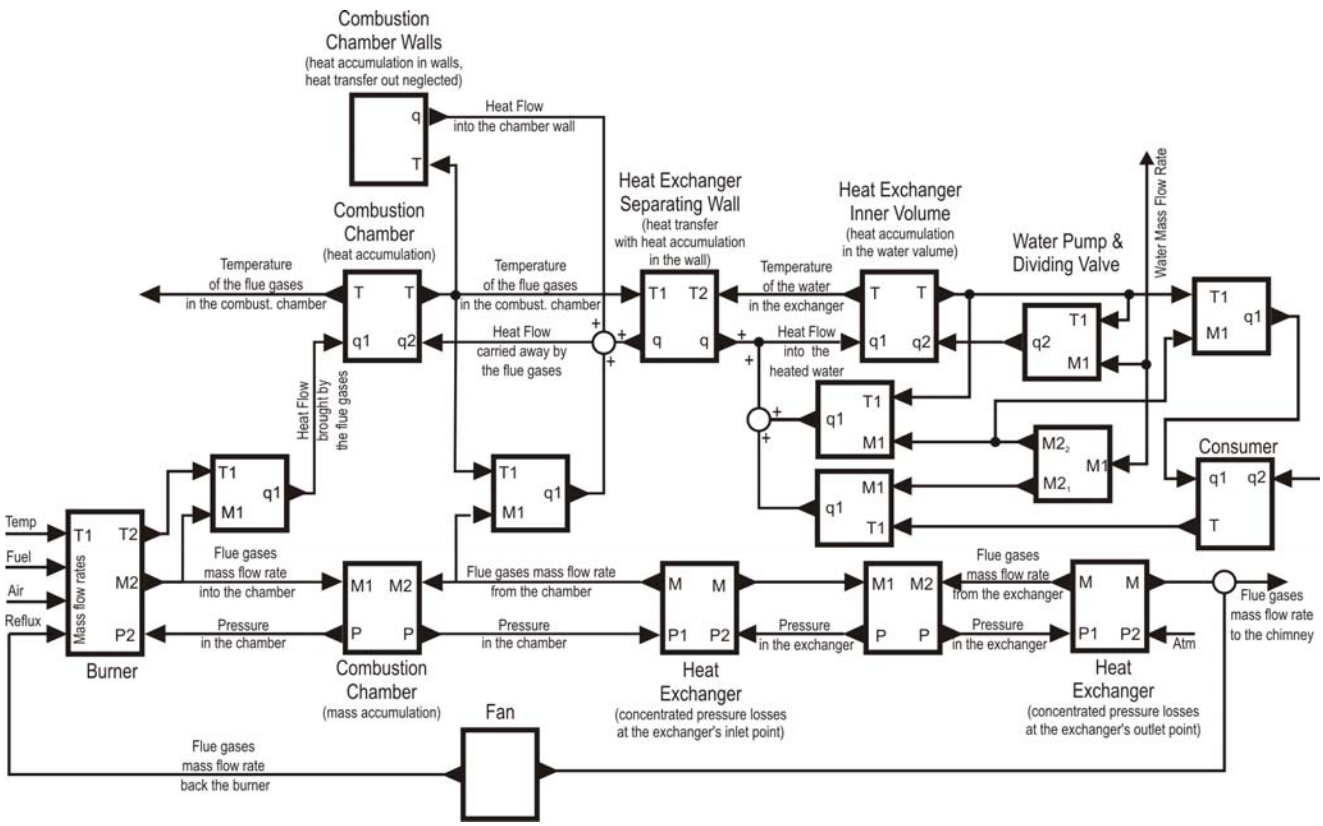

Fig. 5 Block scheme of a Flow – Pressure – Temperature Model of the pilot boiler

discredibility detection, this function is called a residual function or a residuum e. The residuum $e(t)$ is obtained as the difference between the real sensor output $y(t)$ and the output of the model of the sensor $y_m(t)$,

$$e(t) = |y_m(t) - y\,(t)|, \qquad (1)$$

where the residual variable $e(t)$ indicates the rate of variance between the output estimated via a sensor model and the value acquired by the real sensor.

In most sensor models it is assumed that the sensor output is proportional only to one input, so that the sensor model equation is

$$y_m = k_m\, y_{est} + q_m, \qquad (2)$$

where parameter k_m represents the gain of the sensor model, and parameter q_m, expresses the shift factor, and y_{est} is the estimated sensor model input, which has been explained in [14].

The idea underlying control variable sensor discredibility detection consists of two parts:

1 Indirect detection of changes in sensor properties via adaptation of the sensor model parameters so that the residuum is minimal. Our method minimizes the residuum using evolutionary algorithms (simulated annealing algorithm, or standard genetic algorithms) or using the least squares method, as presented in [13], [14]. Typical results obtained while testing minimization of the residuum using the simulated annealing algorithm and the least squares method are presented in Fig. 6, Fig. 7.

2 Interpretation of the changes in the sensor model parameters (evaluation of the development of the sensor model parameters). This decides whether the changes have already reached the stage where the control variable sensor is regarded as discredible (Fig. 8).

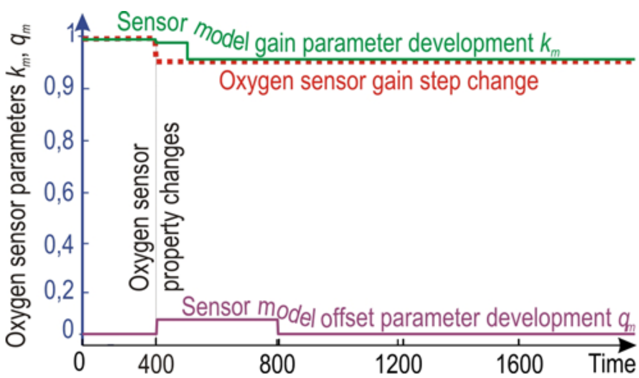

Fig. 6 Detection of a step change in the oxygen sensor via the least squares method

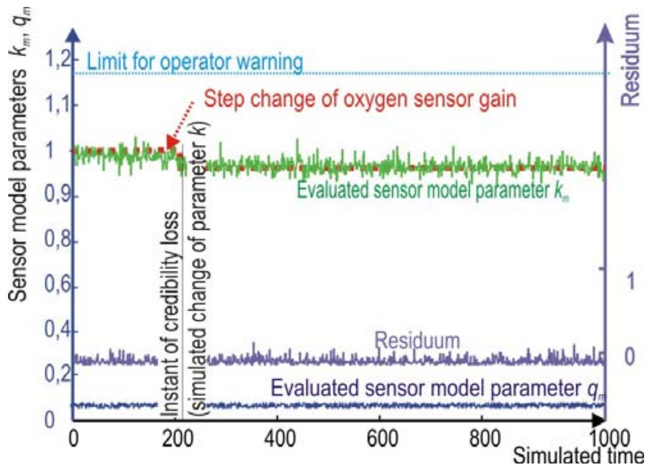

Fig. 7 Detection of a step change in the oxygen sensor via the simulated annealing method

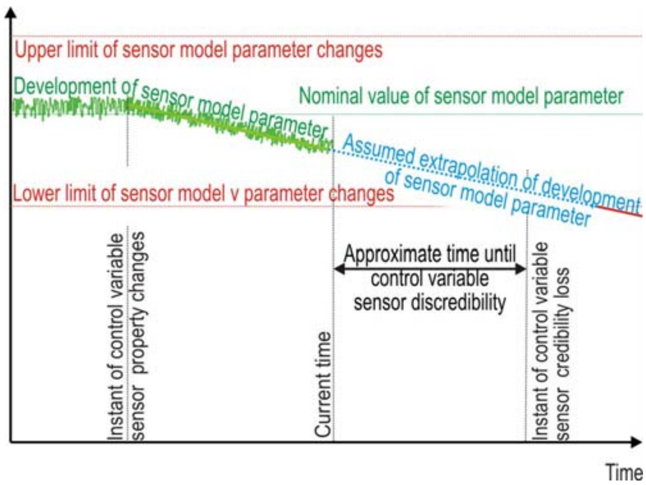

Fig. 8 Principle of extrapolation of the development of sensor model parameters and the approximate time until control variable sensor discredibility evaluation

The graphical user interface has been developed to test the methods (Fig. 9). It offers a selection of methods for testing. Both methods are implemented with the use of the Matlab S-function, because results computed by means of S-functions are obtained faster than by standard M-function blocks.

Simulated experiments on the proposed model-based discredibility detection method have proved its ability to indicate control variable sensor changes together with discredibility detection. This method informs operator about the estimated time until the occurrence of sensor discredibility. If the time is critical, the operator also receives a warning about the situation. No difference was found between the used algorithms; their good convergence depends mainly on the algorithm settings.

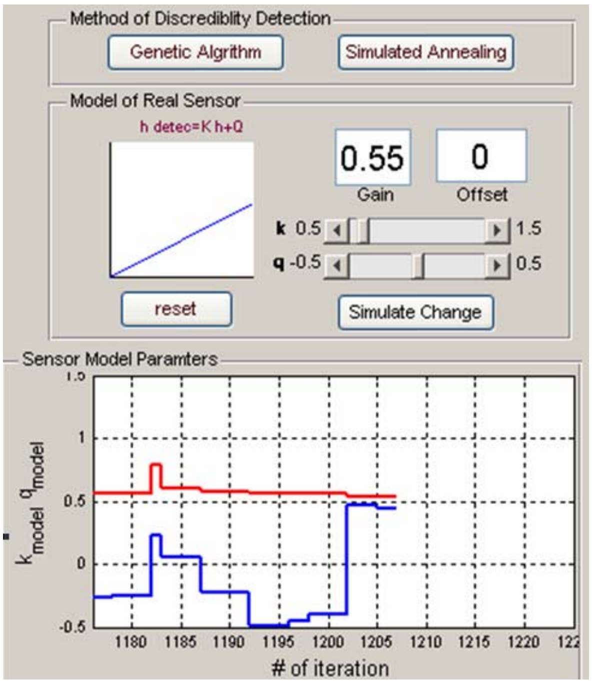

Fig. 9 Dialogue window providing a selection of discredibility detection methods, sensor discredibility simulation and sensor model parameter development.

5 Conclusions

The aim of the paper is to show a way to contribute to the general trend of using renewable energy sources by using a device for biomass combustion. We have shown how equipment in the field of control can improve the ecological operation of a device. As a specific example of a technical solution, experimental Verner biomass boiler equipped with an oxygen sensor was used. Any malfunction of the oxygen sensor is detected by the software. A Matlab/Simulink model designed using engineering modeling was used to test the detection. The positive results will be used in higher power combustion devices, in which oxygen sensor malfunction detection will be of great ecological and economical importance.

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