Analitical Redundancy for Better Safety Features – an example of boiler

Stojan Persin, *Member, IEEE* and Boris Tovornik, *Member, IEEE*

Abstract — On-line monitoring of industrial processes is extremly important for plant safety and product quality. An early detection of the fault occurrence is vitally important since it contributes to avoidance of product deterioration, performance degradation, major damages to the machinery itself and damages to human health or even loss of lives. Some fault detection methods using analytical redundancy are described and principles are outlined of some most important techniques of model-based residual generation using parameter estimation, parity space and state estimation approaches. As the real systems are usually non-linear, a non-linear state estimation observer is described. A water vessel (boiler) of a heat exchanger was chosen for the experiment. Although there was no water level sensor installed in it, the leakage of the vessel was successfully detected using a non-linear observer.

Index Terms — boilers, fault diagnosis, nonlinear systems, safety, water heating

I. Introduction

The global competitiveness of the production nowadays cannot be achieved if equipment that is used for production isn't installed, applied and maintained properly. The global competitiveness depends to a large extent on effectiveness of the use of factory automation. The early 1980s heralded the creation of the "Factory of the future". The prevalent image then was a "lights off" factory heavily populated by robots, with a few human supervisors keeping track of operations by watching monitors in a central control room. In many cases, this image was not achieved. In few words, workers (and wider environment, living and non-living) are still exposed to harmful effects of the working area and accidents, caused either by process malfunction or incompetence of their colleague workers.

Some studies [1] have shown that main causes related to automation or control are poor instrumentation and operator error. Most of the human errors are usually made during start-up operations of the process. The following conclusion can therefore be drawn: If the degree of automation were higher, consequences of a human error might be smaller. Furthermore, co-operation between automation and a human operator is important in avoiding human errors during operation. Occurrences of equipment faults giving rise to accidents bring up the necessity that potential failures, both in measurement and control equipment as well as in process equipment, should be studied. By preparing for them a proper process design, an equipment failure of the system would not lead to an accident. One of the possible solutions is an early detection of malfunctions, called Fault Detection and Isolation (FDI).

II. Some Process Industry Safety Features

Three types of event are traditionally associated with the chemical branch of the process industry. These are releases and spills, fires, and explosions. Controlling the potential risk means that process equipment must withstand the anticipated stresses caused by hazardous substances and that process parameters must not take on values such that the substances can undergo uncontrolled reactions.

Critical process parameters and hazardous potential ignition sources must not occur in the plant as a result of process upsets or even a human error. These become an additional concern of the plant safety requiring a painstaking cause and effect analysis of all possible errors and malfunctions and institutions of measures to prevent or neutralise situations that could lead to an unsafe condition. Such measures could be technical or organisational. In other words, Process Engineering and Process Control Engineering must consider interconnection of different science disciplines that have to be taken into account to achieve the purpose of a "safe plant" (Figure 3), i.e., following the principles of system engineering.

Unfortunately, a complete absence of all possible hazards (absolute safety) is not possible for two reasons:

- it cannot be ruled out that several safety measures will fail simultaneously;
- people make mistakes, misjudge things, asses them wrongly, fail to notice them.

To go even further, failures usually don't appear without any reason. They must have been caused by groups of events from the past (change of parameters due to ageing, disallowed change of one of unmeasured variables, etc.). The causes from the past (recent or distant) would initiate *symptoms* of a failure before it happens. If they are known or pre-studied and if one is able to detect them, a process or its component can be maintained on time to prevent a failure. If a failure is allowed, its primary source has to be

Authors are with University of Maribor, Faculty for Electrical Engineering and Computer Science, Smetanova 17, 2000 Maribor, Slovenia (e-mail: stojan.persin@uni-mb.si).

found. This is one of the recent tasks of process automation. Modern equipment should provide enough measurement signals to be able to apply early fault detection also for safety reasons.

However, fault diagnosis has become an issue of primary importance in modern process automation and as it provides the pre-requisites for fault tolerance, reliability or security, which constitute fundamental design features in any complex engineering system. It is important to distinguish between:

- fault detection and isolation (FDI) methods based on mathematical or dynamic model of process systems, and
- knowledge based methods, which are in many cases more failure oriented (searching the primary component indicating a failure).

Fig. 1 shows a simple classification of diagnostic algorithms [1].

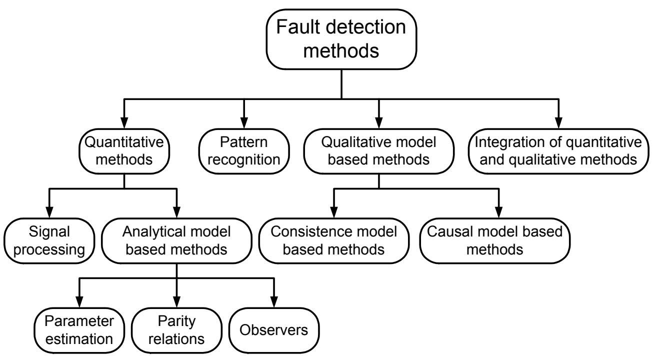

Fig. 1. Simple classification of the fault detection algorithms

In general, fault monitoring systems must be tolerant to signal deviations caused by process parameter uncertainty, disturbances, non-linearities, etc., which are normal functions of the operation of most engineering requirements.

III. FAULT DETECTION, ISOLATION AND ACCOMMODATION IN FEEDBACK CONTROL SYSTEMS

Consequences, even those of simple faults, may be dramatic and there are considerable incentives to enhance computerised feedback loops with methods for fault detection and accommodation.

Feedback is established because actuator demands are calculated from the difference between a reference value and sensor measurements. Any deviation between these signals will cause an immediate reaction on the actuators when actuator demands are updated. The discrete time control algorithm makes use of both current and previous events in the plant. This makes it possible to employ, for example, prediction methods to give the control loop desired characteristics. Response time to changes in the setpoint, disturbance rejection properties, noise sensitivity, and stability properties are key attributes that are always quantified in the requirements to a particular closed-loop design.

Feedback control systems are particularly sensitive to faults. However, faults in feedback loops are in general difficult to handle [3]. If a fault develops gradually, a closed loop will attempt to compensate for it and in this way hide the development of the malfunction. The fault may not be discovered until the control loop stops normal operation. If faults arise suddenly, the effect is amplified by the closed-loop control. Production stops, process damage, or other undesired consequences, may be the result. A feedback sensor fault, for example, may cause a large deviation between the measurement and reference. This will in most cases cause large actuator demands and eventually lead to a rapid change of the process state. Unacceptable excursions in the process state followed by production stop, plant failure or direct damage are experiences from actual events in industry.

In normal operation, feedback control should keep the process state equal to a desired setpoint while the influence from process disturbances and measurement noise are kept minimal. This can be achieved by employing methods that estimate process states and perform optimal dynamic filtering in combination with techniques that adopt parameters in the control method to current process conditions.

In abnormal operation, when faults have occurred, the control loop should react immediately in a way that prevents a fault from developing into a malfunction of the system being controlled. This requires added functionality to well established methods in the control theory.

A general method for design of fault handling associated with closed-loop control includes the following steps:

1. Make a failure mode and effect analysis related to control system components [4].
2. Define desired reactions to faults for each case identified by the analysis from Eq. (1).
3. Select appropriate method for generation of residuals. This implies consideration of system architecture, available signals, and elementary models of components. Disturbance and noise characteristics should be incorporated in the design if available.
4. Select a method for fault detection and isolation. This implies a decision or whether an event is a fault and, if this is the case, the determination of which element if faulty.
5. Consider control method performance and design appropriate detectors for supervision of control effectiveness. Design of appropriate reactions.
6. Design a method for accommodation of faults according to points 2 and 5.
7. Implement the completed design. Separate the control code from the fault handling code by implementation as a supervisor structure.

Faults in a control loop can be categorised in generic types:

- reference value (setpoint) fault,
- sensor fault,
- actuator element fault,
- execution fault including timing fault,
- application software, system or hardware fault in a computer based controller,
- fault in a physical plant.

The chosen diagnostic procedure depends mostly on fault detection demands and available process models. The three basic FDI methods based on analytical models will be presented in the next sections:

- parameter estimation approach,
- parity space approach,
- observer approach.

IV. PARAMETER ESTIMATION APPROACH

As the parameter identification methods are well known and available in literature [1, 2, 3, 7], they are only mentioned here. Parameter estimation is a natural approach to the detection and isolation of parametric faults. A reference model is obtained first by identifying the plant in a fault-free situation. Then the parameters are repeatedly re-identified on-line. Deviations from the reference model serve as a basis for detection and isolation. The identification algorithm can be applied in continuous or discrete time. If continuous time is applied (no need for z-transform), the derivatives of the signals have to be either measured or obtained using observers. Best results are obtained using state variable filters [10]. Another method of obtaining signal derivatives is by using real differentiators. Signals have to be properly filtered before application, thus a high sample rate is required.

V. PARITY SPACE APPROACH

Parity space approach means a comparison of the mathematical model of the plant and measured variables. Any fault can be detected through differences between compared signals. Consider a dynamic system with input vector **u**, output vector **y**, and feedback control system. A plant in general consists of actuators, plant dynamics (components), and sensors. For a realistic representation it is important to model all effects that can lead to alarms and false alarms.

The analytical redundancy approach requires that the residual generator performs some kind of validation of the nominal relationships of the system, using the actual input and measured output (Fig. 2). The redundancy relationships to be evaluated can even simply be interpreted as input-output relations of the dynamics of the system. It is highly desirable to have input and output signals of the actuators of the plant available. This is especially important if the actuators are highly non-linear, because then the required system equations do not contain the actuators non-linearities. If a fault occurs, the redundancy relations are no longer satisfied and a residual, $r_i \neq 0$, occurs. The residual is then used to form appropriate decision functions. They are evaluated in the fault decision logic in order to monitor both the time of occurrence and location of the fault.

For the residual generation a model of the process is required, and for better fault isolation an additional model of the faulty process should be used.

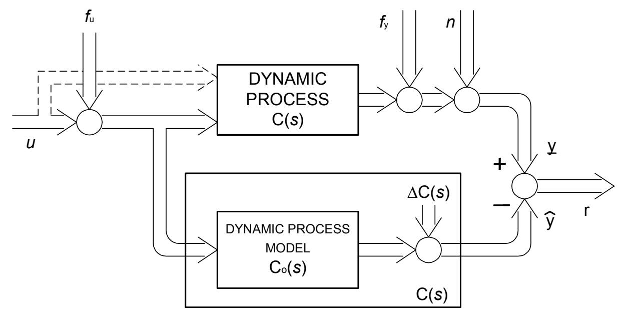

Fig. 2. Principle of the parity space approach to fault detection

The first step in model based analytical redundancy methods is to include all the predefined faults into the mathematical model of the plant.

Output from the parity equations are signals showing inconsistency between normal and faulty operation. In normal process operation the parity equations output is approximately zero. In case of faults the output will be nonzero. Fault isolation is achieved with structured parity equations. One element of the residual vector is unaffected by a specific fault while all the others will be affected. In that way the determination of a fault is possible. The parity equations are designed as follows [3]:

$$\mathbf{e}(s) = \Delta\mathbf{y}(s) - \mathbf{C}(s)\cdot\Delta\mathbf{u}(s) = \mathbf{y}(s) - \mathbf{C}(s)\cdot\mathbf{u}(s)$$
$$\mathbf{r}(s) = \mathbf{W}(s)\cdot\mathbf{e}(s) \qquad (1)$$

The residual vector $\underline{r}(s)$ is found by multiplying a weighting filter W(s) to the error $\underline{e}(s)$. The filter is designed to make the j^{th} residual unaffected by the i^{th} fault. Unfortunately, the residual is also affected by measurement noise $\underline{n}$ and modelling uncertainty ΔC, not only by the fault vector $\underline{f}$ (2)

$$\mathbf{y}(s) = (\mathbf{C} + \Delta\mathbf{C})\cdot\mathbf{u}(s) + \mathbf{n}(s) + \mathbf{S}\cdot\mathbf{f}(s) \qquad (2)$$

where **S** is a fault distribution matrix. Error vector $\mathbf{e}(s)$ is then:

$$\mathbf{e}(s) = \mathbf{y}(s) - \hat{\mathbf{y}}(s) = \mathbf{S}\cdot\mathbf{f}(s) + \mathbf{n} + \Delta\mathbf{C}\cdot\mathbf{u} \qquad (3)$$

In general, the residual vector **r**(s) is affected by all faults **f**(s):

$$\mathbf{r} = [r_1, r_2, \ldots r_n]^{\mathrm{T}} = \mathbf{r}(\mathrm{f}_1, \mathrm{f}_2, \ldots \mathrm{f}_n) \tag{4}$$

Residual r_i should be made unaffected by fault f_i. This is achieved if matrix **[WxS]** has the following structure [5]:

$$r_i \neq r_i(\mathrm{f}_i) \Leftrightarrow \mathbf{W} \times \mathbf{S} = \begin{bmatrix} 0 & \sum_{i=1}^{n} w_{1i} \cdot s_{i2} & \cdots & \sum_{i=1}^{n} w_{1i} \cdot s_{in} \\ \sum_{i=1}^{n} w_{2i} \cdot s_{i1} & 0 & \cdots & \sum_{i=1}^{n} w_{2i} \cdot s_{in} \\ \vdots & \vdots & \vdots & \vdots \\ \sum_{i=1}^{n} w_{ni} \cdot s_{i1} & \sum_{i=1}^{n} w_{ni} \cdot s_{i2} & \cdots & 0 \end{bmatrix}$$

or

$$\sum_{i,j=1}^{n} w_{ji} \cdot s_{ij} = 0 \quad \text{if } \mathrm{i} = \mathrm{j} \tag{5}$$

Here the first residual r_1, depends on all but the first fault, the second residual r_2, on all but the second fault and so on [2]; that is:

$$\begin{aligned} r_1 &= r_1(\mathrm{f}_2, \mathrm{f}_3, \ldots \mathrm{f}_n) \\ r_2 &= r_2(\mathrm{f}_1, \mathrm{f}_3, \ldots \mathrm{f}_n) \\ &\vdots \\ r_i &= r_i(\mathrm{f}_1, \mathrm{f}_2, \ldots, \mathrm{f}_{i-1}, \mathrm{f}_{i+1}, \ldots, \mathrm{f}_n) \\ &\vdots \\ r_n &= r_n(\mathrm{f}_1, \mathrm{f}_2, \ldots \mathrm{f}_{n-1}) \end{aligned} \tag{6}$$

The decision function for the logical evaluation of the residuals is then as follows:

$$\begin{aligned} &\text{if } (r_2 \wedge r_3 \wedge \cdots \wedge r_n \neq 0) \wedge (r_1 = 0) \;\Rightarrow\; \mathrm{f}_1 \\ &\text{if } (\mathrm{r}_1 \wedge r_3 \wedge \cdots \wedge r_n \neq 0) \wedge (r_2 = 0) \;\Rightarrow\; \mathrm{f}_2 \\ &\vdots \\ &\text{if } (r_1 \wedge r_3 \wedge \cdots \wedge r_{n-1} \neq 0) \wedge (r_n = 0) \;\Rightarrow\; \mathrm{f}_n \end{aligned} \tag{7}$$

VI. Observer Approach

The system under consideration is usually non-linear, thus the model in the observer should also be non-linear in order to avoid modelling errors arising from linearization. This leads to the concept of FDI using non-linear state estimators [7]. Consider the non-linear system given by:

$$\dot{\mathbf{x}} = \mathrm{f}(\mathbf{x}, \mathbf{u});\; \mathbf{x}(0) = \mathbf{x}^0 \tag{8}$$

$$\mathbf{y} = \mathrm{c}(\mathbf{x}, \mathbf{u}) \tag{9}$$

where vector **u** denotes the input vector, **y** denotes the output vector, **x** denotes the state vector and f and c are nonlinear functions. Initial conditions are given by **x**(0). The non-linear state estimator equation is then, by definition,

$$\dot{\hat{\mathbf{x}}} = \hat{\mathrm{f}}(\hat{\mathbf{x}}, \mathbf{u}, \mathbf{y});\; \hat{\mathbf{x}}(0) = \mathbf{x}^0 \tag{10}$$

and the state estimation error, $\boldsymbol{\varepsilon} = \mathbf{x} - \hat{\mathbf{x}}$, becomes

$$\dot{\boldsymbol{\varepsilon}} = \mathrm{f}(\mathbf{x}, \mathbf{u}) - \hat{\mathrm{f}}(\hat{\mathbf{x}}, \mathbf{u}, \mathbf{y}) \tag{11}$$

If Eq. (10) is approximated, such that it becomes

$$\dot{\hat{\mathbf{x}}} = \mathrm{f}(\hat{\mathbf{x}}, \mathbf{u}) + \mathbf{H}(\hat{\mathbf{x}}, \mathbf{u}) \cdot (\mathbf{y} - \hat{\mathbf{y}});\; \hat{\mathbf{x}}(0) = \hat{\mathbf{x}}^0 \tag{12}$$

$$\hat{\mathbf{y}} = \mathrm{c}(\hat{\mathbf{x}}, \mathbf{u}), \tag{13}$$

then

$$\mathbf{H}(\hat{\mathbf{x}}, \mathbf{u}) = \left.\frac{\partial \hat{\mathrm{f}}}{\partial \mathbf{y}}\right|_{\hat{\mathbf{x}}, \mathbf{u}} \tag{14}$$

is a time-variant observer gain matrix. If system noise $\mathbf{n}(t)$ and modelling errors $\Delta\mathbf{f}(t)$ are present, the state estimation error equation becomes

$$\dot{\boldsymbol{\varepsilon}} = \left[\frac{\partial \mathrm{f}}{\partial \mathbf{x}} - \mathbf{H}(\mathbf{x}, \mathbf{u}) \cdot \frac{\partial \mathrm{c}}{\partial \mathbf{x}}\right]_{\hat{\mathbf{x}}, \mathbf{u}} \cdot \boldsymbol{\varepsilon} + \Delta\mathbf{f} + \mathbf{n} \tag{15}$$

The output estimation error **e** can be calculated from (15). Considering measurement noise, $\mathbf{m}(t)$, and sensor faults, $\Delta\mathbf{k}(t)$, one obtains

$$\mathbf{e} = \mathbf{y} - \hat{\mathbf{y}} = \mathrm{c}(\mathbf{x}, \mathbf{u}) - \mathrm{c}(\hat{\mathbf{x}}, \mathbf{u}) + \Delta\mathbf{k} + \mathbf{m} \tag{16}$$

If stability of the observer is problematic in practical applications, a constant feedback gain matrix can be used instead of $\mathbf{H}(\hat{\mathbf{x}}, \mathbf{u})$. The structural diagram of the resulting non-linear estimator is illustrated in Fig. 3. A gain matrix $\mathbf{W}(0 < w_i \leq 1)$ is added to the feedback in order to improve the performance of the observer for fault detection purposes (a compromise between modelling errors and difference in dynamics due to leakage as the system will be used in practical application).

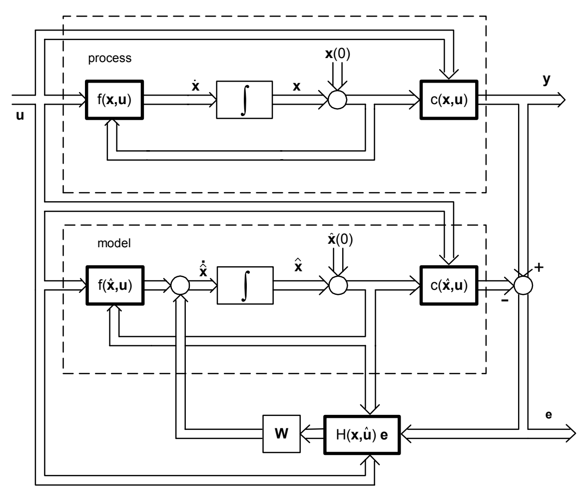

Fig. 3. Residual generation for a non-linear system using a non-linear observer

Non-linear observers are effective tools for residual generation. Additional robustness and even decoupling from external disturbances and unknown system parameters can be provided by non-linear unknown input observers, as is proposed in [11, 12, 13]. The available approaches are generalized, and extended to a wider class of non-linear systems in [14].

VII. EXAMPLE OF FAULT DETECTION METHOD APPLIED ON A BOILER

Heat exchangers play an important role in chemical and process industries. In order to improve their reliability, safety and control performance, intelligent concepts for control, supervision and also reconfiguration are necessary. Fault detection methods will be presented and applied on a boiler, which is a part of a laboratory model of a heat exchanger illustrated in Fig. 4. This is a process that cannot be modelled with a high accuracy. A dynamic response of a heat exchanger depends strongly on its operating point. The device consists of a double-pipe heat exchanger of which the inner tube is connected to a closed system with a water vessel - boiler. In the primary circuit, the electric heater produces hot water in the vessel at a pressure of 1 bar (system is open to the atmosphere).

The whole automation system is designed to be as close as possible to the industrial practice. Only standard commercially available industrial components were chosen for all automation components. The device is connected to Omron PLC (Programmable Logic Controller) and supervised by iFIX SCADA (Supervisory Control and Data Acquisition) system. An additional LCD with touch screen is used for local control and monitoring. A photo of the device is shown in Fig 5.

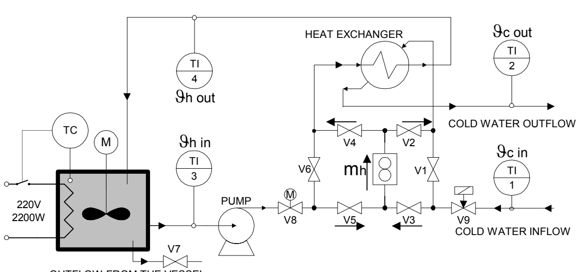

Fig. 4. Laboratory heat exchanger

Fig. 5. Photo of the heat exchanger

The derivation of the mathematical model of the vessel is simple. The vessel is assumed to be ideally insulated. Considering the input-output relationships, the non-linear differential equation (17) of the energy balance of the vessel can be written:

$$0 = \mathrm{P} + m_h(t)\cdot c_p \cdot \vartheta_{h\,out}(t) - m_h(t)\cdot c_p \cdot \vartheta_{h\,in}(t) - \mathrm{M}\cdot c_p \cdot \frac{d\vartheta_{h\,in}}{dt} \tag{17}$$

where:

P power of the electric heater (W)

m_h mass flow of the heating (inner) water (l/s)

c_p specific heat constant (general) (J/kg K)

$\vartheta_{h\,in}$ temperature of the heating water entering the heat exchanger (K)

$\vartheta_{h\,out}$ temperature of the heating water leaving the heat exchanger (K)

M mass of the water in the vessel (kg)

The main problem associated with the vessel is that there is neither level sensor nor pressure sensor installed in it. The question arises how to detect the leakage, when the level sensor isn't applied. Observing the differential equation, which describes energy balance (17), one can see that the water level (mass of the water in the vessel, M) changes the dynamic behaviour of the vessel, while the static behaviour remains unchanged. This means that a change in temperature $\vartheta_{h\,in}$ is needed to detect the anomaly. The vessel is described by a non-linear differential equation, so a non-linear observer can be used as described in section 6. If the procedure from section 6 is applied to Eq. (17), the following equations are obtained:

$$\mathbf{u} = \begin{bmatrix} \vartheta_{\mathrm{h\,out}} \\ m_{\mathrm{h}} \end{bmatrix} \tag{18}$$

$$x = \vartheta_{h\,\mathrm{in}} \tag{19}$$

$$y = \mathrm{c}(x, \mathbf{u}) = x = \vartheta_{h\,\mathrm{in}} \tag{20}$$

$$\dot{x} = \mathrm{f}(x, \mathbf{u}) \;=\; \mathrm{f}(\vartheta_{h\,\mathrm{in}}, \vartheta_{\mathrm{h\,out}}, \mathrm{m_h}) = \frac{d\hat{\vartheta}_{h\,\mathrm{in}}}{dt} = \\ = \frac{1}{\mathrm{M}} \cdot \left[\frac{\mathrm{P}}{c_p} + m_h \cdot \left(\vartheta_{\mathrm{h\,out}} - \vartheta_{\mathrm{h\,in}} \right) \right] \tag{21}$$

$$\mathrm{H}(\hat{x}, \mathbf{u}) = \mathrm{H}(\hat{\vartheta}_{h\,\mathrm{in}}, \vartheta_{\mathrm{h\,out}}, \mathrm{m_h}) = \left.\frac{\partial \hat{\mathrm{f}}}{\partial y}\right|_{\hat{x},\mathbf{u}} = \\ = \left.\frac{\partial \hat{\mathrm{f}}(\hat{\vartheta}_{h\,\mathrm{in}}, \vartheta_{\mathrm{h\,out}}, \mathrm{m_h})}{\partial \hat{\vartheta}_{h\,\mathrm{in}}}\right|_{\vartheta_{\mathrm{h\,out}},\,\mathrm{m_h}} = -\frac{m_h}{\mathrm{M}} \tag{22}$$

The residual is then:

$$r = y - \hat{y} = \vartheta_{h\,\mathrm{in}} - \hat{\vartheta}_{h\,\mathrm{in}} \tag{23}$$

The heat exchanger is controlled by a programmable logic controller (PLC) using a closed-loop control, while a non-linear observer is realized in the Matlab environment. As was proposed by Persin [15], an additional link to the Matlab was established. The process data is available to the Matlab virtually at the same time as to the SCADA system which makes the application suitable for industrial environments. A performance test of the observer (Fig. 3), using w=0,5, is made. The ability of water leakage detecting is tested, for a case of two missing litres of water (the capacity of the water tank is six litres). As shown in Fig. 6, the fault is successfully detected with a residual.

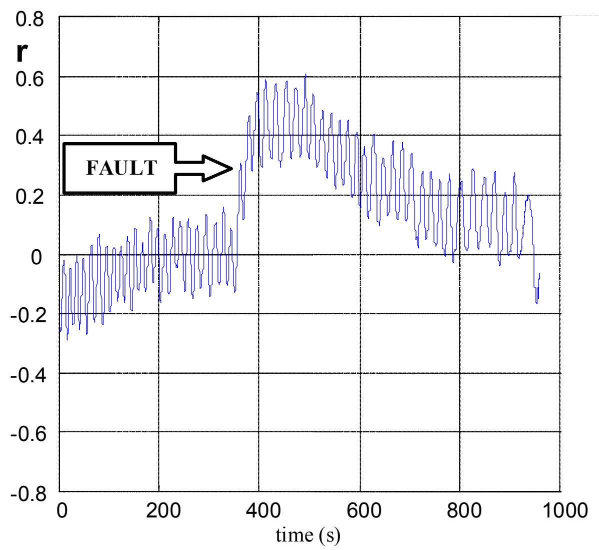

Fig.6. Fault detected with a residual

VIII. CONCLUSIONS

The analytical redundancy is an alternative approach to physical redundancy. Physical redundancy means that redundant signals are generated by means of a set of equal redundant sensors through which the failed ones can be detected. Analytical redundancy uses mathematical models and observers to generate redundant signals. Computations use those signals and present and/or previous measurements of other variables. The resulting differences, called residuals, are indicative of the presence of faults in the system. The three basic FDI methods based on analytical models are parameter estimation approach, parity space approach and observer approach.

Changes in model parameters can be detected by parameter estimation methods. Observer or a set of observers can be used to detect either sensor, component or actuator faults. If symptoms of a fault are well known, the fault can be detected on time to prevent it to develop into a failure that could lead to an environmental damage or loss of a human life. Nevertheless, implementation of FDI schemes increases the occupational safety since humans are excluded from the process. Namely, an occurred fault is detected automatically and a proper reconfiguration is adopted to keep the process in a safe state.

There are several ways of testing the FDI scheme performance. It can be tested either through simulations in which the main problem is that disturbances, unknown inputs and noise cannot be modelled properly. Another way is to work off-line and test the performance of the FDI scheme on previously measured signals. The main problem here is that behaviour of the closed-loop system cannot be tested. The most complex way is on-line testing.

A boiler was chosen for our experiment as it is frequently used in process plants. The main problem associated with the leakage of the vessel was that there was no level sensor installed in it. Successful results were obtained using a non-linear observer based on energy balance equations. A dynamic change in the mass flow is needed to enable detecting a change of the water level from the nominal state.

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