

# On-line Condition Monitoring Tool for Nuclear Research Reactors Coolant System Components.

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Machine condition monitoring is a world wide spread technology to improve predictive maintenance, availability, reliability and productivity. Additionally, in nuclear facilities, machine condition monitoring is an activity that could be used to improve nuclear safety. However, in experimental reactors, commercial technology for machine condition monitoring can be expensive and difficult to implement. This disadvantage leads to the development of an economic focused system capable of a complete on-line diagnosis for the principal rotating components of the experimental reactor, the nearby principal pipe and the decay tank. This requires development of sensors, electronics, software and specific knowledge, in order to obtain an early failure prediction system.

In RA-6 nuclear research school reactor, an off-line condition monitoring technology was developed in the early 80's during the startup and has been used since then. In 2008 an on-line automatic condition monitoring system was designed and installed, and continues in operation to this day. This system is being used as a platform for development of early failure detection techniques. The objective of this project was to develop an automatic condition monitoring system applied to the RA-6 primary coolant pump. The system is capable of performing the identification of the cause of the anomaly detected. Some typical problems in rotating machinery like unbalance, misalignment, shock and loose parts are identified by the system.

In this work a general description of the Condition Monitoring System is presented. Some results in anomaly detection issues and dynamical computation feedback are included. The system uses anomaly detection algorithms, unsupervised machine learning, to determine unusual behavior conditions and it is capable of monitoring these novelties and automatically generates a rule for detection using only relevant ranked features. These results show the potential of the on-line tool to react to early failure conditions, particularly in the primary coolant circuit including the nuclear core.

## 1.1. INTRODUCTION

Advanced technologies have become available for predictive maintenance of motors, pumps, compressors, and rotating machines in general. They are applied in industrial processes for equipment condition monitoring, reliability assessment, aging management and safety evaluations. It is widely accepted that predictive maintenance can keep equipment in service for longer periods of time, while maintaining the same levels of safety and availability.

The Vibration Division of the Bariloche Atomic Center – National Atomic Energy Commission (CNEA) has wide experience on both off-line and on-line condition monitoring techniques. The activity of the Division on this subject begun in the period 1984 – 1988 with an agreement for technology development between CNEA and IKPH Institute – Hannover Germany. Later, in 2008, an on-line monitoring system was implemented on the primary coolant circuit of the RA-6 nuclear research reactor based on classical fault detection rules.

An automatic Condition Monitoring system has been developed based on vibration analysis which has ongoing upgrade capabilities using appropriate signal processing and pattern recognition techniques. Collected experience stored as digital data related to the dynamic behavior can be used in similar machines or processes. Using laboratory tests, valuable information can be extracted and implemented in intelligent systems to extend the knowledge base. Also, behavior patterns can be analyzed and used to detect in-service machinery problems.

In order to identify changes in condition or incipient faults the information provided by a condition monitoring system must be arranged properly. When an intelligent system has to make a decision about a machine or process condition, three large disciplinary groups merge: The mechanical analysis of the machine or process (condition analysis, transducer technology, simulation and testing); signal processing of the collected data from the transducer; artificial intelligence tools to construe the new information collected, enhance the knowledge base and perform a diagnosis process.

## 1.2. CONDITION MONITORING SYSTEM: RA-6 RESEARCH REACTOR

The primary coolant circuit of the RA-6 research Reactor is equipped with an automatic monitoring system, developed and installed by the Vibrations Division. **¡Error! No se encuentra el origen de la referencia.** shows the system's block diagram. **¡Error! No se encuentra el origen de la referencia.** shows the currently installed instrumentation.

**¡Error! No se encuentra el origen de la referencia.** shows a detail of the accelerometer mounted on the primary pump. This transducer measures the acceleration on the pump bearing housing, axial direction. The transducer used is SKF model CMSS 99. Vibration signals from the motor-pump set, piping and decay tank have been acquired and analyzed since year 2008 to date.

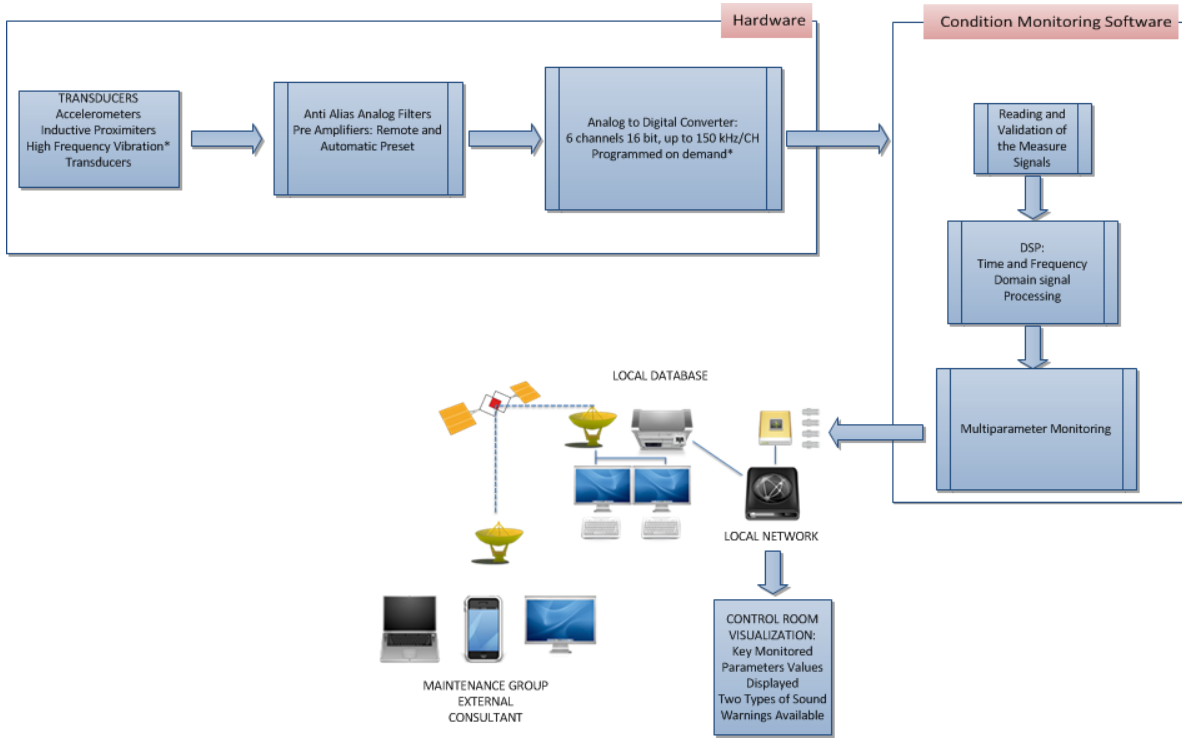


Figure 1. Condition Monitoring system – Block Diagram.

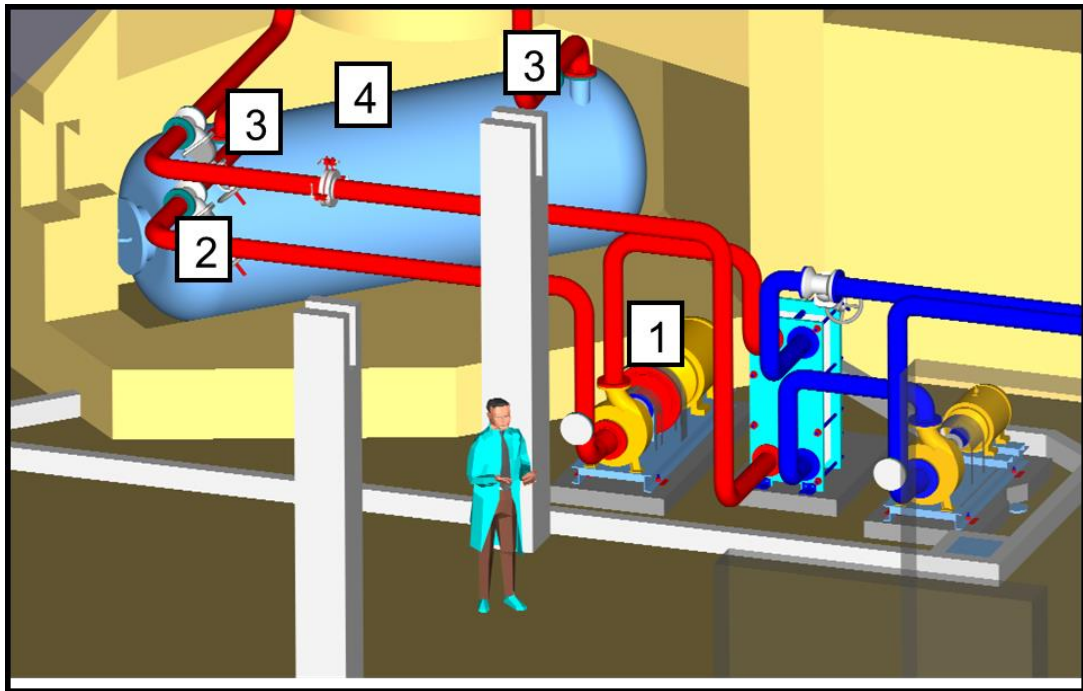


Figure 2. Currently installed sensors. 1: Motor-pump set: Accelerometer on pump bearing housing. 2: Piping: Accelerometer on primary pipe, exit from decay tank. 3: Piping: Two Inductive Proximimeters on the Decay Tank –in / out. 4: Piping: Accelerometer on Decay T

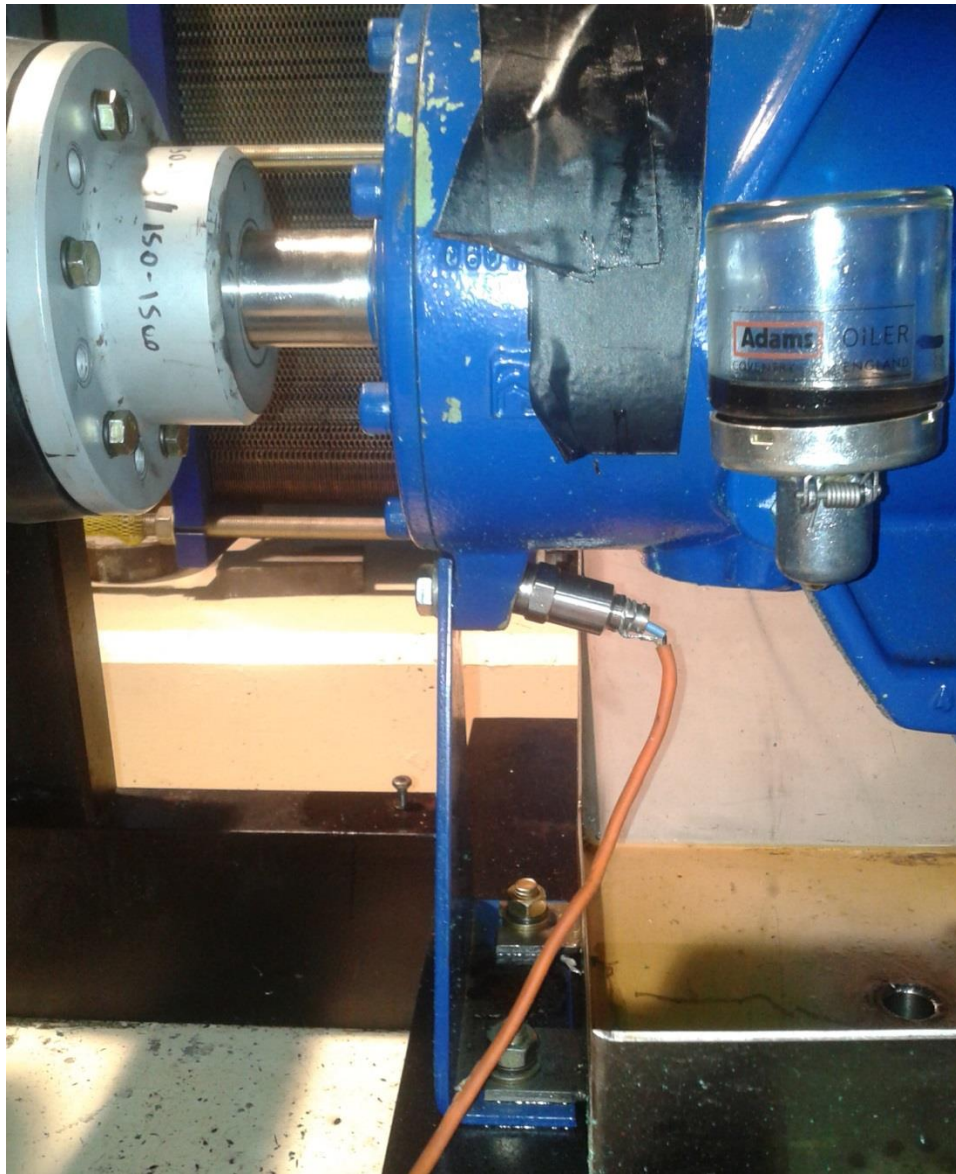


Figure 3. Accelerometer on pump bearing housing. Axial direction. Tentative transducer final position. Final transducer installation is subjected to maintenance plant quality control. Shown for demonstrative purposes.

The monitoring system has an excellent record of service without failures since year 2008. The diagnosis is made using rules interpreted by the condition monitoring software. These rules were written using the expertise gather in the vibration division for machine diagnosis. Also it was used the information collected by the monitoring system in order to determine a vibration signature of the rotating equipments, in this case, the primary pump. Figure 4 shows the vibration signature of the RA-6 primary pump. This spectrum was generated using the reports collected by the system. In order to detect behavior changes, every new spectrum processed by the condition monitoring system is compared with the pattern shown. In order to calculate the vibration signature of the

primary coolant pump, a long irradiation operation data set was used. For each report made by the condition monitoring system, a vibration signal with 4096 points and 1024 Hz frequency sampler is stored. The total acquisition time is therefore 4 seconds; this means that the system has the capacity to generate up to 900 reports per hour<sup>1</sup>.

Using the data collected in an irradiation operation, an average spectrum was calculated. Each spectrum was computed using the FFT algorithm (using Cooley-Tukey Decomposition)<sup>2</sup>. Each frequency component was calculated as it shows in eq1:

$$\bar{F}_{(\theta)} = \frac{1}{C} \sum_{i=1}^C F_{(i,\theta)} \quad (eq1)$$

Where C is the total number of spectrums used in the average operation and  $\theta$  is the angular frequency.

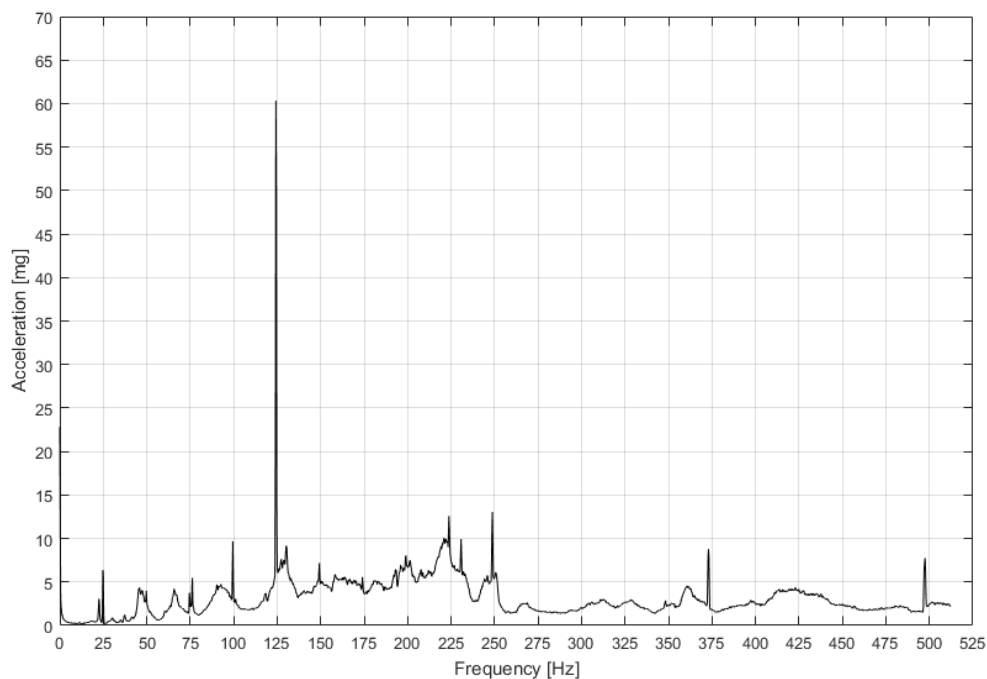


Figure 4. Pump average vibration spectrum

The objective of the average spectrum calculation is to reduce the random signal components, mainly due to pump-flow random interaction. In this case isn't necessary to use time synchronous

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<sup>1</sup> The condition monitoring system is set to report in an interval of ten minutes. This value can be set by the user.

<sup>2</sup> [www.fftw.org](http://www.fftw.org)

average because the intensity of the periodic components is not contaminated with other similar sources. Also the system supports stiffness is invariable.

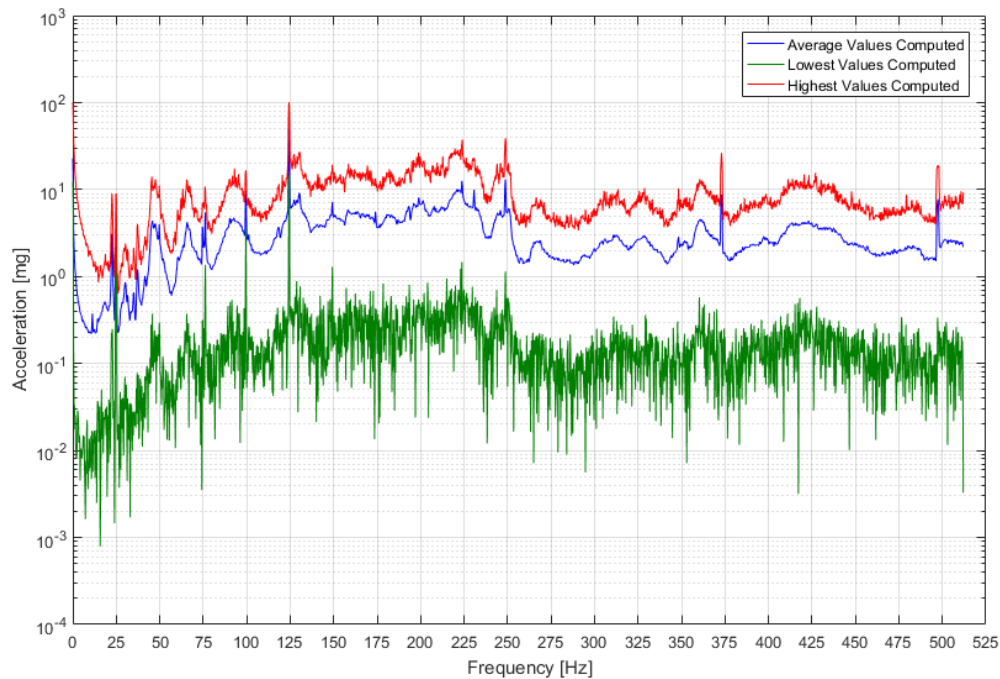


Figure 5. Comparison between average spectrum and peak hold spectrums.

As the amplitude of each frequency component of the average spectrum, is and average of itself, the statistic distribution is important in order to determine the variation for each component. The mean value could be relative low, however it might have a high variance, therefore some components could reach considerably higher levels. In Figure 5 a comparison between the average spectrum and the result of computing the highest peak-hold and the lowest peak-hold spectrums is shown.

### 1.3. DETERMINATION OF RELEVANT DIAGNOSIS FEATURES USING THE MACHINE INFORMATION AND A MECHANICAL DYNAMIC ANALYSIS

The set of features that are needed to achieve an accurate diagnosis must be extracted from the data with prior knowledge of the machine characteristics. Some features are directly related to a diagnosis cause, others behave differently and a larger set of features must be used to achieve a failure analysis. The rotational speed, the alignment condition, the bearing type and number, the impeller geometry –number of vanes- and a modal analysis are valuable information when a well done vibration analysis is needed. A list of the features used to achieve a basic diagnosis will be listed and explained. Also some results of modal analysis is shown.

### 1.3.1. UNBALANCE

Unbalance occurs in a rotating machine when the mass centerline and the rotation axis do not coincide on each other. Unbalanced rotors generate vibration which can end up in damaging their components. In order to extend the life of the machine, vibration due to unbalance must be reduced to acceptable level. Despite the ability to reduce unbalance to low levels, these levels or limits must be defined.

Unbalance amount is expressed as:

$$U = m r$$

Where, m is the “heavy spot” mass and r is the distance from the “heavy spot” to shaft-rotor centerline. The unbalance force generating the vibration is expressed as a rotating vector (phasor):

$$\bar{F}(\omega) = m r \omega^2 \bar{r}(\omega)$$

Where, F is the force,  $\omega$  is angular frequency and  $r(\omega)$  is a phasor rotating in the radial plane:

$$\bar{r}(\omega) = e^{i\omega t + \theta}$$

Expressing the force in the horizontal (x) and vertical (y) directions:

$$F_x = m r \omega^2 \cos(\omega t + \theta)$$

$$F_y = m r \omega^2 \sin(\omega t + \theta)$$

The acceleration measured in the pump due to unbalance is a consequence of the unbalance force, as such, is strongly related to the angular speed of rotation. For the RA-6 primary coolant pump, the rotational speed is 24,8 Hz, and the frequency spectrum component is shown in Figure 4. In order to obtain the unbalance related feature the frequency component is extracted from an average spectrum made with five raw spectrums.

### 1.3.2. MISALIGNMENT

Coupling misalignment is a condition where the shaft of the driver machine and the driven machine are not on the same centerline. For discussion purposes, the non-coaxial condition can be parallel misalignment or angular misalignment as depicted. The more common condition is a combination of the two in both the horizontal and vertical direction. In Figure 6 two types of misalignment are shown.

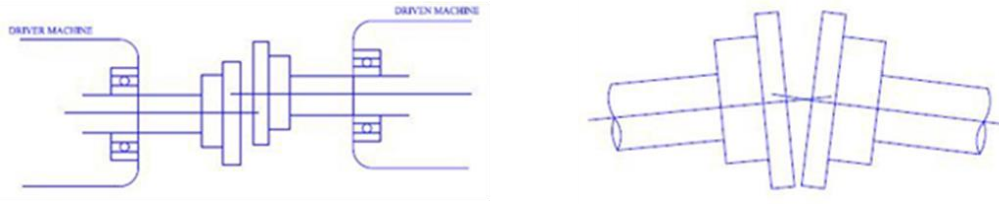


Figure 6. Left: Parallel Misalignment. Right: Angular Misalignment.

When a rotating machine is not perfectly aligned there is a distortion on the measured signal. This distortion changes the sinusoid form of the vibration signal. It can be detected looking for the rotation frequency harmonics. A machine with a well done alignment would have none or practically zero harmonics level –THD, Total Harmonic Distortion-, however a misaligned machine would have a vibration spectrum with higher levels of harmonics. Analog to the unbalance detection process, the feature related to misalignment is extracted from the vibration average spectrum looking for the first harmonic of the rotational speed. For the RA-6 primary coolant pump this frequency component is at 49,6Hz as it is shown in Figure 4. The existence of this frequency component does not represent a failure condition, but this level must be monitored for changes.

### 1.3.3. IMPELLER CONDITION

The impeller condition is monitored by a frequency component in the vibration spectrum. When the pump rotor completes a revolution each vanes of the pump interact with the fluid. This generates a vibration response of the pump a number of times equally to the numbers of vanes per revolution. Any change in the vanes or impeller geometry, a non-homogenous fluid distribution at the inlet of the pump, or an eccentricity of the impeller, will produce a hydraulic unbalance of the rotor with an effect on the amplitude of the vibration in the vane passing frequency. In the case of the RA-6 primary coolant pump the impeller have five blades and a related frequency of 124Hz (5X) as it is shown in Figure 4—five times the rotational speed frequency -. This kind of failure is very important because leads to a malfunction condition of the pump supporting bearings, shortening their useful life. Analog to the unbalance detection process, the feature related to the impeller condition is extracted from the vibration average spectrum.

### 1.3.4. BEARING CONDITION

Bearing damage is the most common cause of machine disruptions or failures. Although they have a robust and compact design, these components are subject to diverse influences that affect their service life:

- High bearing loads –unbalance and misalignment-
- Assembly errors
- Lubrication problems
- High operating temperatures



The bearing condition is monitored using the pump vibration spectrum and envelope analysis. The envelope analysis technique requires an analog constant rise time pre-filtering. The vibration analysis allows the detection of incipient failures occurring in the bearing's components –races, balls, etc.-. These incipient failures are detected as symptoms and are located in the envelope vibration spectrum as frequency components and in the vibration spectrum as broadband medium/high frequency noise. The primary coolant pump bearings are monitored extracting the following diagnosis features from the collected vibration data as:

- Ball pass frequency from outer race (BPFO): 76.2 Hz
- Ball pass frequency from inner race (BPFI): 122 Hz
- Ball spin frequency (BSF): 50.5 Hz
- Fundamental train frequency (TFT): 9.52 Hz

And using the energy measured in frequency ranges and spectrum changes from 500 Hz up to 3000 Hz.

#### **1.4. INSTALLED DIAGNOSIS SYSTEM BASICS**

Using the statistical and spectral features a pattern behavior is determined. This pattern –an average spectrum and statistical results as the RMS vibration level- has upper and lower boundaries calculated automatically with statistic tools. The methodology used to establish the boundaries is to multiply the maximum amplitude of each frequency component in the average spectrum to a factor proportional to the standard deviation of that particular frequency component.

After the data is collected from the transducers an average and real time spectrum is calculated and the relevant features are extracted. The spectrums are compared to the pre-defined boundaries. When a violation of the boundaries occurs, an anomaly situation has been detected. In this case, the violation zones are compared with the diagnosis features, in order to associate the anomaly with a known cause. If none of these features denounce changes, the condition remains normal. However, when a feature changes its behavior –increase or decrease its value- a fault cause is associated. Whenever a feature or more lies out of the calibrated domain it is correlated with the other features values in order to map this pattern to a known and studied cause or failure.

##### **1.4.1. WARNINGS, ALARMS AND DISPLAYED INFORMATION.**

A display in the Reactor Control Room was implemented with the objective of presenting diagnosis information and early warnings to the Operator. The information presented includes the condition of the primary coolant circuit pump set.

The Control Room system is connected to the monitor through the corporate network. In this manner, the processing of the acquired signals is made by the condition monitoring system and communicated to the control Room. In case of a warning or an alarm, the displays show the relevant information to assess the condition and, simultaneously, a sound alarm is triggered. The sound alarm in the Control Room is also directly connected to the monitor, ensuring its function independently of the computer network. From the safety point of view the system has a third independent alarm subsystem which can provide directly real time hardware connected alarms & warnings signals in parallel to the monitor. This alarm subsystem is totally independent from the computer-based processing system.

The parameters used to trigger the online warnings and alarms are: the RMS –Root Mean Square-level for vibration severity [mm/s] in the pump, the general RMS vibration level in the pump [mg] and an indicator of bearings shock pulses.

All the parameters used by the warning and alarm sub-system are displayed in a screen in the control room. When a warning or alarm event take place, the operator has the information available to discriminate which parameter reached a limit. Also, a complete report is generated with all the signals acquired and their correspondent vibration spectrum as others processed parameters. Figure 7 shows the information provided by the condition monitoring system in the control room. The diagnosis information is also displayed and shown in Figure 7.

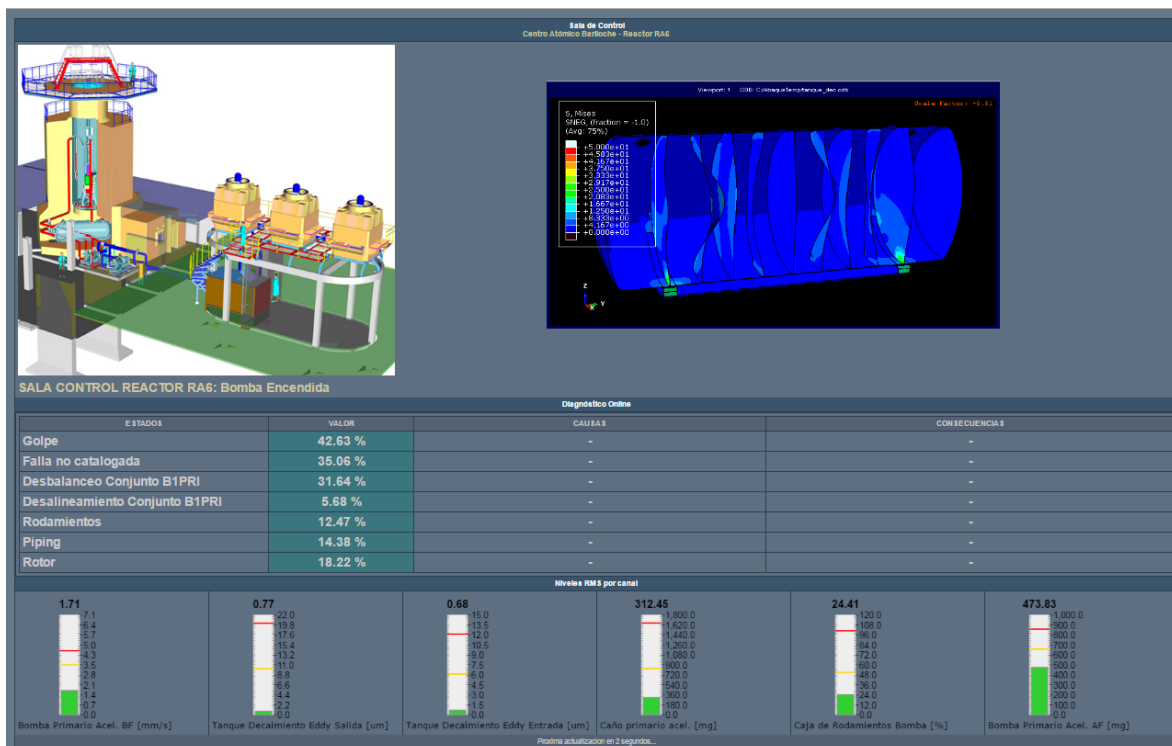


Figure 7. Information provided by the condition monitoring system displayed in the control room.

## 2.1. UPGRADE OF THE CONDITION MONITORING SYSTEM

As part of an IAEA<sup>3</sup> coordinated research project, the vibration division is currently working on computational tools and technological devices to implement efficient condition monitoring programs. Once the raw data is collected from the transducer –wired or wireless technology- the system automatically process them to extract valuable features determined after completing a mechanical analysis of machine and using the expertise available as was explained. These features form a multidimensional space where the machine dynamic behaviors are projected forming clusters. Some features are more relevant to a specific condition, so in order to classified the information a dimensional reduction must be done. There are several ways to achieve dimensionality reduction, one of the most popular is the Principal Component Analysis -PCA- in which a linear transformation is applied to the data, projecting it to a lower dimensional space in maximum variance direction. If new patterns appear, they must be detected and classified. Non-supervised machine learning algorithms are being tested, derived from competitive learning using artificial neural networks. Once the data has been classified into different clusters, relevant features are ranked and general rules of behavior could be formed.

The aim of upgrading the condition monitoring system is to outfit the installed software with “learning” capabilities. This means that the system would have the ability of enhance its knowledge base and would be able to use the learned experience to achieve an accurate diagnosis or a rapid detection of an anomaly. The newest knowledge could be implemented in form of rules, like the previous system or could be stored numerically as synaptic weights of an artificial neural network. In Figure 8 a block diagram of the upgraded system is shown. This new approach is based on extract relevant features, detect anomalies and classify new groups of behavior creating classification rules.

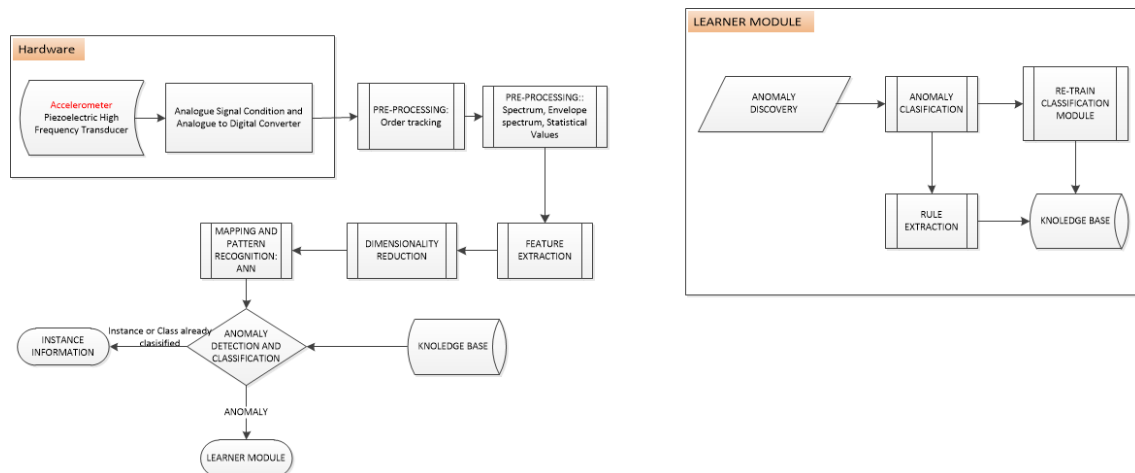


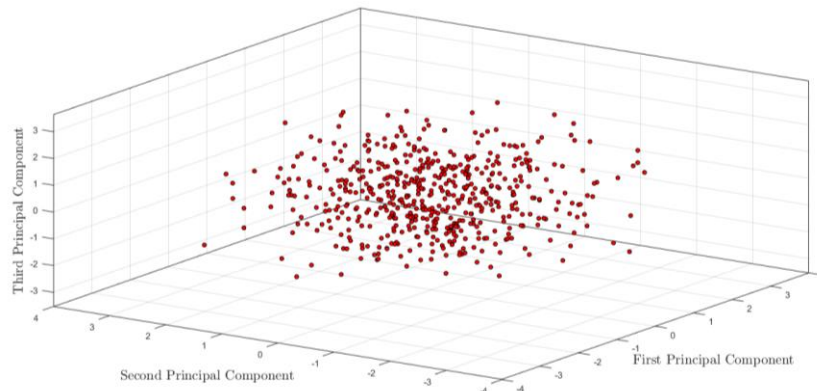
Figure 8. Automatic Condition Monitoring Tool. Block Diagram

<sup>3</sup> CRP: Condition Monitoring and Incipient Failure Detection of Rotating Equipment in Research Reactors

## 2.2. UNSUPERVISED ANOMALY DETECTION

Detecting small changes in stream data is one of the subjects being studied in machine learning field. These changes are commonly known as a novelty, outlier or anomaly. Statistical behaviour of the involving variables is taken into account in order to detect changes or new patterns. The system shall use the features extracted from the measure data to detect changes in the machine's condition.

Once the feature space is determined, on each acquisition the online tool extracts a new set of features describing the pattern behaviour. Each point in this multidimensional space represents a condition of the machine. The Euclidean distances between points reveal which are more similar, that means if a group of points lies in a particular domain of the feature space they form a cluster. Depending on the pattern analysed, some features may present similar statistical behaviour, and a strong correlation might exist. Adding more features, and so more dimensions, increase the probability of having redundant information. Principal Component Analysis (PCA) is used in order to reduce and compact the feature space. PCA is commonly used as an unsupervised machine learning tool to achieve dimensionality reduction. In order to explain this idea the Figure 9 shows a compact cluster with bounded domain representing the normal behavior of a machine.



**Figure 9. Calibration cluster, first three principal components.**

When there is a change in the condition of the machine, one or more features would change their statistical behaviour, resulting in a point placed far away from the original cluster. The distance is measured and this new collected information is therefore labelled as an anomaly as shown in Figure 10-A. Later, if the condition of the machine really changed, a new cluster would form (Figure 10) and further assumptions could be done.

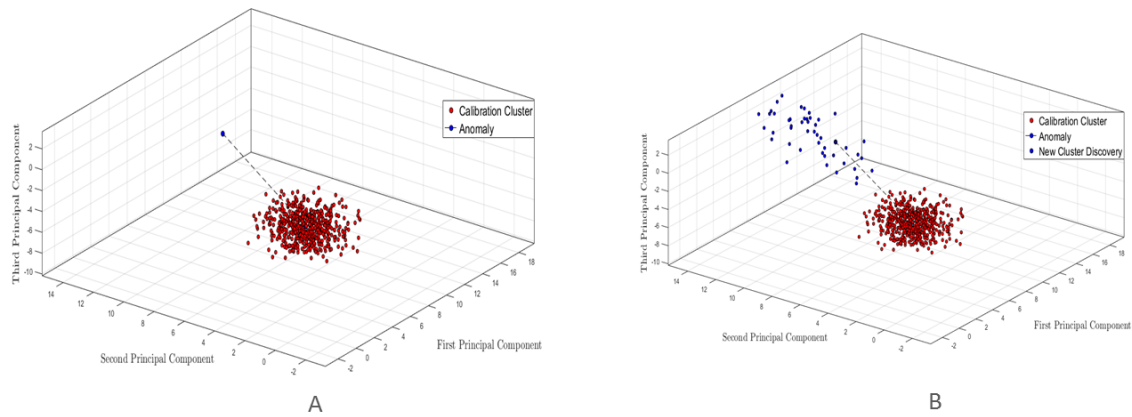


Figure 10. A) Anomaly detected, first data stream of the new cluster. B) Second cluster shown.

The classification system is called unsupervised because there is no need to train it with labeled examples. It must be capable of finding patterns in the stream data. This pattern recognition technique used clustering algorithms derived from the “competitive learning” of artificial neural networks. Every time a new behavior point is collected a synaptic weight from the neural network is activated. This weight is the closer one so is declare the “winner” allowing it to move closer to the input. This means that this synaptic weight will classify the entire cluster.

### 2.3. AUTOMATIC RULE GENERATION

Once the data has been classified into different clusters, relevant features are ranked and general rules of behaviour can be formed. In order to obtain a more comprehensive set of data to explain the detected changes in the machine condition it is necessary to reduce the non-relevant data or features. A feature ranking task would arrange the most relevant features between two sets of observation –previously classified clusters-. Exhaustive correlation search between features is done using the Fisher’s Discriminant Ratio -FDR- and features cross correlation. Once the features are ranked, the rule for the condition classification is generated. The rule generation process uses the statistical changes in the most relevant features ranked using IF-THEN statements.

### 3. STUDY CASE

Before installing the upgrades for the condition monitoring systems several tests must be done. One test carried out in the laboratory is presented. In this test, rolling bearing condition is monitored using the vibration spectrum and envelope analysis. All signals are expressed as a function of shaft revolutions and converted to the order domain. Digital order tracking is used to remove the effects of speed fluctuations. Vibration analysis allows the detection of incipient

failures occurring in the bearing's components –races, balls, etc.-. These failures are detected as symptoms and are located in the vibration spectrum as the following frequency components:

- Over-rolling Frequency of One Point on the Outer Ring ( $F_e$ )
- Over-rolling Frequency of One Point on the Inner Ring ( $F_i$ )
- Rotational Frequency of a Rolling Element About its Own Axis ( $F_{rb}$ )
- Over-rolling Frequency of One Point on a Rolling Element ( $F_b$ )
- Rotational Frequency of the Rolling Element and Cage Assembly ( $F_c$ )

Using a rolling bearing test bench, the signal processing and machine learning techniques are used in order to identify abnormal behavior and extract rules to characterize each pattern.

### **3.1. EXPERIMENTAL SETTING**

#### **3.1.1. TEST BENCH DESCRIPTION**

Experimental practice is performed on a rolling bearing test bench developed by the vibration laboratory. It allows the testing of bearings with sizes varying from ID = 25mm to ID = 100 mm and OD up to 160mm. The facility allows the use of axial and radial loads, control bearing temperature and vary the angular speed of the shaft. The driving force is provided with a Three-phase squirrel cage electric motor connected to an inverter control unit.

#### **Transducers:**

- A 256 points incremental encoder is used to measure the shaft instantaneous angular speed – IAS -.
- Medium frequency accelerometer mounted on bearing support, vertical direction. Brüel & Kjaer model 4371. Analog bandpass filter 2 Hz – 20 kHz.
- High frequency piezoelectric sensor developed in the vibration laboratory, mounted on bearing support, vertical direction. Analog bandpass filter 15 kHz – 60 kHz.

The signals are simultaneously acquired with an ADC with sampling frequency up to 150KHz.

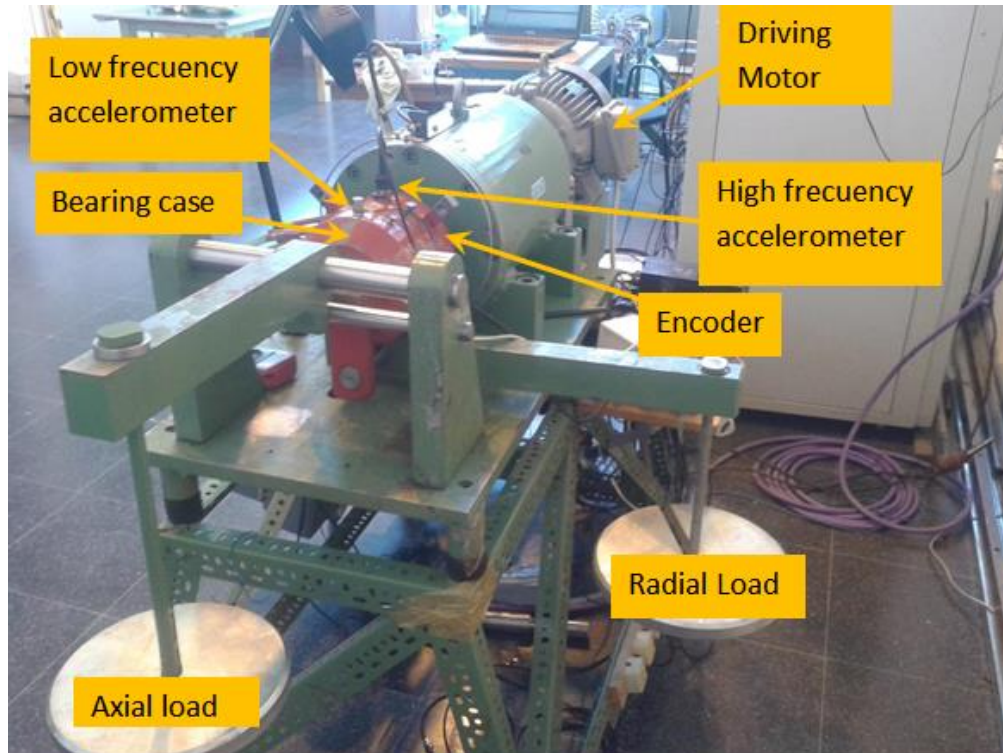


Figure 11. Bearing test bench developed by the Vibration Division.

### 3.1.2. CONDUCTED TEST

For this test a SKF 6307 - C3 deep groove ball bearing was mounted on the test bench. The lubricant used was Klüber – Klüberplex BEM 41-132 grease. The new bearing was tested under two magnitudes of pure radial load, as depicted in Table 1. Then, small size marks were conducted on the inner race to simulate a distributed inner-race fault. The damaged bearing was tested again with the previous load and lubrication conditions, and additionally without lubrication, as shown in Table 1.

Table 1: Test conditions

<i>Condition</i>		Load	Lubrication
<i>New</i>	1	3 kN	Grease
	2	12 kN	Grease
<i>Damaged</i>	3	12 kN	Grease
	4	3 kN	Grease
	5	3 kN	None

### 3.1.3. DATASET

For each test condition three time series signals are collected. Two vibration signals from piezoelectric transducers covering frequency domain up to 60kHz and an encoder TTL signal dividing each shaft revolution in 256 parts. In Figure 12 an example of the raw signals acquired is shown for a complete revolution of the shaft. Each vibration transducer is focused on a part of the spectrum due to pre-analog filtering. The accelerometer signal is low pass filtered in the band 1 Hz - 20kHz. Meanwhile the piezoelectric transducer is being filtered with an analog passband filter in the band 15kHz - 60kHz. All signals are sampled at 150kHz.

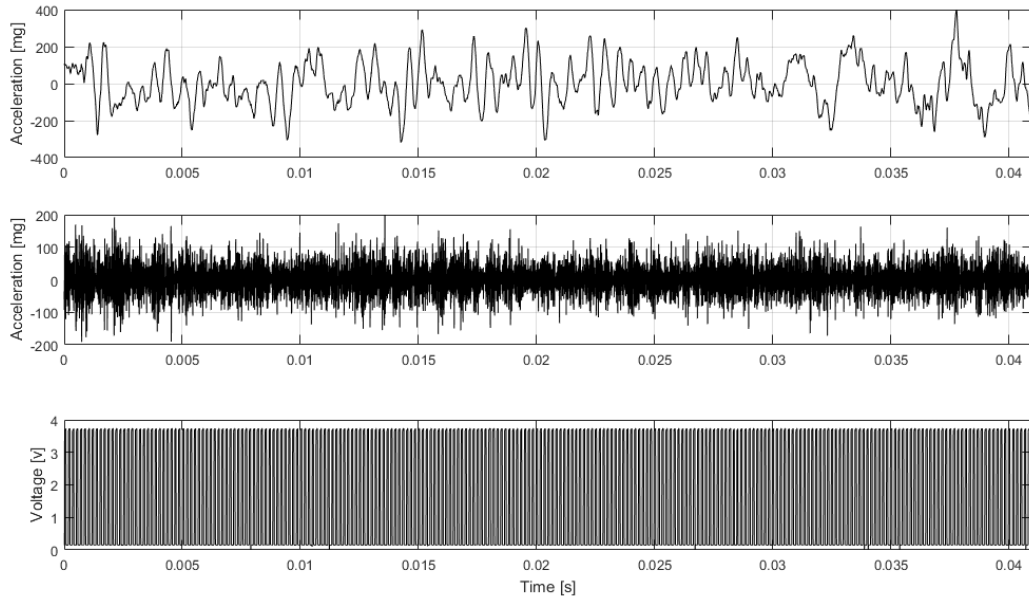


Figure 12. Time series acquired from the test benchmark - Healthy bearing with normal load -. From top to bottom the signals are: Accelerometer [1-20kHz]; Piezoelectric Vibration Transducer [15kHz-60kHz]; Encoder Signal.

### 3.1.4. FEATURES

The features chosen for this experience were spectral components related to the dynamical behavior of the test bench and the condition status of the bearing and its components. The features extracted are shown in Table 2.

Table 2. Extracted Features

FEATURE	ORDER
MAGNITUDE 1X	1
MAGNITUDE 2X	2



<b>MAGNITUDE OF ROTATIONAL FREQUENCY OF THE CAGE ASSEMBLY (FC)</b>	0.383
<b>MAGNITUDE OF OVER-ROLLING FREQUENCY OF ONE POINT ON THE OUTER RING (FE)</b>	3.061
<b>MAGNITUDE OF OVER-ROLLING FREQUENCY OF ONE POINT ON THE INNER RING (FI)</b>	4.939
<b>MAGNITUDE OF ROTATIONAL FREQUENCY OF A ROLLING ELEMENT ABOUT ITS OWN AXIS (FRB)</b>	2.012
<b>MAGNITUDE OF OVER-ROLLING FREQUENCY OF ONE POINT ON A ROLLING ELEMENT (FB)</b>	4.024

### 3.1.5. RESULTS

Due to test conditions, the bearing was removed from the test bench, damaged, and installed again. Therefore, the processing was made off-line. However, in order to approximate to real life condition, the data was streamed as it was and on-line event. Figure 9 and Figure 10 shows the first results of the developed tool. The first cluster detected - Figure 9- corresponds to a healthy bearing with a 3kN of radial load. As it was expected, this condition formed a compact cluster. Once the cluster was detected the load was increased to 12 kN. The results of the change in the condition are rapidly detected as an anomaly shown in Figure 10-A. The first two condition behaviors were determined. Two features are the most relevant ones and were ranked resulting in the following order: 1X and bearings Rotational frequency of a rolling element about its own axis. Finally, the conditions tested were, according to Table 1, from group 1 –healthy bearing, 3kN of radial load- to group 2 - healthy bearing, 12kN of radial load -; from group 2 to group 3 - unhealthy bearing, 12kN of radial load -; from group 3 to group 4 - unhealthy bearing, 3kN of radial load – and finally from group 4 to group 5 - unhealthy bearing, 3kN of radial load without grease-. The results with the more relevant features are presented in Table 3. The complete dataset is shown in Figure 13, with discrimination between the groups with closest distances, the ones with damaged bearing condition.

**Table 3. Feature ranking results between automatic detected clusters**

Group	Features	Features comparison to calibration group
1 – 2	1X – mean value decrease and dispersion rise Fb – mean value remains unchanged and dispersion decrease	1X – mean value decrease and dispersion rise Fb – mean value remains unchanged and dispersion decrease
2 - 3	1X – mean value decrease and dispersion decrease Fe – mean value rise and dispersion rise Fi – mean value rise and dispersion rise	Fb – mean value remains similar and dispersion increase Fe – mean value rise and dispersion rise Fi – mean value rise and dispersion rise
3 - 4	1X – mean value rise and dispersion rise	1X – mean value decrease and dispersion

	Fb – mean value decrease and dispersion decrease Fe – mean value decrease and dispersion decrease	decrease Fe – mean value rise and dispersion rise Fi – mean value rise and dispersion rise
4 - 5	1X – mean value decrease and dispersion decrease Fb – mean value rise and dispersion rise Fe – mean value rise and dispersion rise	1X – mean value decrease and dispersion decrease Fe – mean value rise and dispersion rise Fi – mean value rise and dispersion rise

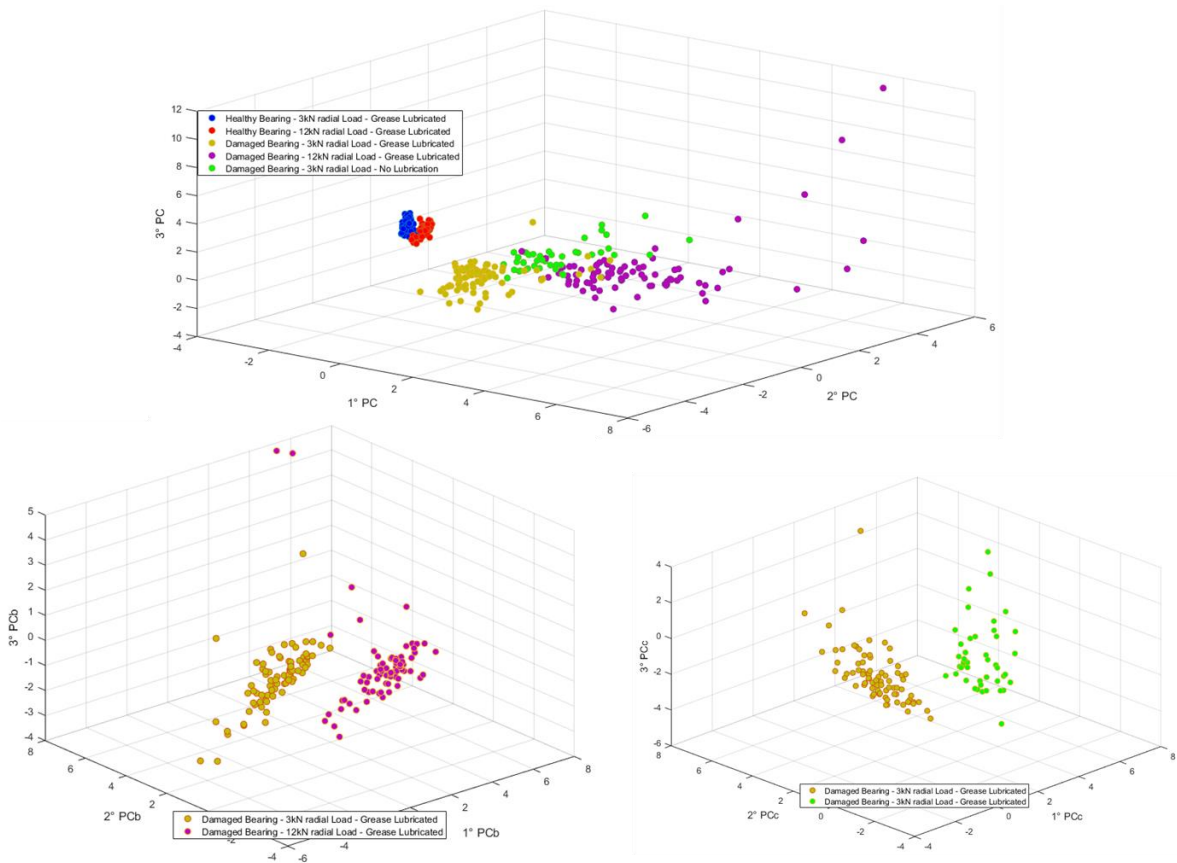


Figure 13. Top: All dataset projected in to their principal components. Bottom: Discrimination between groups of similar behaviour –Damaged Bearing-

### 3.1.6. CONCLUSIONS

The new developed tool achieves 100% success rate to discover the patterns in the presented test with the features selected. Once the bearing was damaged, the amplitude of the frequencies related to the inner and outer bearing ring damage become more relevant in the detection of this condition cluster.

Nowadays classification and anomaly detection is done using as much features as it is needed to obtain maximum classification rates, however the nature of the changes remain unknown if non-

posterior analysis is made. The online tool described in this paper conducts the anomaly detection and then informs the characteristics that were responsible of the anomaly.

It is a powerful tool to apply in industrial facilities with similar machines working in similar conditions. Once a new pattern is discovered in one machine, and a rule for that pattern is made it can be used as a rule for early failure detection in another machine. Especially if similar bearings are used. These capabilities are being studied and further investigations must be done in this area.