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A COMPARATION OF MODEL AND SIGNAL BASED FAULT DETECTION METHODS

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Abstract: In industrial processes, physical components or automatic control components, sensors, and/or actuators are often affected by un-permitted or un-expected deviations from their normal operation behavior. The fault detection task consists in determination of the fault occurrence and time of detection. The diagnostics procedures are based on the observed analytical and heuristical symptoms and the heuristic knowledge of the process. In this paper a comparison between different methods of fault detection and an overview of the fault diagnosis procedure for technical system is provided. For some classes of processes the structure and some parameters are well known but for others only rough models are available. Therefore the methods for fault detection and diagnosis are mainly different and several examples are explained.

Key words: fault detection; analytical model based methods; signal based methods.

1. INTRODUCTION

Fault detection and diagnosis (FDD) methods consists, in general, in a two level procedures a residual generation and fault detection part and a symptom generation and diagnostic part. In the first level, the difference between measurements and computed variables are called residuals and these quantities are indicative of the presence of faults in the system. In the second level, the relations between symptoms based residuals and faults are established. To detect and isolate a fault is important to find the significant symptoms, which are robust against noises or disturbances. In order to avoid the possible loss of the systems performance because of a fault appearance, many research efforts in the field of process supervision, fault detection and diagnosis have been made [7, 10, 15].

A general FDD scheme for a process consists of two levels procedure depicted in Figure 1.

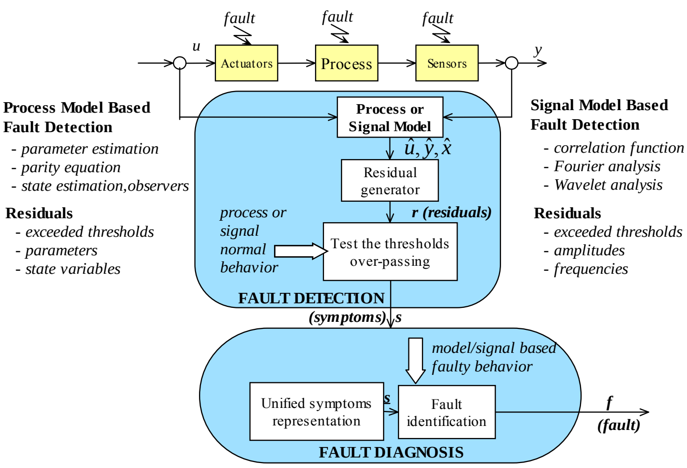

Figure 1. FDD model-based general scheme with process/signal model

The objective of FDD is not only to determine some fault presence in the system and the time of fault occurrence (fault detection), to establish the kind and location of fault (fault isolation) and to estimate the behavior of the fault in time and amplitude as well as the cause of this un-expected system behavior.

The model-based fault detection methods rely on the concept of analytical redundancy. In contrast to physical redundancy, when measurements from parallel sensors are compared to each other, now sensor's measurements are compared to analytically computed values of the respective variable. Such computation use present and/or previous measurements of other variables, and the mathematical plant model describing their nominal relationship to measured variable. The idea can be extended to the comparison of two analytically generated quantities, obtained from different sets of variables. In either case, the resulting differences, called residuals, are indicative of the presence of faults in the system.

Advanced methods of fault detection are using mathematical process and signal methods. A survey and a comparison of these methods are discussed in the following section.

2. FAULT DETECTION METHODS

The basic fault detection methods are using models and by comparison between measurements and normal behavior models residuals are generated. These variables, residuals, are compared against thresholds and a decision test decides if a fault occurred.

The comparison of the different methods for fault detection is not easily performed because the final practical results depend on many aspects like process type, un-permitted or un-expected disturbances, open or close loop structure, processes nonlinearities, etc. The structure and at least some parameters are relatively well known for some types of processes, like electrical, mechanical, thermo or hydraulic processes. For others processes only rough models are available, as e.g. industrial processes with moving parts, chemical, mineral or metal processing.

Figure 2 summarizes the basic fault detection methods.

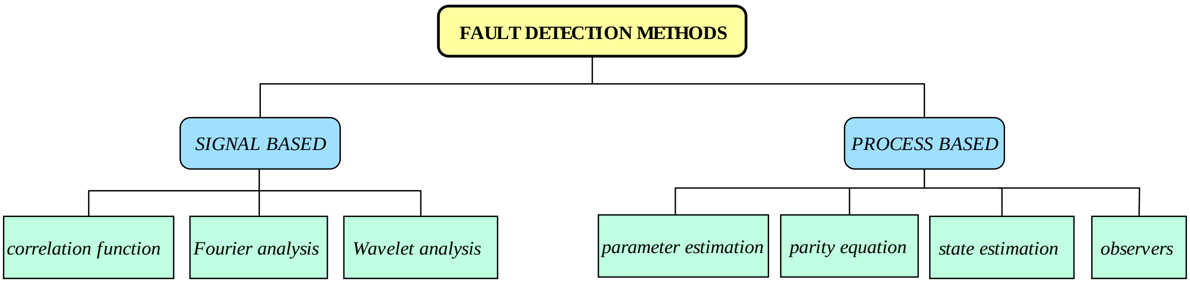

Figure 2. Basic fault detection method

Fault detection with process models are considered if additive or multiplicative faults within the process influence the input/output measurable signals. The process models could be considered by using parameters estimators, parity equations or state observers and state estimation.

These methods are based, for example, on discrete state-space models [2], time continuous state-space models [10], observers [8] or transfer function models [9,12].

Parity equations and observer – based methods have partially almost identical properties, but parity equations are much simpler to be design, to be implemented and to be used. Parity equations and observers-based methods are well suited for additive faults, but are not in general well suited for multiplicative faults. For multiplicative faults the parameter estimators are best suited.

Another essential difference is that parity equations and observers based methods need more than one inputs measurement to detect and isolate several faults, but for parameter estimation methods one input and one output is sufficient to detect and diagnose different faults.

A qualitative comparison of properties of different fault detection methods for SISO (Single Input Single Output) and MIMO (Multi Input Multi Output) processes is depicted in table 1.

Signal processing is another way to deal with fault diagnosis [1]. This approach is based on a signal model. Signals may be analyzed either using time-domain methods (e.g. correlation, mean-change) or frequency domain methods (e.g. Fast Fourier Transform, FFT), or with more sophisticated methods including time-frequency or wavelet analysis [18]. Decision may be based on the normal process behavior knowledge (for instance the signal is zero-mean) or on some faulty behavior knowledge (for instance, a fault gives rise to some extra frequency contents in the spectrum).

Table 1.

	Parity equations	**State estimation**	**Parameter estimation**
Assumptions:			
Model structure and parameters	known	known	known/ unknown
Detectable faults:			
Abrupt, incipient, single faults	yes	yes	yes
Multiple faults	SISO: no MIMO: yes	SISO: no MIMO: yes	SISO: yes MIMO: yes
Fault isolation	SISO: no MIMO: yes	SISO: no MIMO: yes	SISO: yes MIMO: yes
Additive	yes	yes	yes
Multiplicative	no	no	yes

All these approaches have a common difficulty: how to ensure that a change in some quantity is characteristic of a particular fault [10]. Signal based model fault detection can be applied especially for machine vibration, the position, speed or acceleration measuring, for example imbalance or bearing faults (turbo machines), knocking (gasoline engines), chattering (rolling mills), etc.

Detection tests based on signal model that aim to detect a change in the mean or the standard deviation of a signal are now often used [1, 11].

Frequency representations are particularly useful for studying rotating machines because of the extra frequency contents that generally appear under the influence of a fault. For instance [3] deeply study faults in a three phase induction machine. The spectral analysis of electric and electromagnetic signals shows that mechanical abnormalities such as broken rotor bars generate characteristic frequency contents in the signals. The Fourier Transform is unable to accurately analyze and represent a signal with non periodic features, for instance a transient signal. To study non stationary signals, time-frequency methods replace traditional spectral analysis. The Short Time Fourier Transform interpretation is close to a local Fast Fourier Transform analysis. The signal to analyze is multiplied by a sliding signal with finite duration (such as a rectangular, a Hamming, a Blackman window, etc.). Thus the spectrum is computed in real time and its important variations are used to detect faults. This method has been applied for instance in the metallurgical industry [8]. Rise in productivity in modern rolling mill plants induces an increase of the rolling speed. This also increases the potential vibrations of the system. Different vibration frequencies appear that correspond to particular faults [18]. Thus monitoring the frequency contents can help to localize the faults.

3. MODEL BASED FAULT DETECTION EXAMPLE

A MIMO model was choose in order to offer proper conditions to design model based FDD procedures using parity equations. An example of a heat exchanger model, a MIMO system with m inputs and r outputs is presented in [10]. For each output a linear local model could be considered taking into account all process input:

$$y(s) = u(s)\frac{B_P(s)}{A_P(s)}; \quad y(s) = [y_1(s) \quad \dots \quad y_r(s)]^T; \quad u(s) = [u_1(s) \quad \dots \quad u_m(s)]^T \tag{1}$$

The FDD scheme was tested on a heat exchanger case by presenting several different process and sensor faults, using the model library (Figure 3).

The considered system inputs are: water input temperature θ_{Li}, water speed w_L (or water flow M_L), air-wall thermal flow q_{WG} (or air flow M_A) and air input temperature θ_{Ai}. The system outputs considered of major interest are the water output temperature θ_{Le} and secondary, the air output temperature θ_{Ae}.

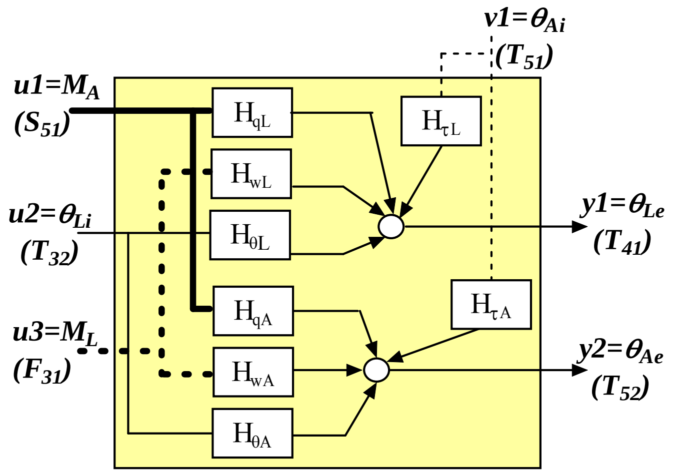

Figure 3. Heat exchanger MIMO model structure

The above transfer functions, their gains and time constants are calculated in [4]. Considering the MIMO transfer function model for the heat exchanger [4, 5] the next equations systems is obtained, where H_1 and H_2 take into account the sensor model and channel model between heat exchanger and sensors:

$$\begin{bmatrix}\theta_{Le}\\ \theta_{Ae}\end{bmatrix}=\begin{bmatrix}H_1 & 0\\ 0 & H_2\end{bmatrix}\cdot\begin{bmatrix}H_{qL} & H_{wL} & H_{\vartheta L}\\ H_{qA} & H_{wA} & H_{\vartheta A}\end{bmatrix}\cdot\begin{bmatrix}\dot{M}_A & \dot{M}_L & \theta_{Li}\end{bmatrix}^T \quad (2)$$

The model based FDD is design with parity equations that starts with the mathematical model of the process for water-air heat exchanger, Figure 3 and equation (2).

The residuals are calculated based on equations (3):

$$r(s)=w^T(s)\cdot\left[\begin{bmatrix}1\\0\end{bmatrix}\cdot\theta_{Le}(s)+\begin{bmatrix}0\\1\end{bmatrix}\cdot\theta_{Ae}(s)-\begin{bmatrix}H_1(s)\cdot H_{qL}(s)\\ H_2(s)\cdot H_{qA}(s)\end{bmatrix}\cdot\dot{M}_A(s)-\begin{bmatrix}H_1(s)\cdot H_{wL}(s)\\ H_2(s)\cdot H_{wA}(s)\end{bmatrix}\cdot\dot{M}_L(s)-\begin{bmatrix}H_1(s)\cdot H_{\theta L}(s)\\ H_2(s)\cdot H_{\theta A}(s)\end{bmatrix}\cdot\theta_{Li}(s)\right] \quad (3)$$

To obtain the decoupled residuals for each measured signal, $w^T(s)$ is computed imposing zero value for each terms of the r(s) equation.

For example the residual $r_{\vartheta Li}$ is decoupled for the measurement of the water input temperature sensor θ_{Li} by satisfying a condition like:

$$w^T(s)\cdot\begin{bmatrix}H_1(s)\cdot H_{\theta L}(s)\\ H_2(s)\cdot H_{\theta A}(s)\end{bmatrix}\cdot\theta_{Li}(s)=0 \text{ where } w^T_{\theta_{Li}}(s)=\left[-H_2(s)\cdot H_{\theta A}(s) \quad H_1(s)\cdot H_{\theta L}(s)\right] \quad (4)$$

A solution for the decoupled residual generator elements is underlined:

$$\begin{bmatrix}r_{\vartheta_{Le}}(s)\\ r_{\vartheta_{Ae}}(s)\\ r_{M_A}(s)\\ r_{M_L}(s)\\ r_{\vartheta_{Li}}(s)\end{bmatrix}=\begin{bmatrix}0 & 1\\ 1 & 0\\ -H_2H_{qA} & H_1H_{qL}\\ -H_2H_{wA} & H_1H_{wL}\\ -H_2H_{\theta A} & H_1H_{\theta L}\end{bmatrix}\bullet\left[\begin{bmatrix}1\\0\end{bmatrix}\theta_{Le}(s)+\begin{bmatrix}0\\1\end{bmatrix}\theta_{Ae}(s)-\begin{bmatrix}H_1H_{qL}\\ H_2H_{qA}\end{bmatrix}\dot{M}_A(s)-\begin{bmatrix}H_1H_{wL}\\ H_2H_{wA}\end{bmatrix}\dot{M}_L(s)-\begin{bmatrix}H_1H_{\theta L}\\ H_2H_{\theta A}\end{bmatrix}\theta_{Li}(s)\right] \quad (5)$$

The design residuals relation (5) is necessary for fault detection and identification. Each residual was designed to become independent to a specific measurement. In case that some of the measurements are damaged, the decoupled residual rest at a low value, instead all the other residuals are affected.

The relation (5) is completed with another two that represent the deviation of estimation values from the measured ones representing the residual build up with an output error method:

$$r^P_{\vartheta_{Le}}(t) = \hat{\vartheta}_{Le}(t) - \vartheta_{Le}(t)\,; \quad r^P_{\vartheta_{Ae}}(t) = \hat{\vartheta}_{Ae}(t) - \vartheta_{Ae}(t) \tag{6}$$

The group of residuals affected or not permits to locate certain faults. The residuals have the property to become zero if any fault exists or be different from zero if a fault appears in measurements or process.

In order to detect or to identify a fault a threshold value k_i must be settled for each residual in order to decide if the zero value of the residual has been reached or not. This value could be settled upon statistical or experimental considerations. In the last case this value can take into account the noise effects and the modelling errors too. The optimal selection of the thresholds is made through a compromise between false alarms and leak of fault detection. The thresholds values established for these residuals could cover the noise effects as well as modelling errors.

The detection of a fault depends on the most sensitive residual and its isolation on the less sensitive one (but not on the decoupled residual).

To isolate the fault source a set of residuals with different responses for each fault is needed. This principle is illustrated by incidence matrix (Table 2), each column representing a fault signature. The results presented in previous incidence matrix are valuable for investigated faults. This set of residuals is build to be very sensitive to faults in temperature sensors, so a small deviation like 1÷3 ^{o}C (1÷6% from maximal value) could be detected and isolated. For other faults the sensitivity is decreasing and only faults greater then 10% could be isolated. Smaller errors could be only detected.

Table 2. Incidence Matrix

	Sensor's and actuators fault				
	F_{31}	S_{51}	T_{32}	T_{41}	T_{52}
$r_{\vartheta_{Le}}$	1	1	0	0	1
$r_{\vartheta_{Ae}}$	0	1	1	1	0
$r_{\dot{M}A}$	0	0	0	1	0
$r_{\dot{M}L}$	0	1	1	1	1
$r_{\vartheta_{Li}}$	1	1	0	0	1
$r^P_{\vartheta_{Le}}$	0	1	1	1	0
$r^P_{\vartheta_{Ae}}$	1	1	0	0	1
0 – un-deflected residual					
1 – significant residual deflection					

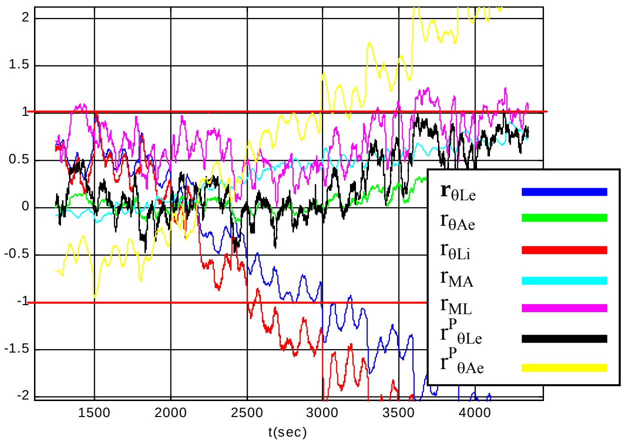

Figure 4. Unified representation of residuals for an incipient fault on actuator F31 started at time t=2000 s

To illustrate the above considerations a fault analysis will be presented. Considering an incipient fault in an actuator for water flow M_L (F31), that appears at moment t=2000s, it could be detected and isolated due to its value. The residuals deflections are depicted in Figure 4 and for a better illustration these results were normalized by its thresholds. This operation allows uniform representation of information and implies a unique threshold to be used for all residuals. The early detection of the fault will depend on the most sensitive residual ($r_{\theta Li}$).

4. SIGNAL BASED FAULT DETECTION EXAMPLE

In order to detect "low" frequency vibrations that are characteristic for a specific fault, a signal based detection method is presented in this section. The fault detection method uses the Stationary Wavelet Transform (*SWT*).

Wavelet decomposition can be implemented for FDD purpose when a fault occurrence is revealed by a signal singularity. The proposed detection method analyses the changes that appear over the different decomposition levels to detect the singularity. The hypothesis for fault isolation is that different faults induce different effects on the wavelet coefficients over the decomposition levels. The isolation method proposed analyses the modification of the wavelet coefficients over the different levels of decomposition to deduce which fault is present.

The detection procedure works in three steps. *The first step* transforms the signal into wavelets coefficients. It decomposes the signal on J scales. This step also allows characterizing the frequency contents that define the "normal" behavior of the system. *The second step* corresponds to the wavelet coefficient thresholds. A fuzzyfication of the threshold's coefficients is implemented:

$$\mu^j(\delta_k^j) = \begin{cases} 1 & \left|\delta_k^j\right| \geq 2\alpha^j\lambda^j \\ \dfrac{\left|\delta_k^j\right|}{2\alpha^j\lambda^j} & 0 < \left|\delta_k^j\right| < 2\alpha^j\lambda^j \\ 0 & \delta_k^j = 0 \end{cases} \tag{7}$$

where α^j is a parameter that defines the membership function of the coefficients.

The third step corresponds to the detection decision. In order to give a unique indicator, the various fuzzy coefficients are considered as partial criteria and the detection problem is regarded as a fuzzy decision making one with partial criteria. Fuzzy decision making allows formal modelling of decision-making for imprecise and uncertain conditions. The decision (here the detection decision) is considered as a fuzzy set described by its membership function μ_d that is computed using the membership functions of the various partial points of view on the final decision $c_i(d)$:

$$\mu_d = h\left(c_1(d), c_2(d), \ldots, c_p(d)\right) \tag{8}$$

where h is a fuzzy set operator to be determined in function of the properties that are required for the decision.

When a singularity occurs in the signal, at least one level of decomposition must reveal its appearance, and the singularity may not be present over all scales. Thus, (9) is proposed for the detection decision:

$$D1_k = \max_j(\mu_k^j);\ j = 1:J \tag{9}$$

From a practical point of view, it can be observed that the wavelet coefficients may be very small, during a very short time, even when there is a singularity in the signal. Thus (10) may be preferred to (9), to favor a clearer decision:

$$D2_k = \max_j\{\max(\mu_{k-l}^j); l = 0:N-1\};\ j = 1:J \tag{10}$$

where N is a small time window. [18] proposes a comparison of different aggregation operators to detect extra vibrations (considered as faults) in a rolling mill.

For fault isolation, the singularity appearance must modify differently the various levels of decomposition, depending on the considered fault. A learning phase shows which levels are modified by a specific fault. For example, consider a signal that is decomposed over 5 levels. Moreover, suppose that the wavelet coefficients on levels i and j are modified by the fault, while the coefficients on levels k, l, m are not modified. This situation can occur for instance when the fault gives rise to oscillations in a specific frequency range as reported by [3] for electrical drives or [17] for rolling mills. The isolation decision for this specific fault can be given by:

$$D3_k = \min\left(\mu_k^i,\ \mu_k^j,\ (1-\mu_k^k),\ (1-\mu_k^l),\ (1-\mu_k^m)\right) \tag{11}$$

The decision rule D3 expresses that the coefficients on levels i and j must be "high" at the same time, and the other coefficients must be "small", to decide that this fault is present.

For a wide range of applications, particular additive frequency contents are related to the occurrence of a particular fault (e.g. faults in rolling mill process or abnormalities such a broken rotor bars in induction motor). In other applications, the signals recorded on the process exhibits impulses in amplitude or a pseudo frequency occurrence when a fault occurs. All these situations can be handled with *SWT*. Table 3 gives three academic examples that illustrate these situations.

The parameters are f = 50Hz, f_1 = 20Hz, f_2 = 350Hz, f_3 = 175Hz. Scenario 0 corresponds to the reference signal (i.e. "normal" behavior): it corresponds to a noisy sinusoidal signal. ε is a Gaussian white noise with zero mean and variance σ^2 chosen such that the Signal-to-Noise Ratio is $SNR \approx 10dB$.

In scenario 1, extra frequency contents f_1 and f_2 occur at time $t = \tau_1$ during a time interval $\tau_2 - \tau_1$ and another additive frequency f_3 occurs at instant $t = \tau_3$ during a time interval $\tau_4 - \tau_3$ ($\tau_1 < \tau_2 < \tau_3 < \tau_4$). Scenario 2 corresponds to a fault characterized by the appearance of periodic impulses while scenario 3 deals with the appearance at time $t = \tau_1$ of a pseudo frequency of duration $\tau_2 - \tau_1 > 0$.

Table 3. Scenario and simulated signal

Scenario no.	***Simulated signal***
0	$x_{ref}(t) = \sin(2\pi ft) + \varepsilon(t)$
1	$x_1(t) = x_{ref}(t) + 0.7(\sin(2\pi f_1 t) + \sin(2\pi f_2 t))(u(t-\tau_1) - u(t-\tau_2)) + 0.7\sin(2\pi f_3 t)(u(t-\tau_3) - u(t-\tau_4))$
2	$x_2(t) = x_{ref}(t) + 40\sum_{k=1}^{n}(-1)^{k+1}\delta(t - k\tau_1)$
3	$x_3(t) = x_{ref}(t) + 2e^{-0.25(2\pi f_1 t)}\sin(2\pi f_1 t)(u(t-\tau_1) - u(t-\tau_2))$

In order to detect and isolate the faults described in scenarios 1 to 3, some parameters of the *SWT* must be discussed. The sampling frequency f_e of the signal and the number of decomposition level of the wavelet transform are related to the frequency that must be detected. Actually, the *SWT* can be performed with different wavelets. For instance, the Mallat wavelet is used in [16] for detection and identification of faults in HVDC systems. The Morlet wavelet has been used in the literature for the analysis of vibration signals recorded on rotating machineries [17]. This is due to the fact that the Morlet wavelet is able to pick up impulses generated by the rotating elements. Other wavelets are used in the literature but the Daubechies' wavelets [4] are used in a wide range of applications [13, 14]. This is certainly due to their "nice" properties (compact support, number of vanishing moments, orthogonality, etc.).

For the examples in Table 3, a wavelet decomposition over 5 levels (J = 5) is sufficient to ensure a good detection. The sampling frequency is equal to 1 kHz. The Daubechies 12 "*db*12" wavelet has been used because it is able to highlight the "faulty" extra frequency contents. The thresholds λ^j have been computed with the reference signal x_{ref}. x_1, its *SWT* decomposition and the thresholds d^j are given in Figure 5.

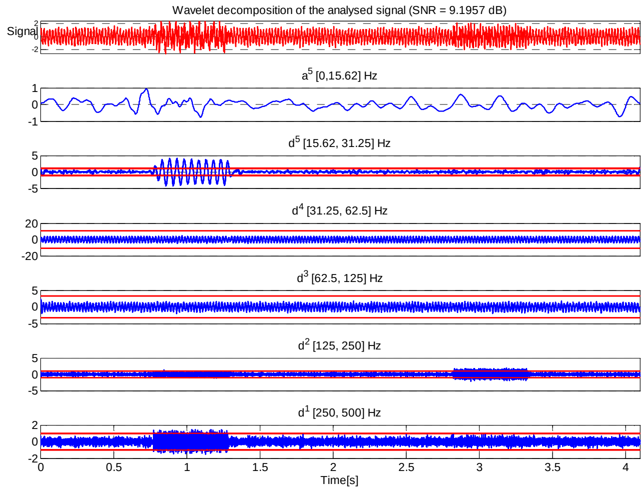

Figure 5. The signal x_1 and its SWT decomposition

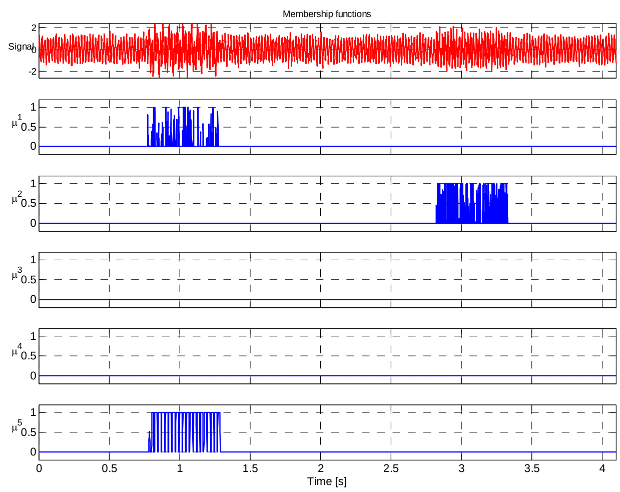

Figure 6 Fuzzyfication of the thresholded coefficients

The *SWT* coefficients d_5 and d_1 clearly exhibit the extra frequency contents f_1 = 20Hz and f_2 = 350Hz. This can be explained by the dyadic split of the frequency domain. The other extra frequency content is characterized by $f_3 = 175\text{Hz}$. It is exhibited in the coefficients d_2 on the second level of decomposition. The threshold's coefficients are fuzzyfied with the membership functions $\mu^j,\ j = 1:5$ calculated with (7). The result is shown in Figure 6. The abnormality in each frequency band is clearly exhibited.

The fault detection indicator *FD* is computed with (10). It measures the appearance of an abnormal behavior over all the levels of decomposition. When fault isolation is considered, specific aggregation operators must be defined. These new operators take into account some knowledge on the kind of singularity that appears when a particular fault occurs. Thus, the fault isolation decisions that are defined are given by:

$$FI_{F1} = \min\{\mu_1, (1-\mu_2), (1-\mu_3), (1-\mu_4), \mu_5\};\ FI_{F2} = \min\{(1-\mu_1), \mu_2, (1-\mu_3), (1-\mu_4), (1-\mu_5)\} \quad (12)$$

Results are shown in Figure 7.

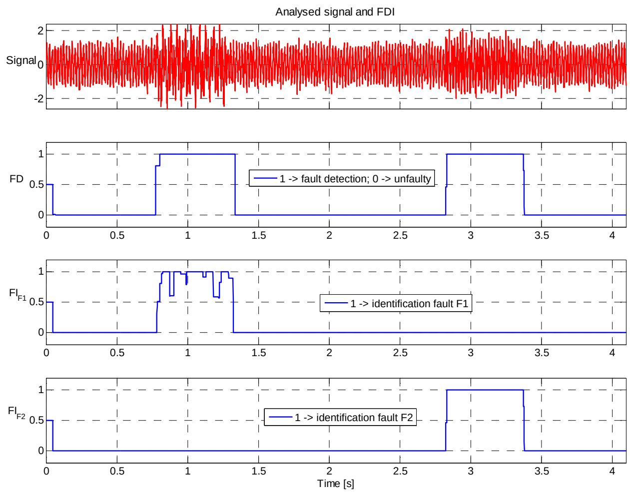

Figure 7. The signal x_1 and *FD*, FI_{F1}, FI_{F2}

It can be observed that the isolation decision FI_{F1} that is devoted to the detection of frequencies f_1 and f_2 clearly identifies this fault. Identically FI_{F2} is able to detect the fault characterized by f_3.

For the second and third scenario the fault detection and isolation procedure is similar to the one presented for scenario 1 but the decision rule that takes into account all the decomposition levels could be different.

5. CONCLUSIONS

The diagnostics procedures are based on the observed analytical and heuristical symptoms and the heuristic knowledge of the process. In this paper a comparison between different methods of fault detection and an overview of the fault detection and diagnosis procedure for technical system is provided. For some classes of processes the structure and some parameters are well known but for others only rough models are available. Therefore the methods for fault detection and diagnosis are mainly different.

Two examples of process model/signal based FDD methods were illustrated within the paper.

A process model based approach for FDD was presented based on analytical relations between characteristics of analyzed process and on the measured signals, also. However, in many processes the sensors and actuators already exist for control and supervision purpose, but the analytical relation between the measured signals is not exploited. In these cases the approach can easily improve the process supervision.

Analytical model's parameters have been used to generate the suitable equations to detect and isolate faults. A powerful method for this purpose seams to be building residuals with parity equations support. The set of affected and unaffected residuals points to the fault location. Design of the parity equations is suitable for processes with more than one measured output. Herein, MIMO processes were considered. For each residual it was set a suitable threshold that allows detection or isolation decision for a fault by monitoring the residual deflections. The residual sensitivity depends on parity equation parameter and input measured signals. It was underlined that detection of a fault depends on the most sensible residual but, in the mean time, the fault isolation depends on the less sensible residual (no the decoupled one).

The capability for the stationary wavelet transform to deal with different faults for fault detection and isolation has been investigated. A detection procedure based upon the thresholds of the wavelet coefficients has been considered. These coefficients are fuzzyfied and aggregated in order to provide a symptom. The tuning parameters of this procedure are the wavelet itself, the number of decomposition levels, the thresholds and the decision method. The wavelet choice depends on the features that must be detected in the signal under analysis. This selection is sometimes not unique. For detection purpose, the final choice is made in order to maximize the symptom sensitivity.

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