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Incipient fault detection of motor-operated valves using wavelet transform analysis

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ABSTRACT

The necessity of improvements in monitoring and diagnosis methods started to be of extreme relevance in the predictive maintenance field, establishing the reliability and readiness of system components as an achievable goal. Taking into account these reasons, this paper presents an approach for incipient fault detection of motor-operated valves (MOVs) using wavelet transforms. The technique applied in this paper is the wavelet transform analysis using wavelet toolbox, where the main goal is to obtain more detailed information contained in the measured data, identifying and characterizing the transient phenomena in the time and frequency domains, correlating them to failure situations in the incipient stage. The wavelet analysis has provided good results establishing a new qualitative methodology for monitoring and diagnostics of motor-operated valves.

1. Introduction

The reliability aspect of plant components, specifically the motor-operated valves, is one of the important issues to be investigated in nuclear power plants, considering safety and life extension.

Motor-operated valves are used in almost all nuclear power plant fluid systems. The purpose of motor-operated valves (MOVs) is to control the fluid flow in a system by opening, closing, or partially obstructing the passage through itself.

The readiness of nuclear power plants depends strongly on the operational readiness of valves, especially MOVs. They are applied extensively in control and safety-related systems.

Non-intrusive diagnosis methods (Bauernfeind et al., 1993) have provided the ability to detect abnormal functions in plant components during normal operation. The measurement system is shown in the block diagram in Fig. 1.

The methodology developed in this research used the motor power signature analysis during open-to-close and close-to-open stroke time (Snowden and Upadhyaya, 1997; Carneiro et al., 2001). The motor power signature is acquired through three-phase current and voltage measurements at the motor control center. Typical motor power signature of a gate valve for open-to-close and close-to-open strokes are shown in Figs. 2 and 3, respectively.

The technique used in this project is based on the electric motor power signatures analysis, during open-to-close and close-to-open strokes and the timing of various events. Once the baseline measurements of an MOV are made, it is possible to detect long-term deviations during the lifetime of the valve, thus facilitating the advanced detection of valve failures.

The objective of this paper is to present the results of incipient failure detection of motor-operated valves using wavelet transform analysis.

2. Wavelet transform

The class of functions that represent the wavelet transform are those that are square-integrable on the real line (Chui, 1992; Chui et al., 1994). This class is denoted as $\mathbf{L}^2(\mathbb{R})$. Thus, the notation $f(x) \in \mathbf{L^2}$ means:

$$\int_{-\infty}^{\infty} \left|f(x)\right|^2 \mathrm{d}x < \infty \tag{1}$$

The sets of functions (Strang and Nguyen, 1996; Kaiser, 1992; Mallat, 1989) that are generated in the wavelet analysis are obtained by dilating (scaling) and translating (time-shifting) a single prototype function $\psi(t)$, which is called a basic wavelet. The dilating and translating process is shown in Fig. 4.

The wavelet function $\psi(x) \in \mathbf{L}^2(\mathbb{R})$ has two characteristic parameters, called dilation "*a*" and translation "*b*", which vary continuously.

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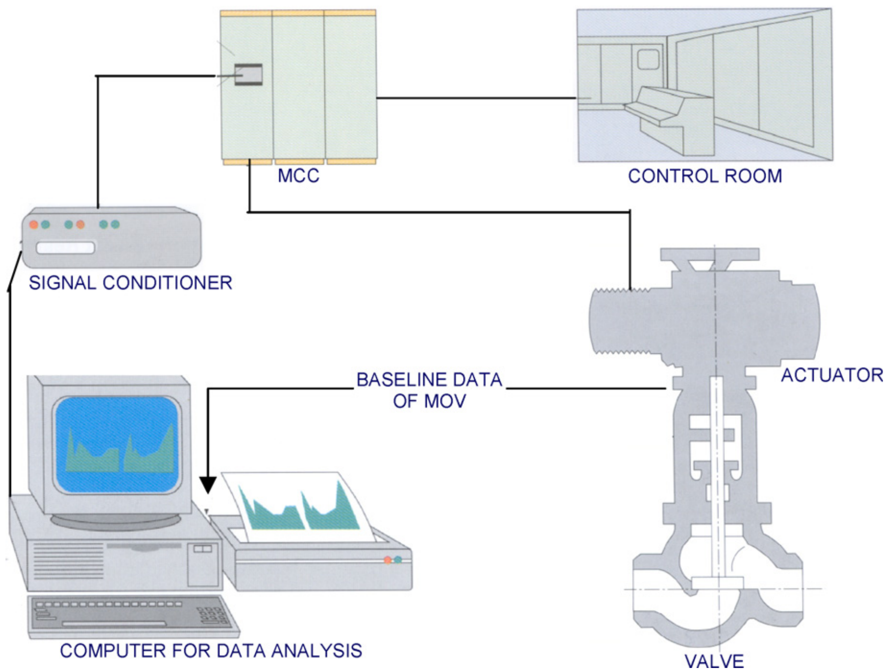

Fig. 1. Measurement system diagram. (Siemens Power Generation, 1995; Carneiro, 2001).

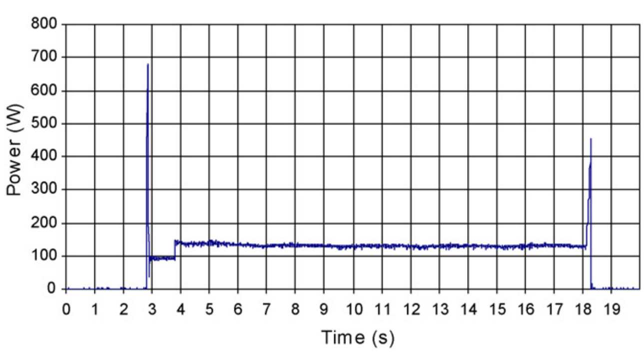

Fig. 2. Motor power signature during open-to-close valve stroke.

The basic wavelet $\psi(x)$ is defined as:

$$\psi_{a,b}(x) = \frac{1}{\sqrt{|a|}}\psi\left(\frac{x-b}{a}\right), \quad \text{where } a, b \in \mathbb{R}; \quad a \neq 0 \tag{2}$$

The continuous wavelet transform (CWT) is defined as the sum over all time of the signal multiplied by scaled, shifted versions of

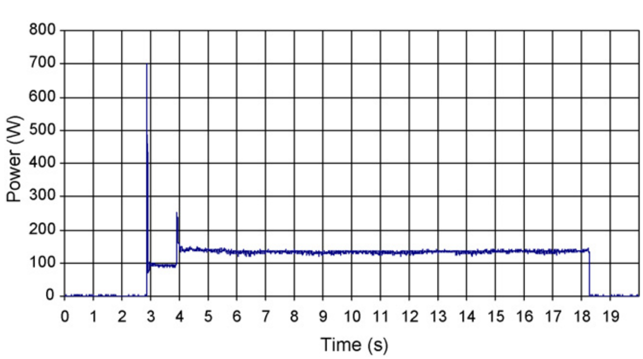

Fig. 3. Motor power signature during close-to-open valve stroke.

the wavelet function ψ:

$$\mathrm{CWT}_{a,b}(f) = \int_{-\infty}^{\infty} f(x)\psi_{a,b}(x)\,\mathrm{d}x \tag{3}$$

The result of the CWT is the generation of many wavelet coefficients C, which are a function of scale and position. The computation of wavelet coefficients using the continuous wavelet transform requires a considerable effort. The purpose of using the discrete wavelet transform (DWT) is to reduce the computational burden. The scales and positions are chosen based on powers of two (Da Silva, 1997), so called dyadic scales and positions, which make the analysis much more efficient and accurate. Therefore, assuming that the dilation parameter "a" and translation parameter "b" take only discrete values:

$$a = a_0^j \quad \text{and} \quad b = kb_0a_0^j \tag{4}$$

where

$$k, j \in \mathbb{Z}, \quad a_0 > 1 \text{ and } b_0 > 1 \tag{5}$$

$\mathbb{Z}$ denotes a set of integers.

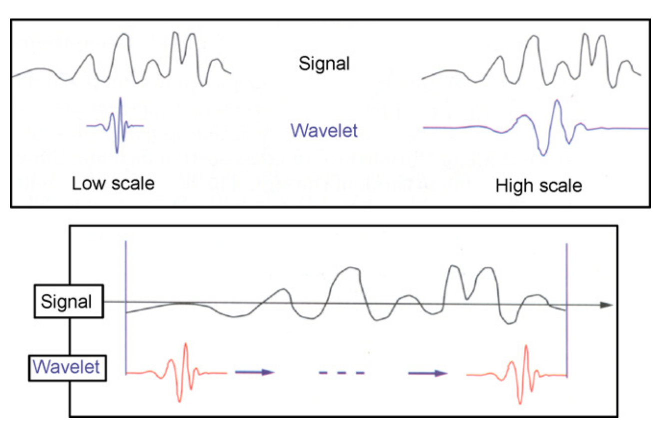

Fig. 4. Wavelet functions showing dilation and translation (MathWorks, Inc., 1995).

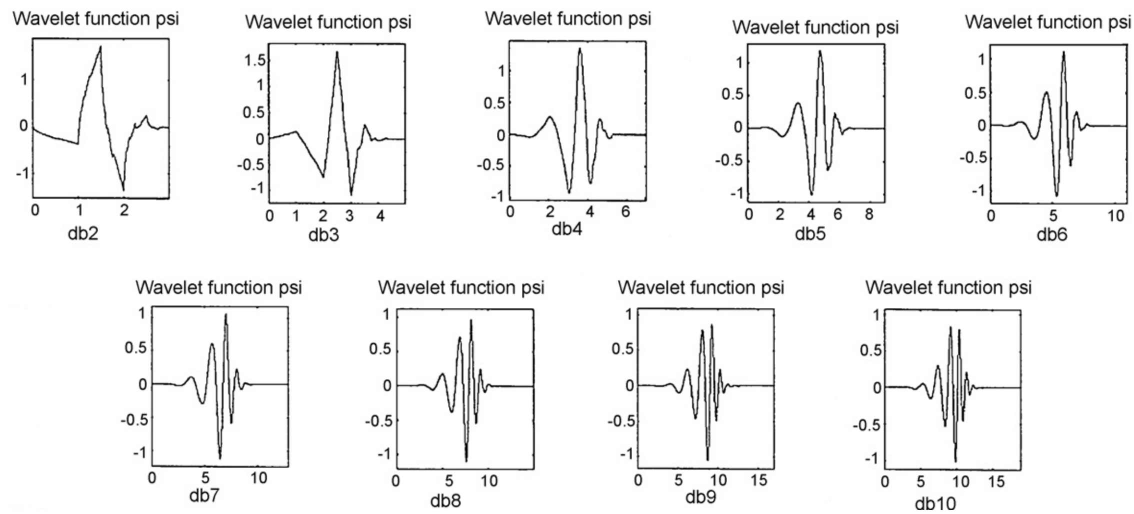

Fig. 5. Daubechies wavelet functions (MathWorks, Inc., 1995).

The wavelet function may be rewritten as:

$$\psi_{j,k}(x) = a_0^{-j/2}\psi(a_0^{-j}x - kb_0) \tag{6}$$

The discrete wavelet transform (DWT) is defined as:

$$\mathrm{DWT}(f) = \langle f, \psi_{j,k}\rangle = \int_{-\infty}^{\infty} f(x)a_0^{-j/2}\psi(a_0^{-j}x - kb_0)\,\mathrm{d}x \tag{7}$$

The inverse discrete wavelet transform reconstructs the function $f(x)$ as:

$$f(x) = \sum_{j=-\infty}^{\infty}\sum_{k=-\infty}^{\infty} \langle f, \psi_{j,k}\rangle\, \hat{\psi}_{j,k} \tag{8}$$

where $\hat{\psi}_{j,k}$ are dual functions of $\psi_{j,k}$.

An efficient algorithm can be constructed to evaluate the integral wavelet transform defined in Eq. (7). In this case, the frequency axis is partitioned into bands by using power of two for the scale parameter *"a"*. Considering only samples at the dyadic values, the parameters b_0 and a_0 assume the following values ($b_0 = 1$ and $a_0 = 2$) then, $b = k2^j$ on the time-axis, when $a = 2^j$. The DWT equation can be rewritten as:

$$\mathrm{DWT} = \langle f, \psi_{j,k}(x)\rangle = \int_{-\infty}^{\infty} f(x)\{2^{-j/2}\psi(2^{-j}x - k)\}\,\mathrm{d}x \tag{9}$$

The function $\psi_{j,k}$ is given by:

$$\psi_{j,k}(x) = 2^{-j/2}\psi(2^{-j}x - k); \quad j, k \in \mathbb{Z} \tag{10}$$

Several families of wavelets have proven to be useful on different signal analysis applications, such as Haar, Biorthogo-

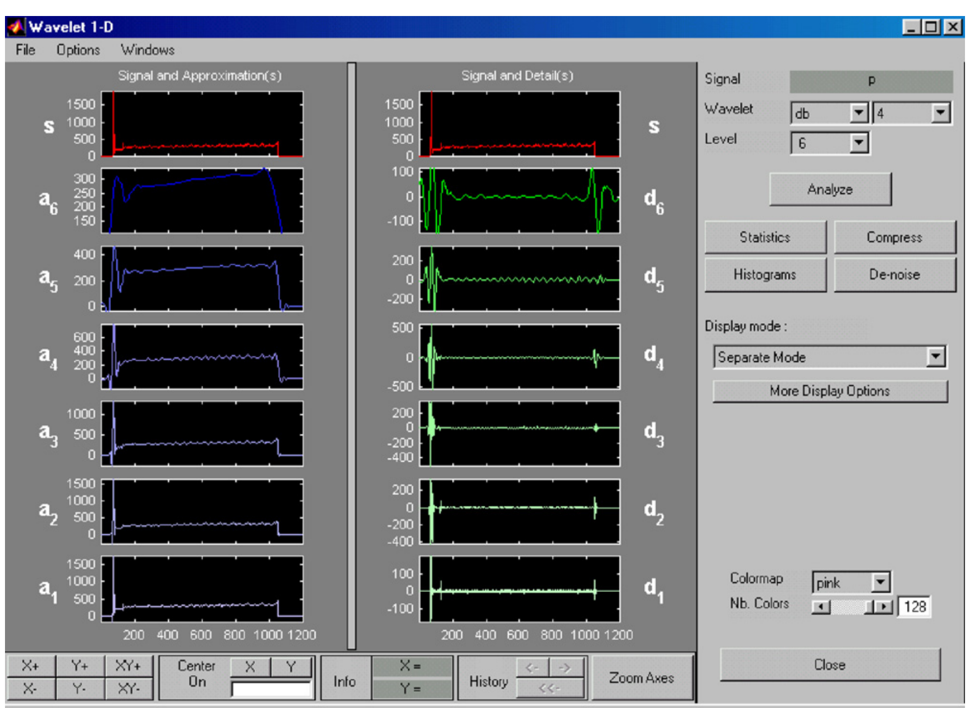

Fig. 6. Results from levels 1 to 6 using Daubechies wavelet function db4.

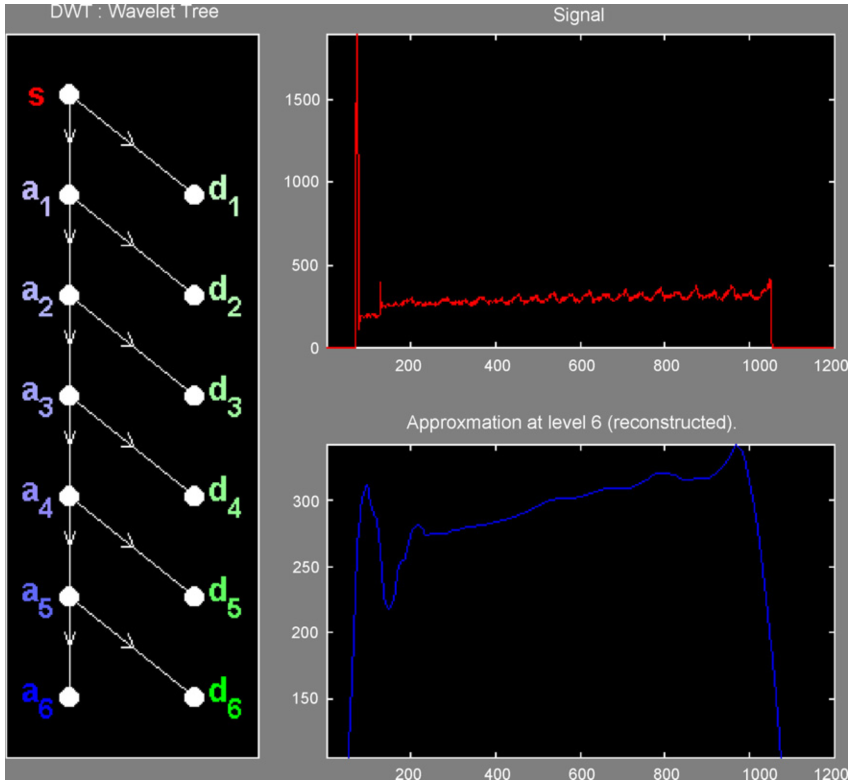

Fig. 7. Computer screen of the wavelet tree decomposition, the motor power signature, and the graphics of the approximation coefficients level 6.

nal, Coiflets, Symlets, Morlet, Mexican Hat, Meyer, and Daubechies.

The Daubechies (Daubechies, 1992) are the wavelet functions used in this project and examples and are shown in Fig. 5.

The technique applied in this paper is the discrete wavelet transform analysis implemented using the MATLAB platform and the Wavelet toolbox. The main goal is to obtain detailed information contained in the measured data, identifying and characterizing the transient phenomena in the time and frequency domains, correlating them to failure situations in the incipient stage.

3. Motor power signatures analysis

The analysis technique using discrete wavelet transform presented previously was implemented for a certain group of data that contain mechanical faults due gear degradation and obstruction in the valve seat area or due to bent stem. The technique was implemented using the MATLAB Wavelet Toolbox (MATLAB, 1996). Several wavelet families are available in the Wavelet Toolbox, allowing the exploration of the results of the analysis in an efficient manner.

The choice of the best wavelet to be used for analysis of a certain signal is a topic of considerable research, because there is no rule for the best wavelet function choice to be applied. Some basic aspects can be observed for an approach of the best choice, such as the similarity of the signal with certain wavelet functions and experiments as much as possible using data with known anomalies indicating MOV faults.

The family of Daubechies wavelets was selected as a good option for signal analysis in different fields, including rotating machinery vibration diagnostics (Wang and McFadden, 1993, 1996) and applications in image processing (Dennis, 1995).

After several experiments on this work, Daubechies "db4" wavelet with decomposition level "6" was chosen because db4 performs the best fit for motor power signature analysis and upper values on decomposition levels did not show any improvement on the MOV fault detection (Carneiro, 2001). Increasing levels of decomposition correspond to lower frequency components in the signal.

Figs. 6 and 7 show the computer screens of the sequence of the analysis emphasizing the motor power signature of the valve with an obstruction during the stroke time and the graphics of the approximations and details coefficients from level one to level six. The results analysis and discussions are presented in the next section.

4. Data analysis and results

4.1. *Case study (Carneiro, 2001)*

Two cases with known anomalies, caused by mechanical failures were analyzed.

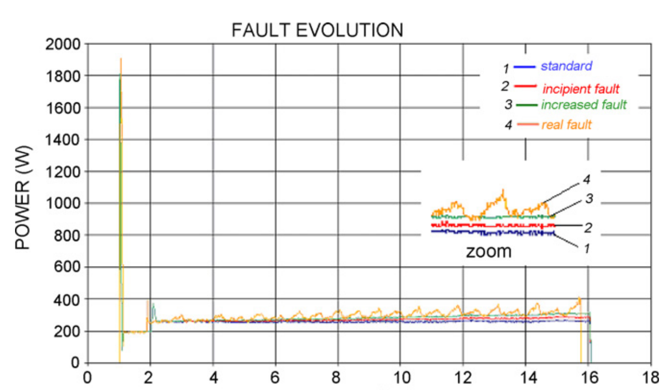

Fig. 8. Motor power signatures overlapped (Case 1).

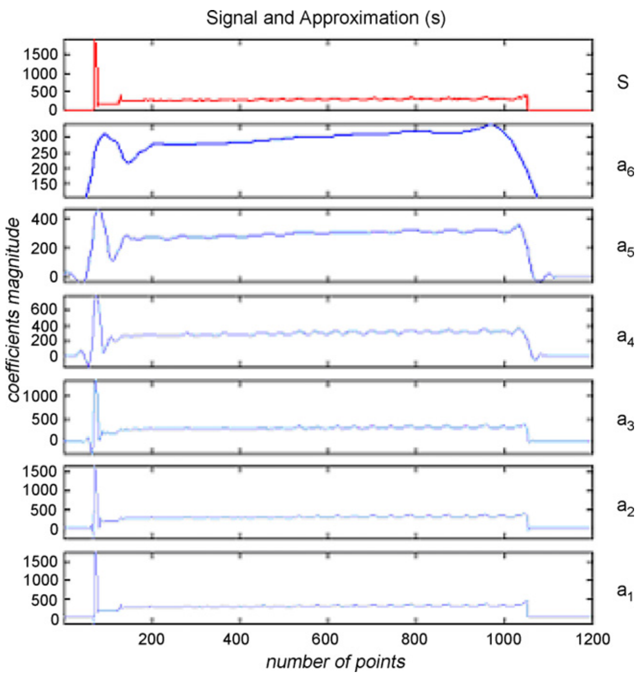

Fig. 9. Power signature (S) and approximation coefficients (a) for the six levels decomposition.

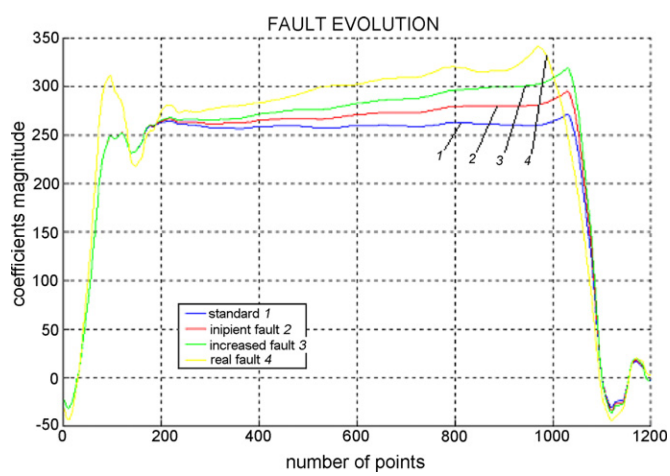

Fig. 10. Results of the wavelet approximation coefficients during whole opening cycle (four situations).

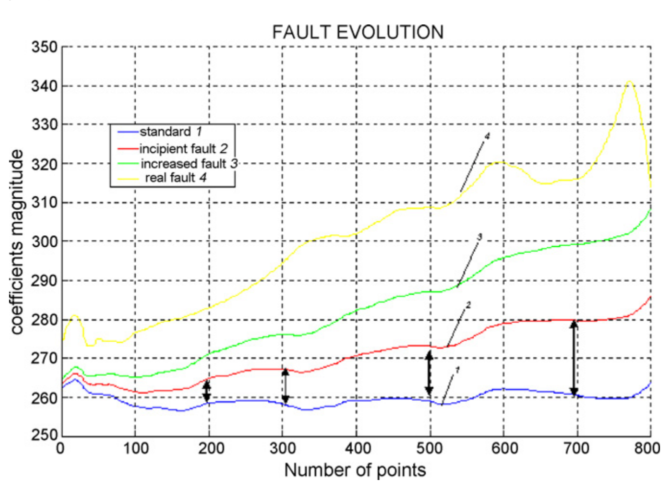

Fig. 11. Results of the wavelet approximation coefficients during the shaft motion.

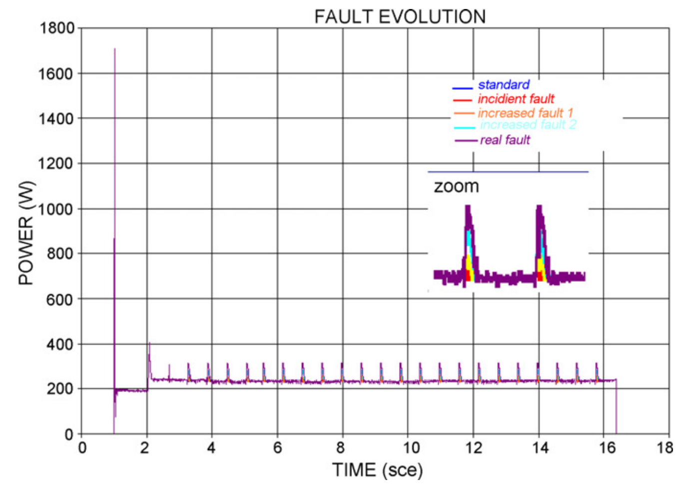

Fig. 12. Motor power signatures overlapped (Case 2).

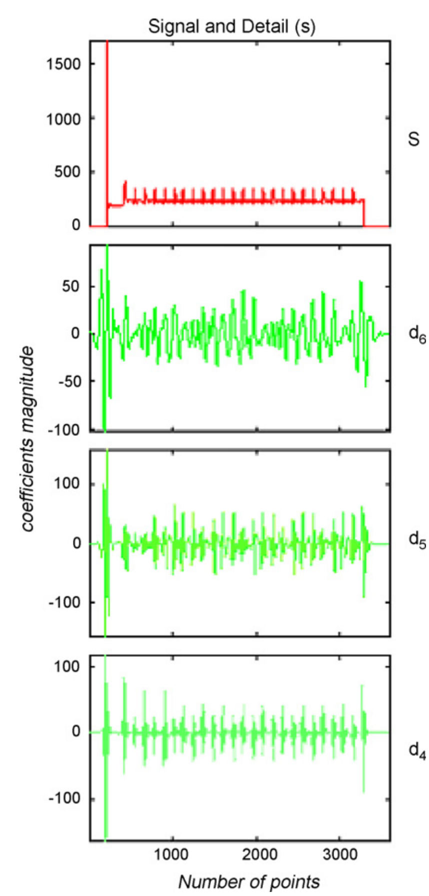

Fig. 13. Power signature (S) and details coefficients (d) for the decomposition levels 4–6.

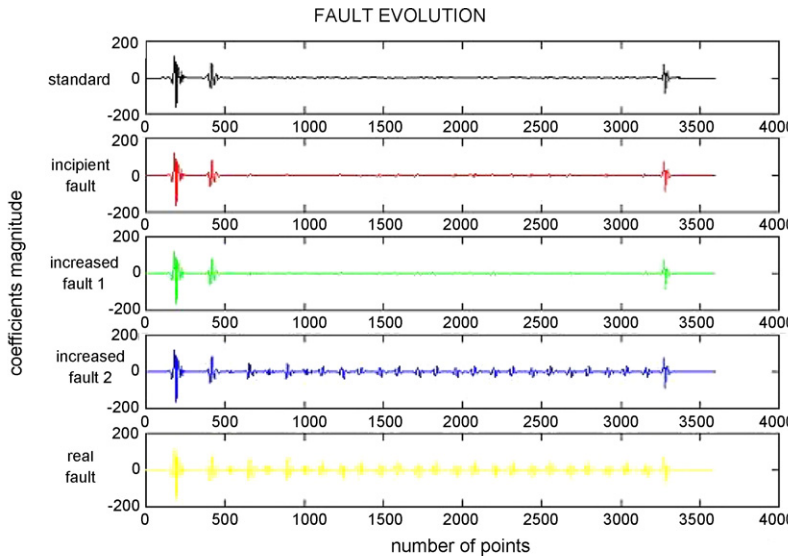

Fig. 14. Results of the wavelet details coefficients during whole opening cycle.

Case 1 is a mechanical obstruction during the stroke time caused by bent stem.
Case 2 is a mechanical failure caused by gear degradation.

In both cases, we have normal operation data for the baseline (standard) and data with real fault.

There are simulated data among the baseline and real fault. The idea of introducing these data is to check the sensibility of the system to detect the faults in the incipient stage, since that in the real faults data the occurrence of failures are somewhat evident.

4.2. Mechanical obstruction during the stroke time caused by bent stem (case 1)

Fig. 8 shows the motor power signatures overlapped with the following situations: standard, baseline or no anomaly power signature; incipient fault, simulated power signature with incipient fault; increased fault, simulated power signature with increased fault; real fault, power signature with a real fault.

In the Case 1, the best fault analysis is using the wavelet transform approximation coefficients that are related to the low frequency response. Fig. 9 shows the signal of original power signature and approximation coefficients for the six levels decomposition.

Figs. 10 and 11 show the analysis results using wavelet Daubechies db4 function and the approximation coefficients results at the decomposition level 6 for each situation (from normal stage to real fault).

Fig. 10 shows the results of the whole opening cycle from the action opening command until the end of the stroke.

Fig. 11 shows the beginning of the shaft motion until the end of stroke. Clearly one can observe the increasing of the power due to the resistance of the bent shaft moving.

4.3. Mechanical failure caused by gear degradation (Case 2)

Fig. 12 shows the power signatures overlapped as following: standard, no anomaly power signature; incipient fault, simulated power signature with incipient fault; increased fault 1, simulated power signature with increased fault; increased fault 2, simulated

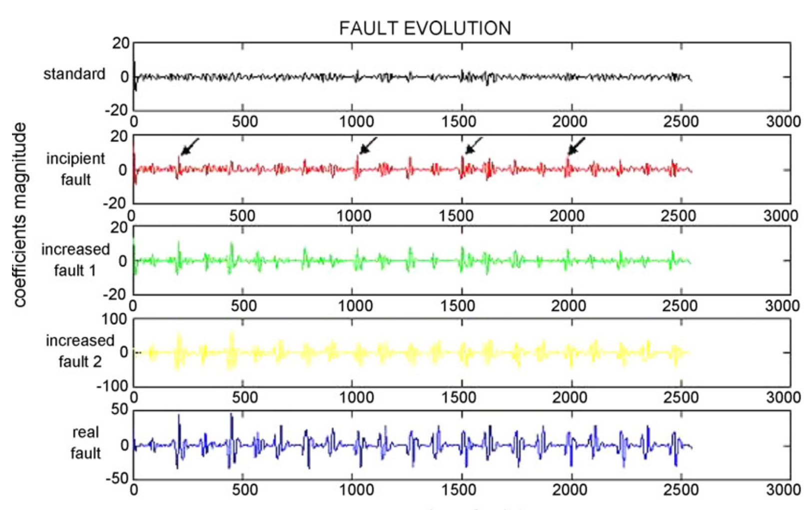

Fig. 15. Results of the wavelet details coefficients during the shaft motion.

power signature with increased fault; real fault, power signature with a real fault.

In the Case 2, the best way to detect the fault in the incipient stage is analyzing the details coefficients response which are related to the high frequency components, as it is shown in Fig. 13.

Figs. 14 and 15 show the results of the details coefficients for the decomposition level 6, using Daubechies db4 wavelet function, for each situation (from normal to the real fault). Fig. 14 represents the whole opening cycle and Fig. 15 shows the beginning of the shaft motion until the end of the stroke.

In Fig. 15, the peaks can be observed in the incipient stage, meaning the beginning of the gear degradation.

5. Concluding remarks

The development of non-intrusive diagnostics methods has provided the ability to detect failures in plant components during plant operation. Motor power monitoring and signatures analysis is being considered the most promising for a real predictive maintenance approach. Diagnostic techniques based on dynamic signal analysis have become an important tool for early detection of faults in components of nuclear plant.

The results of this research demonstrated the effectiveness of wavelet transforms on incipient fault detection of motor-operated valves. In the two cases considered in the application, the technique was able to detect incipient faults.

In the first case, the power increased during the shaft motion due to mechanical obstruction caused by bent stem (see Figs. 10 and 11). Similarly, in the second case, the fluctuations in the motor power signature caused by gear degradation are reflected in the decomposed wavelet levels. (see Figs. 14 and 15).

The check of the efficiency on the sensitivity of detection was illustrated using simulated data. The wavelet analysis gives a large amount of details about the signals; it is fast and does not require heavy computation.

The wavelet analysis showed the advantages of this method in detecting incipient changes in transient data and it does not depend on the brands of MOVs made by different manufacturers, but requires only the knowledge of motor power signature and the timings of various valve events.

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