Enhanced function of standard controller by control variable sensor discredibility detection

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Abstract: The gradual loss of the credibility of sensors measuring control variables in control loops (so-called control variable sensor discredibility) may cause serious problems in control. As it will be shown, if such a sensor produces biased data, which are not correct but not totally wrong, then there is a danger that the controlled variable exceeds limits of a tolerance range without displaying any difference from the set point. However, this is not the only negative consequence, sometimes, undesirable side effects may occur and they remain unrecognized. The problem of these indirect unrecognized impacts becomes important especially in combustion processes. In case of a pilot stoke-fired boiler, which has been used for experiments in the CTU labs, the sensor discredibility problem is related with function of the oxygen probe used to accurate control of the burning air. Discredibility of this sensor will affect hidden increase of penalized gaseous emissions, above all CO and NO_x. The general aim of our research is to enhance the function of the controller so that it will be able to warn the operator about changes in the properties of the control variable sensor. This paper introduces model-based control variable sensor discredibility detection method using evolutionary algorithms and documents the results obtained from testing the methods in simulated examples. A newly enlarged method also includes the ability to approximate the time until the control variable sensor discredibility.

Key-Words: malfunction detection, evolutionary algorithm, software redundancy, control variable discredibility

1 Introduction

When operating a control loop, unrecognized hidden inaccuracy of the control loop operation may be present. This control loop inaccuracy arises due to so-called discredibility of the controlled variable sensor. Notion of the control variable sensor discredibility means, that the sensor is not faulty, but its properties have been gradually changing, and thus the sensor has started to provide biased data about the control variable. Such a discredible sensor may cause serious problems in control that are difficult to detect, as it is demonstrated further.

The problem of sensor discredibility detection is usually not so important until side effects of the controlled process are negligible and they need not be taken into account. This paper attempts to show new ways toward discredibility detection that differ from the usual hardware redundancy. To avoid additional costs, we are working on a way to detect sensor discredibility with the use of software tools.

The importance of discredibility detection can be illustrated by the case of the combustion process control. Fig. 1. shows an illustrative example of a combustion process. The aim of the temperature control loop is to maintain the heating water temperature at the desired value by changing the fuel supply; and the oxygen control loop represents maintaining the air factor (fuel - air ratio) α. at its desired value (in an attempt to produce minimal gaseous emissions and steady fuel combustion).

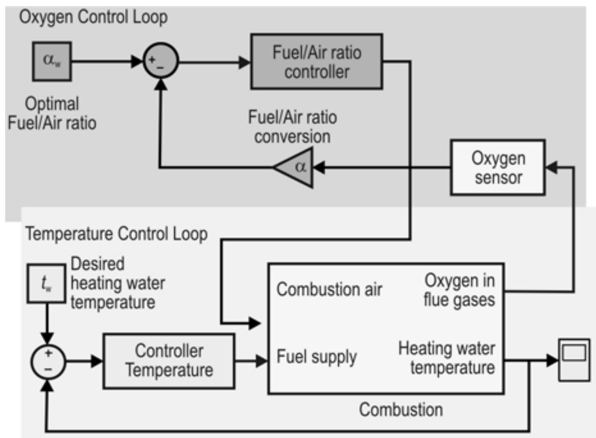

Fig. 1. Illustrative depiction of control loops in a combustion process

The influence of the changes in the oxygen sensor properties on the control process is depicted in Fig. 2. It is apparent that when the oxygen sensor starts to provide biased data (at simulation time 100), the oxygen control loop reacts to incorrect information about the fuel/air ratio by removing (imaginary) the control error. The main loop of the heating water temperature control works properly, because it returns the control error back to zero. The desired value of the temperature can be achieved at the cost of increasing the fuel supply, because the oxygen control loop has changed the combustion air delivery, so environmental impacts will occur but they will remain unrecognized.

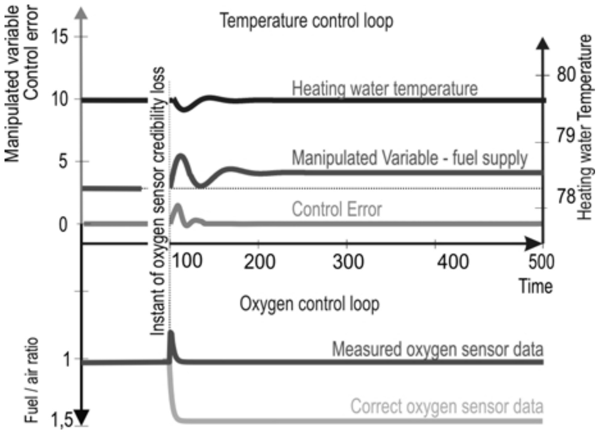

Fig. 2. Impacts of changes in the control variable sensor changes on the development of control loop signals

Fig. 3. depicts the optimal range of the air factor. If the air factor is between α_{min} and α_{max}, then the emissions of CO and NOx will not exceed the maximum acceptable level. However, the problem is that oxygen probes are vulnerable to faults [8]. If the oxygen probe starts to provide biased information about the oxygen content in the flue gases, the emissions of CO and NOx will exceed, and penalties can be incurred for undesirable environmental impacts. Thus it is essential to avoid any unrecognized increase of emissions, particularly of CO and NOx, by oxygen sensor discredibility detection.

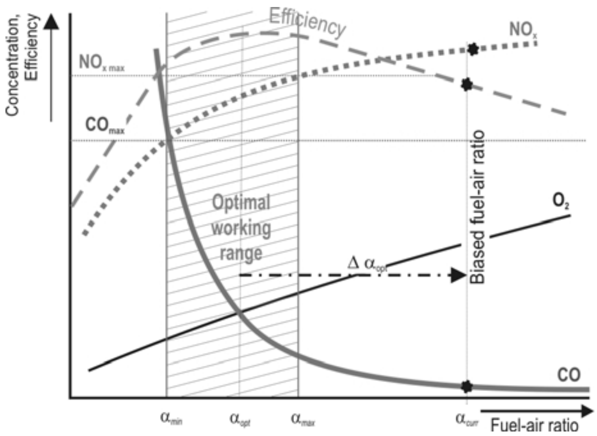

Fig. 3. Optimal operating range in dependence on the fuel - air ratio

Control variable sensor discredibility has been considered for an application to the pilot stoker boiler depicted schematically in Fig. 5. This device is available for experiments in the CTU labs. In its flue gas exhaust, an oxygen probe was experimentally placed in order to measure the oxygen content in the flue gases. The flow rate of the air supplied to the combustion chamber is manipulated by a valve and the controller, in an attempt to keep the portion of oxygen in the flue gases at the desired value.

We have suggested a software tool which is able to detect changes in the control variable sensor 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.

2 Model-based sensor discredibility detection

Model-based control variable sensor discredibility detection method via an evolutionary algorithm (namely the method of simulated annealing and the method of genetic algorithm) has been presented i.e. in [11]. The general requirement of successful application of any of the proposed methods is to design so - called objective function. In terms of the sensor 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 output of the model of the sensor $y_m(t)$,

$$e(t) = |y_m(t) - y(t)|, \tag{1}$$

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

$$y_m = k_m\, y_{est} + q_m, \tag{2}$$

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 [10].

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

1) Indirect detection of the sensor properties changes via adaptation of the sensor model parameters with the help of evolutionary algorithms.
2) Interpretation of the sensor model parameters changes. This decides whether the changes have already reached the stage where the control variable sensor is regarded as discredible.

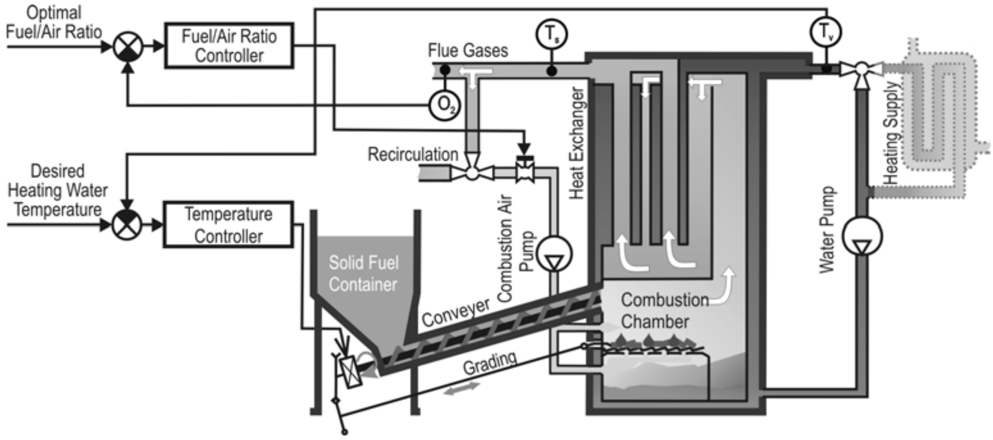

Fig. 4. Pilot stoker-fired boiler for biomass combustion

3 Application of the model-based discredibility method

The sensor discredibility detection method was applied to a simple example of a control loop, the Simulink block scheme of which is presented in Fig. 6. As an object where is measured the control variable by a sensor, is a cascade of two tanks. The level in tank 2 is the control (process) variable. Fig. 5. represents the scheme for discredibility detection realization in a block form. The general aim of this control scheme is to enhance the function of a standard PID controller so that the controller will be able to warn the operator about changes in the properties of the control variable sensor.

In the simulation, the model of the real level sensor behavior is modeled by the same equation as the sensor model for discredibility evaluation part, it means that the real physical value of the controlled variable y_{real} is transmitted to the measured value y according to the equation $y = k\, y_{real} + q$. Evidently, if must be: the gain of the sensor $k = 1$, and the shift factor $q = 0$. The sensor model for discredibility evaluation part uses just estimated value y_{est} of the real physical value of the controlled variable, because the real physical value is not viable for us. This value (y_{est}) is transmitted to the value marked as y_m according to equation $y_m = k_m\, y_{est} + q_m$. In principle, the discredibility detection algorithms try to find such parameters (k_m, q_m) of sensor model for discredibility evaluation part, which minimize a residuum $e(t)$ (1). The sensor discredibility detection is based on the continual evaluating of the sensor model parameters; because when no sensor discredibility occurs, the parameters do not change.

It is clear that the level sensor, as the object whose malfunction should be detected, is not an expensive device. Discredibility detection becomes important in more complex sensors than a level sensor; this application has been used as an example where it is easy to model the controlled process and to verify the obtained results. Experiments on discredibility detection via both simulated annealing and the genetic algorithm have been carried out.

The algorithm of the model-based control variable sensor discredibility detection method can be described as follows:

1) *Initialization stage.* At the beginning, at the time when the control variable sensor is providing correct data, the nominal vector of the sensor model parameters is obtained (Fig. 7.). Based on the nominal values of the sensor model

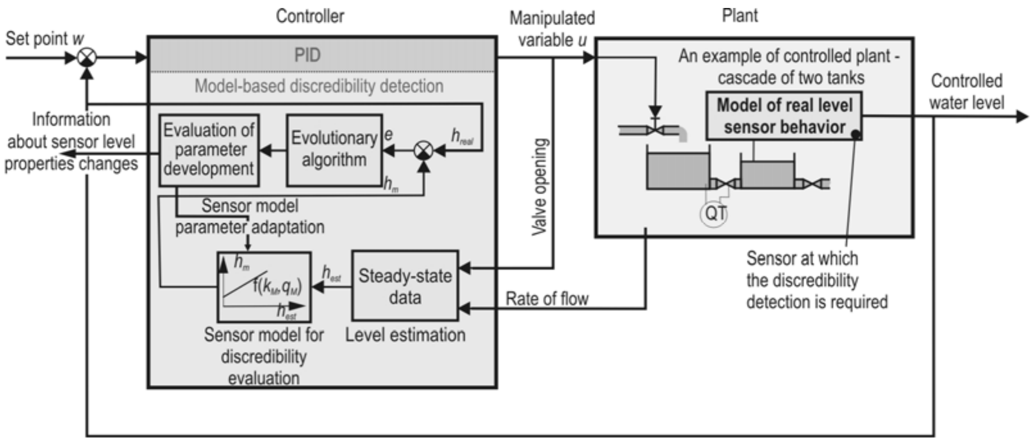

Fig. 5. Enhanced controller function for discredibility detection of the control variable sensor

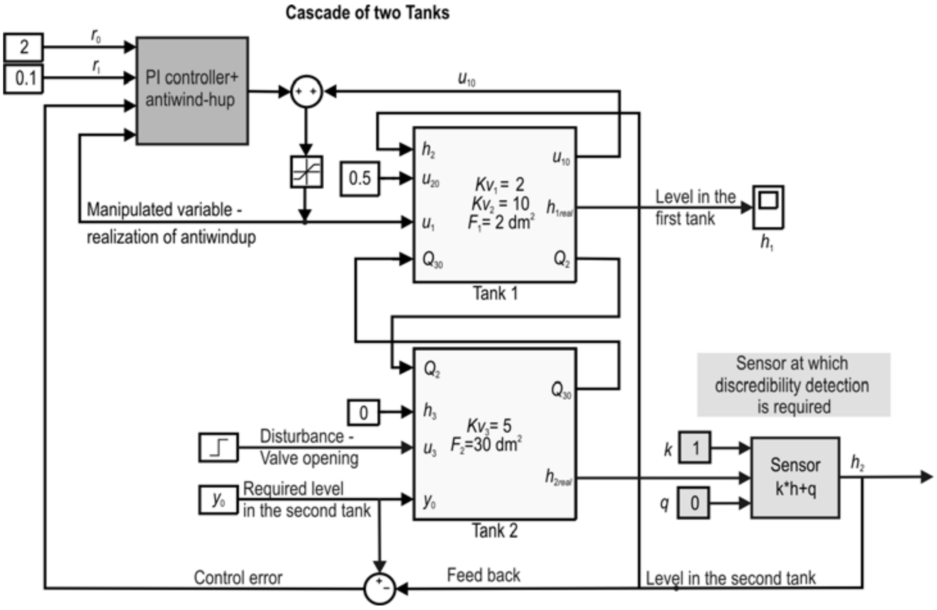

Fig. 6. Simulink block scheme for testing sensor discredibility detection

parameters, maximum acceptable changes for each of the parameters are designated (as a percentage of the nominal value of the given parameter).

2) *Working stage*. When the initialization stage is processed, the method provides a continuous evaluation of the development of the sensor model parameter vector. It means that the regression coefficients of the vector development are computed. Using the extrapolation function, it is obtained assumed development of the sensor model parameter vector, as well as the approximate time until control variable sensor discredibility. If the development of the vector of the sensor model parameters indicates that the time is shorter than the given time (usually n times the sampling period), the operator is warned about this situation.

4 Discredibility detection testing

By the Fig. 7. it is also shown the comparison of both used evolutionary algorithm methods. It is evident, that that the simulated annealing needs more evaluation time for one evaluation period – a period for simulated annealing required 80 iterations, while genetic algorithm needed 40 1) iterations. This difference is because genetic algorithm works with a group of potential solutions, while simulated annealing compares only two potential solutions and accepts better one.

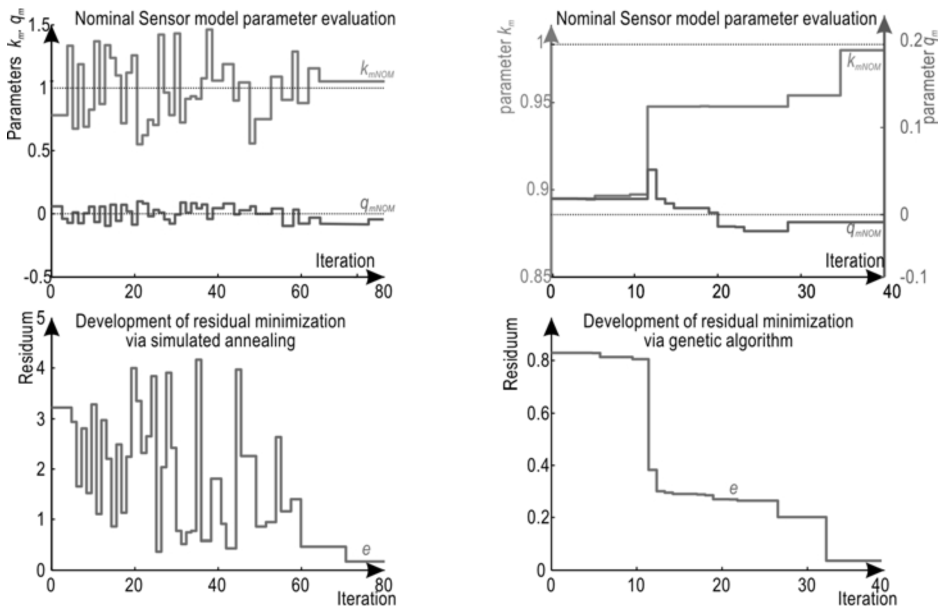

Fig. 7. Nominal vector of sensor model parameter evaluation by minimization the residual function

The model-based control variable sensor discredibility detection method was tested to find whether the method is able to detect the control variable sensor properties changes and also, based on this detection, to decide about the sensor discredibility and to forecast the estimated time until sensor discredibility.

Fig. 8. depicts a simulation run when the sensor gain has been gradually decreased from 100 %, at simulation time 200, to 80 % (at simulation time 1000).

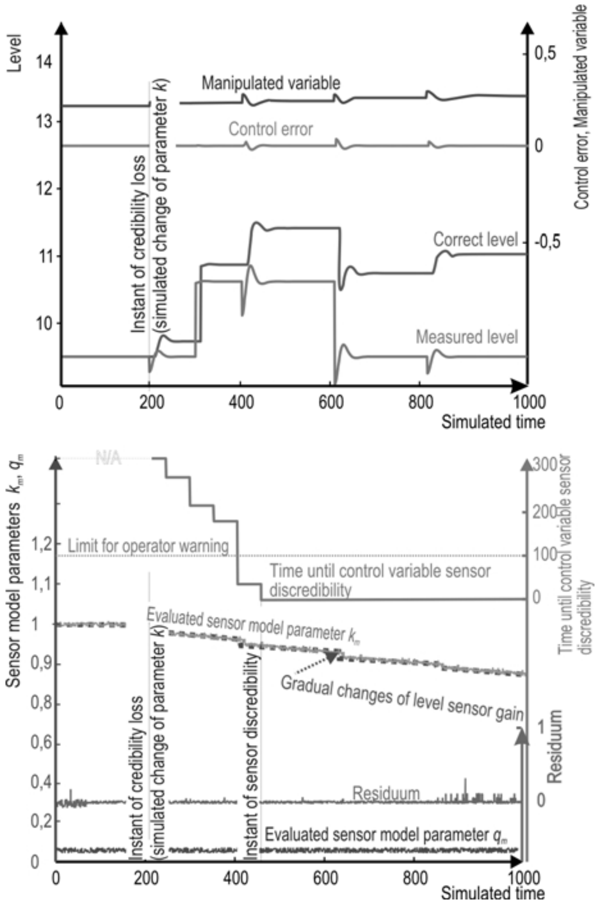

Fig. 8. Detection of gradual changes of the level sensor gain via genetic algorithm

It can be seen that when (at simulation time 200) the sensor properties are changed, the measured value of the water level is different from the correct value. It is apparent that the algorithms used for sensor model parameter detection (in this case the genetic algorithm) is able to find the sensor model gain k_m. Detection of shift factor q changes is less important, because the control loop is mostly vulnerable to sensor gain changes (when the linear model of the sensor is considered).

The sensor level discredibility detection results obtained using the simulated annealing algorithm, were similar. Fig. 9. shows results obtained when model-based method using the simulated annealing algorithm was tested. The step change of sensor gain was simulated and it is obvious that the algorithm was able to capture the change.

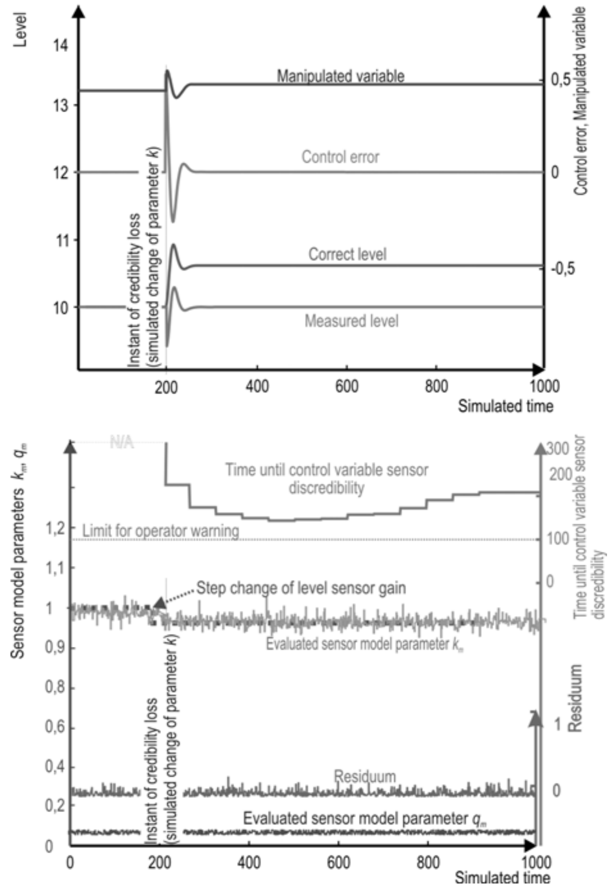

Fig. 9. Detection of the step change of the level sensor gain via simulated annealing method

5 Conclusions

The model-based control variable sensor discredibility detection method via an evolutionary algorithm has been shown to be a suitable tool. We have proved its ability to indicate control variable sensor changes together with discredibility detection. By this method the operator is informed 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 two evolutionary algorithms used here; their good convergence depends mainly on the algorithm settings. Although evolutionary algorithms are generally much more time consuming than other optimizing procedures, this consideration does not matter in control variable sensor discredibility detection. This is because control variable sensor discredibility has no conclusive impacts on the control results and the time needed for the detection does not affect the control process.

Future research will be directed at optimization of the combustion process, the experiment should discover possibilities for the oxygen probe credibility verification, and it is an important step toward the non-simulated applications.

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