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Wavelet Decomposition Applied to Fluid Leak Detection and Isolation in Presence of Disturbances

M. A. Djeziri, S. Benmoussa, B. Ould Bouamama and M. Ouladsine

Abstract— **This paper deals with wavelet decomposition applied to fluid leak detection and isolation in process engineering. The developed algorithm is sensitive to minor leaks and robust to all the disturbances (hydraulic and thermal perturbations) and transient operating modes. The proposed approach is based on the Discrete Wavelet Transform (DWT) of the sensor measurements, the Fast Fourier Transform (FFT) and the properties of the cross-correlation function. Experimental results obtained on different processes show the efficiency of the proposed approach.**

I. Introduction

The detection and isolation of fluid leakage is a major economic and environmental challenge in several areas (nuclear, petroleum, petrochemical, distribution networks of drinking water,...). This issue explains the growing interest by the scientific and industrial communities for the development of a reliable algorithms of leak detection and isolation. Several research studies have been published in the literature, and propose different approaches based on qualitative or quantitative models.

Among the studies using quantitative models for leak detection and isolation, *C. Verde[2001] [4]* which considers a dynamic model with distributed parameters of the pipeline including several leaks, and uses the principle of analytical redundancy for residual generation. In *M. A. Djeziri & al[2008] [7],* a robust Fault Detection and Isolation (FDI) approach based on bond graph model in Linear Fractional Transformation (LFT) form is 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, those later are complex to achieve because of the multiphysical and non-stationary aspect of the process engineering systems.

Qualitative methods use the principle of pattern recognition, which consists in 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. Unfortunately, it is not usually possible to identify all possible operating modes of a complex systems, because of their non-stationarity, the imperfect knowledge of parameter values and their random variations. Those approaches has been the subject of several publications in recent years, such as: *J.T.Hsiung & al[1996] [3],* where three methods of classification (quadratic discrimination, nearest neighbor and the artificial neural networks) are compared for detecting leaks in a heat exchanger. The classification stage is preceded by a signal processing step, which consists in filtering an acoustic data issued from hydrophones by an autoregressive model. The acoustic signals are extremely noisy, and distorted by reflections on the pipe walls, it is very difficult to extract useful information (leak) from external noise. *S. A. Tassou & al[2005] [10]* propose a fault diagnosis and refrigerant leak detection system based on artificial intelligence and real-time performance monitoring. The system has been used to distinguish between faulty operation and an other situation like steady-state and transient operation. *H.V. da Silva & al[2005] [5]* use a fuzzy classifier for the detection and isolation of leaks in pipelines, the algorithm takes into account the permanent and transient operating modes, and generates adaptive thresholds depending on the operating modes of the system. The using of a fuzzy classifier does not solves the problem of the decision in the borders of the operating classes and causes false alarms. In *H. Habbi & al[2009] [9],* a procedure for detecting leaks in a heat exchanger using a fuzzy dynamic model is presented. The model is implemented simultaneously with the real system, then the leakage indicator represents the difference between the real operating system and the reference model.

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. *A. F. Colombo [2009] [8],* presents a comparative analysis of several FDI techniques based on signal processing. The electrical, acoustic and electromagnetic signals are widely used for leak diagnosis, but these techniques uses the local characteristics of the leakage, and can not locate leaks in great scale. Another techniques uses the signature of the transient operating mode of the system to detect and isolate leaks. Signal processing methods do not require a large number of sensors comparing to quantitative approaches, and their implementation on the system is so easy and possible.

In this work, a method of leak detection based on wavelet decomposition is presented. This work is realized in the frame of a scientific partnership between the University of Sciences and Technologies of Lille (USTL) and OSYRIS R&D *[11]* company (high-tech company specializing the in field of the laser), for developing a Fault Detection and

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Isolation (FDI) system, able to detect and to isolate a minor leak and robust to all the disturbances (hydraulic and thermal perturbations) and transient operating modes.

This manuscript is organized as follows:

Section 2 presents the leak detection algorithm , highlighting its advantages and limits. *Sections 3* presents the application of this method in real time on a large scale system. The paper ends with concluding remarks and synthesis.

II. Leak detection algorithm

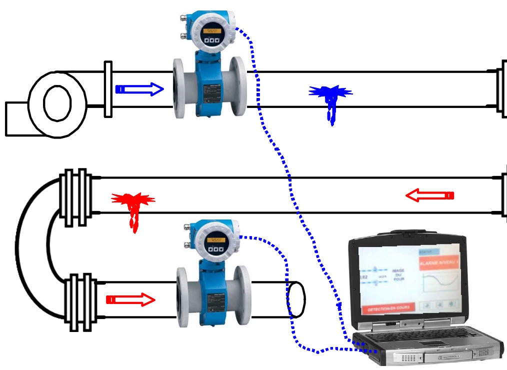

Fig. 1. Schematic diagram of the system instumentation

As illustrated in the Schematic of Fig.1, a 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 an optic fiber cables, to better retain information and to avoid electromagnetic disturbances. The diagnosis system consists of a processor, on which is programmed a FDI algorithm. This later is summarized in the following steps:

- Wavelet decomposition of the input signal $E(k)$ and output signal $S(k)$,
- FFT of the signals issued from the wavelet decomposition,
- Calculation of the product of the treated signals in the frequency domain in order to reduce computation time, which is important from a FDI viewpoint,
- $(FFT)^{-1}$ of the obtained result.

A. DWT of the measurements

The wavelet transform allows an analysis of a local structures of a signal with a zoom depending on the considered scale. There are bases of $L^2(R)$ (space of integrable square functions) in which a signal can be decomposed in two parts: approximation A and details D. Let's recall the definition of the wavelet transform:

The mother wavelet Ψ in $L^2(R)$ with zero mean, which can be translates by a factor b and dilated by a factor a is given in expression (1):

$$\Psi_{a,b}(t) = \frac{1}{\sqrt{a}}\Psi\left(\frac{t-b}{a}\right) \tag{1}$$

The coefficients CW of the Continuous Wavelet Transform (CWT) of a function f at time b and scale a are given as follows:

$$CWf_{a,b} = \int_{-\infty}^{+\infty} f(t).\frac{1}{\sqrt{a}}\Psi\left(\frac{t-b}{a}\right)dt \tag{2}$$

The coefficients DW of the Discrete Wavelet Transform(DWT) are given by expression (3)

$$DWf_{l,m} = \sum_{k=1}^{N} f(k).\frac{1}{\sqrt{2^p}}\Psi\left(\frac{k-m}{2^p}\right) \tag{3}$$

with p and m represent respectively the scale and translation factors. $f(k)$ are the discretized values of $f(t)$. $k = [1,..,N]$ is the number of samples.

The main objective of the wavelet transform in this work is to extract the useful information (leak) from the raw signal. Unlike the transient operating modes which are a high frequency phenomena, the fluid leak is continuous in the time, it is therefore a low frequency phenomenon, which can be located in the approximation part of the decomposed signal. The thermal and hydraulic disturbances may also be contained in this part, so the Mallat algorithm of equations (4) and (5) is used in this work to decompose the signal into several levels l. The useful information (leak) is located in the approximation part of the determined level, as shown in the schematic diagrams of Fig. 2. The decomposition level l is determined experimentally in order to distinguish the leak from the thermal and hydraulic disturbances.

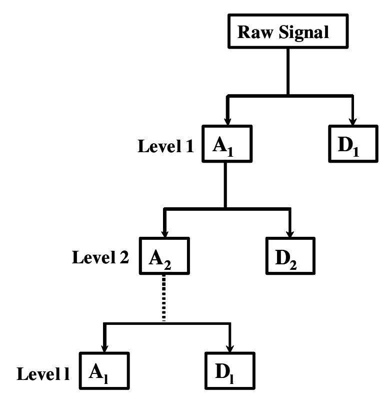

Fig. 2. Schematic diagram of Mallat decomposition algorithm.

$$\begin{cases} E_A(k) = \sum_{j=1}^{N} E(j).g(2k-j) \\ E_D(k) = \sum_{j=1}^{N} E(j).h(2k+1-j) \end{cases} \tag{4}$$

$$\begin{cases} S_A(k) = \sum_{j=1}^{N} S(j).g(2k-j) \\ S_D(k) = \sum_{j=1}^{N} S(i).h(2k+1-j) \end{cases} \tag{5}$$

with $E_A(k)$ and $S_A(k)$ $(k=[1,..,N])$ are respectively the k^{th} sample of the approximation part of the decomposed signals $E(k)$ and $S(k)$, $E_D(k)$ and $S_D(k)$ are respectively the details part of the decomposed signals $E(k)$ and $S(k)$. N is the size of the observation window. g and h are respectively a low frequency pass and high frequency pass filters (Quadrature mirror filters).

B. Cross-correlation function

The fault indicator (residual) represents the discrete cross-correlation function of acquired and treated flow signals $E_A(k)$ and $S_A(k)$, this function is calculated in several forms on finite energy signals. Due to the importance of the early detection of the leak, the correlation of the input and output signals is calculated in the frequency domain, where the calculation represents a simple multiplication (product). So, the FFT of the signals

$E_A(k)$ and $S_A(k)$ is calculated using the equations (6) and (7)

$$\begin{aligned} e_A(j) &= \sum_{k=1}^{N} E_A(k).e^{-\frac{2.\pi.i}{N}.(j-1).(k-1)} \\ j &= 1,..,N \end{aligned} \tag{6}$$

$$\begin{aligned} s_A(j) &= \sum_{k=1}^{N} S_A(k).e^{-\frac{2.\pi.i}{N}(j-1).(k-1)} \\ j &= 1,..,N \end{aligned} \tag{7}$$

where $i^2 = -1$ is the complex operator.

The product c_{es} of the signals $e_A(j)$ and $s_A(j)$ $(j = 1,..,N)$ is calculated by the expression (8)

$$c_{es}(j) = e_A(j).s_A^*(j) \tag{8}$$

with $s_A^*(j)$ the conjugate of $s_A(j)$.

The cross-correlation function of the treated signals is obtained using the FFT^{-1} of equation (9)

$$\begin{aligned} C_{ES}(k) &= \frac{1}{N}.\sum_{j=1}^{N} c_{es}(j).e^{\frac{2.\pi.i}{N}.(j-1).(k-1)} \\ k &= 1,..,N \end{aligned} \tag{9}$$

Finally, the residual r represents the time evolution of the mean value of C_{ES} as given in equation (10)

$$r = \frac{1}{N}\sum_{k=1}^{N} C_{ES}(k) \tag{10}$$

	$N.flow$	$\lvert r-Th\rvert$
Application 1	0.82 $m3/h$	0.005
Application 2	2.77 m^3/h	0.08
Application 3	6.77 m^3/h	0.1

TABLE I

DSTANCE IN ABSOLUTE VALUE BETWEEN THE RESIDUAL AMPLITUDE AND THE THRESHOLD IN PRESENCE OF LEAK OF 0.1 M3/H.

C. Threshold generation

The normal operating threshold Th is determined experimentally after a battery of tests .The results summarized in Table1, show the residual amplitude in presence of the same value of the leak $(0.1\ m^3/h)$, and an increasing values of the input flow. The results show that the sensitivity of the algorithm to the leak increase with the increasing of the nominal input flow.

The decision procedure is defined as follows

$$\begin{cases} \text{If } \ r \leq Th \text{ Then } Faulty\ operation \\ \text{If } r > Th \text{ Then } Normal\ operation \end{cases} \tag{11}$$

III. APPLICATION

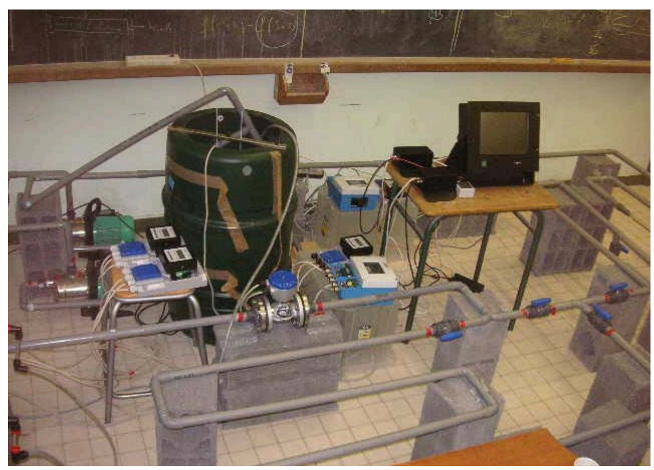

Fig. 3. Overview of the system.

The system of Fig.3 presents a 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 $1600W$ of 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, allowing thus the introduction of a significant hydraulic disturbances in real time. The tank of water supply is equipped by a heater of $3750W$ of power, 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, in order to show that the performances of the leak detection algorithm are independent on the type of the used sensors.

A. Experimental results

Fig. 4 shows the evolution of the residual during normal operation. The minimum amplitude of the residual is about $-0.004 > -0.1$, then no alarm is generated. The input-output flows in normal operation are given in Fig. 5.

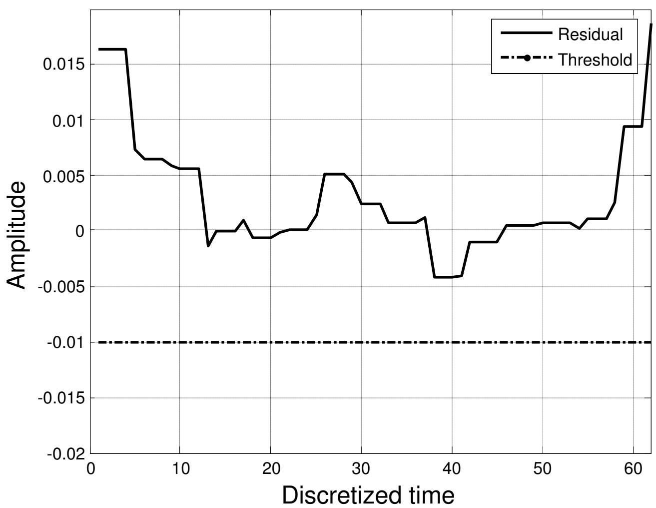

Fig. 4. Residual in normal operation.

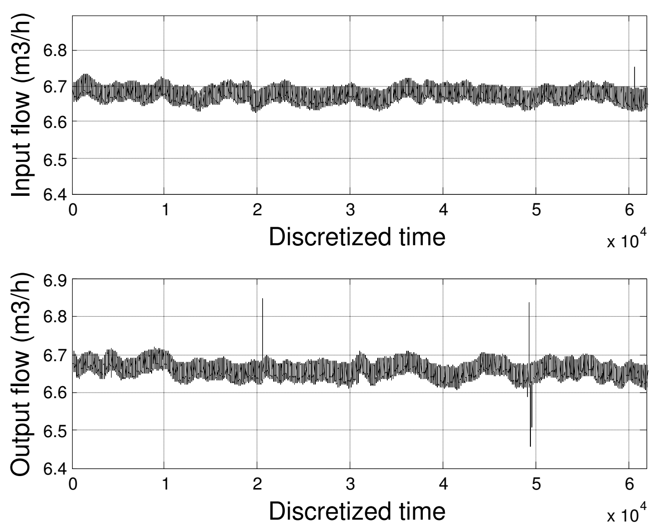

Fig. 5. Input flow and output flow in normal operation.

The residual evolution in presence of a leak of $0.1 m^3/h$ is illustrated in Fig.6. The input nominal flow is about 6.8 m^3/h. The residual reached a minimum magnitude of $-0.6 < -0.01$, then an alarm is generated. The input-output flows in presence of the leakage are given in Fig.7.

Tests of robustness to thermal perturbations are achieved by both activating the heater and adding hot water directly in the supply system. Fig. 8 shows the evolution of the residual in presence of a sudden change in the water temperature from $30°C$ to $45°C$, this represents a variation of 50% of

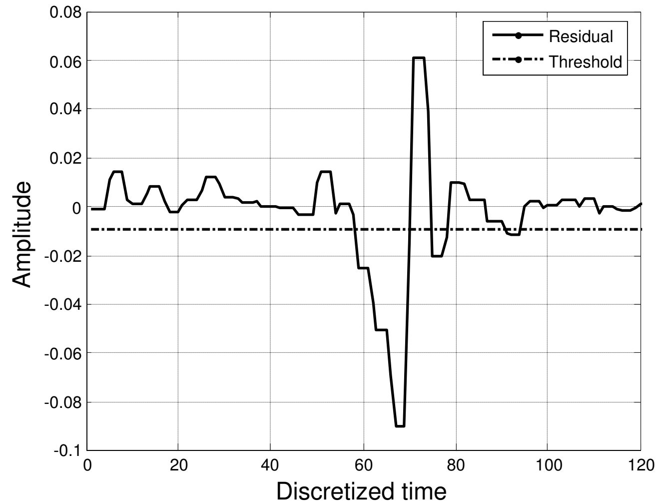

Fig. 6. Residual in presence of a leak of 0.1 m^3/h.

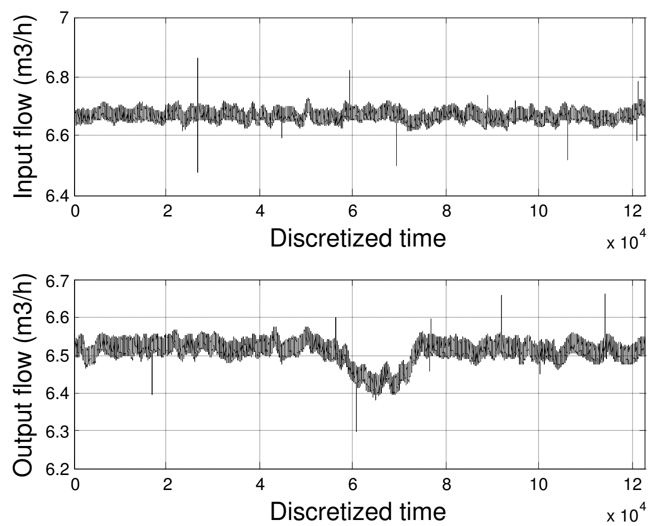

Fig. 7. Input and output flows in presence of a leak of 0.1 m^3/h.

the nominal temperature of the water. The water temperature is then gradually increased until $60°C$ by using the heater. The minimum amplitude of the fault indicator is equal to $-0.003 > -0.01$, thus the algorithm is robust against thermal disturbances. The input-output flows in the presence of a variation of the temperature of water supply from $30°C$ to $45°C$ are given in Fig.9.

the test bench is equipped with valves placed between the two flow meters, in order to create hydraulic disturbances by changing the flow circuit. The evolution of the residual in presence of hydraulic disturbances is given in Fig.10 The minimum magnitude of the fault indicator is equal to zero, thus no alarm is generated. The algorithm is robust to hydraulic perturbations. The input-output flows in presence of hydraulic disturbances are given in Fig.11.

Fig.12 shows the residual profile above and after the starting of the two pumps. The minimum magnitude of

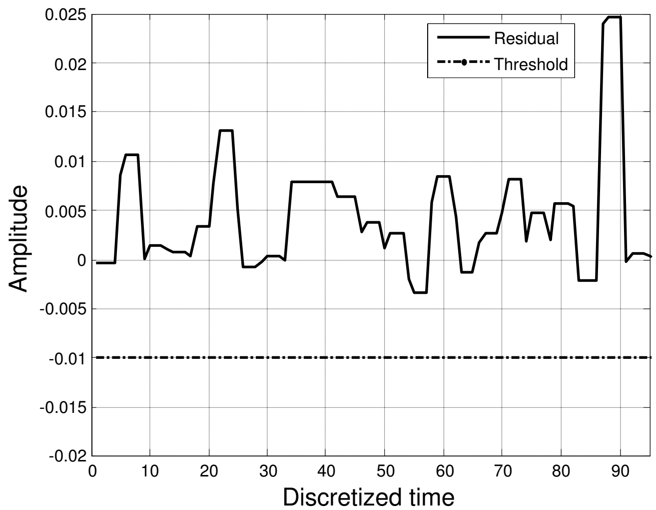

Fig. 8. Residual in presence of thermal perturbations.

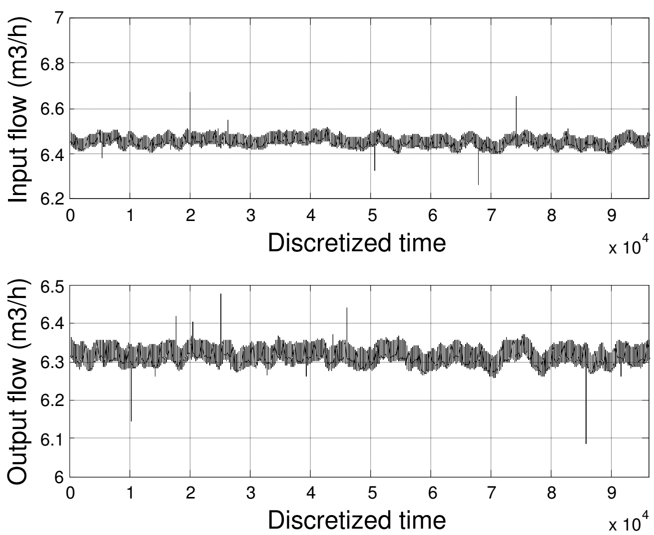

Fig. 9. Input and output flows in presence of a thermal perturbations.

the fault indicator is equal to $0 > -0.1$, thus no alarm is generated. The developed algorithm is so robust against transient operating modes like the starting mode. The input-output flows in starting mode are given in Fig.13.

Abrupt variation of the input flow is introduced in the system by stopping one of the two pumps, in order to tests the robustness of the algorithm to this transient operating mode as shown in Fig. 15. The residual evolution is given in Figs. 14 where the minimum amplitude of the fault indicator is equal to $80 > -0.1$, widely above the threshold, thus no alarm is generated. The developed algorithm is so robust against transient operating modes like the abrupt variation of the actuators power.

IV. Conclusion

In this work, a method of leak detection and isolation based on signal processing theory is presented. The developed approach uses the Discrete Wavelet Transform (DWT) of the sensor measurements, which allows to control the filtering of high frequency and interfering parts of the measurement signals, while preserving the relevant information (leak). Then, Fast Fourier Transform (FFT) is applied to the resulting values from the DWT of the input and output signals, in order reduce the computation time of the cross-correlation function. This later is calculated in the frequency domain then the result is translated to the time domain. The time evolution of the cross-correlation function represents the fault indicator. Experimental results show that the developed method can be implemented on the large scale processes without any learning for threshold generation. Obtained results in real time on different systems confirms the sensitivity of the algorithm to the leaks and its robustness to all the perturbations and transient modes.

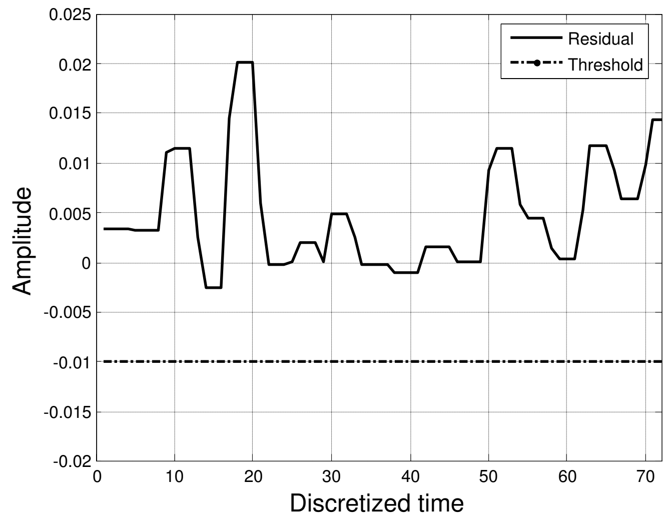

Fig. 10. Residual in presence of a hydraulic perturbations.

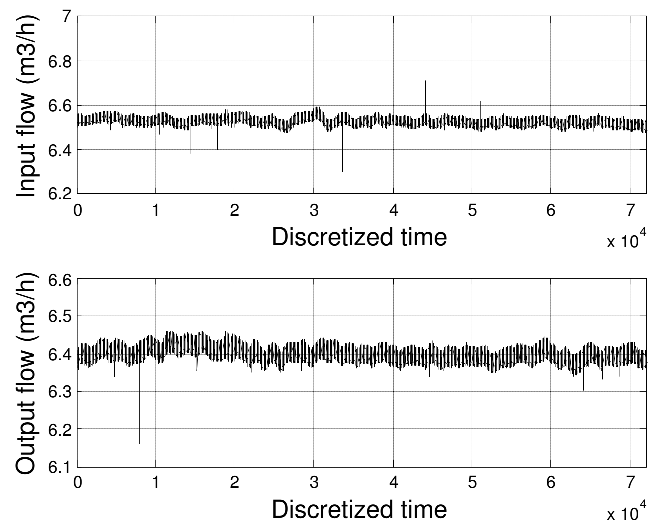

Fig. 11. Input and output flows in presence of a hydraulic perturbations.

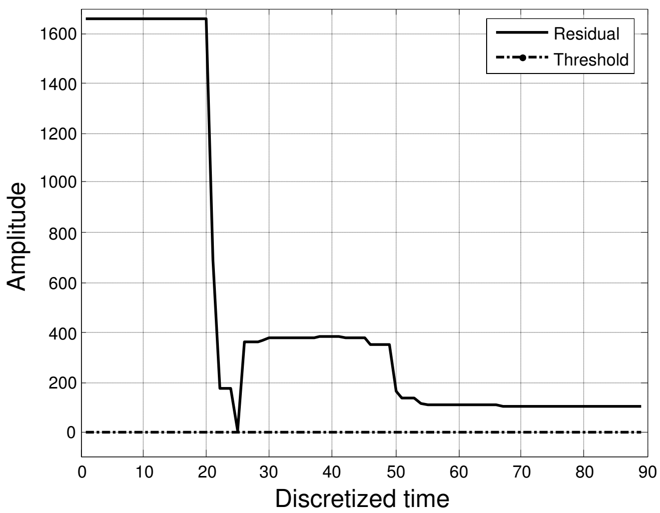

Fig. 12. Residual in transient mode (starting mode).

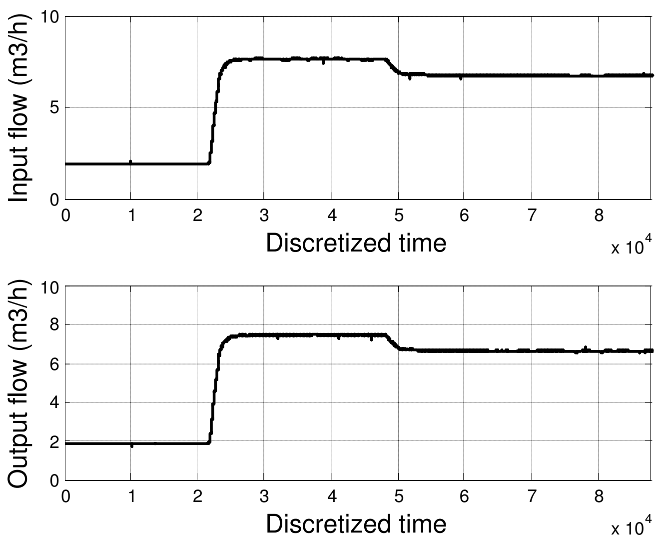

Fig. 13. Input and output flows in transient mode (starting mode).

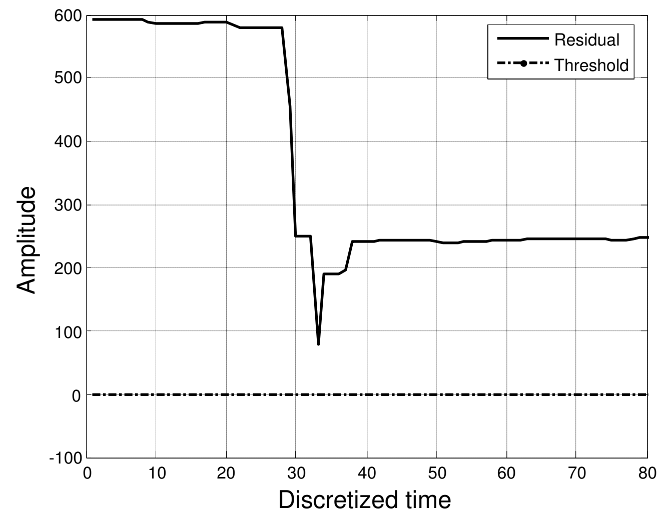

Fig. 14. Residual in transient mode (significant variation of a pump power).

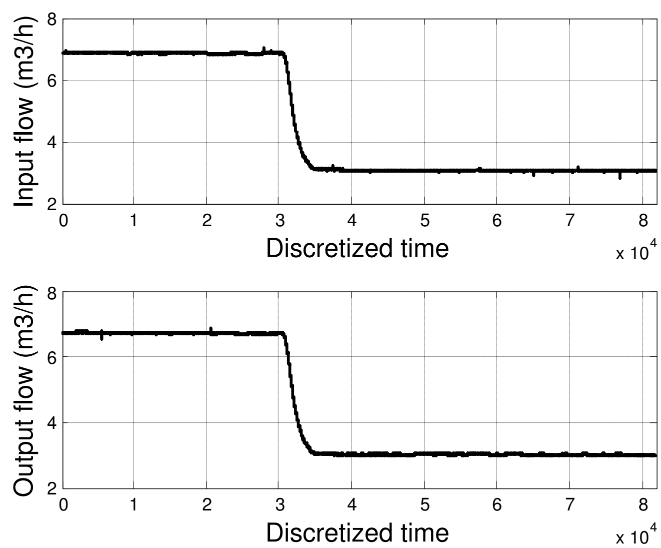

Fig. 15. Input and output flows in presence of a significant variation of a pump power.

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