Control Variable Sensor Discredibility Detection in Bioenergetic Processes

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Abstract: In control loop operation we can encounter the problem that the properties of the control variable sensor start to change. This is not usually a case of total sensor failure, but the sensor starts to provide data that is not correct and thus not reliable for the controller. As will be shown, the problem is that such an incipient control variable sensor fault may lead to so-called control variable sensor discredibility: a specific and a barely detectable status, in which the indicated value of a control variable does not match its real value. However, this is not the only negative consequence, as undesirable side effects may sometimes occur and remain unrecognized. As will be shown, there may be unacceptable side effects. These are especially undesirable in bioenergetic processes, because they lead to an increase in harmful emissions. This paper presents results obtained while testing model-based sensor discredibility detection, using the least squares method, and also a proposal for discredibility detection using a statistical approach.

Key-Words: malfunction detection, incipient fault, control variable discredibility, bioenergetic processes

1 Introduction

Information about the value of the control variable in control loops is usually acquired by a control variable sensor. In the event of total sensor failure, it is easy to recognize this status, because the control loop will no longer maintain the control variable at the desired value. By contrast, gradual changes in control variable sensor properties are not easy to recognize. The data acquired by the sensor becomes increasingly biased. After it exceeds the tolerance limits, the acquired data is no longer credible. This leads to the co-called control variable sensor discredibility status, in which the control loop performs its function, but with barely detectable inaccuracy. There is not only a danger that the control variable exceeds the limits within which it can be tolerated as correct, but there can also be undesirable site effects. As far as the operator of the process is concerned, everything appears to be working properly, because the control loop of standard instrumentation does not provide a second reading of the control variable through which the control loop inaccuracy could be discovered.

In practice, the problem of control variable sensor discredibility detection is usually left unsolved. If discredibility detection is required, it is usually provided by hardware redundancy. However, this involves additional costs. A cheaper solution of the discredibility detection problem is offered by a controller that is enhanced by a software function for discredibility detection.

According to [1], fault detection methods are classified in three general categories: quantitative model-based methods, qualitative model-based methods, and process history based methods. The methods developed to detect incipient sensor faults presented, e.g., in [1], [5], [6] are based on Bayesian belief networks, fault tree analysis and observer-based fault detection. From the viewpoint of control variable sensor discredibility detection, the lack of suitable methods involves expensive reconfiguration in the search for a cheap and easily applicable method.

In contrast to the common sensor incipient fault detection approaches, described i.e. in [2], [3], [4], where a prior knowledge about the control process is needed, the method presented in the paper provides the information about the control variable sensor discredibility from the standard process data that is in any case acquired and recorded for the control process.

The main advantage of our solution is that necessary information about changes of sensor properties is obtained from standard operation data; it means that no extra measuring points or experiments are necessary.

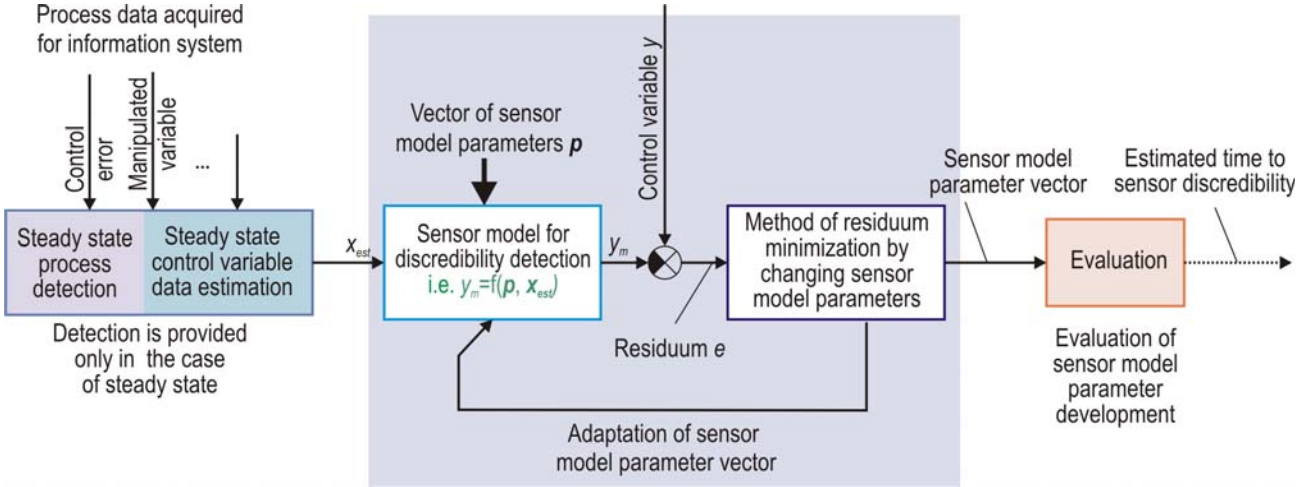

Fig. 1. Block scheme of the model-based control variable sensor discredibility detection method

The aim of our study is to develop a tool which will be able not only to detect changes in the control variable sensor at their source, but also to warn the operator about undesirable side effects. In the case of bioenergetic processes, malfunctions can lead to an increase in harmful emissions (CO, CO_2, NO_x). For discredibility detection we have suggested a model-based control variable sensor discredibility detection method.

2 Model-based sensor discredibility detection

The block scheme of the model-based control variable sensor discredibility detection method is depicted in [19] The key part of the scheme is the sensor model for discredibility evaluation. In most sensor models it is assumed that the sensor output is proportionalonly to one input, so that the sensor model equation is

$$y_m = k_m\, x_{est} + q_m, \qquad (1)$$

where parameter k_m represents the gain of the sensor model, parameter q_m expresses the shift factor, and x_{est} is the estimated sensor model input, which represents the physical (real) value of the control variable. The physical value of the control variable is not available for us, but we can estimate the value from the process data that is acquired for the purposes of the information system. This estimation is usually based on steady-state data, so that it is important to detect the steady state of the process.

The general requirement for successful application is to design the objective function. In terms of sensor discredibility detection, this function is called a residual function or residuum e. Residuum $e(t)$ is obtained as an absolute value of the difference between the real sensor output $y(t)$ and the output of the model of the sensor $y_m(t)$,

$$e(t) = |y_m(t) - y\,(t)|, \qquad (2)$$

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.

The idea underlying control variable sensor discredibility detection consists of two parts Fig. 2. :

1) Indirect detection of changes in the sensor properties via adaptation of the sensor model parameters so that the residuum is minimal. Our method aims to minimize the residuum using evolutionary algorithms (simulated annealing algorithm, or standard genetic algorithms); this approach was introduced in [9], [10]. It is now possible to minimize the residuum using the least squares method. The main features of this last mentioned approach will be indicated below.
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. The algorithm of the evaluation block can be described as follows:
   a) *Initialization stage.* At the beginning, when the control variable sensor is providing correct data, the nominal vector sensor of the model parameters is obtained. Based on the nominal values of the sensor model parameters, the maximum acceptable changes for each of the parameters are designated (as a percentage of the value of the given parameter).
   b) *Working stage*. When the initialization stage is processed, the block provides an evaluation of the development of the sensor model parameter vector. This means that the regression coefficients of the vector development are computed. Using the extrapolation function, we obtain the assumed development of the sensor model parameter vector, as well as the approximate time until control variable sensor discredibility.

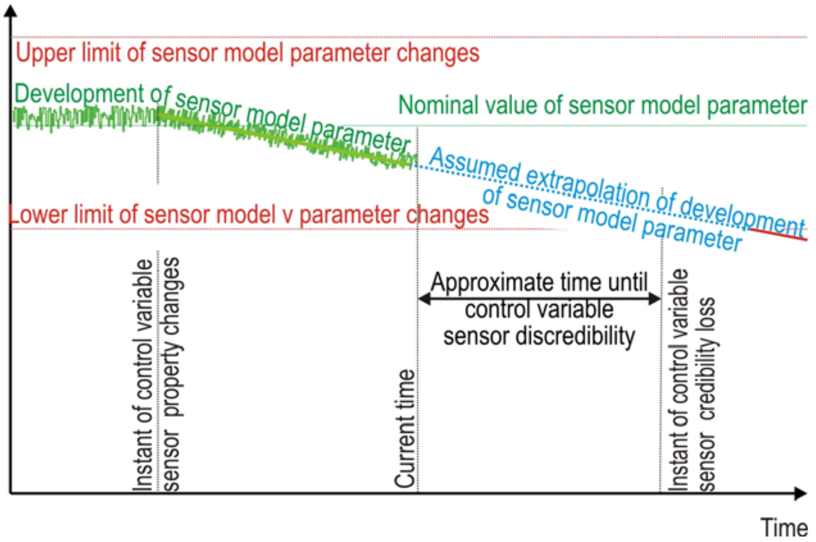

Fig. 2. Principle of extrapolation of the development of sensor model parameters and the approximate time until control variable sensor discredibility evaluation

If the development of the sensor model parameter vector indicates that the time is shorter than the given time (usually *n* times the sampling period), the operator is warned about this situation.

3 Sensor discredibility in bioenergetic processes

The importance of discredibility detection can be illustrated by the case of combustion process control. Fig. 3. shows an illustrative example of a combustionprocess. 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.

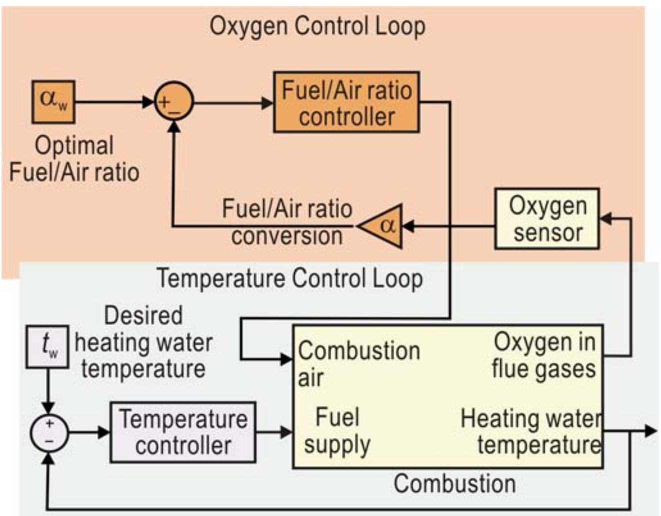

Fig. 3. Illustrative depiction of control loops in a combustion process

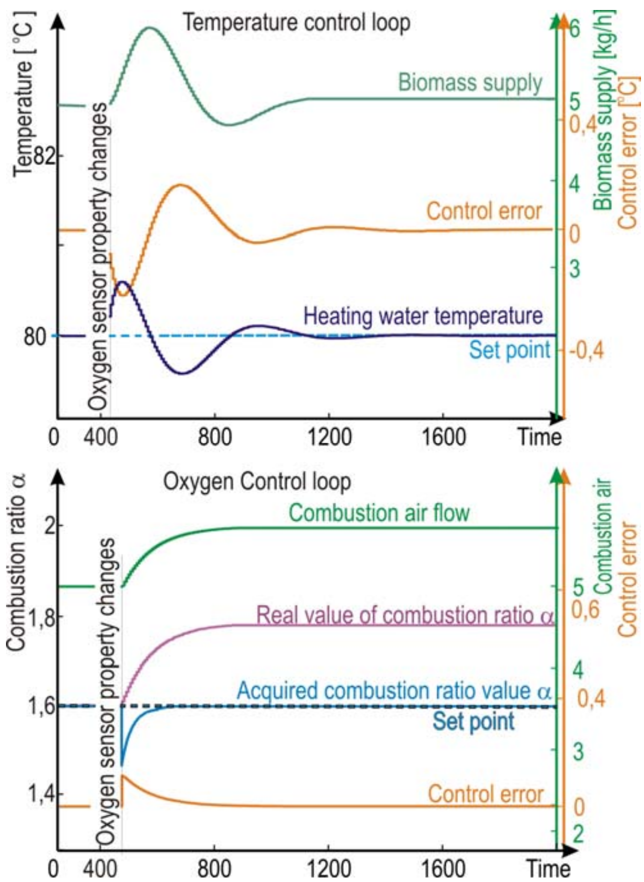

Fig. 4. Impacts of changes in the oxygen sensor on the control loop signals

The influence of changes in oxygen sensor properties on the control process is depicted in Fig. 4. It is apparent that when the oxygen sensor starts to provide biased data, the oxygen control loop reacts to incorrect information about the fuel/air ratio by attempting to remove (unreal) 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 temperature value 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.

4 Model-based sensor discredibility detection via least squares method

When the equation expressing residuum (2) is supplied by the sensor model equation (1) it results in the following equation

$$e(t) = | k_m x_{est}(t) + q_m - y(t)|. \quad (3)$$

From the viewpoint of discredibility detection, the real sensor output $y(t)$ and the estimated sensor model input $x_{est}(t)$ are given variables. If we apply the least squares method to minimize the residuum, it is necessary to record the history of the sensor model input x_{est} and the real sensor output y so that we obtain the required form of the equation to be able to evaluate k_m, q_m. This can be solved using Matlab software [7]. The algorithms for minimizing the residuum using the least squares method were applied to detecting oxygen sensor property changes. A typical result is depicted in Fig. 5. Fig. 5. shows that

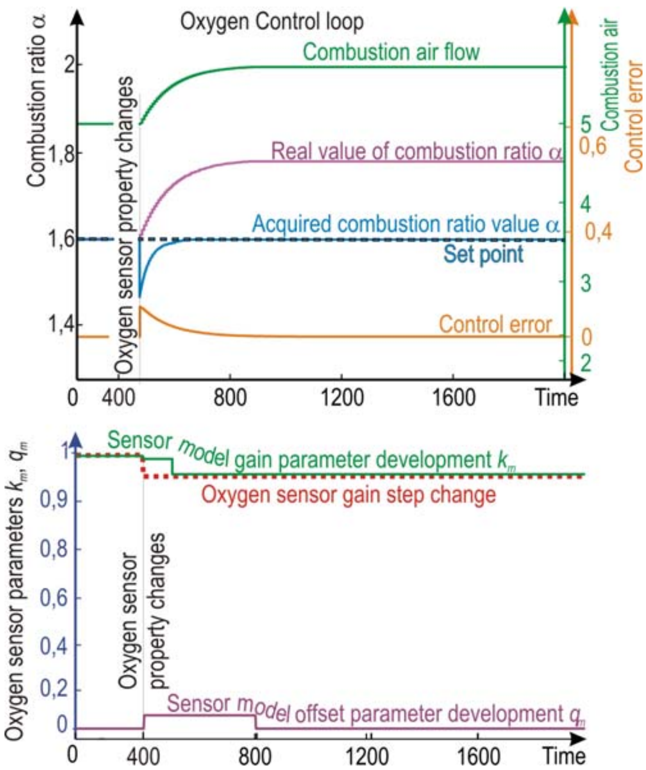

Fig. 5. Detection of a step change in the oxygen sensor via the least squares method

the algorithm was able to indicate the oxygen property changes, because a development is evident in the sensor model gain k_m.

5 Sensor discredibility detection via statistical methods

The idea of control variable sensor discredibility detection via statistical methods has been motivated by statistical methods used to evaluate process capability indices C_p and C_{pk}. Both of the capability indices are based on the rule of "6σ", where σ is the variability of the process under investigation [20].

The C_p index measures how close the process is running to its given specification limits, relative to the real variability of the process. The larger the index, the less likely it is that any item will be outside the specification limits.

The C_{pk} index measures how close the process is to its desired value, because the process may be performing with minimum variation (value index C_p is low), but it can be away from the required value towards one of the specification limits, which is indicated by lower C_{pk}.

Generally, indices C_p and C_{pk} are given by the following equations

$$C_p = \frac{USL - LSL}{6\sigma},$$
$$C_{pk} = \min\left(\frac{\overline{x} - LSL}{3\sigma}, \frac{USL - \overline{x}}{3\sigma}\right), \quad (4)$$

where USL and LSL are the upper and lower tolerance limits of the process variable that are given by a norm, a customer etc., $\overline{x}$ is the mean value of the measured process variable and σ is the standard deviation of the process variable (process variability). The standard deviation is not available, but can be substituted by an estimated value marked as $\hat{\sigma}$ by the equation [16]

$$\hat{\sigma} = \sqrt{\frac{\sum_{i=1}^{n}(x_i - \overline{x})^2}{n-1}}, \quad (5)$$

where x are values of the process variable and n is number of sampled values.

Graphical interpretations of indices C_p and C_{pk} are presented in Fig. 6. and Fig. 7., respectively.

In terms of sensor discredibility detection, the process variable is the control variable y provided by the sensor for which discredibility detection is required.

Sensor discredibility evaluation consists of two parts:

1) *Initial stage*: specification limits LSL and USL are obtained. Specification limits LSL and USL are then given by the sensor producer, or can be

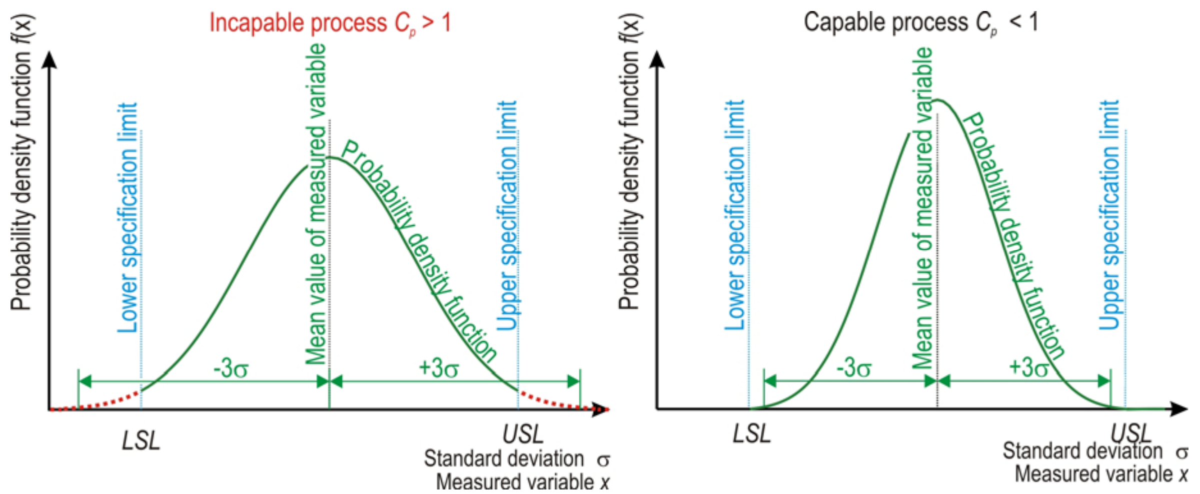

Fig. 6. Graphical interpretation of the C_p index, which indicates whether the process variation is within the given tolerance range

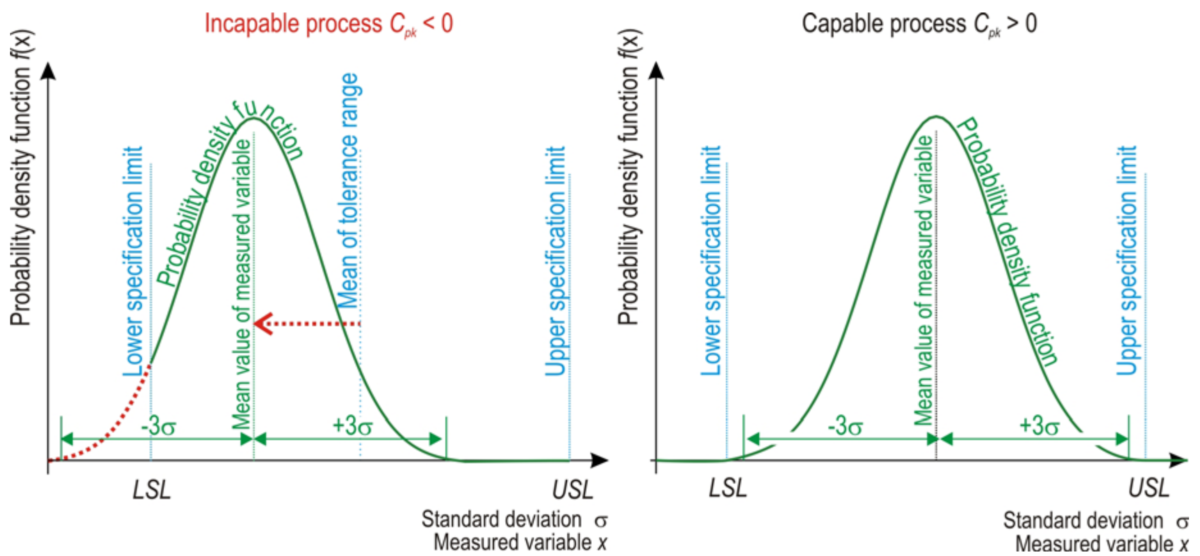

Fig. 7. Graphical interpretation of the C_{pk} index, which indicates whether the actual process average is close to the specification limit over the standard deviation

obtained in the initial detection stage from the control variable data recorded at a time when it is assumed that the sensor is providing correct data. The limits are then given by the following equation

$$USL = y_{est} + 3\hat{\sigma}, \quad LSL = y_{est} - 3\hat{\sigma}, \tag{6}$$

where y_{est} is the estimated value of the control variable and $\hat{\sigma}$ is the standard deviation control variable data.

2) *Working stage*: based on the chosen capability index (C_p or C_{pk}), the value of which is continuously evaluated, discredibility detection is carried out. The sensor is regarded as discredible if the value of the index decreases below the given critical value $C_{pCRITICAL}$ or $C_{pkCRITICAL}$.

6 Conclusions

The model-based control variable sensor discredibility detection method via the least squares method 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. The time to evaluate sensor discredibility was shorter using the least squares method than when using evolutionary algorithms.

The idea of statistical sensor discredibility detection introduced here will be verified in future research. The advantage of the method is that we can use the statistical process control (SPC) module for evaluating the capability indices. SPC is available in the most of SCADA (Supervisory Control and Data Acquisition) software.

Future research will be directed at optimizing the combustion process. An experiment will investigate ways of verifying oxygen probe credibility. This will be an important step toward non-simulated applications.

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References:

[1] Venkatasubramanian V., Rengaswamy R., A Review of Process Fault Detection and Diagnosis. Quantitative Model-based Methods, *Journal of Computers & Chemical Engineering,* Vol. 27, No. 3, 2003, pp. 293–311.

[2] King R., *Computational Methods in Control Engineering*, Basel, 1999.

[3] Witczak M., *Identification and Fault Detection of Non-Linear Dynamic Systems*, University of Zielona Gora Press, Poland, 2003.

[4] Chen J., Patton R., *Robust Model Based Fault Diagnosis for Dynamic Systems,* Kluwer Academic Publisher, 1999.

[5] Korbic J., *Fault Diagnosis: Models, Artificial Intelligence, Applications*, Springer, 2004.

[6] Neuman P., Sulc B., Zitek P., Dlouhy T., Non-linear Engineering Simulator of a Coal Fired Steam Boiler Applied to Fault Detection of Optimum Combustion Control, *Preprints of the 4th Symposium on Safety Processes (IFAC),* 2002, pp. 927–932.

[7] *Writing S-Functions*. Mathworks, Inc. [online]. [2006-08-08]. Available:
URL: http://mathworks.com/access/helpdesk/help/toolbox/simulink/.

[8] Sulc B., Klimanek D., Discredibility Detection of a Sensor in a Control Loop via Computational Intelligence, *Proceedings of the 5th WSEAS International Conference on Applied Informatics*, 2005.

[9] Sulc B., Klimanek D., Sensor Discredibility Detection via Computational Intelligence, *WSEAS Transactions on Systems*, Vol. 4, No. 11, 2005, pp. 1906–1915.

[10] Klimanek D., Sulc B., Evolutionary Detection of Sensor Discredibility in Control Loops, *Proceedings of the 31st Annual Conference IEEE*, 2005, pp. 136–141.

[11] Klimanek D., Sulc B., Improvement of Control Loop Function by Control Variable Sensor Discredibility Detection, *Transactions of the VSB–Technical University of Ostrava,* 2006, pp. 120–126.

[12] Klimanek D., Sulc B., Sensor Discredibility Detection by Means of Software Redundancy. *Proceedings of the 7th International Carpathian Control Conference*, 2006, pp. 249–252.

[13] Steger C., Weiss R., Model-based Real-time Fault Diagnosis System in Technical Processes, *Proceedings of the 10th International Conference on Applications of Artificial Intelligence in Engineering,* 1999, pp. 25–30.

[14] Patton P., Frank R., Clark G., *Issues of Fault Diagnosis for Dynamic Systems*, Springer, 2000.

[15] Koushanfar R., On-line fault detection of sensor measurements, *Proceedings of IEEE Sensors 2003,* Vol. 2, No. 8, 2003, pp. 974–979.

[16] Johnson N., Kotz S., *Continuous Univariate Distributions*, Wiley-Interscience, 1995.

[17] Mehranbodn M., Panjapornpon C., A Method of Sensor Fault Detection and Identification. In *Journal of Process Control*, 2005, Vol. 15, Issue 3, pp. 321-339.

[18] Ding, E. L., H. Fennel – Ding, S. X, Model-based Diagnosis of Sensor Faults for ESP Systems. In *Control Engineering Practice,* Vol. 12, Issue 7, 2004, pp. 847-856.

[19] Klimánek, D., *Detection of a Biased Control Loop Function via Evolutionary Algorithms*. Ph.D. Thesis. CUT in Prague, 2007.

[20] Johnson N., Kotz S., *Continuous Univariate Distributions*, Wiley-Interscience, 1995.