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DEVELOPMENT OF AN INTELLIGENT MAINTENANCE SYSTEM FOR ELECTRONIC VALVES

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Abstract. *The technological evolution of sensors, electronics, embedded systems and simulation algorithms have been improving the maintenance activities, especially the predictive maintenance. These technological advances have provided a new view over the existing maintenance practices. The advent of new computer systems, the development of signal processing and simulation algorithms, have provided new approaches in industrial control systems leading to the propose new reliability and availability models for equipments and systems. Moreover, they have increased the precision in failure pattern recognition, have extended the assessment and diagnosis of damages in equipments and systems, and have added intelligence to existing control systems. Several techniques of signal processing and artificial intelligent, for example, were implemented by the Industry/University Cooperative Research Center on Intelligent Maintenance Systems (IMS) in a toolbox called Watchdog Agent*^{TM}*. This toolbox is already used successfully to prevent failures in several industry manufacturing systems. This paper presents the implementation of a intelligent maintenance system, using signal processing techniques and statistical methods existing in the Watchdog Agent*^{TM}*, to prevent damages and additional costs due to unexpected faults in electronic valves. These electronic valve has been assembly by Coester Automação S. A. company. The main idea is to determine and assess the performance degradation of valves and prevent failures. This system uses torque data from sensors installed in the valve. In this paper we present the configuration and model development for a correct application of the toolbox, as well as four examples of use of these models.*

Keywords: *Maintenance, Prediction, Diagnosis, Failures, Watchdog Agent.*

1. INTRODUCTION

The equipments or industrial processes, as they are used, are submitted to several kinds of degradation: wear out, dust, corrosion, humidity, cracks, and other anomalies.

In case that some corrective practices are not taken in order to restore the equipments, they will present some defect: noise, vibration, increase of temperature, and others. Remaining the defect, not being carried through a corrective action, the equipments or processes might fail.

Thus, it has become crucial for manufacturing industries to find out and prevent failures in equipments through quantifying the degradation in a way that the damages and maintenance time of a machine can be reduced to a minimum.

In order to anticipate and reduce the number of failures, reducing the costs, it is desirable for the companies to maintain a high level of confidence and availability.

Today, very sophisticated sensors and computerized systems are capable of giving important information about the equipment to which they are connected.

Moreover, when these sensors, with intelligent devices, are connected in an industrial bus and their data are continually analyzed by sophisticated embedded systems, it is possible to go beyond the predictive maintenance, evolving to an intelligent maintenance system.

After the implantation of an intelligent maintenance system, it is possible to locate exactly the components, parts, mechanisms that tend to fail.

This evaluation, executed quickly and precisely through the reading of performance indicators, allows forecasting the present and future behavior of machines and equipments [2].

The assessment, diagnosis and prediction of the performance for machines/equipments, achieved through sophisticated algorithms, signal processing techniques and artificial intelligence, have provided a change from the traditional paradigm of reactive maintenance practices, with focus on the machine adjust and precision, to predictive practices, with focus on prevention and precision of information, making the maintenance tasks intelligent [4].

A great variety of signal processing and artificial intelligence techniques, that are used in maintenance and have the ability of diagnosing an anomaly and compute the remaining lifetime of components and equipments, have been described in literature [9] and are mostly developed for specific applications.

Some examples are Fourier and Wavelet transforms, that have been used in signal processing, and features extraction with Artificial Intelligence techniques, as Neural Networks and Fuzzy Logic.

These techniques, in turn, also have being used in prediction and diagnostic of the performance of machines and equipments. These tools allow answering, through performance analysis, which is the most critical part in a machine that needs maintenance [7].

Performance degradation of equipments is considered as a result of aging and wearing out of components. This degradation reduces the performance confidence of machines and increases the failure probability.

Therefore, performance degradation is a failure indicator and can be used to predict an unacceptable performance of an equipment, before a failure occurs.

Moreover, quantifying the performance degradation allows signaling the appropriate moment for a maintenance activity and eases disassembly and reuse of parts or components [1].

This paper is organized as follows: Section 2 presents the definition of Confidence Value while Section 3 shows a description of the Watchdog Agent Toolbox. Section 4 shows the data of the case study and Section 5 presents the obtained results for this case study. Finally, in Section 6 the final conclusions and future works are presented.

2. CONFIDENCE VALUE DEFINITION

For the implementation of an intelligent maintenance system it is necessary to have information to evaluate the equipment performance degradation and to predict its behavior.

Several algorithms have been developed for the Watchdog Agent (WA) for the performance assessment of a system. These algorithms include signal processing methods, features extraction, and sensor fusion [8].

A device used to implement an intelligent maintenance system, developing by IMS, the WA, has a variety of tools to the assessment and prediction of equipments performance through multi sensor analysis.

The IMS Center has developed a methodology for the implementation of intelligent maintenance systems, based on a collection of analysis tools embedded into the Watchdog Agent. In this new methodology the system state is analysed according to the similarity/dissimilarity of the normal and the recently observed behavior, through a measure called Confidence Value (CV).

The performance assessment of parts/equipments done by the WA is made extracting degradation features of devices connected to it. From the reading of temperature, vibration, or force, for example, given by sensors installed in the devices, a performance indicator, the CV, is computed.

The CV is a quantitative indicator of the quality of a system. It is determined from the analysis of performance signals observed during the normal behavior of the equipment and those recently observed.

CV varies from zero to one, where a higher value indicates a performance that is closer to the normal. As the equipment degrades, the current performance signals differ from those of normal behavior, reducing the CV, as seen in the Fig. 1. The values were obtained through time/frequency distributions of the load readings from the shaft of an automotive process [5].

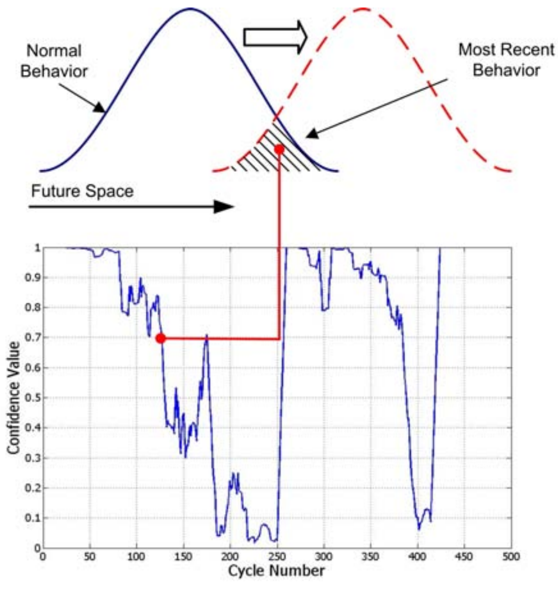

Figure 1. Concept of Confidence Value.

The performance prediction may be done through the modeling and surpassing of the current behavior, that is, by comparing current and previous signals read from the equipments.

In this paper, we will show the achieved results with two performance assessment methods: Logistic Regression and Statistical Pattern Recognition.

2.1 Statistical Pattern Recognition

Statistical Pattern Recognition (SPR) is a performance assessment method that analytically compares the distribution of features. By calculating the overlap of the current feature distribution and the normal mode or failure mode, it can obtain a systems confidence value or probability of failure [3].

This method is based on the assumption that the feature distribution representing a certain level of system degradation is represented by a Gaussian. SPR can be used in situations where a repeatable process is involved, as a robot, for example.

Assume, a feature vector $\vec{X}$, $\vec{X} = (x_1,\, x_2,\, \dots, x_n)^T$, is characterized as an n-dimensional random variable with multivariate normal distribution (MVN) with a average $\vec{\mu}$ and symmetric variance matrix K, that is:

$$\vec{X} \approx MVN(\vec{\mu}, K) \tag{1}$$

Usually, one can observe a high degree of correlation between the features extracted from the signal. The uncorrelated portion can be extracted through the use of the well-known Principal Component Analysis (PCA). PCA compute the most significant eigenvector of the covariance matrix of the distribution of features, that is, the ones that present the greater eigenvalues.

In this work, the PCA is used to convert $\vec{X}$ into lower dimensional random variables with independently-distributed components. The symmetric variance-covariance matrix can be represented as:

$$K = \sum_{i=1}^{r} \lambda_i \, \vec{v}_i \, \vec{v}_i^T = V \Lambda V^T \tag{2}$$

where: $r = rank(k)$, λ_i, $i = 1, \, ,2, \, \dots, r$ are the non-zero eigenvalues of K, $\vec{v}_i$ are the corresponding normalized eigenvectors, $V = [v_1 \, v_2 \, \dots \, v_r]$, and $\lambda = diag(\lambda_1,\, \lambda_2,\, \dots,\, \lambda_r)$.

Because K is positive semi-definite, all its eigenvalues are real and smaller than zero ($\lambda_i < 0$). λ_i depicts the amount of the covariance matrix energy projected in the direction of the corresponding eigenvector $\vec{v}_i$. When there exists a high degree of correlation among the components of $\vec{X}$, only a few of the eigenvalues in λ account for most of the energy in the matrix K.

Thus considering that the eigenvalues are organized in descending order, K can be rewrite as:

$$K = \sum_{i=1}^{p} \lambda_i \, \vec{v}_i \, \vec{v}_i^T = V_p \Lambda_p V_p^T \tag{3}$$

where: $V = [v_1 \, v_2 \, \dots \, v_p]$, $\lambda = diag(\lambda_1,\, \lambda_2,\, \dots,\, \lambda_p)$, p this is among components of K, λ_i are the most significant eigenvalues and $\vec{v}_i$ are the eigenvectors of corresponding unitary norm.

With this, the initial set of characteristics can be transformed into a new lower dimension set:

$$\tilde{X} = \Lambda_p^{-1/2} \, V_p^T (\vec{X} - \mu) \tag{4}$$

The variance-covariance matrix of X is:

$$\tilde{X}\tilde{X}^T = \Lambda_p^{-1/2} \, V_p^T (\vec{X} - \mu)(\vec{X} - \mu)^T V_p \Lambda_p^{-1/2} = I_p \tag{5}$$

Therefore X has a p-dimensional multivariate normal distribution:

$$\tilde{X} \approx MVN(0, I_p) \tag{6}$$

and:

$$\tilde{X}^T \tilde{X} = \sum_{i=1}^{p} \tilde{x}_i^2 \tag{7}$$

where p is the degree-of-freedom Chi-Square distribution.

Therefore, while using the Statistical Pattern Recognition, in WA, CV is defined as:

$$CV(\vec{X}) = 1 - F_{x_P^2}(\tilde{X}^T \tilde{X}) = 1 - F_{x_p^2}\Big(\sum_{i=1}^{P} \tilde{x}_i^2\Big) \tag{8}$$

where: $\tilde{X}$ is a vector with multivariate normal distribution of dimension p, that is, $\tilde{X} = (\tilde{x}_1,\, \tilde{x}_2,\, \dots, \tilde{x_P})^T$, achieved from the eigenvalues and eigenvectors of $\vec{X}$, T is the transposed matrix, and F is the Cumulative Density Function [1] [1].

[1] In probability theory, the Cumulative Density Function completely describes the probability distribution of a real-valued random variable X.

2.2 Logistic Regression

The Logistic Regression is method that belongs to the class of statistical models called generalized linear models. This method allows to predict a discrete outcome, such as a group membership, from a set of variables that may be continuous, discrete, or dichotomous, for example. Generally, the response variable is dichotomous, such as presence/absence, success/failure, or normal/faulty behavior, for example.

The Logistic Regression tries to fit a mapping from the k-dimensional input space to a one-dimensional logic output space. Defining the output variable as being y, $y = 1$ it denotes that the set of entrance presents the characteristic of interest, and $y = 0$ denotes that the characteristic is not present.

Mathematically speaking, the model can be presented as follows:

$$p(x) = P(y = 1|x) = \frac{1}{1 + e^{-(\alpha + \beta_1 x_1 + \ldots + \beta_k x_k)}} = \frac{e^{(\alpha + \beta_1 x_1 + \ldots + \beta_k x_k)}}{1 + e^{(\alpha + \beta_1 x_1 + \ldots + \beta_k x_k)}} \tag{9}$$

where: α, β_1, β_2, $\ldots$, β_n are constants and usually can been obtained by a maximum likelihood estimation method.

The Model show in Eq. 9 can be rewritten in a linear model format, in terms of probability event $p(x)$:

$$g(x) = \ln[p(x)/(1 - p(x))] = \alpha + \beta_1 x_1 + \ldots + \beta_k x_k \tag{10}$$

where: $g(x)$, called Function Logit, is a linear combination of the independent variables x_1, x_2, $\ldots$, x_k. The Function Logit becomes the linear and possible model of being decided.

While using the Logistic Regression Method, the CV is defined as:

$$CV(\vec{X}) = \frac{1}{1 + e^{-(\alpha + \beta_1 x_1 + \ldots + \beta_k x_k)}} \tag{11}$$

After the model parameters are obtained from training samples, the CV of the system can be calculated.

3. WATCHDOG TOOLBOX

With the intention to evaluate and predict the performance of the equipment in different conditions, taking into account the signal nature, processing speed, available processor and memory resources, the WA presents an open architecture.

The WA has an interface implemented in Matlab, known as Watchdog Toolbox. This is a software that has as input the readings of sensors installed in a system and has as output the current degradation level.

The Watchdog Toolbox has two main groups, data manipulation and performance assessment, and four main modules, signal processing, feature extraction, performance evaluation and sensor fusion [5], as depicted in Fig. 2.

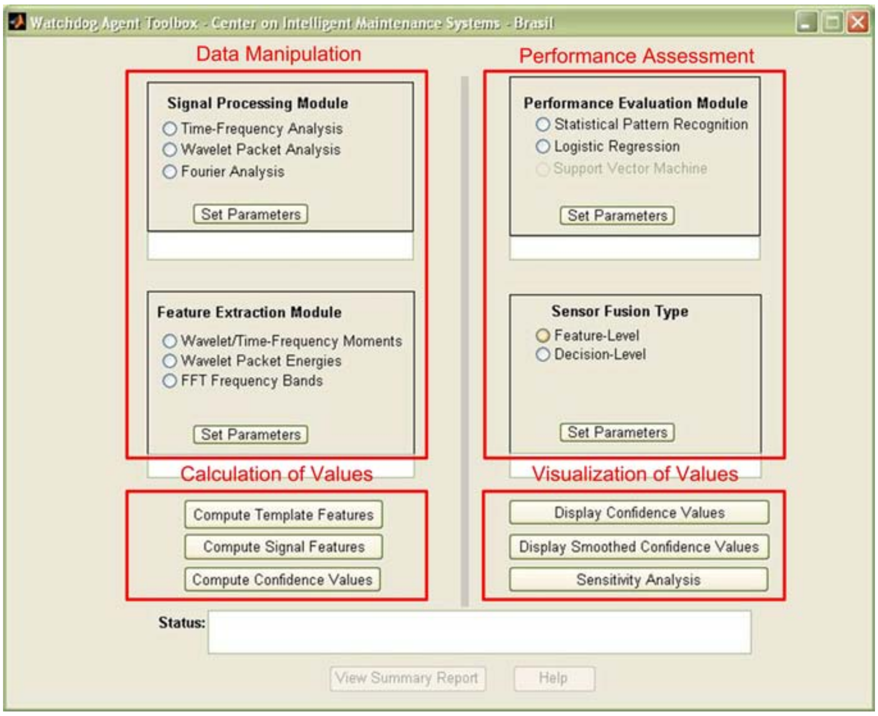

Figure 2. Watchdog Agent Toolbox main window.

The tools embedded into this device make it possible the quantification, evaluation and prediction of the degradation level of key parts of machines, offering the physical possibility of monitoring and managing the equipment life-cycle.

The data manipulation function is used to process the signal and extract performance features. Data manipulation tools use data which define the normal behavior of the equipment, as well as test data.

The performance assessment function performs the fusion of the information from the various sensors and calculates the Confidence Value.

The signal processing tools implemented in the Watchdog are based on the Fourier Transform, Wavelet Transform and Time Frequency Analisys. The Logistic Regression and Statistical Pattern Recognition are tools for performance assessment.

The performance assessment methods in the Watchdog Toolbox are based on the analysis of the signature curves. These signatures curves correspond to the frequency data, the frequency bands, or the signal energy content, for example.

Thus, the performance evaluation depends on the signal processing tool used and signatures extracted from these tools.

3.1 Affinity Analysis

The Watchdog Toolbox presents the same techniques and classification for features extraction. Thus, it is important that there exists a tool that allows to evaluate whether the choice of some analysis method is appropriate to a particular application.

Therefore, the affinity measure has been implemented to evaluate the sensitivity the chosen methods. This measure is acquired by the Bhattacharyya distance [2]. It is usually used to measure the separability of classes in classification.

The Bhattacharyya distance, B, is defined as:

$$B = -\log \rho \tag{12}$$

where: ρ is the Bhattacharyya coefficient [6].

For a multivariate Gaussian distribution the Bhattacharyya distance (that is the function added to the Watchdog Toolbox which allows to compute the affinity measure) is done by:

$$-\log \rho = \frac{1}{8}\left(\mu_1 - \mu_2\right)^T \Sigma^{-1}\left(\mu_1 - \mu_2\right) + \frac{1}{2}\log\left(\frac{det(\Sigma)}{\sqrt{det(\Sigma_1)det(\Sigma_2)}}\right) \tag{13}$$

In Eq.(1): μ_1 is the average of signatures describing normal behavior, μ_2 is the average of signatures describing the faulty behavior, Σ_1 is the covariance of normal behavior signatures, Σ_2 is the covariance of the faulty behavior signatures, and:

$$\Sigma = \frac{(\Sigma_1 + \Sigma_2)}{2} \tag{14}$$

This equation measures how distant is a data set from another data set, as well as the separation between the data sets. In the Watchdog Toolbox the affinity value is give by Bhattacharyya coefficient.

Lower values (near zero) for the affinity measure indicate a greater separation between the data sets and a better localization of signatures in each kind of behavior, normal or faulty. The minimum affinity should produce values greater than zero [5].

The Affinity measure can also be used to the CV for normal and faulty situation, in order not only to evaluate the adequacy of the characteristics, but also to achieve performance evaluation.

4. CASE STUDY

The case study presented here in uses data from opening and closing movements of a valve. These data came from a load cell installed in an electronic valve by Coester Automação S.A. The valves are used in several industrial plants of the chemical sector and sewage treatment.

The valves are devices whose basic purpose is the control the flow. There are many types of valves (globe, gate, or butterfly, for example), each one indicated for a particular type of application.

The choice of the valve does not depend only of the nature of the application, but also of the physical and chemical properties of the fluid, the pressure and temperature to which the valve is submitted, and the type and frequency of control.

Electrical actuators are devices which allow the control of valves, dampers, floodgates and similar equipments. The electrical actuators by Coester are composed of electrical (a squirrel cage machine and control) and mechanical parts (rolling and gears to transfer the movement of rotation and torque of the engine to the coupling of the valve).

The actuators can monitor the torque exerted on the valve, can detect many problems as the heating of the engine and extreme torque, and can register in its internal memory the 500 last operations carried out.

This paper deals with the performance of the shaft movement control of a gate valve (Fig.3) done by an electrical actuator.

[2] In statistics, the Bhattacharyya distance measures the similarity of two discrete probability distributions.

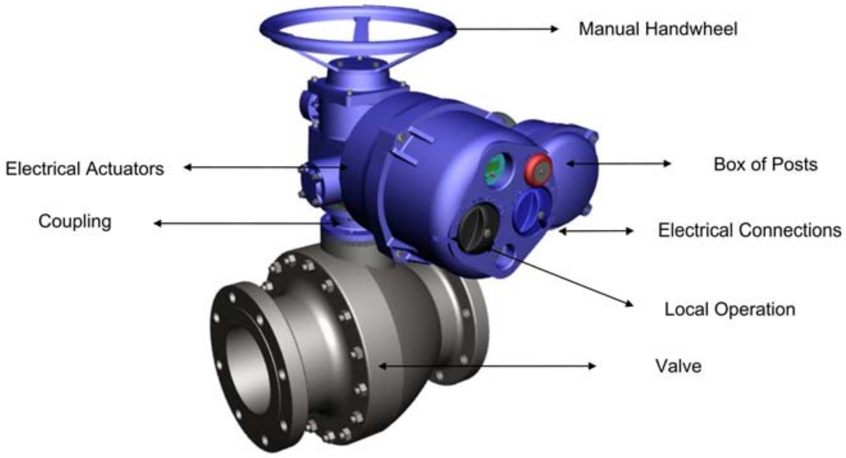

Figure 3. Valve and a Coester actuator [yielded by Coester Automação S.A.].

Data come from a load cell that measures the torque exerted by the actuator in the valve and from a potentiometer that measures the opening/closing movements of the valve connected to the actuator.

The torque ranges depend on the model used, and can reach up to 500Nm. Potentiometer data correspond to the percentage of opening/closing of the valve and may vary from 0 to 100%.

Through the actuator motor system, there is a transfer of the effort suffered to the load cell. In its turn, the load cell deforms and sends an analog signal proportional to the converted effort to the controller board of the PLC, which processes these signals, as seen in Fig. 4.

The control software evaluates the effort value and verifies if it should turn off the motor and generate an alarm signal, for example. The effort and position during movement data are saved in memory for analysis and visualization.

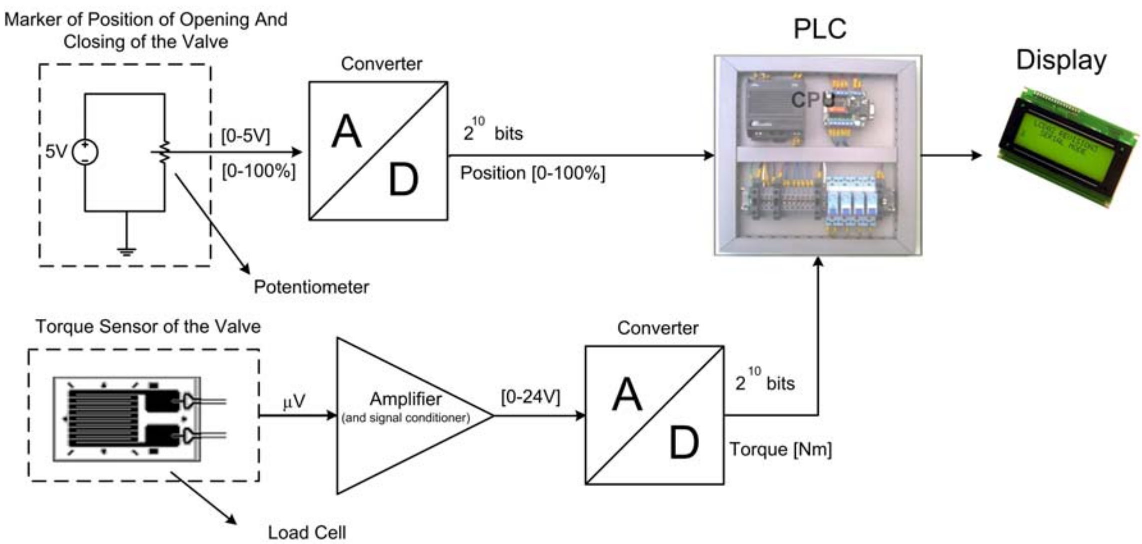

Figure 4. Acquisition of the position and torque data of the valve.

The torque exerted by the engine must be enough to win the existing attrition between the gate and the seat, as well the attrition of the stem with the gasket. The situation of highest demand of torque occurs when the valve is in the closed position and starts opening in the flow presence. At this moment, a big difference of pressure occurs between the two edges of the valve disc. Thus, the torque behavior while opening the valve will be different from the torque behavior while closing.

Fig. 5 shows five opening/closing curves of the valve obtained through the load cell. The null values of torque indicate the positions for which the actuator of the valve did not act during the movement.

For this data set, the features were extracted using a Fourier and Wavelet based analysis, analyzing the fundamental frequencies and packet energies of the signal. The computation of performance was made by Statistical Pattern Recognition and Logistic Regression method. The option “Feature Level”, see Fig. 2, was chosen for all the tests described in the sequence.

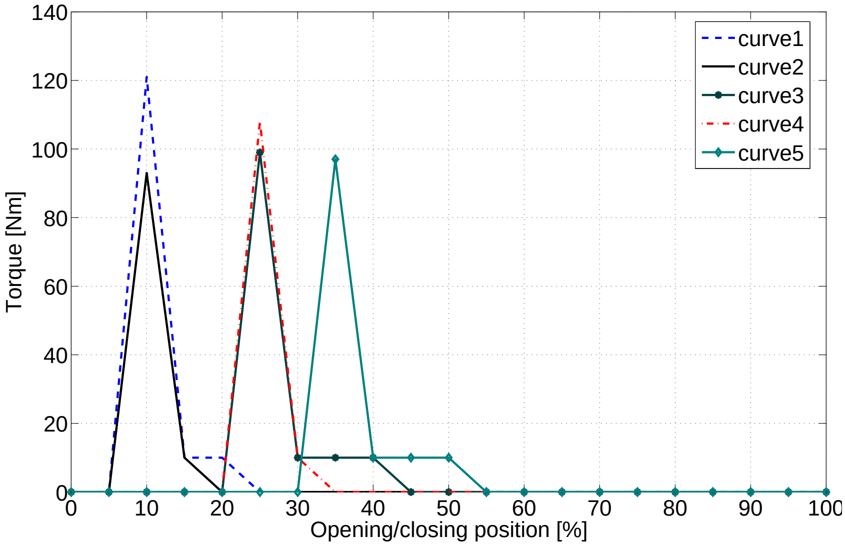

Figure 5. Opening/closing torque curves of the valve.

4.1 Definition of Tests

Among many types of degradation that can occur in the actuator, tests are concentrated in a situation that always occurs in applications of flow of water and sewer: accumulation of residues in the seat of the valve.

These residues can be small sand particles or sediments. This situation is characterized by an increase of necessary torque in the actuator while closing of the valve, so that the gate accommodates on the seat and a perfect seal occurs.

Depending on the amount of sediment accumulated, an increase of the necessary torque for valve opening can be also observed when it is in the closed position.

Residues can be also solid objects, as twigs. In this case, it can be also observed an increase of the torque, thus as a blockage of the gate, disabling that seat reaches its end of course. Then, fluid can simply leak, or mechanical parts can deteriorate, provoking warping stem or breaking gears, for example.

The opening/closing torque curves seen in Fig. 5 represent normal behavior situations. To perform the analysis and to verify the confidence value, it is necessary a data set representing a faulty behavior.

These faulty data were obtained through the addition of an increasing value of torque in normal values until they reach maximum torque allowed to the valve. These data represent a situation normally found in the field, as the performance degrades until the failure.

Having normal and faulty behavior data, it is enough to fill in the test folder. Data have been placed in between cycles 100 and 150, in the test folder.

Thus, according to different signal processing and performance assessment tools, four different tests were performed:

1. Fourier Transform and Logistic Regression;
2. Fourier Transform and Statistical Pattern Recognition;
3. Wavelet Transform and Logistic Regression;
4. Wavelet Transform and Statistical Pattern Recognition.

As the used tools changes, the respective Confidence Value will also change. Thus, it is expected to obtain four different curves for the CV.

It is worth saying that the last test represents a common situation found in the field. It is similar to the behavior expected after the verification of some defect and the replacement of a part or component, with the valve returning to its normal condition of use.

5. RESULTS

In the following curves, it is possible to visualize and compare the Confidence Value in the four tests described previously. It is possible to observe the performance degradation as the torque value increases, or the performance retake as the values are getting normal.

Fig. 6 shows the CV for the first test, the CV should start with a value close to one. From cycle number 100, CV should gradually decrease, and it should start do increase again from cycle number 150. In this test, the WA distinguish the normal and faulty features.

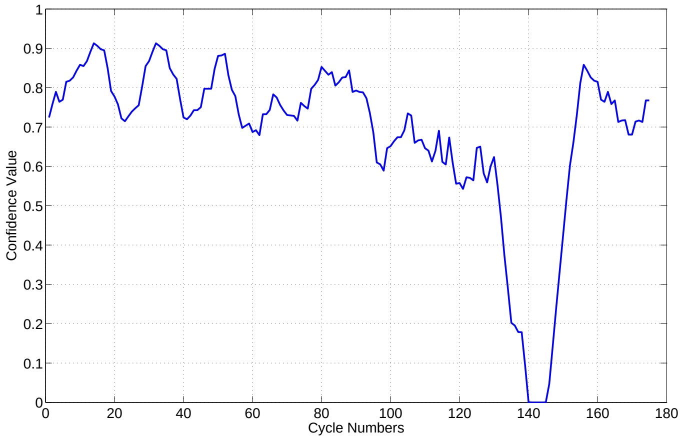

Figure 6. CV calculated for test 1.

In the second test, as seen in Fig. 7, the WA do not distinguish the normal and faulty features.

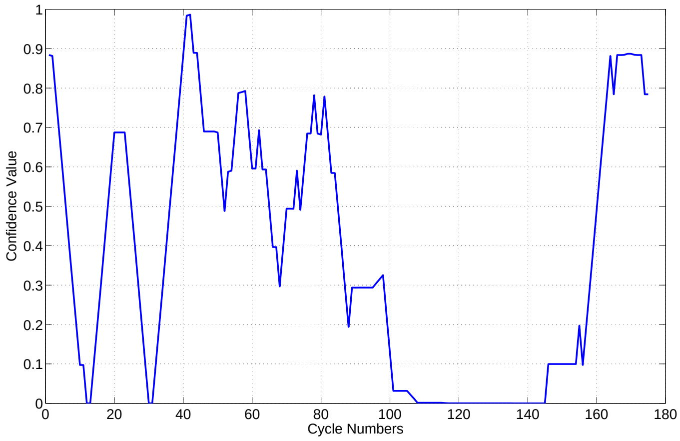

Figure 7. CV calculated for test 2.

In the third test, shown in Fig. 8, the WA distinguishes the normal and faulty features. However, the values are lesser than those seen in test 1.

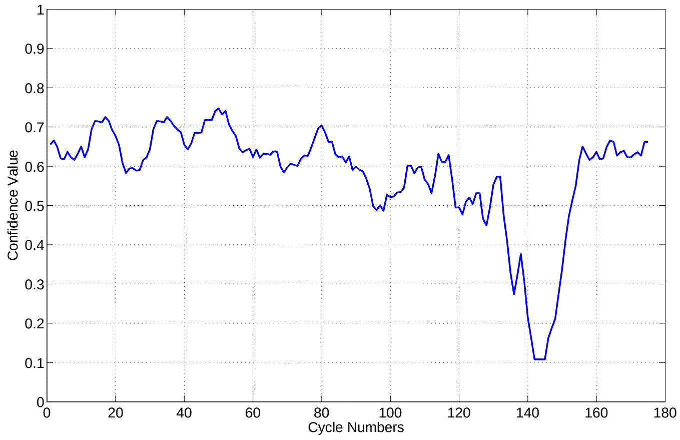

Figure 8. CV calculated for test 3.

Finally, in the last test in Fig. 9, the WA distinguishes the normal and faulty features. However, the values are lesser than those seen in test 1, similarly to test 3.

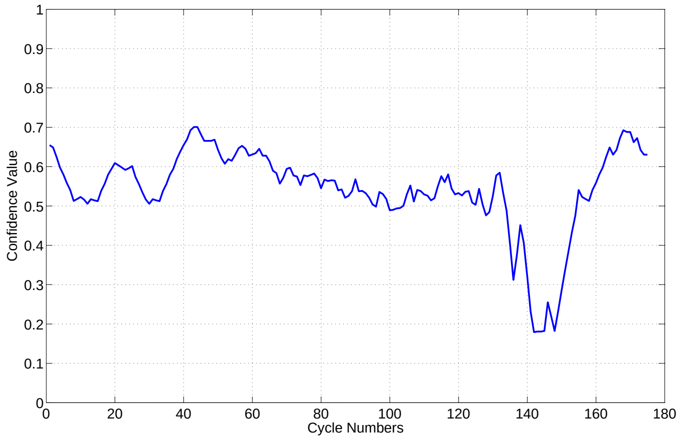

Figure 9. CV calculated for test 4.

As it can be seen in Fig. 6, 7, 8 and 9, the analysis based in Fourier Transform and on the Statistical Pattern Recognition have presented good results in the four cases.

5.1 Affinity Analysis Results

From Tab. 1, it could be observed that test 1 obtained the smallest value for the affinity measure, considering the behavior and confidence value, so it was the case that presented the best separation between normal and faulty behavior.

Table 1. Measure of affinity for the tests.

	Test 1	Test 2	Test 3	Test 4
Behavior	0.167039	0.176209	0.510527	0.511406
Confidence Value	0.563362	0.764846	0.787541	0.811383

6. CONLUSIONS

The torque data allowed performing a precise diagnostic for the valve degradation and a correct analysis about the Watchdog Toolbox use.

The Watchdog Toolbox makes it possible to easily obtain the Confidence Values using all the possible combinations of tools for assessment and data manipulation.

It helps to determine which is the best combination for a particular application. Moreover, the affinity analysis can be used to determine which is the best combination of tools for a specific application and which is the best range for the expected behavior, normal or faulty.

It was observed that the Watchdog Toolbox is capable of evaluating the performance of an equipment, specially the Coester valve, in several situations.

The Watchdog Toolbox modules allow different signal processing, features extraction, performance assessment and sensor fusion methods to be used. Moreover, other feature extraction and performance assessment methods can be easily added to the Watchdog Toolbox.

As future works it could be mentioned: to deepen the study of the Watchdog Toolbox, to acquire more data sets from the valves (through a valve model, to be implemented and validated), to perform more tests and analysis, to simulate, to analyze and to classify the failures.

Failure classification could be performed using artificial intelligence methods, as neural networks, Markov models and Fuzzy Logic, for example.

Through a training of the main faults, using neural networks for example, it will be possible to predict when an imperfection is going to occur.

7. ACKNOWLEDGEMENTS

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