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# Nozzles Classification in a High Pressure Water Jet Systems

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***Abstract*** *– In this paper, a technique for classifying the working condition of a Water Jet System is presented. The classifier is based on the DFT of the electrical power signal. It is show that this information can characterize the working condition of the system and to predict the presence of (an incoming) faulty behaviour.*

***Keywords*** *– Water Jet Systems, classification, diagnosis.*

## I. INTRODUCTION

Water Jet and Abrasive Water Jet Technology (WJ/AWJ) presents some particular characteristics which make it suitable in application fields where particular manufacturing operations on special material are required; machining activities such as cutting hard to machine materials (*e.g.*, steels, titanium alloys, aluminium alloys, brittle materials) or carrying out operations such as turning and milling as well as surface treatments such as peening, cleaning, decoating, descaling represent some of the possible applications of WJ/AWJ technology.

The AWJ cutting process has the peculiarity that it is a cold process as the water takes heat away from the interested area of the work piece. This characteristic is very important because allows to work without damaging the metallic material structure.

Starting from the simple consideration that the acquired electric signals gives useful indications for diagnosis purposes [1], it is a little step to consider a continuous non-intrusive on-field monitoring activity during all the plant components' life.

It is well known that a very important part for the definition of the efficiency of these systems is the water nozzle; in effects this component plays an important role in the definition of the overall efficiency, measured as the ratio between the available fluid-dynamic power and the electric active power from the network. Hence, monitoring the efficiency of the nozzle allows to predict the efficiency of the overall AWJ system.

In the aforementioned paper a comparison between the performances of different nozzles in terms of the electric power necessary to carry out the same mechanical operation has been reported. Different power consumptions lead to differences, sometimes relatively large, in terms of cutting performance and also of operating costs of the system. Moreover, it is shown that it possible to extract information on the behaviour of the plant from of the power signal; this could allow to detect and foresee wrong operating conditions.

The aim of this paper is setting up a technique for extracting information from the electrical power signal about the working condition of the system. In particular, we are interested in both identifying the nozzle type and its working condition by means of a signature for each nozzle in each working condition which allows the correct classification.

The availability of suitable signatures allows to build up a nozzle footprints database. Such a database constitutes the knowledge for the automatic recognition of the mounted nozzle and its working condition. All these aspects will be further discussed in the following sections.

## II. SYSTEM ARCHITECTURE

The water jet technology is characterized by phenomena belonging to different fields of physics. The utilized water jet system will be here briefly described using the schema in Fig. 1. The main components of a water jet cutting system is depicted. Considering a complete Waterjet cutting system, electrical energy is provided at first to the 380 V - 50 Hz

three-phase induction motor which pressurizes the oil by means of the radial pistons oil pump. The pressure reaches a value of 20 MPa in the oil circuit.
The oil provides its hydraulic energy to water by means of the double-acting intensifier as depicted in Fig. 1: at this stage the energy means of transport changes and, due to the increasing of pressure (which reaches 400 MPa), the compressibility of water has to be considered. An accumulator reduces the water pressure fluctuations [1-6]. When water reaches the cutting head and it flows through the orifice, the pressure energy changes into kinetic energy and the jet is formed. Further, when abrasive water jet is considered, solid particles join the water jet inside the mixing chamber, being entrained by the air flow generated by the jet itself. In this case, the kinetic energy of abrasive particles is dramatically increased thanks to the exchange of momentum with water inside the mixing chamber and the focusing nozzle.

The AWJ cutting quality typically depends on the process parameters selection (water pressure, abrasive mass flow rate, abrasive granulometry, cutting head feed rate, stand off distance), as well as on the fluid-dynamic parameters, such as the orifice and focuser diameters and the mixing chamber geometry. Besides the aforementioned parameters, considered as directly valuable variables, some external factors exist and play a non negligible role on the cutting quality in terms of roughness and waviness (such as water pressure fluctuation, due to the alternate motion of the pumping system, abrasive mass flow rate fluctuation, workpiece and fixturing system vibrations, granulometric distribution of the abrasive particles).

In order to monitor the complete water jet cutting system, a DSP-based system has been defined. In particular, the plant has been equipped with sensors in order to acquire the signals of the most relevant parameters describing its behaviour: oil pressure, water pressure, and piston velocity.

Electrical motor signals are acquired by an Analog-to-Digital conversion board with simultaneous sampling up to 200 kHz sampling rate on a single channel with a 16-bit resolution.

Voltage and current transducers have been specially realized in order to adapt the signal levels to the ADC and to ensure an adequate insulation level among channels and between the supply and measuring devices over a wide band.

## III. PATTERN RECNOGNITION

Object recognition, description and classification are very important tasks for the daily life [7], [8], [9]. In particular, Pattern Recognition (*PR*) is the scientific discipline dealing with methods for both object description and object classification. Applications of *PR* techniques are numerous and cover a broad scope of activities, for example: crop analysis, soil evaluation, analysis of telescopic images, automated spectroscopy, automated cytology, genetic studies, traffic analysis and control, assessment of urban growth, fault detection, character recognition, speech recognition, automatic navigation systems, pollution analysis, seismic analysis, analysis of electrocardiograms, analysis of electroencephalograms, analysis of medical images, detection and classification of radar and sonar signals, automatic target recognition, identification of fingerprints, surveillance systems an so on. It is important to note that the patterns to be analysed and recognized can be signals, images or plain tables of values. Pattern recognition approaches are based on the notion of similarity: between two different object or between an object (*i.e.*, signal or image) and a reference object (the target or prototype object).

The classification task is performed using the features or attributes distinctive of the object. The collection of the features that characterize the object of the classification is called *signature* or *footprint* of the considered object.

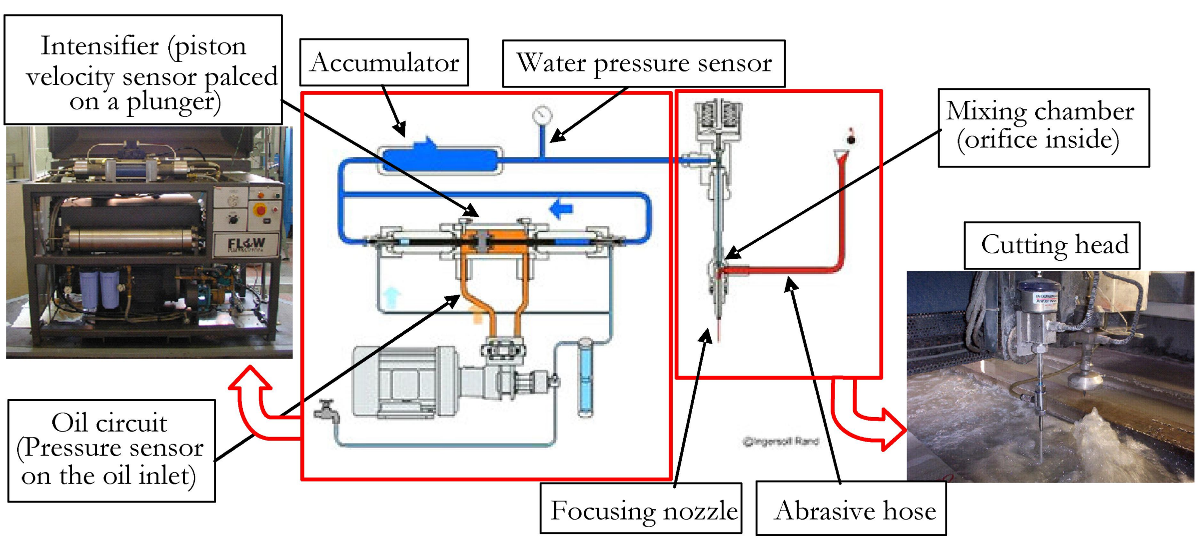


Fig. 1 - Main components of the water jet cutting system (scheme in the middle by Ingersoll Rand; pictures by Politecnico di Milano).

The aim of assigning an object to a class is an example of classification task. In the present case it is possible to define a vector with specific features:

$$\mathbf{x} = \begin{bmatrix} x_1 & x_2 & \ldots & x_N \end{bmatrix} \quad (1)$$

where $x$ are the features and $N$ is the number of them. In the simple case where only two features are used the classification task can be represented as in Fig. 2. The main goal of a classifier is to divide the feature space in regions assigned to a classification classes: the decision regions. In a multiple class problem – as the discussed problem – several decision surfaces can be presents and arbitrarily complex decision regions can be expected; the separation of the classes is achieved in essentially two ways: 1) *absolute separation* when each class can be separated from all the others; 2) *pair wise separation* when the classes can only be separated into pairs. For sake of simplicity we would like to use only a limited number of features and this task is obtained thanks the previous knowledge of the object or problem. So if the acquired signals can be patterns, measurements, attributes or primitives derived from the acquired signals can be useful features. The feature space is also called the "*representation space*". The representation space has data-driven properties according to the defined similarity measure.

As the footprint of an object is generally more simple and compact than the object, processing in the features space is computationally less expensive.

The choice of the features can be based on the domain knowledge given by experts or can be made using some feature selection technique. The deep knowledge of the mechanics and the physics of the particular machinery used may help to choose well performing features, but their use may not be generalized to the class of devices.

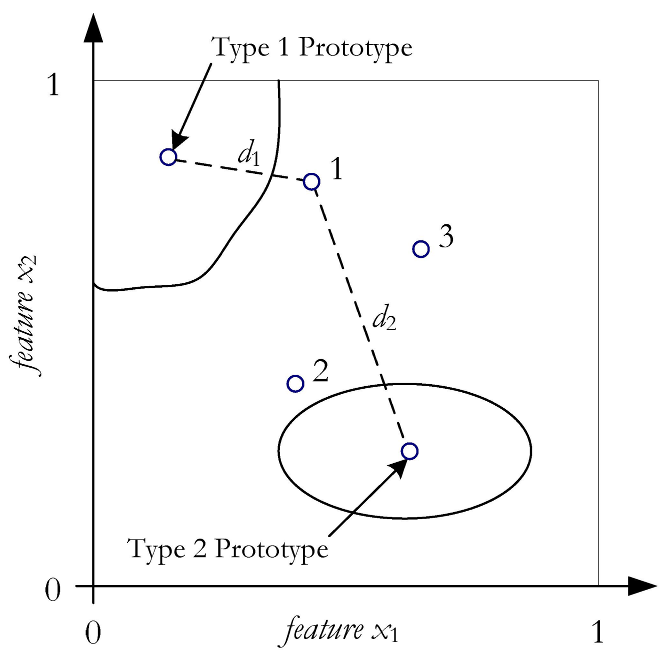


Fig. 2. $f_1 - f_2$ plane. Euclidian distance are also depicted on the plane. Classification of object 1 or 2 is a simple task. However, classification of point 3 is a more problematic task.

## IV. THE CLASSIFICATION TOOL WORKS AS A DIAGNOSTIC TOOL

In [1] the authors have just shown the strict correlation of the load current and instantaneous power signals to the water pressure values and their behaviours; in this way any operating conditions of the monitored system appears on the main side as a variation in the motor current and, in the same way, in the instantaneous power [10], [11]. In Fig. 3, in fact, it is possible to note that the measured power profile shows a modulation strictly correlated to the motion of the piston; moreover, it is possible to observe that the shapes of the power signal depend by the working condition. Signals obviously depend also on the water pressure level and on the changes of machine status.

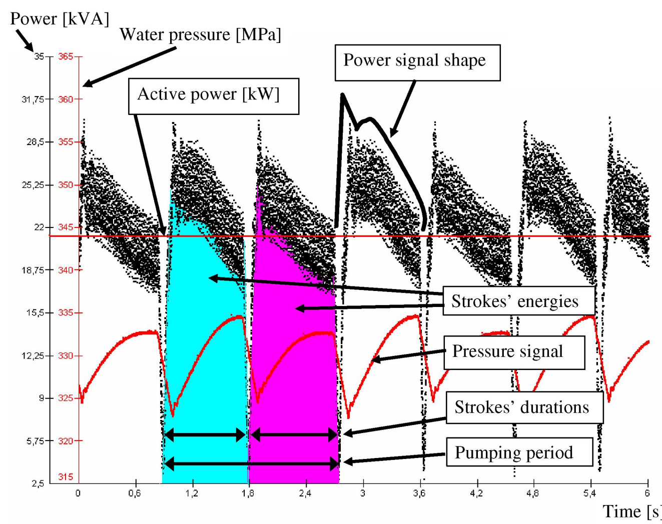


Fig. 3. Reference signals for a specific nozzle; sampling rate: 3.2 kHz; sampling period: 6 s.

For this reason, an analysis of the variation of the profiles from the reference condition can be considered as a good support for monitoring the efficiency and effectiveness of the system.

In this work we explored a different method for characterizing the power signal with respect to the different working conditions. The proposed method is based on an analysis of the shape of the Discrete Fourier Transform (DFT) of the power signal. Hence, the characterizing features of the power signal are obtained by a processing operated in the frequency domain. The features, $f_i$ used for the analysis are the first $k$ coefficients of the DFT of the power signal:

$$f_i = F(i), \quad i = 1, \ldots, k \quad (2)$$

where

$$F = \left\| DFT(P) \right\| \quad (3)$$

is the normalized DFT of the power signal, $P$. For this application, we chose $k$ = 20, as it allows to use the most significant coefficients. It would be noted that a study considering different (bigger) value for parameter $k$ (such as $k$ = 30 for example) has been conducted. However, the obtained results are very similar to ones here obtained.

The experimental results are obtained considering many case of study. For sake of simplicity, in this paper a reduced set of tests are reported. In particular, the classifier, here presented, has been configured using a dataset composed by 143 samples of the power signal in 12 working conditions (two type of nozzle having an orifice of two different diameter, for three different values of pressure).

For each class, $j$, identified by the triple composed by nozzle type ('G' or 'T'), diameter of the orifice (20 and 30 for 0.20 mm and 0.30 mm respectively), and working pressure (200, 250, and 300 MPa), we compute the class footprint, $f(j)$, as the average of the feature vectors, $F_l$, (computed as in (3)) of the signals belonging to the class, $\{P_l\}$:

$$f_i(j) = \frac{1}{n_j} \sum_{l=1}^{n_j} F_l(i), \quad i = 1, \ldots, k \qquad (4)$$

where $n_j$ is the number of sample data for the $j$-th class, $n_j = |\{P_l\}|$.

The footprints of the classes G-20-300, T-20-300, G-30-300, T-30-300 are reported in Figs. 4-7.

Observing these figures, it can be noticed the apparent similarity between the signals which refer to the same orifice diameter.

We choose to use the Euclidian distance as similarity measure. Hence, when the classifier receives an unknown power signal, $s$, as input, it computes the feature vector for $s$ as in (3) and classify it as belonging to the class, $j$, such that the footprint $f(j)$ is the closest to the feature vector of $s$.

In order to asses the ability of the classifier, we challenged it on the dataset used for the configuration phase (configuration error) and on new power signals, sampled in different working conditions (test error). For the test case, three samples for each working condition have been used.

The configuration error has been of 1.40% as 2 data out of 143 were erroneously classified (Fig. 7), while the test error has been of 0%, as all the 36 data were correctly classified (Fig. 8). These figures represent the histogram of the classification, where each bin is identified by the indices of the class from which the signal belongs to and the one of the class predicted by the classifier.

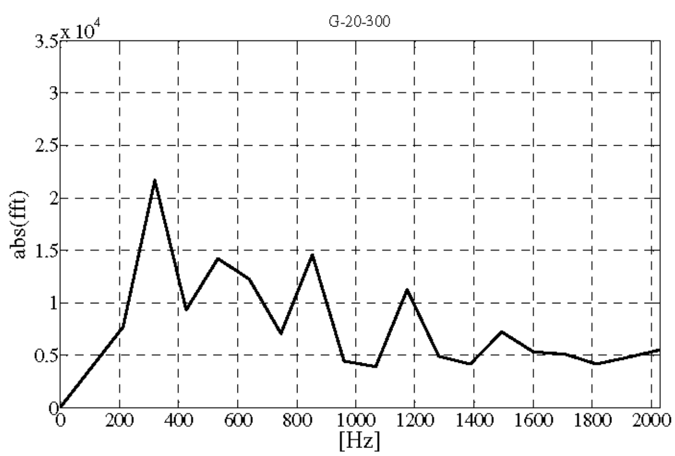


Fig. 4. Footprint of the class representing the G-20 (0.20 mm) nozzle working at 300MPa.

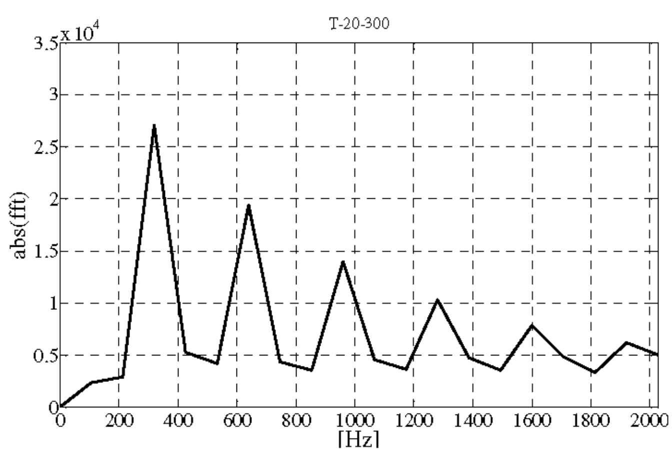


Fig. 5. Footprint of the class representing the T-20 (0.20 mm) nozzle working at 300MPa.

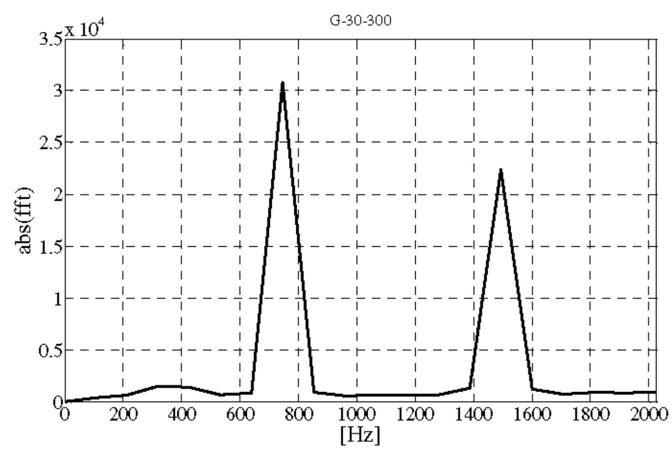


Fig. 6. Footprint of the class representing the G-30 (0.30 mm) nozzle working at 300MPa.

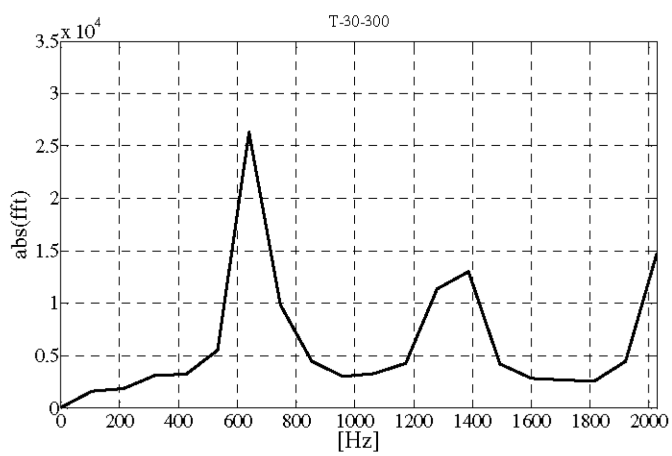


Fig. 7. Footprint of the class representing the T-30 (0.30 mm) nozzle working at 300MPa.

The more the couples fall in the diagonal, the better the classifier performs.

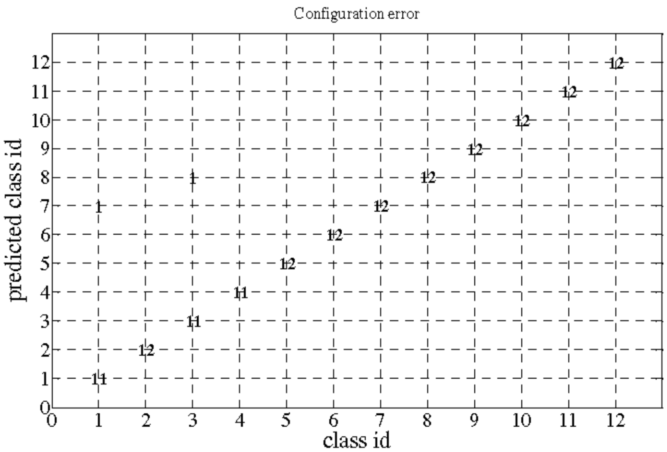


Fig. 7. Classification error in configuration: when challenged with the data used in the configuration phase, the classifier erroneously classify 2 data out of 143 (1.40%).

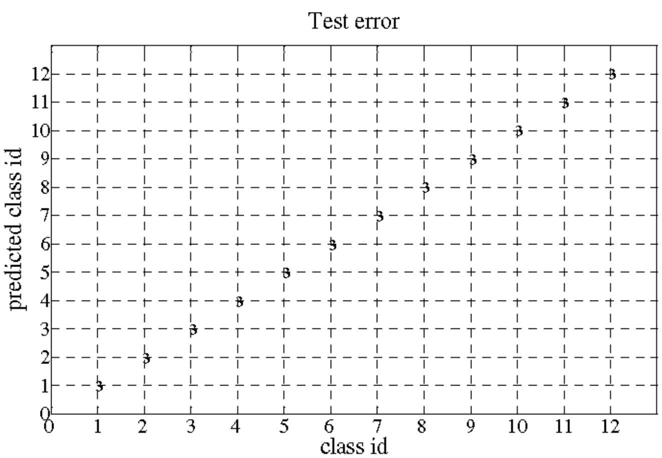


Fig. 8. Classification error in testing: when challenged with unknown data, the classifier correctly classify all the 36 test data (0%).

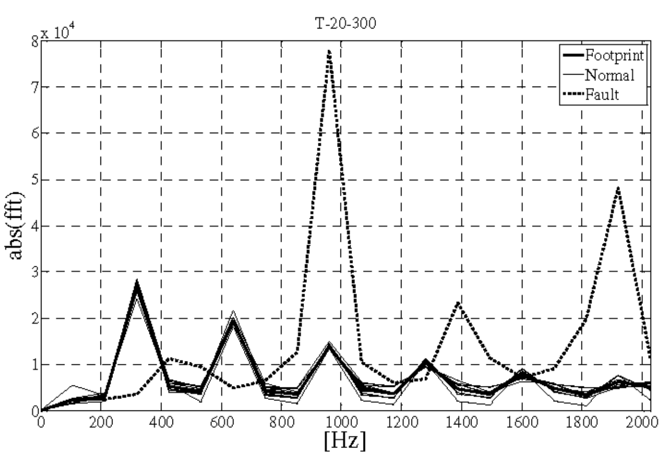


Fig. 9. Example of Classification cases. Footprint is represented with the largest line. An example of fault case is represented with dashed line and, finally, non-fault cases are represented too. The non-fault cases footprints are closer to the class footprint than the fault case.

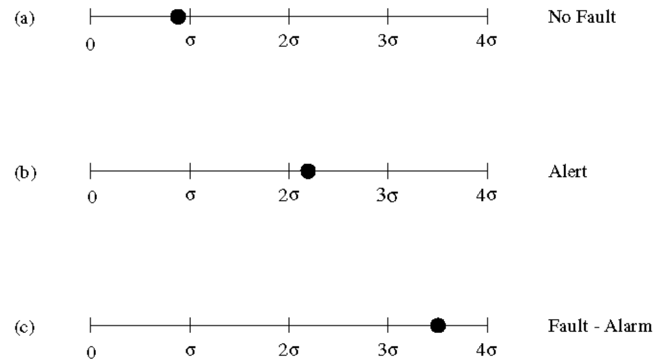


Fig. 10. Different working conditions may be recognized by observing the distance of the footprint of the actual power signal from the footprint of the considered class with respect to the distribution of the distance of footprint in normal working condition.

The classification tools can be utilized even for fault recognition tasks. In fact, when working condition is known, if the footprint of the correspondent power signal is not well positioned in the "*representation space*" with respect to the footprint of the same working condition, it leads automatically to consider the possibility of the presence of a faulty situation. These very important tasks can be demanded to an automatic procedure. In Fig. 9 the footprint of a typical malfunctioning case is compared to the footprint of the class that, for the mounted nozzle and the working pressure, it should belong to: it is evident that the distance of the fault case from the class footprint is greater than the mean distance of the footprint at normal working condition. This allows to use, as a reference for fault diagnosis, the distribution of the distance of the footprint of signals acquired during normal working condition sessions from the footprint of the class they belong to. Hence, during the configuration phase the standard deviation of the distance of the footprint of the signals of each class from the class footprint can be computed, and used to enrich the classification response with a measure of conformity to a standard working condition (*e.g.,* as in Fig. 10). It would be noted that the process mean always shifts to the right hand side when the process is out of control and this is well depicted in Fig. 10. In fact, the distance of the actual footprint from the class footprint can be only positive. These information can be used when a Control Chart for process control must be realized.

## V. CONCLUSIONS

The present work has the aim to show that the electrical power signal is greatly influenced by the machinery setup and the working conditions. As the measurement of this entity is much more feasible than the direct measure of the other parameters which influence the working conditions of the system, the exploitation of its relation may lead to an automated method for revealing the machinery state and the presence of (an incoming) faulty behaviour.

This fact can be suitably exploited to increase the reliability and availability of the system, thanks to the defined diagnostic algorithm. The simplicity of the proposed approach lead to consider the possibility of realizing a low cost real time diagnostic system.

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