

TURBOMACHINERY PREDICTIVE MAINTENANCE BY INTELLIGENT ON LINE CONDITION MONITORING

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Abstract. *On line condition monitoring of rotating machinery became a widespready technique and is justified by low cost and high reliability of data acquisition systems and microcomputer operational systems. In general, the task of a monitoring system may consist in detecting the deviation of a process from normal conditions and to detect a new pattern. The use of artificial intelligent techniques is a suitable solution for handling the large amount of information that is generated. Neural networks associated to fuzzy systems permits to verify the input data quality, to improve the alarms and to detect features that will permit to develop a reliable diagnostic. This paper introduces the system AD4 (hardware and software) for on-line which is running at oil plants and offshore production platforms and involves the acquisition/analysis of vibration data and proceess data via ethernet. The AD4 system is installed and supervising turbomachines at PETROBRAS facilities and represents a succeed project supported by ANP and FINEP.*

Keywords. *turbomachinery, vibration, predictive maintenance, neural networks, fuzzy systems*

1. Introduction

Predictive maintenance is a methodology based on the direct monitoring of mechanical condition of rotating machinery to determine the actual mean time to failure. Based on trend analysis of the machinery condition, it will be possible to evaluate when a fault will become critical. The predictive maintenance will permit to identify a problem before the machinery condition is seriously affected. Therefore, it will generate information to be applied to decide the best period to repair the equipment. Otherwise, this kind of methodology is able to prevent catastrophic accidents.

It is estimated that more than 15% of the equipments monitored periodically, regarding to predictive maintenance, is critical enough to production and might be monitored continuously. Monthly or even weekly measurements have not proven frequent or consistent enough to detect developing problems on many of these critical machines. The change in approach from periodically measurements to continuous monitoring is aided by substantially lower costs for online monitoring systems based on PC software/electronics and lower transducer costs too [Lopes,1997].

The vibration signature analysis is a technique commonly practiced to determine the mechanical condition [Mitchel,1993]. The failure modes usually have components that can be identified and theirs magnitudes will depend on fault evolution and machine operating conditions [Alguindigue,1993]. It must be clear that vibration analysis alone will not provide enough information to evaluate accurately the machinery condition. Therefore, information about axial displacements, lubricating oil condition, process parameters and other parameters should be available and analysed together the vibration signals.

Artificial neural networks associated with fuzzy expert systems can be applied to perform sensor validation, to evaluate the abnormal conditions classification and for the trend evaluation [Javed,1993]. To perform classification is necessary to attach to each vibration signature a label that describes the operational state of the machine and the input to the network are features extracted from the vibration spectrum. Figure 1 presents the main components of AD4 concept.

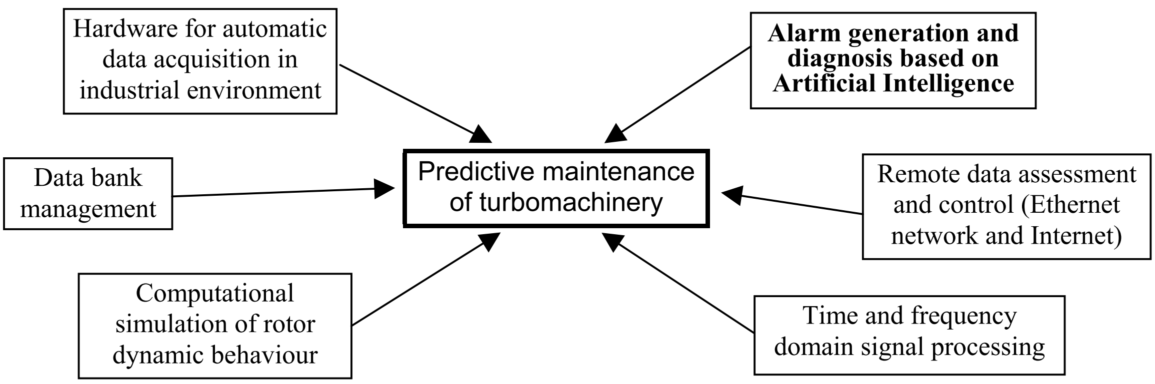

Figure 1 – Main components of AD4 concept

The AD4 system includes software and hardware and a brief description is introduced. The computer program for online turbomachinery monitoring, which is running in oil plants, offshore platform and oil transfer stations, is based on the analysis of vibration data and operational parameters. The introduction of neural networks associated to fuzzy systems, which is the objective of SUPCON project, will permit to verify the input data quality, to produce consistent alarms and to detect features for online preliminary fault diagnosis and severity evaluation.

2. Methodology

2.1 Introduction

The diagnosis of a process is a key element for predictive maintenance. The aim of a diagnosis system is, on the basis of multiple measurements, to detect the machine condition of the process (normal/faulty) and to identify and quantify the faulty behaviour [Boudaod,2000]. Diagnosis techniques are classicaly divided into two main categories. In a model-based approach, decision-making is based on residual signals computed from analytical relationship among measured variable. In a pattern-recognition approach, the knowledge of the systems limited to a learning set with recorded measurements and associated operational parameters.

Fault Detection and Identification techniques for turbomachinery condition can be classified, for practical applications, in two aproaches: (a) data simulation and (b) actual data. In the data simulation approach, faulty patterns are considered from previous experience and literature. In the actual data approach, knowledge about the system is assumed to consist exclusively in a learning set of feature vectors and associated operating conditions. Pattern recognition methodology is usually divided in two stages: feature extraction and classification [Toyota,2001].

The condition monitoring of machinery generally considers the vibration spectrum and its frequency components for each measured point. The mechanical condition evaluation can be obtained by evaluating the measured spectrum with a reference one, usually from a new machine or a newly serviced machine. The objective of the vibration diagnosis is the identification of a mechanical problem and its origin and severity, by using the vibration features. The vibration signature analysis is the most applied method for fault detection and identification and is based on the premise that usually exist characteristics that identify the faults. This technique composes a methodology that is of great usefulness in the predictive maintenance of rotating machinery. Nowadays, an essential step in the predictive maintenance is the improvement and the automation of the capability to interpret the vibration data. This is a vast field for the application of artificial intelligence techniques, as neural networks and fuzzy logic [Cox,1998].

The combination of fuzzy logic with neural networks has been proceeding at an increasing mode during the last years. A natural integration follows the same succesfull path of hybrid neural networks and expert systems by using fuzzy rule based systems instead of conventional expert systems. As shown in table 1, fuzzy systems and neural networks have several characteristics in common and complementary attributes [Medsker,1995].

Table 1 - Properties of Neural Nets and Fuzzy Systems

Properties	**Fuzzy**	**Neural**
Function estimators	y	y
Trainable, dynamic	y	y
Improvement with use	y	y
Improvement with use	y	y
Tolerance for imprecision	y	n
explicit knowledge representation	y	n
Adaptative	n	y
Optimizing	n	y
Interpolative	n	y
Tolerance for noise	n	y

2.3. Proccedure based on data simulation

As developed on a previous work [Lopes,2000] [Freixo,1999], the evaluation of the neural networks capability to interpret the vibration signature was based in three types of topologies:

- Multilayer Perceptron (MLP)
- Self Organizing Map (SOM)
- MLP with fuzzy input (MLP/fuzzy)

Table 2 presents selected faults and the assumed mean pattern for the previously defined frequency intervals and vibration ratio in the axial and radial directions. The selected faults are: unbalanced (1), rubbing (2), angular misalignment (3), parallel misalignment (4), defective bearing (5), bearing or slack support (6), defective coupling (7), friction whirl (8) and oil whirl (9). The eight input data for the classifier compose the fault mean vector [Freixo,1999].

The classification error was calculated for the evaluation vector for each network topology , according to (1):

$$E = \sum_{i=1}^{450} \sqrt{\frac{1}{9} \sum_{j=1}^{9} \left(\mathrm{T\,arg\,et}_{ij} - \mathrm{Networks}_{ij} \right)^2} \tag{1}$$

where:
Target_{ij} = desired output for the example i in relation to the class j
$\mathrm{Network}_{ij}$ = network output for the example i in relation to the class j
i= number of samples for evaluation vectors
j= number of possible outputs

Table 2 - Fault mean vectors data

Fault	0-40	40-55	55-90	1xRF	2xRF	nxRF	Rad	Axial
1	0	0	0	0.9	0.05	0.05	0.9	0.1
2	0.11	0.22	0.11	0.22	0.11	0.22	0.7	0.3
3	0	0	0	0.4	0.5	0.1	0.4	0.6
4	0	0	0	0.4	0.5	0.1	0.6	0.4
5	0.09	0.06	0.05	0.3	0.2	0.3	0.7	0.3
6	0.6	0.4	0	0	0	0	0.9	0.1
7	0.1	0.2	0.1	0.2	0.3	0.1	0.7	0.3
8	0.8	0.1	0.1	0	0	0	0.9	0.1
9	0	0.7	0	0.3	0	0	0.9	0.1

The main objective is to evaluate the neural networks techniques to diagnose mechanical faults in turbomachinery. The capability of each type of neural network to classify several faults was demonstrated through its learning capacity and its behavior in diverse classification cases. Three types of neural classifiers were examined: MLP network, a MLP network with fuzzy inputs and a SOM network. The network with the best performance is the MLP/fuzzy. Although the data used for the training of these networks were obtained from the variations around typical fault vectors coming from literature, this methodology does not disagree with the demonstrative character of [Freixo,1999].

Turbomachines are equipments that runs at high speeds. They are generally large and are essential for the process plants. The main configurations include steam and gas turbines and centrifugal and axial compressors. These machines are commonly used in petrochemical industries and offshore oil production platforms. There are several techniques of signal processing for extracting the vibration features [Sohn,2000] [Cunha,2003]. Some recent works suggest the compression of temporal and spectral data by using algorithms to extract the features as Principal Components Analysis or Autoregressive Algorithms. These algorithms reduces the input vector dimension by minimizing the loss of relevant information. The following faults are considered: unbalance; misalignment; oil film instabily (oil whirl); friction instability (friction whirl); rubbing; bearing problems; coupling problems; casing or support slack and ressonance.

2.3. Procedure based on actual data

In general, the conditions for applying a pattern recognition methodology are: (a) possibility to identify in advance all possible normal and faulty states; (b) the availability of data samples for each normal and faulty state. However, there are a large number of applications in which does not know the number of classes or can not do any recording for some classes for safety reasons. Therefore, a pattern recognition approach should have the ability to detect innovation in the inputs, a property that is generally absent from pattern classifiers. Another limitation is that the conventional pattern recognition schemes fail to take into account the dynamic behaviour of the system. In rotating machinery, transient behaviour are frequently obeserved.

Based on actual data, the diagnosis of a mechanical system condition by means of pattern recognition can involve two different steps: off-line learning and on-line learning [Boudaod,2000].

The analysis is an off-line step which leads to the design of the classifier. It begins by first making a selection of features from measurements in order to build a vector of m features in a m-dimensional space. This step is carried out a signal processing or model-based method.

Off-line learning

At first, during the learning step, the data are acquired and processed to produce a pattern vector in a feature space. Classes C1, C2, ... , Cn, representative of possible conditions of the system (nominal1, nominal2, fault1, fault2, ...), are defined by regions in the feature space. To delimite these regions, on the basis of the past recorded patterns it is necessary a classifier for discrimination among the n classes. Several methods can be used as the Bayes decision rule, the k-nn rule and fuzzy classifiers. Fuzzy sets theory was originally introduced in pattern recognition to automatic clustering. If a fuzzy approach is considered, a state of the system is represented as a fuzzy subset of the feature space and is described by a membership which quantifies the degree that any pattern can be a representative sample of a class. Therefore, each pattern vector can be assumed to belong to a class C_j with a degree of membership u_i defined as:

$$d(x) = C_j \quad if \quad u_j(x) = \underset{i=1,N}{Max}\, u_i(x) \tag{2}$$

On-line learning

Once the classifier is available, the diagnosis can be run on-line for supervising the system. New patterns gathered from the the system are classified into a specific class C_j , which corresponds to a different operating condition or to a new fault. However, is necessary to take into account that the learning set is often incomplete as, in general, only data from the normal operating condition is available. After rejecting a number of patterns far from the known classes, a new off-line training must be performed and these new classes are includded in the classifier: adaptation of the classifier is carried out off-line.

Usually, the adaptation of the classifier is carried out off-line although the alarm procedure should react as soon as possible. To enable the real time adaptation of the alarm procedure, the supervising system should detect and update the classifier on-line as soon as new state appears: the main problem is to detect its ocurrence. Three typical cases could be considered as following [Freixo,2003]:

- the supervision system has to indicate that the system is in a stationary state;
- the supervision system has to indicate that the system is in a transient state;
- the supervision system has to indicate that the system is in stabilization in a new class.

A fuzzy diagnostic system can be developed for this purpose and must have characteristics as: on-line adaptation when a new pattern vector is classified; detection of slow evolutions from a given operation mode, detection of stabilization in a known or unknown state and on-line learning of new classes.

A computer program, based on MathLab, was developed for simulation and has the purpose to build the Membership Functions which are able to consider the distribution for each operational state [Freixo,2003]. The following neural networs paradigms were considered:

- Radial Basis Function (RBF) neural network: applied for the estimation of the probability density function, based on the equations 3 [Parikh,1999].

$$y_k(x) = \sum_{j=1}^{M} w_{kj}\, \phi_j(x) + w_{k0} \quad and \quad \phi_j(x) = exp\left(- \left\| x - m_j \right\|^2 \Big/ 2\sigma_j^2 \right) \tag{3}$$

- Adaptative Ressonance Theory (ART) neural network: applied for the on-line updating of RBF parameters

2.4. Objectives

Sensor Validation

Fault tolerance in most real world problems has been generally achieved via some degree of hardware redundancy. Even for this situation, where safety is predominant, the use of multiple-redundancy may still not be the best solution. An alternative approach is based on the idea that dissimilar sensors, although measuring different variables, are being guided by the same dynamic state of the physical system and are related to each other. Features must be extracted from the input signal taking into account that [Eryurek,1992]: the characteristics of a "healthy" sensor must be available; suitable processing ensigns possible failure modes; extensive processing indicates the most feasible fault and its cause.

Alarms and Fault Diagnosis

For the sake of condition monitoring, an alarm can be considered as a low level diagnosis of a mechanical problem. The AD4 alarm module was developed to be able to detect changes and associate them to symptoms as: changes (offsets) in definite directions; changes due to selected patterns; changes with certain time dependencies and changes due to variances and covariances. Artificial neural networks are trained in order to evaluate the expected abnormal behaviour of the equipment, taking into account that machinery faults do not always give the same signal pattern and different malfunctions can cause a machine to exhibit similar vibrational symptoms. The inherent capacity of generalization of neural networks is very helpfull to deal with this situation. Fault behaviour evaluation using ANN is attained by feedding an input vector with fault information into a trained neural model which outputs the fault classification pattern [Hoffman,2001] [McLauchlan,2001] [Murakami,1999] [Uhrig,1993].

Trend Evaluation

Predictive maintenance aims to evaluate when a defect will become critical based on trend analysis of mechanical condition decay and complementary parameters. The intrinsic capability of neural networks to deal with details without the loss of generalization can be very helpful for trend evaluation. The analysis of function approximation performed by ARMA and ANN usually indicates that an adequate neural network could produce better results than statistical methods. For such kind of problem, connectionist expert systems may also generate the best solution [Lopes,1996].

3. AD4 Computer System

3.1. Hardware

The AD4 hardware is based on the PC104 standard : the MASTER CPU, SLAVE CPU, data acquisition and anti-aliasing filter boards are the main components of the hardware. Figure 2 presents a diagram for the AD4 hardware.

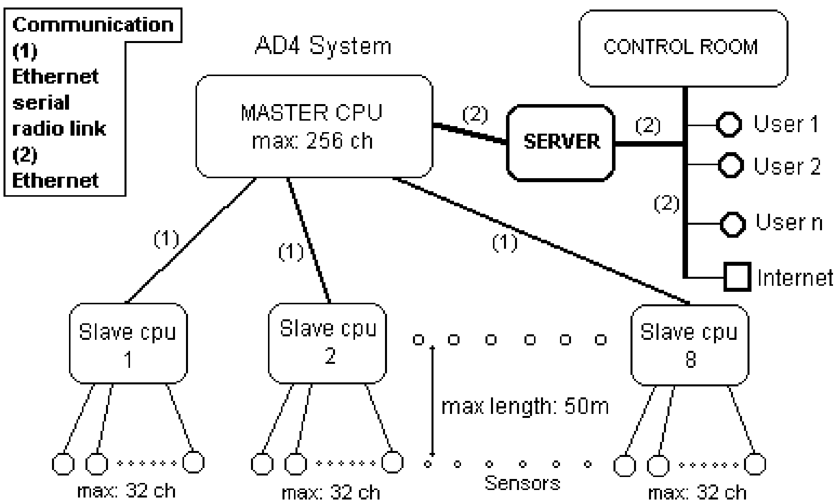

Figure 2 – AD4 hardware

On-Line Data Acquisition and Processing

This module is intended to perform the continuous monitoring of the machine. Vibration signals and process parameters data are acquired and analised by the software based on intelligent procedures. The AD4 system can be operated locally or remotelly as the hardware is connected to ethernet network. Up to 8 machines or 256 channels can be monitored for sensor data acquisition, generating alarms data whenever an abnormal condition is reached. Besides this vibration data, process parameter information is also acquired via PLC (modbus or serial communication) or via Plant Information (PI) server. The condition is indicated by three colors (green: normal; yellow: alert and red: critical) and indicates the alarmed sensors at the window on the screen. Normal operating condition spectra may be selected as well as operational parameters data. An example is presented in figure 3 and corresponds to four turbocompressors, installed at an PETROBRAS oil plant. The following operations are performed by on-line processing module:

- P1 vibration signals are acquired and the rms values are calculated in order to be compared to pre-defined limits; as long as the rms values continue inside the new range, the operation proceeds with no changes.
- P2 at the moment any rms level crosses one of P1 limits, a procedure for spectrum calculation is started for the alarmed sensors and the result is recorded into the preliminary database.
- P3 four times a day, all rms values, vibration spectra and process parameters data are acquired and recorded on the hard disk in order to provide a vibration history for the equipments (useful for trend analysis).
- P4 similar to P2, but is considered the vibration spectrum and selected ranges; the ranges are selected by user and this kind of alarm, together data from process, will be used to generated pre-diagnostic.

P5 similar to P2, but the ranges are defined by two fixed values: Alert (yellow) and Critical (red); at the moment any rms value crosses Alert or Critical levels, several procedures are started. (see AD4 Alarm Monitor).

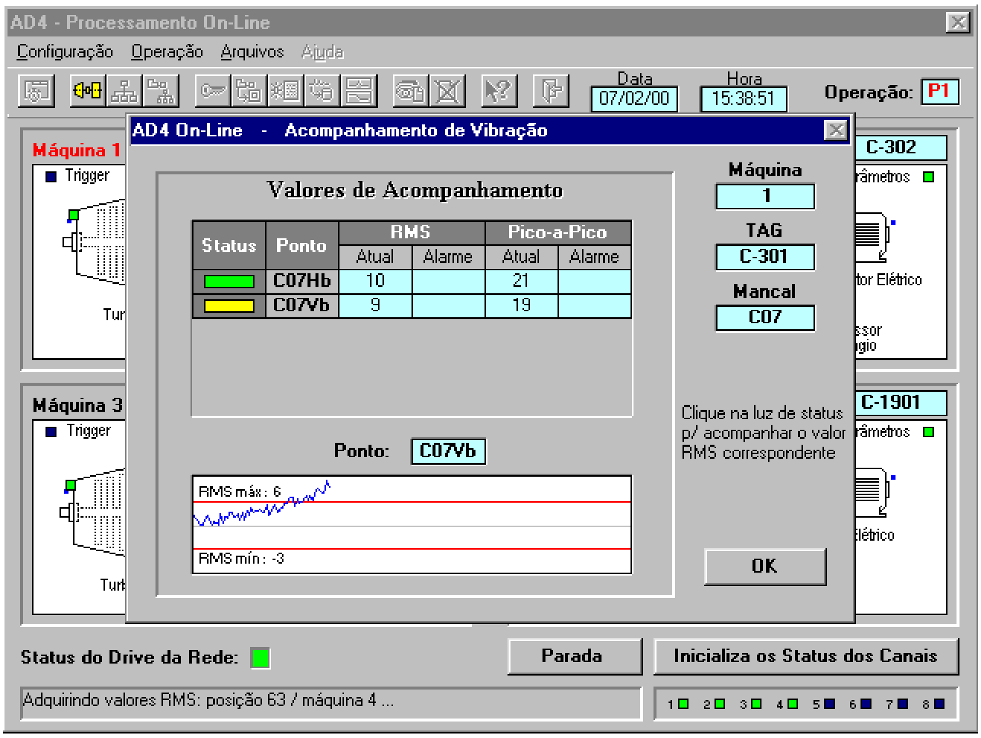

Figure 3 - Example of On-line Processing module

Alarms Generation

Tests can be defined for the rms vibration level, vibration spectral signature and process parameters and a complete check may be executed for a selected measurement. All detected alarm conditions are registered on the AD4 database and alarm report files are generated. Some aspects of this module are presented in figure 4.

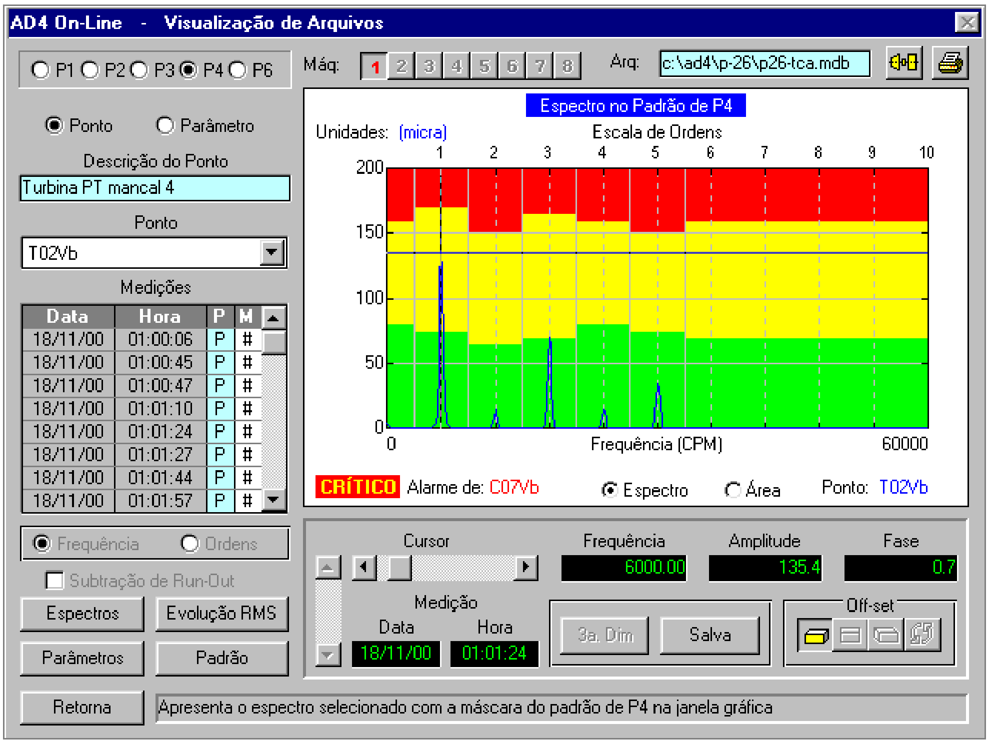

Figure 4 – Example of local alarms generation (P5 procedure)

As for sensor validation, a fuzzy/neural approach is able to reach these objectives taking into account both data from vibration and process. Multisensor fusion is a methodology on which each sensor classification can be obtained by neural networks and the decision fusion can be performed by a fuzzy logic algorithm [Du,1995].

At the time an alarm is generated by the Online Processing module, this information is released to the user via Email and via Intranet message to selected computers through the network. At each selected computer, on which must be running the AD4 Monitor, the message is displayed. In figure 5 is presented an example for the message that is received by the user in real time. In a near future this kind of will also include a pre-diagnostic and a list of the most probable causes of the alarm.

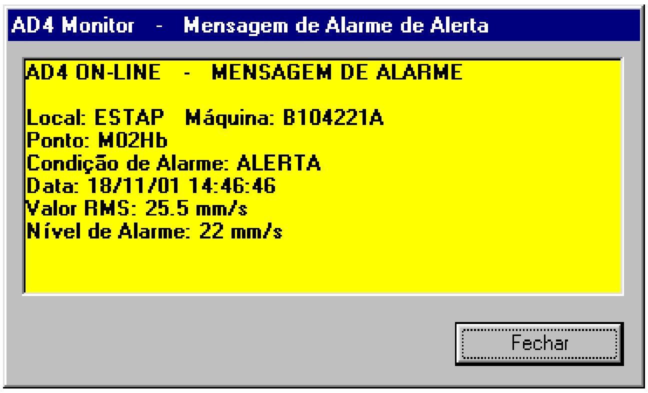

Figure 5 – Example of alarm message from the AD4 Monitor module

4. Conclusions

On-line mechanical condition monitoring is not just the continuous measurement of vibration and other parameters. It must be considered that some procedures, as sensor validation, efficient alarms and fault diagnosis capability, reliable trend analysis and assessment to important interconnected parameters (as lubricating oil condition) are critical to permit a real improvement in view of off-line monitoring results, regarding to both technical (reliability and safety) and economical aspects.

The Ethernet networks and the Internet permit a reliable information assessment and is becoming the main tool for communication to Online Condition Supervisors.

Reasoning about the data quality and the mechanical condition could be achieved by means of artificial intelligence techniques and the couple artificial neural networks/fuzzy expert systems are assuming a substantial role on this matter.

5. Acknowledgements

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