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Reliability Analysis of Fluid Leak Detection and Isolation System

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Abstract: Reliability analysis of a leak detection system developed by OSYRIS R&D is dealed with in this paper. The developed algorithm is based on signal processing theory; and it uses the properties of the cross-correlation function in order to distinguish the fluid leak from a various disturbances. Experimental results obtained on different processes, in presence of thermal and hydraulic disturbances, show the advantages and limits of the proposed approach.

Key words: Fault detection and isolation, thermo-fluid process, signal processing.

1. Introduction

The detection and isolation of fluid leakage is a major economic and security challenge in several areas (nuclear, petroleum, petrochemical, steel, distribution networks of drinking water). Several research studies published in the literature proposed different approaches based on qualitative or quantitative models.

Among the studies, quantitative models for leak detection and isolation where used: a dynamic model with distributed parameters of the pipeline including several leaks was considered, and the principle of analytical redundancy for residual generation was used in Ref. [1, 2]. In Ref. [3], a robust Fault Detection and Isolation (FDI) approach based on bond graph model in Linear Fractional Transformation (LFT) form was developed, then applied on a steam generator. Leak detectable value is identified a priory using a residual sensitivity analysis.

The performances of quantitative approaches depend directly on the accuracy of models, which later are difficult to be achieved because of the multiphysical and non-stationary aspect of the process engineering systems.

Qualitative methods use the principle of pattern recognition, which consists of dividing the parameter space into classes, corresponding to the known operating modes. Mathematical relationships between the effects (comments of experts, sensor measurements and statistics) and causes (faults) are determined by learning. Those approaches have been the subject of several publications in recent years [4-6].

The signal processing methods are a part of the qualitative FDI approaches. These methods use the signal theory for extracting useful information (faults) from the raw signals issued from sensors. In Ref. [7], presents a comparative analysis of several FDI techniques based on signal processing was presented. The electrical, acoustic and electromagnetic signals are widely used for leak diagnosis, but these techniques use the local characteristics of the leakage, and can not locate leaks in a great scale. In Ref. [8], a cross-correlation of an acoustic signals is used for leak detection in distribution networks of drinking water, this algorithm is implemented using a Digital Signal Processing (DSP) processor, in order to improve the calculation time of the cross-correlation. Another

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techniques uses the signature of the transient operating mode of the system to detect and isolate leaks.

In this work, a method of leak detection based on signal processing is analyzed. This approach developed by OSYRIS R&D [9] is based on the crosscorrelation of flow input-output signals of the pipe. Reliability tests are performed on different processes, to show the robustness of the algorithm to the thermal and hydraulic perturbations and its sensitivity to faults (leaks).

2. Leak Detection Algorithm

The leak diagnosis method developed by OSIRIS R&D is a qualitative method based on signal processing. It uses the properties of the crosscorrelation function, so it is necessary to recall the definition and properties of the crosscorrelation function.

The crosscorrelation functions is used to evaluate the similarity of the pair of functions x(t) and y(t) which may be random or deterministic. When stationarity conditions are met, mutual covariance becomes the raw crosscorrelation function, noted usually $C_{xy}(\tau)$ [10]:

$$C_{xy}(\tau) = E\lfloor x(t).y^*(t+\tau)\rfloor \tag{1}$$

Where E is the mathematical expectation, and y* is the conjugate of y.

Each function must be defined by the same origin, and τ represents the delay of y(t) according to the origin [10].

For functions satisfying the ergodic principle, the mean calculation can be generalized on the variable t:

$$C_{xy}(\tau) = \lim_{T\to\infty} \frac{1}{T} \int_{-T/2}^{T/2} x(t)\cdot y^*(t-\tau) \tag{2}$$

In the general case of non-stationarity, the moments and covariance depend on the parameter t. This makes the study of nonstationary random functions be difficult. However, many physical phenomena or measurement data are managed by stationary random functions. We can say that a random function is strictly stationary if its statistical properties are independent of the parameter t.

If we consider two samples, x_{t1} and x_{t2}, of a random function x(t), the strict stationarity implies that the probabilities or probability densities associated with x(t) are independent of the choice of t_1 or t_2, property that can be expressed as [10]:

$$P(x_{t_1}) = P(x_{t_2}) \tag{3}$$

Where $P(x_{t_1})$ and $P(x_{t_2})$ are the probability densities of x at times t_1 and t_2 respectively.

2.1 Properties of the cross correlation function:

A change of variable shows that the crosscorrelation function is insensitive to the permutation functions x(t) and y(t), which means that we can write:

$$C_{xy}(\tau) = C_{yx}(\tau) \tag{4}$$

- When the functions x(t) and y(t) do not have a stochastic dependence, the crosscorrelation function is independent of the delay τ;
- Unlike the autocorrelation function, $C_{xy}(\tau)$ is not a pair function, the maximum is not necessarily centred on the origin;
- The crosscorrelation between x(t) and y(t) reaches a maximum for a delay τ if:

$$x(t) = y(t+\tau) \tag{5}$$

- If one calculates the correlation of raw signals x and y with non-zero means, a constant is added to the results:

$$C_{xy}(\tau) = Cx'y'(\tau) + \bar{x}.\bar{y} \tag{6}$$

With $x' = x - \bar{x}$ and $y' = y - \bar{y}$. $\bar{x}$ and $\bar{y}$ are respectively the mean values of x and y.

2.2 Method Developed by OSYRIS R&D

Measurements are issued from flow sensors placed at both ends of the pipes to monitor. These signals are then transmitted to the diagnosis system via optic fibber cables, to better retain information and to avoid electromagnetic disturbances. The diagnosis system consists of a processor, on which the crosscorrelation function of the two signals of flow measurement is programmed.

An observation window of 1,024 samples per second is considered. On each window, the mean value is calculated and removed from all the samples of the window. During the operation of the system, a sliding mean is calculated every 30 windows, then removed from all the samples of 31 window.

The fault indicator (residual) represents the discrete crosscorrelation function of flow signals acquired in real time, this function is calculated in several forms on finite energy signals. The crosscorrelation function used by OSYRIS R&D [9] is given as follows:

$$C_{HS}(j) = \sum_{k=0}^{n-1} H_k . S_{j+k} \quad (7)$$

Where $Hk = (E_k - S_k)$; E_k are the values resulting from sampling the measurement of input signal E(t) (vector of size n); S_k are the values resulting from sampling the measurement of output signal S(t) (vector of size n); n is the total number of samples E_k and S_k in a defined observation window; k is an integer varying from 0 to (n-1); j is an integer varying from -(n-1) to (n-1), which takes thus the following successive values:

-(n-1), -(n-2),..., -2, -1, 0, 1, 2,...,(n-1);

$C_{ES}(j)$ is a vector of size 2n-1, and the residual represents the time evolution of the central peak of $C_{HS}(j)$.

For example, to compute the crosscorrelation with 1000 successive samples E_k and S_k (k varying from 1 to n and n=1000), the sampling frequency is of 1 kHz. For each set of n samples, a crosscorrelation vector is calculated every second. In this example, every second, 1999 values are calculated from $C_{HS}[-(n-1)]$ to $C_{HS}(n-1)$ as follows:

$$\begin{cases} C_{HS}[-(n-1)] = H_0.S_{n-1} \\ C_{HS}[-(n-2)] = H_0.S_{n-2} + H_1.S_{n-1} \\ .... \\ C_{HS}(n-2) = H_{n-2}.S_0 + H_{n-1}.S_1 \\ C_{HS}(n-1) = H_{n-1}.S_0 \end{cases} \quad (8)$$

The operating thresholds are determined experimentally after a battery of tests on a test-bench. Signatures (maximum amplitude of the crosscorrelation function) of each mode (Normal, faulty and in the presence of various disturbances) are recorded and saved.

If the signature of the leak is different from that of normal operation, the fault (water leak) is detectable.

If the signature of the fault is different from those caused by any disturbance, the fault is isolable.

The fault detection threshold is determined using the system for a leak of 0.05 m³/h on a nominal input flow of 0.82 m³/h, and corresponds to a residual amplitude of (-0.2). So, the leak is detected and an alarm is generated when Rsidual<Threshold.

The thresholds calculated on the test bench can be generalized to other equivalent systems when the conditions of stationarity are satisfied, as on the systems proposed in sections 3 and 4, where the conditions of stationarity are met, but the used powers and flows are very different.

The diagnosis system developed by OSYRIS R&D [9] is designed to meet the following specifications:

- Sensitivity to the fault (fluid leak): sensitivity announced depends on the nominal input flow and can reach about 0.1% of a nominal flow.
- Robustness to hydraulic disturbances and thermal disturbances.

3. Application to the First System

The first process is a laboratory system, constituted by a set of interconnected pipes forming a flexible circuit. Intermediate valves placed along the circuit can change the direction of flow in order to create hydraulic disturbances. Two electromagnetic flow meters (KROHNE IFC010) are placed at the input and output of the system. The measured flows are transmitted to the diagnosis system by fiber optic cables, in order to preserve the measuring signals against electromagnetic disturbances. The diagnosis system is a controller on what are programmed: the crosscorrelation function of the two flow measurements, the thresholds determined experimentally, the user interface displaying two alarm levels and a graphical window showing the residual evolution in real time. The system of water supply consists of a tank assumed full filled and a pump of 1600 W power, generating an average input flow of 0.82 m³/h. The output flow is fed back into the feed tank forming a closed circuit.

3.1 Experimental Results

The experimental scenario aims to verify the specifications. After checking the normal operation of the system, the following tests are achieved:

- Review of the normal functioning of the system
- Test of sensitivity to the fault (leaks);
- Test of the robustness to hydraulic disturbances;
- Test of robustness to thermal disturbances;

The thresholds of the normal operating are determined experimentally, and give rise to alarms depending on the intensity of the leak. The alarm levels are determined after a battery of tests on the system. All operating modes are considered (normal, disturbed and failing). The fault detection threshold is set in this application for a leak of 0.05 m^3/h on a nominal input flow of 0.82 m^3/h corresponding to 6.09% of the nominal input flow. It corresponds to residual amplitude of (-0.2).

Fig. 1(a) shows the evolution of the fault indicator during normal operation. The maximum amplitude of the residual is about (-0.002) , widely less than the fixed threshold, then no alarm is generated. The input and output flows in normal operation are given in Figs. 1(b) and 1(c) respectively.

The residual evolution in presence of a leak of 0.1 m^3/h is illustrated in Fig. 2(a). The input nominal flow is about 0.82 m^3/h, thus the leak is about 12% of the nominal flow. The residual reached a magnitude of (-0.25), well less the threshold of normal operation, then an alarm is generated. The input and output flows in presence of the leakage are given in Figs. 2(b) and 2(c) respectively.

The test bench is equipped with valves placed between two flow meters, in order to create hydraulic disturbances. The evolution of the residual in presence of hydraulic disturbances is given in Fig. 3(a). The minimum amplitude of the fault indicator is (-0.04), widely above the threshold, thus no alarm is generated. The algorithm is robust to hydraulic perturbations. The input-output flows in presence of hydraulic disturbances are given in Figs. 3(b) and 3(c) respectively.

Tests of robustness to thermal perturbations are achieved by introducing hot water at different temperatures directly in the supply system. Fig. 4(a) shows the evolution of the residual in presence of a sudden change in the water temperature from 30 ℃ to 45 ℃, and this represents a variation of 50 % of the nominal temperature of the water. The water temperature is then gradually increased until 65 ℃ which is the maximum temperature supported by the test bench. The minimum amplitude of the fault indicator is (-0.04), thus, the algorithm is robust against thermal disturbances. The input and output flows in the presence of a variation of the temperature of water supply from 30 ℃ to 45 ℃ are given in Figs. 4(b) and 4(c) respectively.

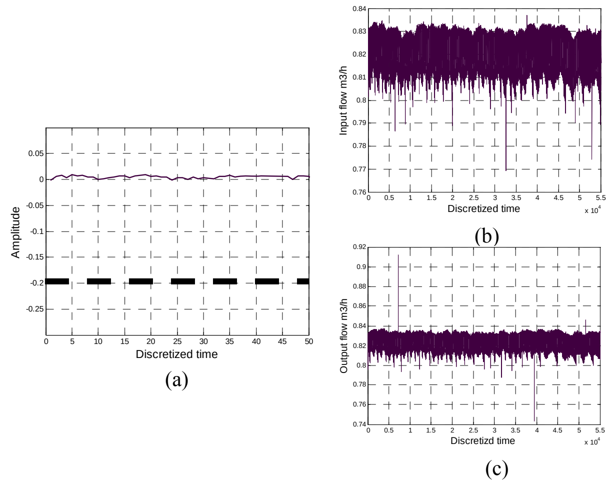

Fig. 1 (a): Residual in normal operation. (b): Input flow. (c): Output flow.

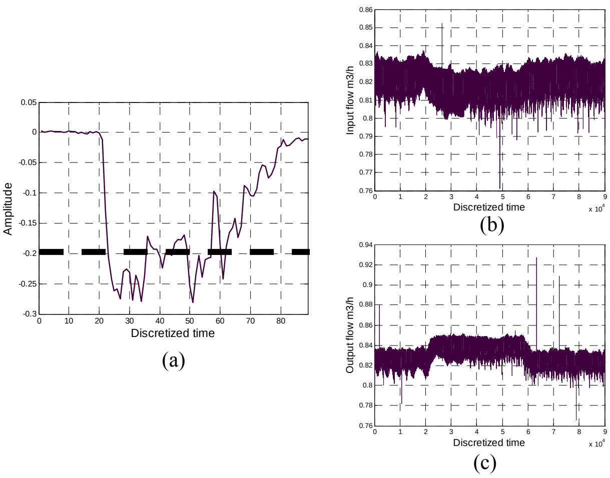

Fig. 2 (a): Residual in presence of a leak. (b): Input flow. (c): Output flow.

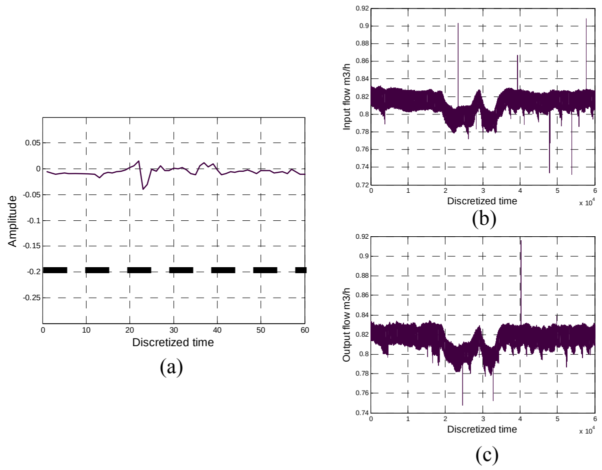

Fig. 3 (a): Residual in presence of hydraulic disturbances. (b): Input flow. (c): Output flow.

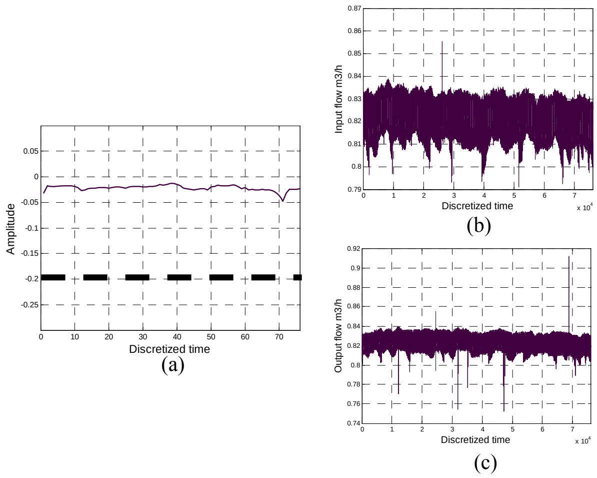

Fig. 4 (a): Residual in presence of thermal disturbances. (b): Input flow. (c): Output flow.

The technical specifications and obtained results in the first application are summarized in Table 1

4. Application to the Second System

The second system presents very similar characteristics to those found in industrial installations, such as cooling circuits of nuclear power plants and steel furnaces. The system is constituted by a tank assumed full filled, which feeds the circuit through two pumps of 1600 W power installed in parallel, delivering a nominal input flow about 6.77 m^3/h. The circuit is an interconnected set of pipes with valves, thus allowing the introduction of significant hydraulic disturbances in real time. The tank of water supply is equipped with a heater with a power of 3750 W, allowing the introduction of thermal disturbances. Two different electromagnetic flow meters (KROHNE IFC010 and EH PromagW) are installed at the input of the system and tow at the output of the system, to show that the performances of the leak detection algorithm are independent on the type of the used sensors.

The experimental scenario is similar to that performed in the first application, without any learning step for determining the threshold of normal operation. The threshold generated in the first application is used in this application in order to show that: if the stationarity conditions are satisfied, the system of supervision can be implemented without the learning step for thresholds determination, because the learning can not be performed on real industrial plants.

4.1 Experimental Results

Fig. 5(a) shows the evolution of the fault indicator during normal operation. The minimum amplitude of the residual is about (-0.12), then no alarm is generated. The input and output flows in normal operation are given in Figs. 5(b) and 5(c) respectively.

The residual evolution in presence of a leak of 0.03 m^3/h is illustrated in Fig. 6(a). The residual reached a magnitude of (-0.8), well less the threshold of normal operation, and then an alarm is generated. The input-output flows in presence of the leakage are given in Figs. 6(b) and 6(c) respectively.

The test bench is equipped with a valves placed between the two flow meters, in order to create hydraulic disturbances. The evolution of the residual in presence of hydraulic disturbances is given in Fig. 7(a). The minimum amplitude of the fault indicator is (-0.1), thus no alarm is generated. The algorithm is robust against hydraulic perturbations. The input and output

Table 1 Specifications of the first application.

Specification	*Application 1*
Nominal flow	0.82 m^3/h
Pipes section	7 mm
Used sensors	KROHNE IFC010
Detected value of leak	0.05 m^3/h

flows in presence of hydraulic disturbances are given in Figs. 7(b) and 7(c) respectively.

Fig. 8(a) shows the evolution of the residual in presence of a change in the water temperature from 30 ℃ to 45 ℃, and this represents a variation of 50% of the nominal temperature of the water. The water temperature is then gradually increased until 50 °C. The minimum amplitude of the fault indicator is (-0.15), thus the algorithm is robust against thermal disturbances. The input and output flows in the presence of a variation of the temperature of water supply from 30 ℃ to 45 ℃ are given in Figs. 8(b) and 8(c) respectively.

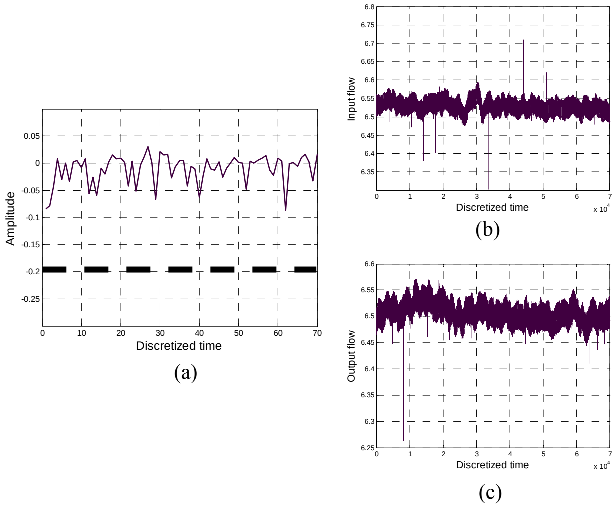

Fig. 5 (a): Residual in normal operation. (b): Input flow. (c): Output flow.

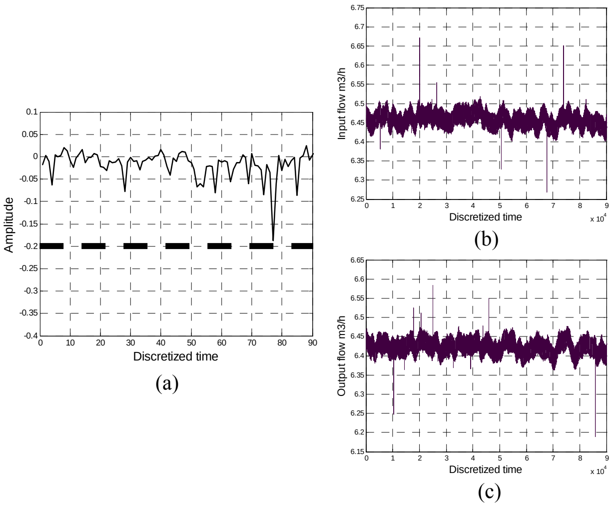

Fig. 6 (a): Residual in presence of a leak of 0.03m³ / h. (b): Input flow. (c): Output flow.

An other set of tests is realized on the second system by stopping one of the two pumps. The nominal input flow is about 2.77 m³/h. Figs. 9(a), 9(b), 9(c) and 9(d) show the profile of residual in normal situation, presence of leak of 0.035 m³/h, presence of hydraulic disturbances and presence of thermal disturbances respectively. The technical specifications and obtained results in the second and the third applications are given in Table 2

The first system is connected to the second system to simulate a complex process consisting of subsystems of different sizes fed by a single source, as shown in the schematic in Fig. 10. A nominal input flow of 6.5 m³/h is generated by the pumps, then distributed on the two

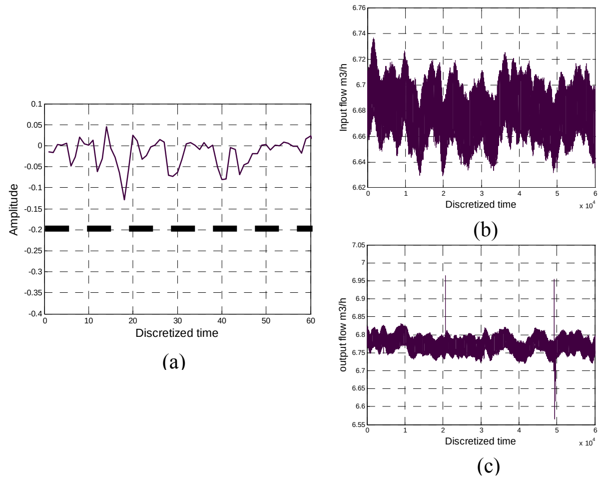

Fig. 7 (a): Residual in presence of hydraulic disturbances. (b): Input flow s. (c): Output flow.

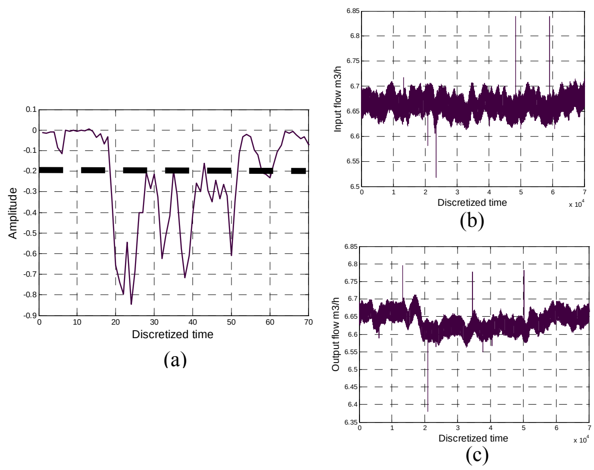

Fig. 8 (a): Residual in presence of thermal disturbances. (b): Input flow. (c): Output flow.

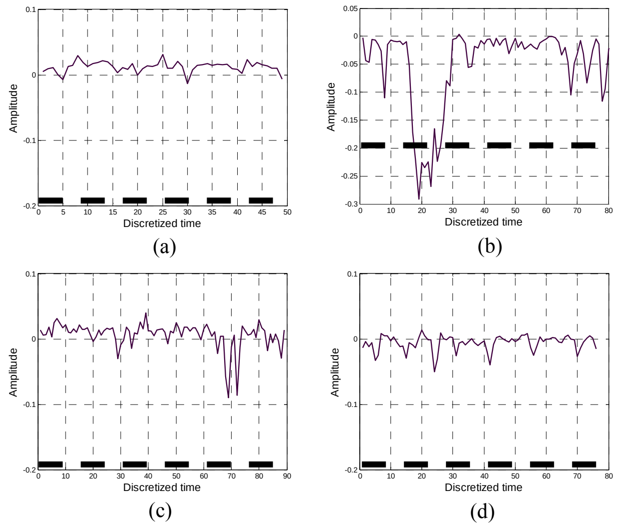

Fig. 9 (a): Residual evolution with nominal input flow of 2.77 m³/h. (a): Residual in normal operation. (b): Residual in presence of a leak of 0.035 m³/h. (c): Residual in presence of hydraulique disturbances. (d): Residual in presence of thermal disturbances.

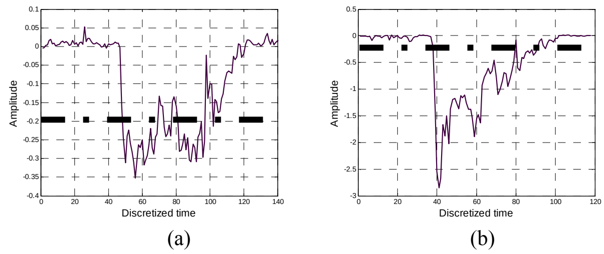

Fig. 10 (a): Residual in presence of a small leak in the system of small dimension. (b): Residual in presence of a decreasing leakage in the system of large dimension

Table 2 Specifications of the second application.

Specification	*Application 2*	*Application 3*
Nominal flow	6.77 m^3/h	2.77 m^3/h
Pipes section	32 mm	32 mm
Used sensors	IFC010 ; PromagW	IFC010
Detected value of leak	0.03 m^3/h	0.035 m^3/h

systems. The nominal output flow of the system of small size is about 0.45 m^3/h and that of the system of a large size is about 5.56 m^3/h.

Two situations are tested: the presence of a small leak in the system of small dimension, then the presence of a decreasing leak in the system of large dimension.

Fig. 10(a) shows the residual in presence of a small leak (0.05 m^3/h) in the system of small dimension. By keeping the same threshold used in the two previous applications [amplitude of (-0.2)], the leak is clearly detected and an alarm is generated.

Fig. 10(b) shows the residual in presence of a decreasing leak in the system of large dimension. A leak of 0.15 m^3/h is caused, then gradually reduced to 0 m^3/h. The residual decreases sharply and reaches a magnitude of (-2.8), then increase gradually following the reduction of the leak.

5. Conclusions

In this work, a reliability study and analysis of a leak diagnosis method based on signal theory are performed. The method developed by OSYRIS R&D is based on the properties of the crosscorrelation function of random signals, applied to the measurement of the flow sensors placed at the input and output of the pipes to monitor. This approach is applicable when the stationarity condition is satisfied, which is used for fluid leak detection on the systems in a permanent operating modes, and experimental results obtained on different systems demonstrates the robustness of the method to hydraulic and thermal disturbances and its sensitivity to leaks. The approach developed by OSYRIS R & D is not applicable in transient operating modes of the system, such as starting and stopping modes, because the condition of stationarity is not satisfied. The method developed is aimed particularly to the diagnosis of leaks in cooling systems in industrial plants, where the transients modes are short and not continuous in time, then fluid leakage can be easily distinguished because it is a continues phenomenon.

The innovative interest of this approach is the facy that when the stationarity conditions are satisfied, the system of supervision can be implemented without the learning step for thresholds determination.

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