ON LINE MONITORING OF RELIABILITY OF SIGNALS TO BE USED TO CONTROL PURPOSES

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Abstract. *With the increase in competition, it is necessary to optimize and improve the manufacturing procedures and the quality of the products, investing in new technologies and new procedures. Through techniques of predition, it is possible to detect and identify beforehand developing defects in industrial equipaments before the breakdown. Thus, allowing its mantainence. Hence predictive mantainence become importante in industrial instalations as it manage to attend the two outstanding requirementes, cost reduction and reliability of assembly lines. The use of vibration measurements and comunication by Internet for redictive mantainence made possible the control of the integrity of the equipaments and the operating conditions of the machines and measuring instruments in real time. Remote monitoring presents difficultily of checking the integrity of the signal received, such as due to a misplaced vibration sensor, a defective cable, a disconnected machine, etc. Therefore to overcome such problems, this paper studies the use of techniques that involve reasoning, such as fuzzy inference systems and artificial neural networks to obtain solutions close to human reasoning to verify signal integrity in predictive mantainence of rotary machines. Both techniques were applied to a rotary machine composted of a eletrical motor and a ventilator. The getting results using the PNN procedures are better of the fuzzy logic ones. As a matter of fact, cannot be observed great discrepancies between them. So, the use of one or other approach is an analyst experience function.*

Keywords*: Monitoring conditions, Fuzzy Logic, Neural Network*

1. Introduction

Predictive Maintenance assumes a role of great importance in industrial plants when it can take care of the two main demands of the competitive market nowadays: costs reduction and availability guarantee [Trigo, A. A., 2004].

Through the adoption of predictive techniques, it is possible to detect and to diagnosis defects in development in the industrial equipment before the breakdown, propitiating the punctual programming of the interventions of maintenance. Thus, the supply of spare parts and the cost of the intervention are reduced, together with the elimination of the products losses proceeding from a possible non programmed stop. A reduction of up to 40% in the quantity of exchange of bearing with the adoption of the predictive maintenance has been verified [Trigo, A. A., 2004]. On the other hand, it is possible to use all the projected useful life of the equipments by guaranteeing it good condition of functioning of industrial equipment. By consequence, the number of breakings or "failure rate" is diminished. By definition, the reliability is the probability of the equipment being operational. If the failure rate diminishes, then, it is guaranteed trustworthiness of the equipment. Therefore, the more time the equipment is available for the production regimen, one can say that is the main impact of Predictive Maintenance.

A real time monitoring is of utmost importance in the application of the techniques of predictive maintenance. The knowledge of the integrity condition of the equipment and structures subjected to damages promoted by the operational conditions is the great concern and the cause of accidents. A significant combination for the control of integrity of the equipment in real time is obtained by association of the techniques of measurements of vibration with the resources of the Internet.

With the Internet in mind as a tool of information and communication, it is possible to evaluate how critic and how severe the defects are when the equipment and structures are submitted to different operational conditions. Thus is possible to have an interaction on-line taking the intervention decisions, withdrawal or operational continuity [Feres et all, 2004].

However, to use the predictive maintenance via vibrations monitoring, on line, it is necessary to observe the integrity of the measured signal, in other words, if the vibration sensor is placed in the right place, if a connection cable meets the perfect readiness, if the instrumentation is on or not, and too many problems related with the measurements processes. For this, techniques are used that involve the reasoning approach getting as close as possible to the human reasoning.

The fuzzy systems have being used successfully in the last years in problems that involve the reasoning approach [Zadeh 1965, Bojadzieve 1996, Gottgtroy 1996, Kandel 1996, Kasabov 1996, Nguyen 1999]. The "fuzzy" set was initially proposed by Zadeh [Zadeh, 1965] to be an extension of the classic sets.

The utility of this set is based on its ability do model uncertain or ambiguous data found in the real life[Pal & Miter, 1992].

The main difference between the classic proposal and "fuzzy" is in the band of its truth values [Klir & Yuan, 1995]. In the classic theory an element belongs or not to one definitive set. In the theory "fuzzy" the element can belong, not to belong or to be partially present in one determined set.

A relevancy degree is given to each element of the "fuzzy" set. This value of relevancy is inside a range from 0 (not pertaining element to the set) up to 1 (total pertaining element to the set). A relevancy function is the ratio between the values of an element and its degree of relevancy in a set.

The "fuzzy" set allows representing express vague concepts in the natural language. The representation of the "fuzzy" set depends not only on the concept, but also of the context in which it is used [Klir & Yuan is used, 1995].

The techniques of standard recognition patterns based on neural networks have been applied in data of vibration in the frequency and time domain [Tandon, 1999], being distinguished in the verification of measurement conditions and alarm levels. The method consists of solving problems of artificial intelligence, constructing a system that has circuits that simulate the human brain, also its behavior, or in other words, learning by try and error and making discoveries. They are more than this, are computational techniques that present a model inspired by the neural structure of intelligent organisms and acquire knowledge through the experience [Yuri et all, 2004]. A great artificial neural net can have hundreds or thousand of processing units, while the brain of a mammal can have many billions of neurons.

Despite the complexity of the neural networks not allowing a unique definition, the following lines is an attempt of the innumerable definitions or interpretations of what is really a neural net.

A directed graph is a geometric object that consists of a set of points, called nodes, throughout a set of segments of lines directed between them. A neural network is a processing structure of information parallelly distributed in a directed graph form, with some proper restrictions and definitions.

The nodes of this graph are called processing elements. Its edges are connections, which function as paths of instantaneous signals conduction in one direction only. This way the processing elements can receive any number of input connections. These structures can possess local memory, and also possess any number of exit connections once the signals in these connections are the same ones. Therefore, these elements have only one exit connection that can be divided in copies to form multiple connections, being that all carry the same signal.

Then, the only input allowed for the transfer function (that each element of processing possess) is the values stored in the local memory of the processing element and the current values of the input signals in the connections received for the processing element. The unique output allowed values from the transfer function are values stored in the local memory of the processing element, and its output signal.

The transfer function can operate continuously o occasionally. In the second case, it must exist an input called “activate” that cause the start-up of the transfer function with the current input signal and values of the local memory. It will produce an up-to-date output signal (occasionally modifying value in the local memory). In the first case, the elements are always activated and the input “active” comes trough a reserved connection processing element that also is part of the network.

The input signals for a neural network come from the outside through connections that originate from the external world. The outputs of the net to the exterior are connections that leave the networks.

In a general form, the cell function in a network is summarized by:

- Signals are presented to the input;
- Each signal is multiplied by a weight that indicates its influence in the next exit unit;

- An activity level is produced by weighed summation of the signals;
- The unit produces an output if the activity level exceeds to a limit (threshold).

Therefore, it is intended by using the techniques of artificial intelligence and predictive maintenance to monitor in real time the readiness of the instrumentation used for the maintenance.

This work has as objective the readiness of machine monitoring, the instrumentation and integrity of the measured vibrations signals in real time for a radial fan system. This will be developed on-line using fuzzy logic and artificial neural networks.

2. Methodology

A real time monitoring of signals conditions were realized for vibrations signals acquired from a set-up in the Laboratory of Vibrations and Acoustics at Federal University of Uberlândia, Brazil.

Figure 3.1 Schematic of the used instrumentation, mainly composed of a radial fan and its electric motor.

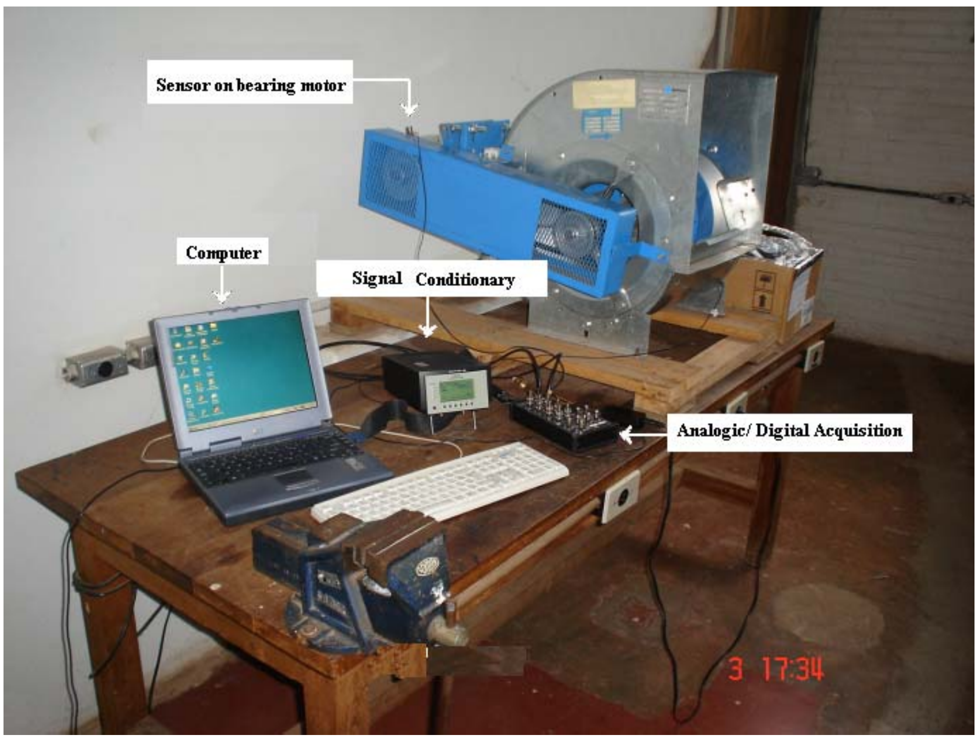

Figure 3.1 Instrumentation and the equipments.

Two piezoelectric accelerometer were fixed at the supports of the motor (see Fig. 3.1), and the fan (see Fig. 3.2).

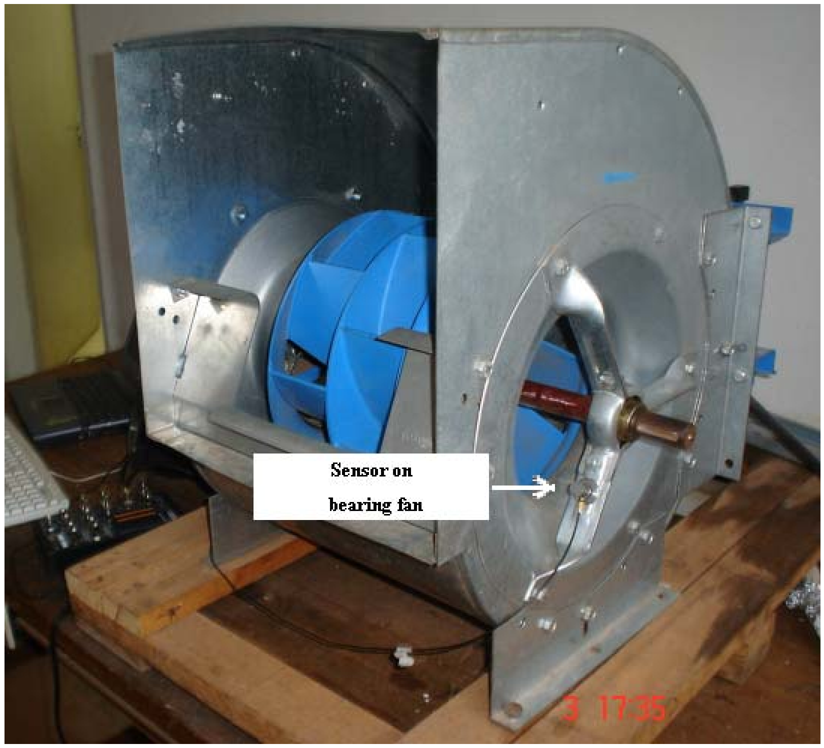

Figure 3.2 Accelerometer at the support bearing of the radial fan.

Thus, as the main goal of this work is to verify the quality of the acquired signal, 113 measurements were performed with the sensors placed in the shown positions and with the instrumentation in adequate operational condition. Those signals were named as “ok”.

With the sensors in wrong positions 60 new measurements were taken, in other words, with the sensors over the table or in interchanged positions. This conditions simulates a real situation where the machine operator can forget to fix some sensors, or change their position after the maintenance be performed.

Another 123 measurements were taken to simulate instrumentation problems, such as damaged cable, detached cable and conditioner signal turned off.

It should be noticed that these trial had been carried out to the motor as to the radial fan system.

The data were collected using a tachometer to measure the rotation speed of the motor and fan, 1744 and 2204 RPM, respectively.

Thus, we have an estimative of 159 parameters, listed in Table 3.1

Table 3.1. Parameters to be estimated

Number of parameters	**Description**
01	Kurtosis
01	Crest factor
01	Signal to noise ratio
26	RMS1
26	RMS2
26	RMS3
26	RMS4
26	RMS5
26	RMS6

On Table the 3.1, Kurtosis is the central moment of fourth order of the signal, the Factor of Crest is defined by the reason between peak value and global level of the signal (RMS). The signal noise ratio is, as the proper name says, the relation between the global level RMS and the energy level of the 60 Hz harmonics ones.

After the definition of parameter to be studied, a sensitivity analysis was carried out to select which of the 159 parameters are the best to be used as indicative parameter signal quality. In this analysis the Null Hypothesis Test was used to compare the averages of the values of the signal parameters "ok" with that ones. In this way, three more sensible parameters had been selected the sensory in a wrong place and three for problems with the instrumentation. A two set of parameter was chosen, one to electrical motor control and other to fan control.

Finally, a system of fuzzy logic and a probabilist neural net (PNN) had been developed to monitoring, in real time, the reliability of the measured signals.

To find the limits of the pertinence functions to be used in inference fuzzy system, the data had been treated in a statistical approach by using boxplot graphic tools. Figure 3.3 illustrates an example of this tool

Figure 3.3. Example of Boxplot Graph

It can be observed in Figure 3.3 that the parameters of the signal "ok" have levels upper of the instrumentation problem ones. In reason of it, the limit of the pertinence function value for a signal "ok" is above of the inferior mustache of its Boxplot curve. For the one with instrumentation problems below, the same analysis results on values above the superior mustache.

To validation purposes, a set of 27 “ok” data and 30 instrumentation problem data were acquired. For the wrong place sensor case, the overall 67 acquired data had been used in the fuzzy analysis. In neural artificial procedure, 60 of them were used on training step and 7 on the test step.

3. Results

Of the sensitivity analysis, the selected parameters to be used as symptom to indicate the quality of the signals acquired for the engine and the rotor, are shown in Table 4.1 and 4.2, respectively.

Table 4.1. Chosen symptom parameters of the quality of the signal for the electrical motor

Wrong place sensor parameters	**Instrumentation problem parameters**
RMS1 - 116.3 Hz central frequency	RMS1 - 184.7 Hz central frequency
RMS1 - 738.9 Hz central frequency	RMS1 - 369.4 Hz central frequency
RMS4 - 738.9 Hz central frequency	RMS2 - 3725.4 Hz central frequency

Table 4.2. Chosen symptom parameters of the quality of the signal for the fan

Wrong place sensor parameters	**Instrumentation problem parameters**
RMS1 - 58.3 Hz central frequency	RMS1 - 370.5 Hz central frequency
RMS4 - 185.2 Hz central frequency	RMS1 - 588.2 Hz central frequency
RMS5 - 1482.5 Hz central frequency	RMS1 - 3725.4 Hz central frequency

With these parameters, had been developed the inference fuzzy rules for the electrical motor and the fan. In these cases, the used method of inference was of Mandani and the defuzzification method that presented better performance was the centroid one.

In the neural network, were used three distinct classrooms of signals to be classified by the PNN procedure. The classrooms are signal "ok", wrong place sensor and instrumentation problem.

On Tables 4.3 and 4.4 are showed the results gotten for the system fuzzy and the PNN, respectively.

Table 4.3. Results gotten for the inference system fuzzy

Eletrical Motor	
Signal Type	**Classification error**
“ok”	0
Wrong place sensor	3
Instrumentation problems	0
Fan	
Signal Type	**Classification error**
“ok”	0
Wrong place sensor	3
Instrumentation problems	0

Table 4.4. Results gotten for the PNN

Electrical Motor	
Signal Type	**Classification error**
“ok”	0
Wrong place sensor	1
Instrumentation problems	0
Fan	
Signal Type	**Classification error**
“ok”	0
Wrong place sensor	0
Instrumentation problems	0

In accordance with Tables 4.3 and 4.4, the results obtained using the PNN procedures are better of the fuzzy logic ones. As a matter of fact, cannot be observed great discrepancies between them. So, the use of one or other approach is an analyst experience function.

4. Conclusion

The mayor conclusion of this work is that the success of an intelligence artificial procedure to control the reliability of monitoring signal is strongly dependent of the preview parameter choice. In this work, the best results were obtained with energy levels in 1/3 of eighth bands, centered in multiple frequencies of the rotation of the machine. Finally, cannot be observed meaningful differences between the results obtained with the use of PNN and Fuzzy approaches.

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