Departament d'Enginyeria Electrònica
CAMPUS DE TERRASSA

Projecte final de carrera

Títol PFC:

Estudio y desarrollo de un sistema de detección de fallos en actuadores electromecánicos mediante el análisis de emisiones acústicas.

Subtítol:

Mechanical fault detection by means of AE analysis

Titulació:

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1. Abstract

Rotating machinery is widely used in all of the industrials fields. In this sense, mechanical components are common elements in these systems. Therefore a periodic revision of the mechanical components of the system is required in order to guarantee the normal running conditions. Any failure or wear must be detected quickly and repaired before it affects to the machine's integrity. The solution is making a preventive maintenance based on defect diagnosis. Acoustic emission is a new technology for fault diagnosis in mechanical elements that is gaining acceptance as a useful analysis tool in mechanical components despite of the classical vibration analysis. The aim of this project is the study of fault diagnosis methods, by means of acoustic emission signal analysis, applied to electromechanical systems. This study is made with the aim of developing a pseudo automatic fault detection system into an embedded platform, such a µprocessor board.

2. Introduction

This project is located in the area of fault diagnosis in **electromechanical systems** (EMS). These systems combine electrical and mechanical components in order to form a complete and functional actuator. Apart from the electrical supply, generally composed by inverters, network filters and others, the principal components that conforms an EMS are shown in Figure 1.

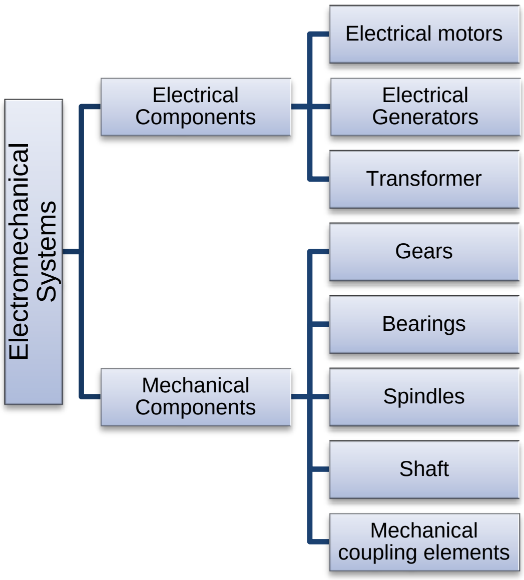

Figure 1 Main components of an electromechanical system.

Nowadays, these systems are used in a wide range of sectors performing different operations. They are very used for example in modern mobility applications, like the electric vehicle, where they play a decisive role by transforming the torque generated by the motor in movement using a transmission train. Also they are used in green energies generation like windmills; where different kinds and sizes of electric motors are used to transform the wind in electrical energy.

When an EMS is working, the mechanical components are submitted to mechanical stress, which imply a set of vibration modes due to degradations, unbalances and others. By the way, electromagnetic components are subjected to electrical unbalances, electrical noise and others. With these real working conditions, far away from the ideal behaviour of a EMS, it is necessary to introduce the concept of electro-mechanical failures. A failure, in this context, could be defined as a permanent or temporal anomaly that affects the correct behaviour of some component of the system.

In this sense, the **failures** could be classified, as shown by D.Basak *et al.* in [2], by means of two different parameters: the physics nature of the fault (electrical or mechanical), and the element that generates de fault inside the EMS.

The Figure 2 shows different kinds of faults depending on their nature and location inside the system.

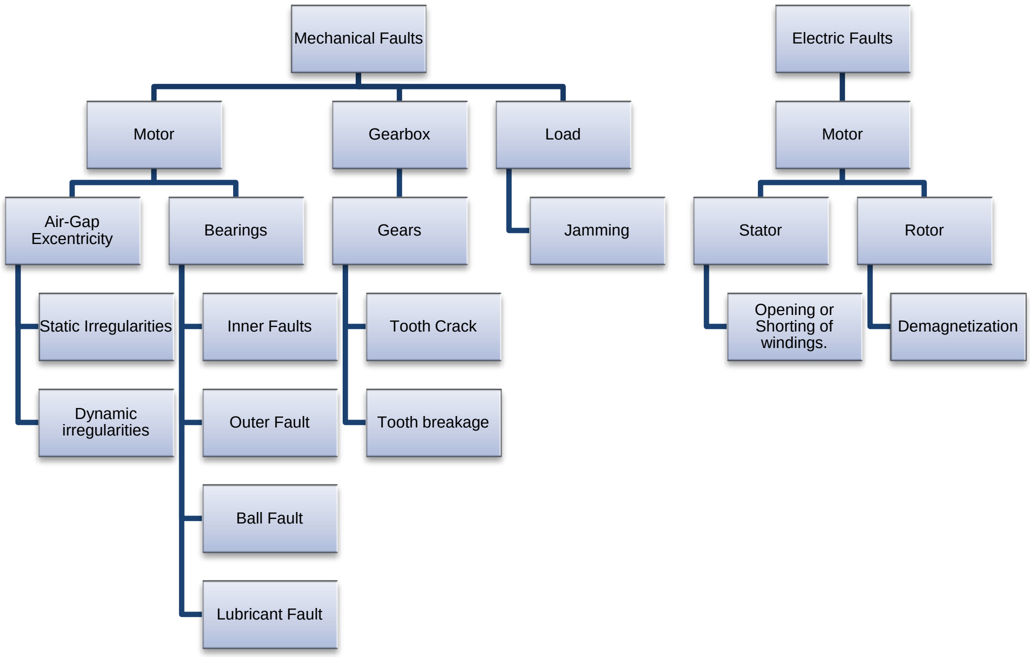

Figure 2 Main electro-mechanical faults and its classification

Once the different types of faults are known, it is needed to detect the fault inside the system. The process related with the determination of a fault that has occurred to a system is called **diagnosis**. The fault generation and its diagnosis over electromechanical systems is a topic of world-renowned scientific research.

In order to give a global view of the research work in this area, some authors like S. Nandi and H. Toliyat in 1999 [1] , M. E. H. Benbouzid in 2000 [3], A. Siddique *et al*. in 2005 [4] and D. Basak *et al*. in 2006 [2] explained the reasons for faults generation in an electric motor.

This project will focus over **gears fault diagnosis**. So, as it can be seen in Figure 2, it is necessary to detect **mechanical faults** in the system. The procedure to detect a fault and with it make a proper diagnosis is shown by the block diagram of the Figure 3 and it is based on the generalized system monitoring scheme made by D. Basak *et al*. [2].

When a fault takes place in an EMS it has to be detected, so an element able to sense it is needed. This element is usually a transducer who transforms some physical magnitude into a voltage or current signal.

In order to select a sensor for any fault diagnosis application, there is a very important fact to consider: a fault is generally reflected in several physical magnitudes, not only in one. For example, a machine eccentricity is the condition of unequal air-gap that exists between the stator and the rotor. Despite the mechanical nature of this fault, which is reflected in an increase of different vibrations modes; it is also reflected in the stator currents through the motor, because it modifies the magnetic fields in both rotor and stator.

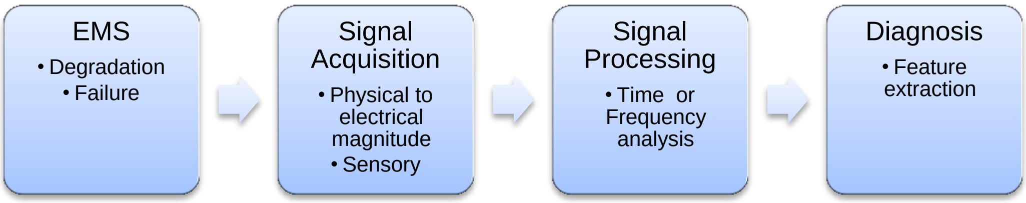

Figure 3 Main steps for fault diagnosis process [2]

So the failures inside the electromechanical system could be correlated with more than one physical magnitude. This fact is very important in order to select a proper sensor. Going back to the air-gap example, current clamps could be used to sense the variation of the magnetic fields by means the stator current analysis, but is always better to select a sensor whose dynamics correspond to the nature of the fault, in this case a vibration sensor.

So in this project where gear faults are studied, **vibrations and acoustic emission sensors have been considered**, although there are other secondary ways to perform a correct fault diagnosis in electromechanical systems.

Going back to **Figure 3**, the next step in the block diagram is the **signal processing**. The output of the sensor is usually a voltage o signal current. This signal is usually mixed with additional noise from the system, so a stage of signal conditioning is needed. In addition, many times the signal acquired from the sensor gives no direct information about the condition of the EMS. In this case time, frequency or time-frequency domain techniques are used to extract the useful information. Nowadays exist further research in this topic and different techniques have been studied [7] [8] [9]. This project will give an overview of different processing techniques.

Once the signal is properly conditioned and processed, a methodology to recognize faults is needed. This methodology (sometimes referenced as an algorithm) should be able to detect the fault based on a set of numerical indicators calculated. An indicator or feature is a statistical or numerical calculated parameter who gives information in regard with the fault type. Based on this parameter, the algorithm should be able to decide if the system is in faulty condition or not. Once the decision has been made, the algorithm gives to the user the diagnosis of the EMS. This diagnosis is usually simplified into a boolean indicator (True/False).

This section covers the general methodology in fault diagnosis. With it, a diagnosis system is able to detect and classify properly a failure in an EMS.

In this section an overview of the fault diagnostic field is given. Further in this project all this topics would be deeply explained, but specifically to the configuration studied. **The chosen configuration in this project is to perform a study about gears fault diagnosis by means of acoustic emission sensors in order to make a pseudo automatic diagnostic system**.

2.1 Justification of this project

Linking with the previous chapter, in this project, the **fault detection in gears using AE analysis is studied**. So there are two questions to be answered:

- Why it is necessary to detect faults in gears instead of other mechanical or electrical components?
- Why to use AE signal analysis?

Rotating machinery is widely used in all of the industrials fields. The selection of the gears for the fault diagnosis is motivated by the high quantity of elements that use a gearbox in order to transmit the rotational movement or modify the torque transmission across a mechanical system. For example, they are widely used in critical applications such as wind turbines.

The wind energy is increasing every year its worldwide generation. Wind power has experienced global growth in 2011 of 21% [10]. The goal set for the 2020 is that 12% of the energy consumed worldwide come from the wind. Hence the wind sector is a sector clearly in growth, development and expansion.

A survey, which focuses on Swedish wind power plants, during 1997-2005, shows that the gearbox is found to be the most critical component, since its downtime per failure is high in comparison to other components in the wind power turbine [11].

Another an article from the Renewable Energy World Magazine called Wind Turbine Gearbox Reliability written by A. de-Beaumont and J. Puigcorbe (engineer in Alstom Wind corporation) [12] focus on the same topic, a short fragment of the article with the information is shown :

"One of the biggest concerns remaining in the wind industry is the reliability of the gearbox. With our current wind turbine fleet currently going out of warranty period, we estimate that we are carrying a potential risk on gearboxes of about US$300 million."

As a conclusion, gears are a critical point in most of the electromechanical systems, so it is necessary to improve the gearbox reliability. In order to achieve this goal, a good preventive maintenance based on and fault diagnosis in gears will highly reduce failures and with it the maintenance costs. This is the main fact for choosing the gears as a component to analyse.

Answering the second question, it should be said that nowadays, a mechanical failure like gear faults cannot be detected until the element has already been damaged. Sometimes, the severity of this damage is so high that could badly affect other mechanical components.

This happens because vibration and current analysis are the most known magnitudes applied for condition monitoring [11] but it can only detect the failure when it has already occurred, they are not able to follow the fault dynamic. Otherwise, with a preventive maintenance, which includes a good and early diagnosis, the failure of the component could be anticipated and the component could be changed before the fault turns critical.

Here is where a new technology based on **acoustic emission analysis** for fault diagnosis comes into play. With this technology, the failure could be detected just at the beginning and the evolution of the fracture could be seen. Considering this characteristic of the AE analysis method, a better and earlier diagnosis could be made as it was shown by T. Toutountzakis *et al.* [13], so this technology seems to be better than vibration analysis in order to perform an earlier fault diagnosis of mechanical elements.

Although this fact is the main reason for selecting the AE analysis in gear fault diagnosis, there also other important characteristic that will be shortly mentioned above this paragraph, but they will be deeply explained further in this project.

Main properties about AE analysis for fault diagnosis are:

- High frequency signal, problems with electromagnetic compatibility.
- Very low amplitude so signal conditioning is needed.
- Influenced by the material type, affects to the propagation of the acoustic wave from the source to the sensor.
- Not affected by the mechanical noise, it works in a higher frequency level.
- Young technology, there is not a clear methodology to apply AE in EMS fault diagnosis.

2.2 Contents and objectives of this project

Once the concepts of fault diagnosis system have been introduced, the objective and the contents of this project will be exposed.

It should be noticed that this project works related to a European project developed by the research group MCIA, inside the Technical University of Catalonia, called MOSYCOUSIS [14].

That acronym means:

"Intelligent Monitoring System based on Acoustic Emissions Sensing for Plant Condition Monitoring and Preventative Maintenance".

The aim of this project is to develop an intelligent and diagnosis system based on acoustic emission detection, for monitoring and preventative maintenance of machinery.

This work is only focused in gear fault detection by means of AE analysis so the theory explained would be more related to this topic. The mentioned MOSYCOUSIS project is important because it fixes some specifications to the technical development of this project. This happens because the entire test performed at the gears, the signal processing techniques and the final algorithm developed should be compatible with the MOSYCOUSIS development platform.

The objectives and the contents of the present project memory should be divided in two different parts:

The first part gives an overview of the theoretical concepts related to the gear fault diagnosis all related to the state of the art in this topic. These theoretical concepts are shown in the same order as the block diagram showed in **Figure 3**.

Then, the properties of an AE signal and a methodology to perform the diagnosis with these signals is studied. It also includes a theoretical comparative between acoustic emission analyses versus the vibrations, in order to perform this comparative; the fundaments of the vibrations systems would be introduced.

Objective of the first part of the project:

- **Explain what fault diagnosis system for electromechanical actuators is and what the different steps to apply it are.**

- **To perform a study about methodologies for gear fault diagnosis by means of acoustic emission signals analysis.**

- **Detect the differences between vibrations and acoustic emission signals analysis for condition monitoring.**

The second part contains all the practical work made in this project. First of all it gives a complete description of the test bench used in this project. Then once the system under study is known, the test configuration and the gears selected for the different tests are explained.

After that, the data obtained from the test is presented and processed. Then an algorithm to detect the failure is generated and posteriorly programmed into a development kit. Finally the diagnostic system is tested with the real test bench.

- Objective of the second part of the project:

    - **To design instrumentation system in order to acquire the AE signals from a test bench.**

    - **Identify which features are related to the specific fault performing an analysis based on acoustic emission signals.**

    - **Include all the knowledge acquired in the previous objective in order to implement a pseudo automatic fault detection algorithm.**

3. The gearbox as the fault origin

Following the block diagram of the Figure 3, **this section is related with the first step, the fault origin**. In this project, as it was justified in section 2.1, **the gearbox is selected as one of the main sources of failures inside an EMS.**

For this reason, the different types of gears used in the industry as well as the main parameters of a gear are introduced next. Also linking with the main project's theme, a revision of the most common faults in gears is made.

Gears can be defined as toothed wheels that transmit circular motion throughout a mechanical system. A gearbox is a combination of different gears in order to mechanically transmit **speed and torque** with a specific ratio of conversion between the input and the output.

Before explaining the different types of gears, a revision of the main geometrical terminology of a gear will be done, extracted from the work made by F. Litvin *et al.* [18]. Figure 4 shows the main geometrical parameters of a gear.

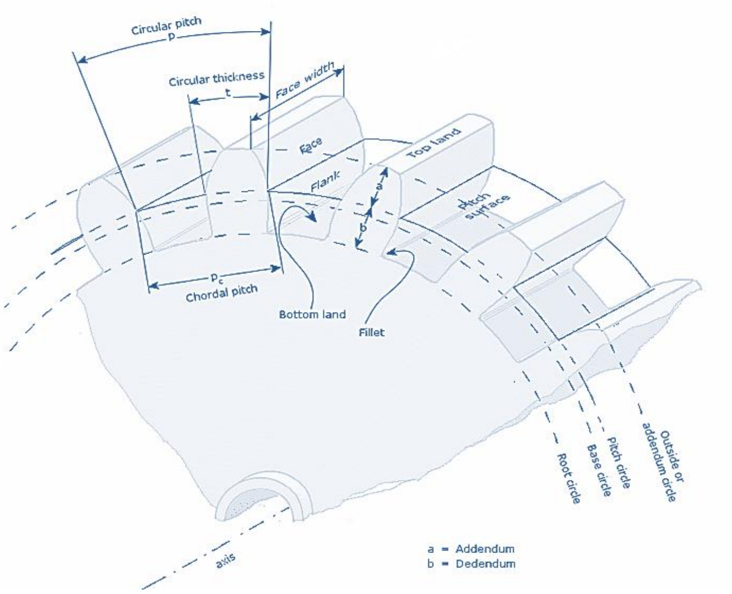

Figure 4 Detail of a gear with geometrical terminology.

The most common parameters used for gears definition and purchased are: the pitch circle, which corresponds to the reference circle used for determination of tooth element proportions. It is the theoretical circumference coincident with the diameter of the gear without any teeth. **The root diameter** is the diameter of the gear measured from the base of the tooth.

The teeth number is an integer number that contains the quantity of tooth in a complete revolution o the gear wheel. The gear tooth has an envelope form. **The module (m)** is the relation between the pitch circle and the number of tooth.

3.1 Types of gears

The most common types of gears (used widely in industrial manufacturing plants) are spur gears, helical gears and bevel gears. The operation principle of all these gears is the same, a driving wheel and a driven wheel, but differs in the shape and arrangement of the wheels. The main properties of the different types of gears are explained next.

3.1.1 Spur gears

Figure 5 Spur Gear

An example of typical spur gears is shown in Figure 5. They are characterized by teeth that are aligned with the shaft axis; therefore the movement is transmitted perpendicular to the transmission axis [16].

They are the most common type of gears due to its simplicity, efficiency and low cost. They are limited to applications with parallel shafts and cannot be used when a change of direction between the two shafts is needed. They are commonly used to perform speed-reduction steps in order to increase the torque generated by the engine. This are the gears used in this project.

3.1.2 Helical gears

Figure 6 Helical Gear

Helical gears are very similar to spur gears except the fact that the teeth are curbed by a specific angle to the shaft, instead of completely parallels like the spur gears. For the same pitch diameter, these gears present longer teeth.

As a result these gears are smoother, less noisy and can work at higher speeds, in the other hand they are more expensive and have less efficiency than the spur gears. These gears are used less frequently in electromechanical systems [16].

3.1.3 Bevel gears

The babel gears are used when the movement needs to be transmitted between intersecting shafts. It is a set of two gears that engine normally in 90 degrees, but they can work in any other angled configuration. Inside this category of gears, there are other sub classification depending of the teeth shape and orientation [16]. The two different types of bevel gears are shown in Figure 7.

Straight bevel gears: Their teeth are cut straight and are all parallel to the line pointing to the apex of the cone on which the teeth are based. They have a good efficiency and have a medium load capacity.

Spiral bevel gears: Thy have the same teeth shape as the helical gears. They can be used with high loads, have a great smoothness capacity but they have a less efficiency level.

Figure 7 Spiral Bevel Gears (left) and Straight Bevel Gears (Right)

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3.2 Main fault in gearboxes

When gears are working, they are submitted to different mechanical forces that degrades the component, like stress, vibrations or friction. Formally, a gear has a failure when it can no longer efficiently perform the action for which was designed to [16].

A study made by Y.Guo *et al.* in 2010 [9], shows the most common gear faults in wind turbines. This work has been accepted by the scientific community to explain the most common types of failure in gears (working inside an EMS).

As it is shown in Figure 8, the author indicates that **the most probably failures that might suffer a gear is a fracture (41%).** It is worth mentioning that in this study, the tooth breakage and the tooth crack are considered as the same fault (fracture).

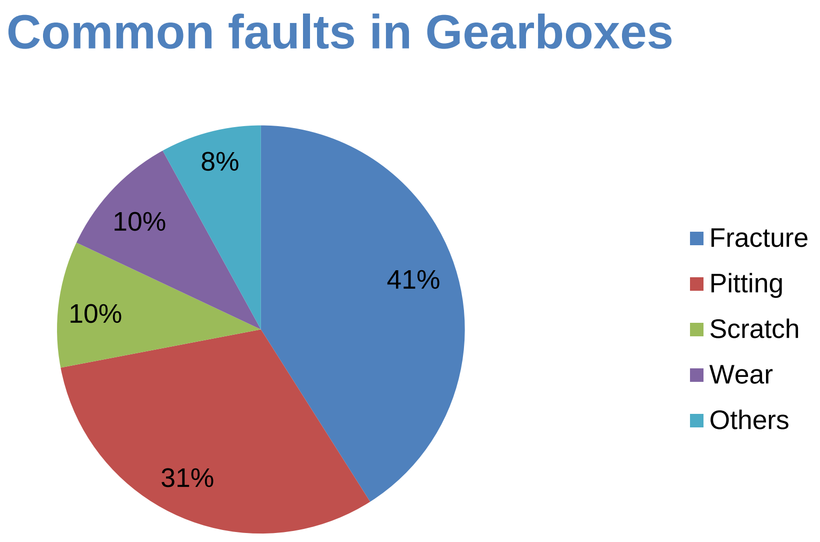


Figure 8 Most common faults in gearboxes applied to Wind Turbines [9]

Other failures and their probabilities are pitting (31%), scratch (10%), wear (10%) and others (8%). In the next section the different kinds of faults that may affect a gear are briefly defined.

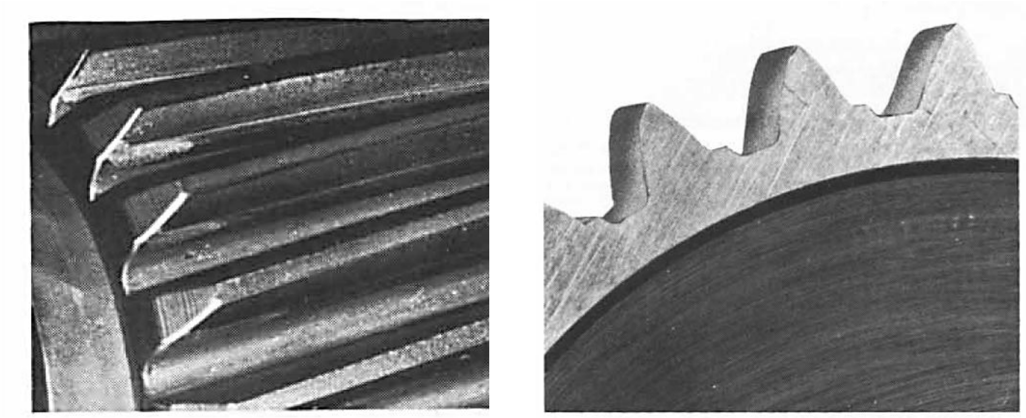
3.2.1 Wear failure

A wear failure is a surface phenomenon in which the top layers of metal are removed, or degraded, with more or less uniformity along the contacting surfaces of the gear teeth. The metal is usually removed from the addendum and dedendum area, it also modifies the continuity of the pitch line [16].

A wear takes place over a relatively long period of time, and as most of the failures, the effect of the wear becomes stronger if nothing is done. When a normal wear has progressed throughout the surface, and the amount of material removed is considerable, it is known as an excessive wear. With this developed failure the pitch line has been highly deteriorated and might show signs of pitting. It is normally caused by an inadequate lubrication film. This problem appears if the gear is not properly lubricated (also appears if the lubrication film is dirty) or the load applied to the system is too high.

The two levels of the wear fault in gears are shown in **Figure 9**. The moderate wear fault (a), shows how the material has been removed from the addendum and dedendum sections, causing the operating pitch line to become visible.

The Excessive wear fault (b) shows how the material has been uniformly removed from the tooth surface. It could be seen how the tooth thickness has been decreased and the involute profile destroyed. Under this condition, the gears run roughly making them unavailable to work.



(a) (b)

Figure 9 Details of a moderate wear (a) and excessive wear (b) faults in a gear [16]

3.2.2 Pitting failure

A pitting is a surface fatigue failure which occurs when the endurance limit of the gear's material is exceeded. It depends on the surface contact stress and the number of stress cycles.

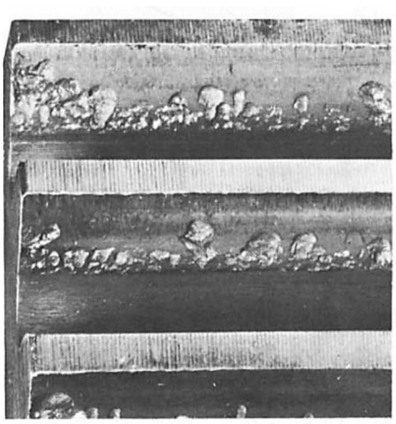


Figure 10 Detail of a destructive pitting fault in a gear [16]

This failure takes place when the gear surfaces are not properly conforming with each other, when the gears do not properly fit or when there is not a correct alignment across the full surface width of the gear mesh [16].

This failure is very common, as was seen in Figure 8 (31%), in every type of gearbox due to misalignments of the shafts and undesired vibrations. The pitting continues until the tooth profile is completely destroyed. Gears working under pitting faults produce extremely rough operation and considerable noise.

If the pits diameter is above 0.4 mm and 0.8 mm it is considered initial pitting. If the diameter is bigger, the fault is considered as destructive pitting. The Figure 10 shows the effect of a destructive pitting in a gear. It can be seen how the tooth profile has been highly degraded. This degradation is concentrated in the dedendum region.

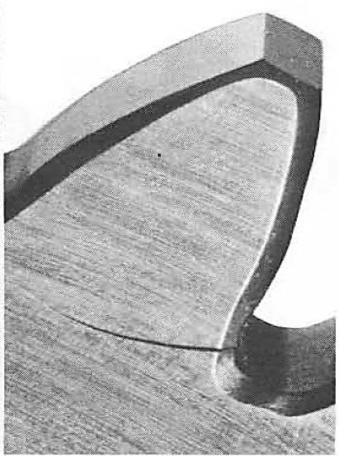
3.2.3 Fracture failure

A fracture is a failure caused by a breakage of a whole gear tooth or a substantial portion of it. This can be a result from an overload or, more usually, by cyclic stressing of the gear tooth beyond the endurance limit of the gear's material [16].

So there are two main causes of a gear fracture:

- Fatigue breakage: failure from bending fatigue results from a crack, of a particular thickness, originating in the root section of the gear tooth. The fatigue breakage is usually named as tooth crack. This break usually starts over a focal point named fatigue "eye". When gears with a tooth crack are subjected to enough repeated stress cycles the gear tooth will fail originating a tooth breakage.
- Overload breakage: an overload fracture results in a stringy, fibrous break showing evidence of having been pulled or torn apart. It directly causes a tooth breakage as a consequence of an overload. This overload exceeds the tensile strength of the gear material; this result in a short break cycle generally starting on the tensile side of the root fillet. Overload may result from a bearing seizure, failure of driven equipment, foreign material passing through the mesh, etc.

The both tooth crack and tooth breakage faults are shown in **Figure 11**. The spur gear (a) shows a fatigue crack caused by stress at the root fillet. The second one (b) shows a multiple tooth breakage, undoubtedly one tooth broke away first, causing an impact that then quickly broke the remainder of the teeth.



(a)

(b)

Figure 11 Details of a tooth crack (a) and a tooth breakage (b) in a gear [16]

A fracture is one of the most common and dangerous faults in a gearbox. It should be noticed how a tooth breakage causes fatal damage to a gear, but a tooth crack could also may progress into a tooth breakage. So a tooth crack is a critical situation that should be early detected and prevented.

One of the positive things from the fracture is the fact that it usually begins with a crack in the root section of the gear tooth. Due to the mechanical properties of a fracture, which in its initial stage propagates high frequency waves across the gear, **an acoustic emission sensor could be used to early detect this initial crack**, so the AE sensors are ideal for this purpose.

If the fracture is detected in its initial phase, the gear could be repaired and further damage could be prevented (no tooth breakage is produced). So the next step to explain is **how to detect a physical magnitude which is related with the failure.**

4. Signal acquisition

Once the gearbox has been identified as one of the main source of failures inside of an EMS, in order to continue with the fault diagnosis procedure, the next step is the signal acquisition, which consists on obtaining information about the system.

Mainly, two different kinds of information can be obtained: the information related with the system operating condition (speed, torque, limit switches, control signals and others), and the information related with the secondary physical magnitudes not directly related with the system control (temperature, vibrations, stator currents and others). In this sense, the most useful information to analyse the system conditions is related with this second set of signals, specially, the most usual magnitudes are the sator currents from the electrical motor and the vibrations from different points of the system.

M**ost of the physical magnitudes are not directly measurable** from the system's control device. For this reason, **a transducer that converts that physical magnitude into an electrical signal is required**. A transducer works based on a physical principle which indicates the relation between the physical magnitude and the electrical signal.

So in this section the physical magnitudes will be presented, then the physical principle used to convert this magnitudes into electrical signals will be explained and as a result, the most common transducer ant its properties will be mentioned.

In this project, where mechanical magnitudes are studied (vibrations and acoustic emission waves), there is only one physical principle to consider, the piezoelectric effect. This principle, as it will be explained later in this section, transforms the mechanical vibrations into a difference of potential in the transducer output..

At the end of the section, the considerations to correctly acquire each signal are explained. This includes the selection of the sample time, the scaling factors and the number of the samples acquired.

4.1 The physical principle of acoustic emission signals

The first magnitude to measure is the acoustic emission signal in some point of the EMS. This magnitude has its origin in the fact that every material when is working is submitted to external forces [14]. For example, in a gear box there are some adverse factors like opposite forces between the gears, anomalies in the rotating sequence of the motor reflected in vibrations across the shaft, misbalances etc. All of these undesired forces could degrade the mechanical components.

The component under any of these forces starts to absorb this energy. When the material cannot hold any more energy, the stored strain energy is consumed by nucleating new external surfaces (cracks in the gear or inelastic deformation) and emitting elastic waves with very low amplitude and high frequency components all across the body of the material.

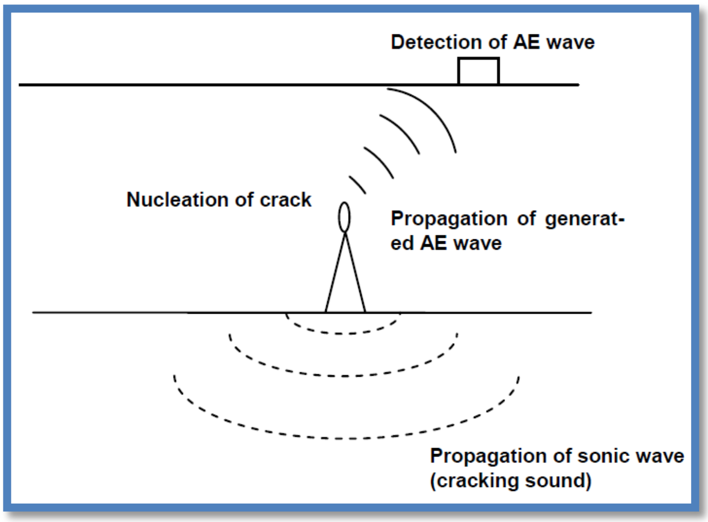


Figure 12 Crack failure process and derivate wave propagation across the material, extracted from reference [14]

The Figure 12 represents schematically how the material collapses. A crack is reflected in the surface of the material and the elastic wave generated travels across the body and arrives to the AE sensor.

As a conclusion**, an acoustic emission signal is low amplitude high frequency elastic wave generated by the internal forces of the material which propagates from the nucleation of the crack to the surface of the material.**

It should be noted that the signal captured by the recording device may be affected by the nature of the stress pulse generated by the source, the geometry of the test specimen, and the characteristics of the receiver, making it difficult to interpret the recorded waveforms [19].

As a conclusion, acoustic emission signal are used in this project because they are able to detect the energy waves generated in each gear tooth collision. And as it has been demonstrated by Christian U. G. *et al.* [14], the signal modifies some of its parameters if the gear is healthy or faulty.

4.1.1 Characterization of an AE signal

In order to extract features to perform the diagnosis, the typical form of an AE signal should be known. There are two different characteristics shapes of an AE signal. There is a constant emission waveform which comes from constant deformation elements like plastics, and a burst emission waveform which comes from an individual emission event occurring within the material.

These burst signals are characteristic of the acoustic emission events resulting from applying load to the metallic materials, so it is more related with the mechanical components studied on the present project.

As a conclusion, **only the burst signals are characterized and analysed because they are related the gears tooth collisions, and thus with the breakage failures that wants to be detected**. A typical burst AE signal is shown in **Figure 13.**

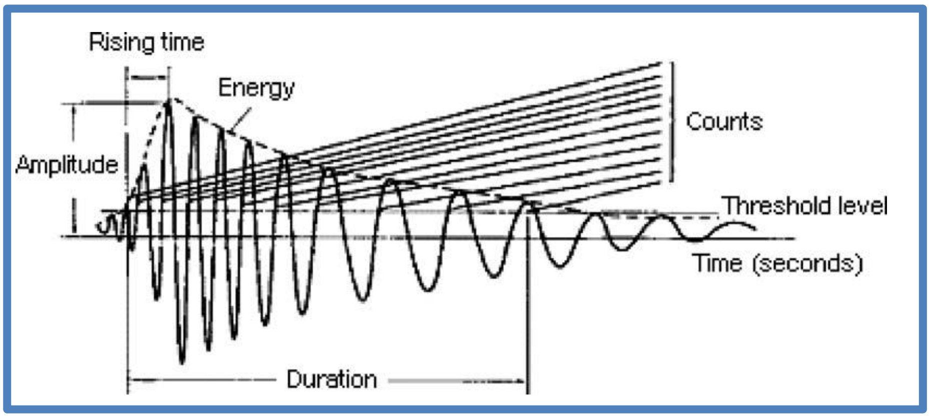


Figure 13 AE signal characterization [14]

The main parameters of the signal and thus the main properties of it are:

The Amplitude: The amplitude of an AE signal is the peak value of the envelope signal. The envelope is used instead of the highest peak because sometimes it's difficult to identify each peak separately due to the high frequency of the AE signal.

The Signal's counts: The signals counts are the number of the times that an AE amplitude exceeds, by a positive edge, a value fixed by the user called the threshold. It is an indication about the quantity of activity and the intensity of the generation source.

The Rising Time: Is the time interval between the time of first occurrence of signals above the threshold and the time at which the maximum amplitude is reached. This may assist in determining the type of damage mechanism.

The AE Energy: The energy of an AE signal is defined as the root mean square (RMS) applied to the signal. This value has to be proportional to the area under the enveloping of the AE signal. This feature is related directly with the mechanical energy, the strain ratio and the deformation mechanism.

4.2 The physical principle of vibration signals

The second magnitude studied in this project is the vibration level of different components of the EMS. **Any low frequency oscillatory motion of a mechanical system about its equilibrium position is called vibration** [21]. Vibration occurs when a system is displaced from a position of stable equilibrium. When the element is displaced, tends to recover the minimum energy position by the action of the restoring forces, this recovery movement causes the appearance of vibrations.

Most vibrations are undesirable in rotatory machines because they produce increased stresses, energy losses; they cause added wear, increase bearing loads, induce fatigue, and absorb energy from the system [20].

Consequently, a vibration is related with the element motion. As a result, a measure of vibration in a system is a measure of the motion referenced to the equilibrium point. By the physical properties of the motion in solid elements, there are three different ways to measure a vibration movement which are:

- Measuring the **displacement** of the element versus the equilibrium point.
- Measuring the **velocity** of the element among the time.
- Measure the **acceleration** (speed variation) of the mechanical element.

Due to the dynamics of a mechanical vibration, the signal that gives more information about the vibration is the acceleration, since it is a measure about how quick the velocity changes. So measuring the acceleration of the mechanical component is the fastest and the most accurate way to detect mechanical vibration. As a result, **measuring the vibration is equal to measure the acceleration of the mechanical component,** and it gives an indication about the healthy or faulty condition in the machine.

4.3 The piezoelectric effect

In order to convert the two previous mentioned physical magnitudes (AE and vibration signals) into electrical signals, piezoelectric effect based sensors are used. The physical bases of this effect are shown below.

The piezoelectric effect was discovered in 1880 by the brothers Pierre and Jacques Curie [22]. **They found that some crystalline were generating an electrical polarization when a mechanical load was applied along some of the crystal directions**. But not all the crystals and elements have these properties, only those who not present a centre of symmetry and non-conducting properties materials, the most common crystals that are affected by the piezoelectric effect are quartz and piezoceramics.

When a crystalline material is polarized, it creates a difference of potential caused by the appearance of electric charges on its surface. This happens because when no stress is applied on the material, the distribution of the electrical charges is uniform. **But when a force is applied, it modifies the charge distribution and generates a voltage across the surface of the crystal.**

The voltage produced could be of thousand volts, but the current is nearly 0, so it only causes a small electric impulse. This voltage could be measured so a new concept is defined, the Piezoelectricity.

So the piezoelectricity is basically defined as a linear electromechanical interaction inside a material having no centre of symmetry. It could be defined as:

$$\boldsymbol{D = \varepsilon \cdot E + d \cdot X}$$

Where *D is the induced electric displacement*, *E the applied electrical field and X the mechanical stress applied to the material*. *The dielectric constant* ε and the *piezoelectric coefficient* are attached to the materials properties. These properties are determinate by the crystal symmetry and the orientation of the crystalline measuring element.

So basically, the sensors based on the piezoelectric effect transform mechanical variations waves into an electrical signal by modifying the charge distribution of its structure. With this behavioural, the forces and the stress waves generated in the material surface could be detected and converted into electrical signals.

4.4 Mechanical Vibration Sensors

To measure the vibration level of a mechanical component its acceleration should be sensed, so the accelerator sensor is the most used element to measure the vibrations of mechanical components like the motor.

The sensor is based on the piezoelectric principle which was explained in the previous section. This means that the transducer is a piezoelectric material who reacts to the mechanical impulses generating a difference of potential proportional to the acceleration caused by the vibration. The common structure of an accelerometer is shown in **Figure 14**.

Basically, and accelerometer is composed by a Piezoceramic attached to a Seismic mass and housed together in a metallic structure.

The piezoceramic is the responsible of detecting the mechanical forces from the material in order to generate a proportional voltage. One of the extremes of the piezoceramic is connected to the sensor's base, the other one is attached to the Seismic mass. The piezoelectric element is also connected to the sensor socket with a pair of electrodes.

The seismic mass is a constant mass attached to the piezoceramic in order to provide a constant m coefficient. With this constant mass and according to the Newton's second law (F=m·a), the acceleration will always be proportional to the force received by the sensor. So the voltage generated by the piezoelectric will be proportional to the acceleration measured and thus to the vibration of the element sensed.

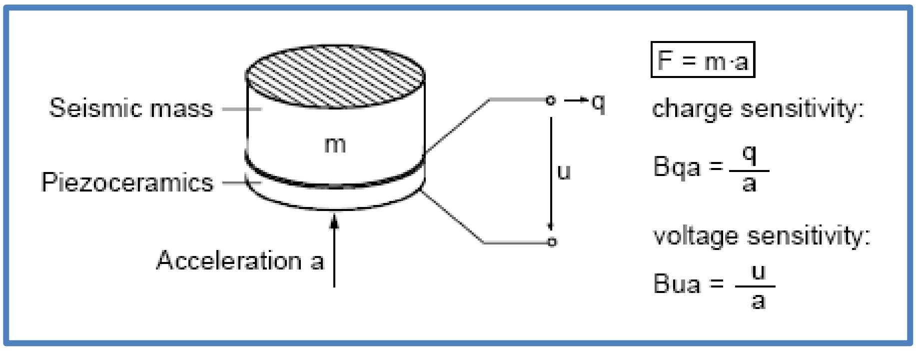


Figure 14 Physic principle of a Piezoceramic accelerometer [23]

Some of the characteristically parameters of an acceleration sensor are [23]:

- **The range of frequencies** which can be sensed by the accelerometer depends of the seismic mass. In order to achieve a wider operating frequency range the resonance frequency must be increased. But this increase is done by reducing the seismic mass. So if the seismic mass is reduced, the sensor has a loss of sensitivity. If the accelerometer has a wide frequency range, it would probably not have a good sensitivity. So in order to meet the application, the frequency response curve of the used sensor should be known.
- **The maximum acceleration** the sensor can detect is given for the frequencies within the operating frequency range and at room temperature. At higher temperatures it may be lower. These limits are determined solely by the sensor's construction.
- **The accelerometer sensitivity** it's a measure of the quality of the sensor. A piezoelectric accelerometer as a sensor is like a voltage source with very high impedance. Consequently, charge sensitivity or voltage sensitivity to the variations of the force is used to describe the relationship between acceleration and electrical output.
- **The operating temperature range** is the maximum operating temperature of the transducer and is limited by the characteristics of the piezoelectric material used in the sensor. There is a specific temperature called Courie's

point, when the piezoelectric element is depolarized causing a permanent loss in its sensitivity. The specified maximum operating temperature is the limit at which the permanent change of sensitivity exceeds 3 %.

4.5 Acoustic emission sensors

A contact type of the sensor is normally employed in AE measurement due to the neutrality of the AE signal origin. The most common AE sensor is made by adding a piezoelectric element inside a protective housing as illustrated in Figure 15. It was made by designed by Beattie in 1983. These sensors are exclusively based in the piezoelectric effect.

When a stress wave is propagated through the material, it goes to the piezoelectric material inside the housing. The piezoelectric is sensitive to the wave's energy and generates a proportional voltage through the connector.

The main difference between the vibration sensors and the acoustic emission ones is the working frequency range. For example the working frequency of the vibration sensors are between 1 Hz and 20 kHz, however the acoustic emission ones work between 20 kHz and 1 MHz. Consequently the piezoelectric material inside the AE sensors should be more sensitive with high frequencies.

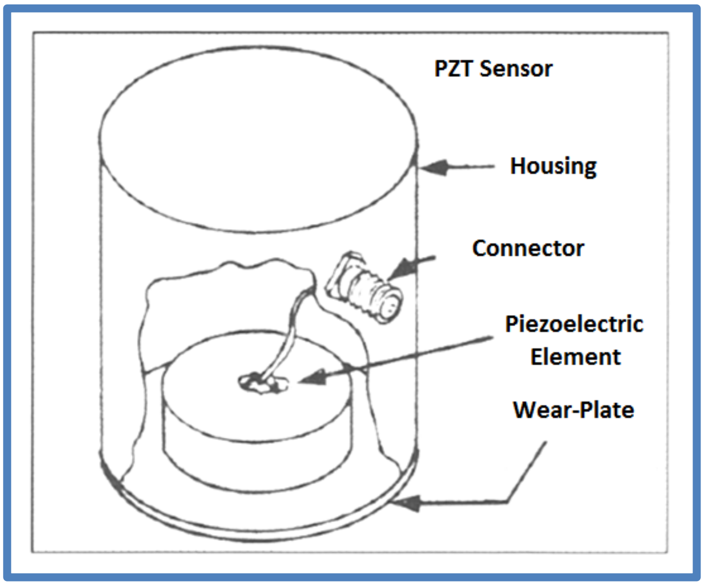


Figure 15 AE Sensor made from a piezoelectric element [14]

The main characteristics of this sensor are very similar to the vibration sensor (both of them are piezoelectric sensors). In this sense, the explained characteristics like the range of frequencies, the operating temperature range and the sensitivity can be used with this sensor but with some differences.

In AE sensors, the range of frequencies depends on the piezoelectric material used in its construction; also it is influenced by the housing dimensions. There is also another wave magnitude limitation known as the maximum pressure that could be detected with this sensor without damaging the piezoelectric material.

It should be noticed that the signal's amplitude and the proportional voltage is very low so an amplifying stage is almost always needed. The main schema for measuring an AE signal is shown in **Figure 16**, the output of the sensor is connected to an amplifying stage in order to improve the SNR ratio of the signal.

Once the signal is amplified a band pass filter is needed in order to provide two basic functions: A low pass filter in order to avoid aliasing problems and a high pass filter in order to discard the data outside the sensor range of frequencies. These two concepts will be explained in next section.

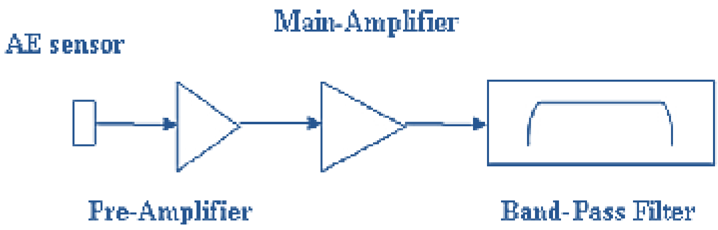


Figure 16 AE measuring system [14]

Another of the main drawbacks of these sensors is the fact that its output and the quantity of stress wave sensed depend hardly on the position of the sensor. So the correctly placing of the AE sensor is a difficult work.

4.6 Signal Acquisition considerations

Once the magnitudes from the system have been acquired (as electric signals) they should be digitalized and with this converted into data. In order to make a proper signal processing some considerations should be taking into account.

4.6.1 Selecting a proper sampling frequency

This factor is critical when the collected data wants to be reconstructed for further signal processing. When working with digital system using as data sources analogue signals, there is always an information loss (due to aliasing effect). Even tough, if a proper sampling frequency is selected depending on the frequency range of the sensors, this loss will be negligible.

According to the sampling theorem made by Nyquist in 1928, which says that a signal which maximum frequency f_{max} could be correctly reconstructed without aliasing if it's sampled with a frequency rate f_s which satisfies the following equation:

$$f_s > 2 \cdot f_{max}$$

This is only the theoretical fundament, in real applications it is recommended to use a sampling frequency in the order of:

$$f_s = A \cdot f_{max} \; where \; A \in [5 \; to \; 10]$$

4.6.2 Filtering the acquired signal

When working with high frequency signals there is some data filtering requirements to consider.

In order to avoid aliasing problems, although selecting a proper sampling frequency, when a signal is acquired for posterior signal processing, a low pass filter is often required.

This happens because when setting the optimal sampling frequency a maximum frequency f_{max} has been considered. This frequency is selected based on the frequency range of the sensor, or the working frequencies of the signal under study. This might be a problem because the transducer is only characterized for a fixed frequency range; however the behavioural of the transducer outside this range is unknown.

But what happens if the acquired signal has content in frequencies over the sampling frequency considered? That undesired information would be captured by the transducer and mixed together with the acquired signal after the digitalization causing aliasing problems or inducing to misleading results. In order to avoid this situation, a low pass filter that eliminates the content of the signal in frequencies higher than the sampling one is required.

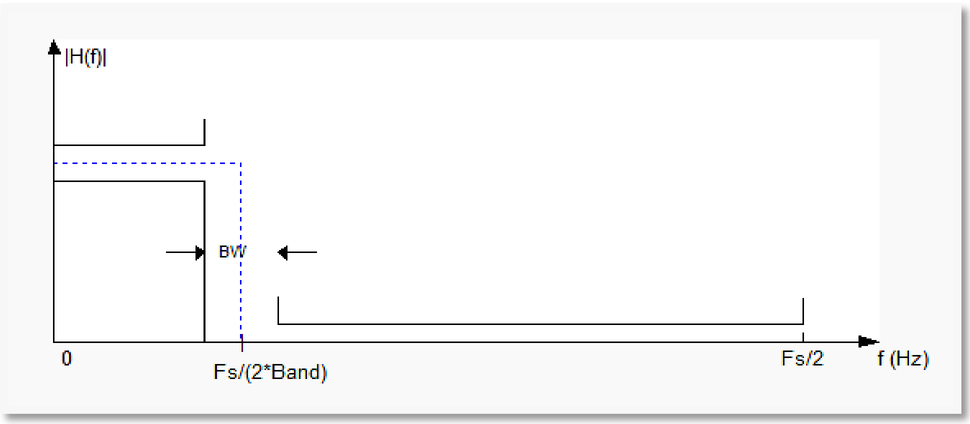


Figure 17 Main antialiasing filter specifications

This filter is also known as an antialiasing filter. This filter prevents aliasing by limiting the bandwidth of the raw analog signal and noise so that its highest frequency component is less than half of the sampling frequency [24].

The filter specification for an antialiasing filter is shown in **Figure 17**, where a classical low pass filter structure where the stop frequency is equal as half the sampling frequency (Nyquist theorem).

Following the same reasoning, the problem with the unknown sensor response takes place in frequencies under the sensor range, for instant, most of acoustic emission sensors are characterized above 20 kHz. For this reason, a high pass filter is used in order to eliminate the spectral content of the signal from 0Hz to the minimum frequency for which the sensor was characterized.

As a conclusion, if the effect of the two filters is considered, only a specific frequency bandwidth of the acquired signal should be processed. Sometimes is mentioned the fact to use a band pass filter as illustrated in the book made by Christian U. G. *et al.* [14].

The band pass filter is the combination of the anti-aliasing filter (low pass filter) plus the high pass one to limit the minimum frequency content. Consequently, this explanation is only the theoretical justification about why to use a band pass filter while acquiring analogue signals in order to perform further signal processing.

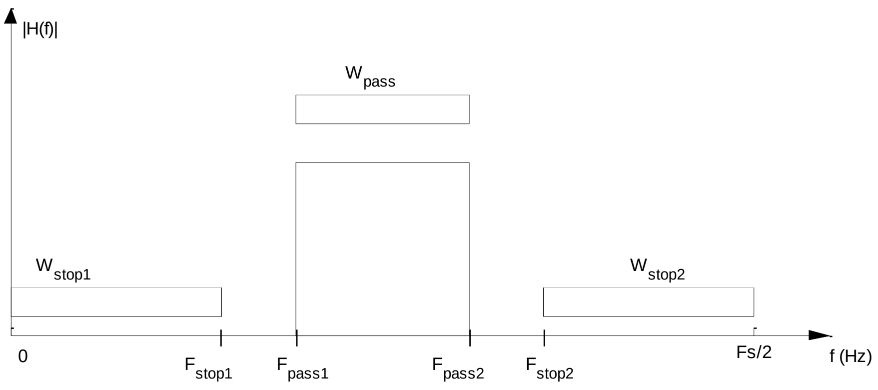


Figure 18 Band pass filter schema applied to acquired data

The final band pass filter applied to the acquired signal is shown in **Figure 18**, where f_{stop1} is the minimum frequency for which the sensor was characterized, and f_{stop2} is half of the sampling frequency used for the quantization of the signal.

5. Signal Processing

The next step of the diagram in order to perform a fault diagnosis is processing the acquired physical signal. In fault diagnosis, the signal processing is the key factor because the failures are not visible without operating. Signal processing is the step just after the acquisition of the data. **The objective of signal processing is to modify the representation of this data, so the useful information contained by the data can be highlighted.**

Feature extraction is an important but also one of the most difficult steps, mainly because the processed data contains irrelevant information. The main objective is to extract features that are related to the faults. As well as the signal processing and the feature extraction can be classified into three groups, time domain, frequency domain, and time-frequency domain, the most used techniques used in each domain techniques are shown in **Figure 19**. It should be said that exist many other techniques despite of the selected.

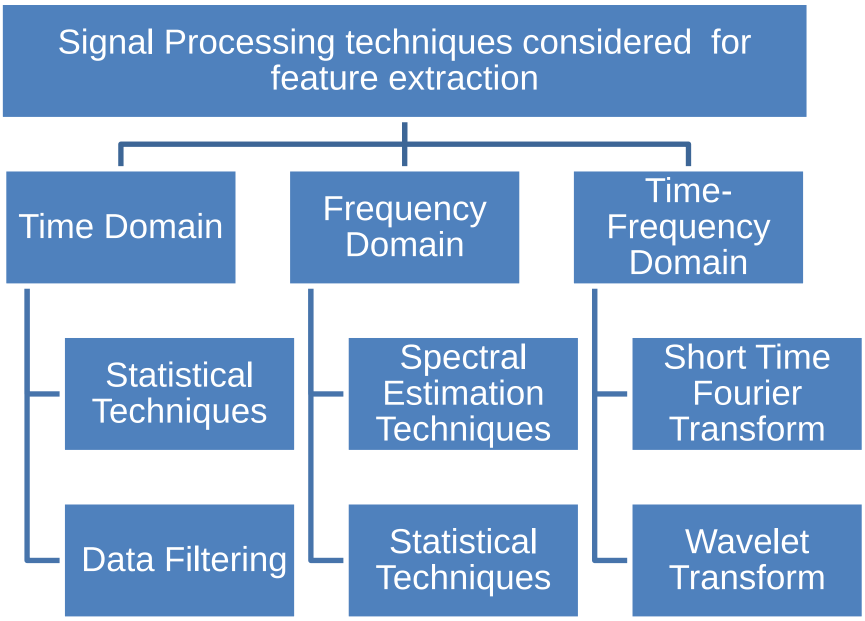


Figure 19 Signal processing techniques classification

A review of the main signal processing analysis techniques for fault diagnosis will be made. It should be remarked that this section only introduces the theoretical background over this techniques.

So, it not tries to explain how to extract conclusions about the failure (diagnosis), it only describes the methods that are available to analyse a signal acquired from an EMS. This explanation should be given because the line between signal processing and fault diagnosis is very thin.

The procedure to analyse the results from the signal processing with a failure in the system is explained in the next section (6. Diagnosis procedure).

5.1 Time domain techniques

Time domain techniques are very good tools for analysing temporal acquired data. They are best suited for when the component is analysed under stationary conditions, but are also helpful for non-stationary conditions.

They provide the basic information about the signal acquired. Is the easiest way to process the acquired data, in order to have a first approach, due to their low computational cost. The time domain techniques include statistical methods, data filtering methods and others.

5.1.1 Statistical methods

The statistical method's goal is to obtain a single value known as indicator calculated in base of the acquired signal using a specific equation. A research made by G. Vachtsevanos *et al.* in 2006 [25], indicates that **the main time domain statistical features are root mean square (RMS), Variance, Kurtosis, Crest factor and Skewness.**

5.1.1.1 Root Mean Square

Root Mean Square (RMS) is the measure of power content of the signal. It is defined as:

$$RMS = \sqrt{\frac{\sum_{i=1}^{n}(x_i)^2}{n}}$$

Where x_i is a sample data and n the total number of samples, this terminology will be used for all the equations. RMS is usually used to track the overall noise level. It is the most important time domain feature and is very effective in detecting any unbalance problem in rotating machinery. However it normally cannot indicate the specific failing component and it is also not sensitive to detect incipient machinery fault [26].

5.1.1.2 Variance

Variance σ^2 is the average squared deviation of each number from its mean. It is the measure of how dispersed is a distribution. It is defined as:

$$\sigma^2 = \frac{1}{2}\sum_{i=1}^{n}(x_i - \bar{x})^2$$

Where σ is the standard deviation, $x_i$is a sample data, and $\bar{x}$ is the samples main value.

5.1.1.3 Crest factor

Crest factor is the ratio of the peak level of the input signal to the RMS level; therefore peaks in the time series signal result in an increase in the crest factor value. The Crest factor can be used to detect impulsive vibration changes such as tooth breakage on a gear or bearing degradation. It is defined as:

$$C_f = \frac{\max[x_i] - \min[x_i]}{2 \cdot RMS}$$

Where RMS is the Root Main Square, $x_i$is a sample data and $\bar{x}$ is the samples main value

5.1.1.4 Skewness

Skewness is the normalized third central moment, and represents a measure of symmetry. A distribution, or data set, is said to be symmetric if it looks the same to the left and right of the centre point. It is defined as:

$$S_k = \frac{\sum_{i=1}^{n}(x_i - \bar{x})^3}{RMS^3}$$

Where RMS is the Root Main Square, $x_i$is a sample data and $\bar{x}$ is the samples main value. Other important time domain feature analysis techniques include correlation, covariance and convolution [83]

5.1.1.5 Kurtosis

Kurtosis is the normalized fourth central moment. It describes how the data is around the maximum peak compared to a normal distribution. It can indicate major peaks in a data set. The Kurtosis method is defined as:

$$Kur = \frac{\frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x})^4}{RMS^4}$$

Where RMS is the Root Main Square, $x_i$is a sample data and $\bar{x}$ is the samples main value. It is a useful tool used in engineering for diction of fault symptoms because it is sharp variant structures, such as impulses [27], but Kurtosis does not provide any information about the diagnosis problem.

5.1.2 Digital filter based techniques

Filter based techniques, in time domain analysis, are used in order to remove the high frequency noise present in the signal. Although, there is another important use of this techniques; they are used to isolate content from the signal in a specific frequency band.

A frequency domain analysis could also give this information with a better resolution for all the frequencies of the signal, but this option is better in terms of computational cost and its implementation in an embedded system.

There is two different ways to implement a digital filter depending on the filter equation, which are the finite impulse response filter (FIR), and the infinite impulse response filter (IIR). It should be noticed that all kind of filters could be implemented in its digital form (for example low pass filters, high pass filters, band pass or band stop filters, etc.).

5.1.2.1 Finite Impulse Response Filter (FIR)

A finite impulse response filter **is a digital filter which output has a constant and finite number of non-null terms**. Another particularity of this filter is the fact that the output only depends of present and past values of the entrance of the filter. The mathematical expression of the FIR filter is:

$$y_{FIR}[n] = \sum_{k=0}^{N-1} b_k \cdot x(n-k)$$

Where y_n is the output signal of the filter, x_n is the input signal of the filter, N is the order of the filter, N is coincident with the number of non-null terms, and the number of the coefficients inside the filter, b_k is the vector which contains all the coefficients that make up the impulse response of the filter.

Some of the properties of a FIR filter are:

- It requires no feedback. It only depends of the input signal x_n. As a result the accumulative error due to rounding is not successively increased.
- For this reason, it is easier to implement and has a less computational cost than the IIR filter.
- This kind of filter are always stable, due to the fact that all the poles are located within the unitary circle (Stability theorem for Z transform systems).
- The coefficients of the filter are related to the desired impulse response of the filter if it is excited with a unitary impulse.

The main drawback of this filter is that it requires a higher order than an IIR filter, and with this the number of coefficients and with it the number of samples required from the signal is always greater.

5.1.2.2 Infinite Impulse Response Filter (IIR)

An infinite impulse response filter is a digital filter which output has an infinite number of non-null terms, in other words, once it is excited; it never turns back to the stationary state. In this filter the output depends of present and past values of the input and the output of the filter.

The mathematical expression of the IIR filter is:

$$y_{IIR}[n] = \frac{1}{a_0} \cdot \left(\sum_{k=0}^{P-1} b_k \cdot x[n-k] - \sum_{j=0}^{Q-1} a_j \cdot y[n-j] \right)$$

Where y_n is the output signal of the filter. x_n is the input signal of the filter, P is the feedforward order of the filter, Q is the feedback order of the filter, b_k is the vector which contains the feedforward coefficients, and a_j is the vector which contains the feedback coefficients.

The main advantage of IIR versus FIR filters is that the general order required to perform the same operation is much lower. Despite this, one the main drawback is the fact that the stability of this kind of filters is not guaranteed, if the Z transform is performed to the previous equation the resulting transfer function if $a_0 = 1$ is:

$$H(z) = \frac{\sum_{k=0}^{P-1} b_k \cdot Z^{-k}}{1 + \sum_{j=0}^{Q-1} a_j \cdot Z^{-j}}$$

So the stability of this filter is related with the coefficients inside the feedback gain. The other drawback is the accumulation of the rounding errors when performing the feedback loop and considering previous outputs for the calculation.

5.2 Frequency domain techniques

Sometimes the information about the fault is hidden under the time domain form of the signal and the differences between a fault and a healthy condition could only be detected by analysing the frequency spectrum of the signal.

As a result, frequency information has a better capability in revealing the fault signature in many cases [25]. Mathematical tools like Fast Fourier Transform can give more information, maybe, about the size or severity of the fault. These new domain open a new field of study even though there are a large number of features to study on them.

The methodology to implement a frequency domain technique is composed by two different steps. The first one includes performing a Fourier analysis in order to obtain the spectral content of the signal. This analysis will give a frequency spectrum for a selected frequency range.

The second step is related with applying one of the statistical methods seen in section 5.1.1 to extract features from the frequency analysis performed. So the statistical methods are common for time domain and frequency domain processing techniques.

The most used technique to perform a frequency analysis is a frequency spectrum based on the Discrete Fourier Transform.

5.2.1 Discrete Fourier Transform

The discrete Fourier transform of a time series is given by the following equation:

$$Y_k = Y(f_k) = \delta t \sum_{j=0}^{N-1} y_j \cdot \omega_N \qquad for\ k = 0,1,\ldots,N-1$$

Where

$$\omega_N = e^{-i\cdot 2\cdot \pi \cdot j\cdot k/_N} \qquad f_k = \frac{k}{N\cdot \delta t}$$

And Y(k) is the complex value of the Discrete Fourier Transform, i is the imaginary operator, y(y) is the actual sampled data and N is the number of samples. This equation performs a discrete numerical integration corresponding to the continuous integration in the definition of the Fourier transform [28].

Some of the main properties of the DFT are:

- This transform represent $k = {}^{N}/_{2}$ discrete amplitudes spaced at a discrete frequency intervals with a fixed resolution of :

  $$Resolution = \frac{f_{sampling}}{N}\ (Hz)$$

  It should be noticed how the resolution could be improved by reducing the sampling frequency, where aliasing problems might occur, but at the same time it could be improved by acquiring more samples, which includes additional computational cost .
- So a compromise between the number of the samples and the sampling frequency must been considered in order to have a proper frequency resolution.
- The maximum frequency represented in the transform is according with Nyquist criteria :

$$f_{max} = \frac{f_{sampling}}{2}$$

It this criterion is not respected aliasing problems might occur if the signal has spectral content above this $f_{max.}$ To avoid this problem the signal should be previous filtered as it was mentioned in section 4.6.2.

In order to simplify the number of operations, the algorithm used in this calculation is known as Fast Fourier Transform (FFT), which takes advantage of a symmetry property of the DFT.

The symmetry happens if the number of data is equal to a power of two $N = 2^x$.Using the FFT algorithm first N/2 set of data returned is the original content of the calculated DFT, the other N/2 set of data (if returned, because some algorithm does not show this data) is a mirror image of the first half.

The main limitation of FFT or DFT is that is not suitable for non-stationary signals, and different temporal signals might have identical frequency spectrum.

Once the DFT has been calculated, the next step is to perform **the Spectral analysis**, which **is the process of identifying component frequencies in the signals data**.

This spectrum is usually divided in two different figures, one with the module obtained from the two components of the resulting DFT (real and complex components) and the phase diagram extracted from this calculation. In order to simplify the frequency spectrum, the transformation is shown in a single plot that shows the absolute value of the whole DFT signal.

5.3 Time-Frequency domain techniques

As it has been seen in the previous section, the frequency domain analysis, and thus the FFT analysis, is already a very useful tool in analysing the data, but is only useful for stationary signals. With stationary signals, signals are meant where the frequency doesn't vary in time. **The reason why the FFT is not suitable for non-stationary signals is that the time values are lost during the transformation.**

This fact has been supported by different articles in the last few years. For instance, the research made by H. Bae, Y.T. Kim *et al.* in 2005 [29] where basic differences between Fourier and wavelet analysis were compared, this fact has been also referenced in the work made by S. Ai, H. Li *et al.* in 2006 [30] , and the one made by P. Jun; Y. Guo-Hua *et al.* in 2010 [31] where the solution is found by using a time-frequency domain analysis techniques.

Like the name indicates, **a time-frequency domain analysis is a technique that shows simultaneously the evolution of the time and frequency**

magnitudes among time. It is useful in case of transients or applications of variable load torque or speed where FFT causes averaging mistakes (non-stationary signals).

It should be mentioned that these methods require a very high computational power while performing at the same time both analysis. In addition, some of these techniques will not offer any information that allows identify a concrete fault by itself.

A mix between different features will be necessary in order to do this correlation. These correlations require a very detailed observation of all features extracted from experiment results. When the number of features is rather big it is difficult to do this matching by human observation.

The most common time-frequency domain methods are the Short Time Fourier Transform (STFT), and Wavelet Transform (WT). Some basic properties of the two different methods are shown below:

5.3.1 Short Time Fourier Transform (STFT)

It uses a fixed data window to locate successive Fourier analysis. This sliding window moves across the time domain signal performing in each movement a Fourier analysis, the STFT is the result of analysing each window separately.

The selection of the window is directly related with the time-frequency resolution. Due to the fixed value of this parameter two opposite situations could be given:

- Using a narrow window: Implies a good temporal resolution and a poor frequency resolution, thus, the power spectra peaks are separated from each other in time, but every peak covers different frequencies.
- Using a wide window: Is the opposite case, it implies a good frequency resolution and a poor temporal resolution, hence the peaks cover a single frequency, but in time domain the peaks cover a wide range of the signal.

So a compromise between temporal and spectral resolution should be made, this fact is illustrated in **Figure 20** where a graphical description of the different resolutions within frequency and time is given.

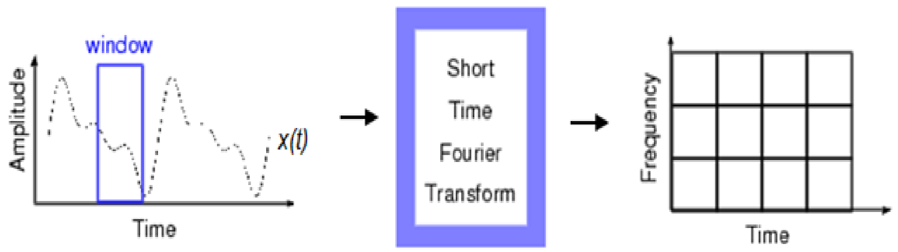


Figure 20 Graphical representation of time and frequency resolution of a STFT

5.3.2 Wavelet Transform (WT)

In the other hand, the WT makes use of the time-frequency window based on a specific function named wavelet to locate the analysis in the time-frequency domain. The average value of a wavelet should be 0, in other words, the wavelet should have no energy over one complete period of the signal.

The resolution is a moving non constant window where:

- In lower frequencies where the spectral content is negligible, so it has a good temporal resolution and a poor spectral resolution.
- In higher frequencies where the most important content is located in the frequency analysis, so the shape of the window change and it provides a good spectral resolution and a poor temporal resolution.

This fact is illustrated in **Figure 21** where the different windows depending on time and frequency could be seen. Nowadays, this method is being used by many researchers in order to perform different fault diagnosis techniques, this fact could be seen in the increasing number of articles using wavelets in order to perform condition monitoring in the last few years.

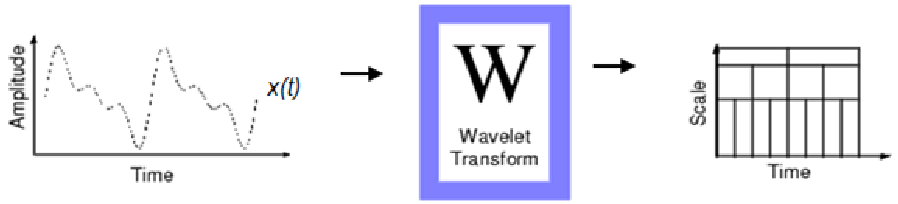


Figure 21 Graphical representation of time and frequency resolution of a WT

5.4 Conclusions

In this section a review of the main signal processing techniques used with fault diagnosis has been made. As a conclusion, there are three different domains to work (time, frequency, and time-frequency). Each domain has a particular time and frequency resolution. This fact is shown in **Figure 22,** where the different windows depending on the method used are illustrated in a graphical way.

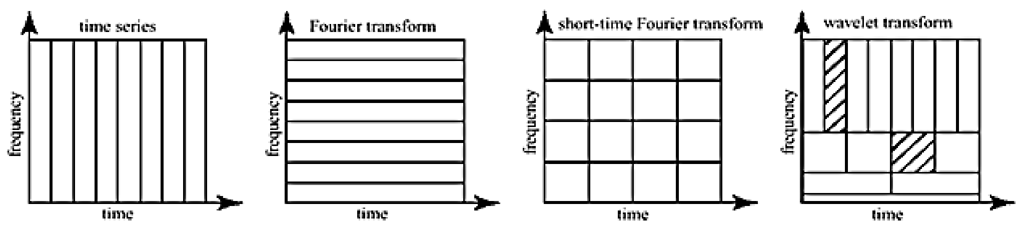


Figure 22 the most common resolution in each domain analysis

It should be noticed how all the windows have a constant size, unless the wavelet transform who has an adaptive (uniform) resolution. All the techniques illustrated in this section have been summarized, with the main advantages and the main drawbacks, in Table 1 Summary of all the different domain techniques and its properties **Table 1** .

	Techniques	Main feature	Weak points
Time domain	Statistical techniques	Simple implementation and low computational cost. Good for a first and quick approach Compatible with all the other domains.	Few dynamic information
	Filter based techniques	Simple implementation. Low computational cost.	The information to extract needs to be known.
Frequency domain	Discrete Fourier transform Spectrogram	Powerful technique and accepted as standard for fault detection on steady state.	Only give what frequency components exist in the signal. No information about time. Not useful in non-stationary signals. Different temporal signals might have identical frequency spectrum
Time-frequency domain	Short Time Fourier transform	Good Time-Frequency analysis equivalent time and frequency resolution. Allow comparison.	Constant window (time-frequency) resolution property, too much computational cost
	Wavelet transform	Powerful tool used as filter functions	Uniform resolution among time and frequency and non-adaptive nature.

Table 1 Summary of all the different domain techniques and its properties

It should be noticed that this field is a very active research area, and nowadays there are more other technics that has been widely accepted for extracting the information inside a signal. For instance, some of these techniques are time synchronous average or stochastic techniques inside the time domain analysis. Also in the frequency domain are other methods despite the Fourier analysis, like using parametric models or high resolution techniques. Other techniques like The Wigner distribution, the Hilbert-Huang Transform, or the empirical mode decomposition are used in time-frequency domain.

6. Fault diagnosis in EMS

One the different techniques to analyse the signal acquired and extract features from the signal, the posterior diagnosis procedure could be made. This fact leads the explanation to the last step of the block diagram shown in **Figure 3**, the Diagnosis procedure.

The diagnosis procedure tries to correlate the features extracted from the processed signal with the failure of the system. In other words, it tries to select which features are more related to the fault that wants to be detected. The fault diagnosis area has been deeply studied and thousands of articles and research works cover a wide range of techniques and methodologies.

6.1 Methodology to perform a diagnosis system

There is not a universal algorithm to say if a machine is in a faulty condition or not, so in order to perform a fault diagnosis system, a basic methodology should be followed. **This fact is one of the main problems while working with acoustic emissions signals, which is a young technology without a well-defined methodology**. In the other hand, the vibration analysis has a well-defined methodology which will be explained in the next section. In order to solve this problem a methodology to perform the analysis is defined in this project. This methodology is shown in **Figure 23** and has been defined according to the developed work.

At the initial phase of the process, a deep knowledge of the system behavioural is always required. So the first step is to study and to analyse the healthy behaviour of the machine. In order to study this behaviour different indicators, which are related to the fault that wants to be detected, are calculated in healthy condition (Step 2).

Once the healthy behavioural is well-known; the data is acquired under controlled faulty conditions (seeded defects) (Step 3). When the new signal is processed, the features are again calculated (Step 4). A correlation between the features and the fault should be analysed, in order to detect which features are giving information about the failure (Step 5). To make easier this part, this search is often based on the art state; there is a lot of research work made in order to identify what features are related to specific faults.

The next step (Step 6) is to select the features that best shows the signs of failure. When the features are selected, the numerical variation of this parameter, from healthy to fault condition, should be calculated in order to set a concrete interval. This interval is the key factor to differentiate the fault behaviour from the healthy in base of that parameter (Step 7).

Once the feature intervals have been defined, an algorithm to automatically perform this action could be made (Step 8). This algorithm has to automatically perform the following tasks: calculate the actual indicators from the acquired signal; check if the value indicates healthy or fault condition and finally give the appropriate result to the user.

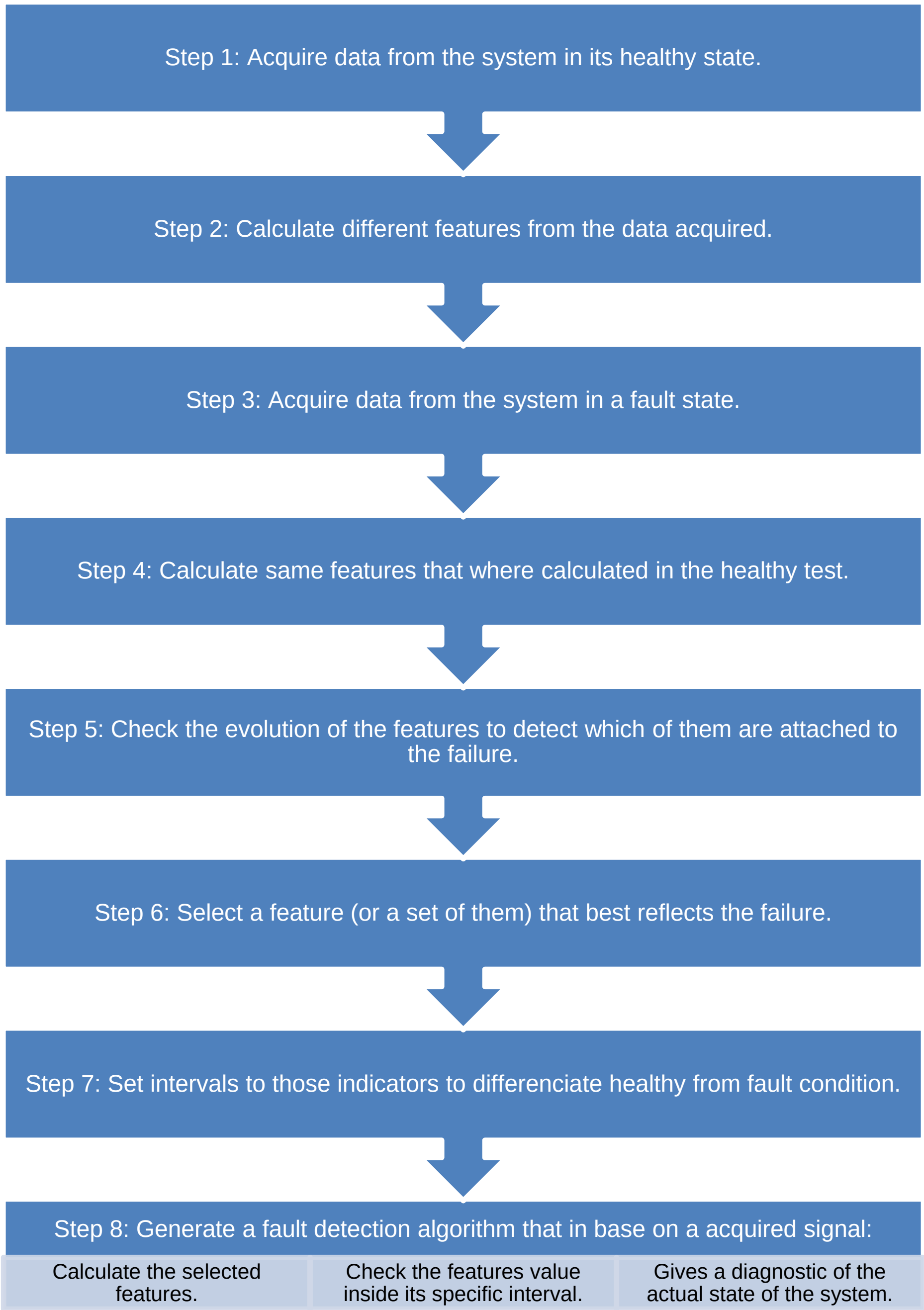


Figure 23 Procedure to perform a pseudo automatic diagnosis system

6.2 Vibration analysis on fault diagnosis

This project focuses on the analysis of acoustic emission signals, but in order to compare this method and the vibration analysis, the main characteristics of the vibration signature analysis would be briefly defined.

Vibration analysis is the most established method for performing fault diagnosis of electromechanical systems. It has been applied during decades. To have an idea about the time that these techniques have been used, the first article in the database was the research performed by G.S. Fang et al. in 1972 [44], which use correlation analysis for the classification of engine-vibration as a basis for automatic mechanical fault diagnosis.

All rotatory machinery has a related vibration frequency spectrum that characterizes healthy machine behaviour. It should be mentioned that generally the vibration analysis is almost performed in frequency domain.

A fundamental premise of this vibration analysis is:

"Each component or each kind of mechanical deficiency of a machine in operation produces one vibration of specific frequency which, in normal conditions of operation, can reach maximum known amplitude".

This is one of the most important characteristic of the vibrations; **all the components or faults usually vibrate in a specific frequency**, so it is easy to detect those frequencies in the healthy spectrum [45]. Although, **when a mechanical part of the system is degraded or damaged, the associated frequency component in the spectrum will change**. So the new value could be compared with reference one in order to perform the fault detection and diagnosis.

It should be noticed that measuring the frequency is not sufficient in order to identify the failure. In rotating machinery, the operating speed displaces the frequency spectrum, therefore, the rotating speed must be known and consequently, the frequency spectrum should be related to the rotating speed.

The vibration range for the frequency analysis, in rotating machinery, is typically from 1Hz to 30 kHz. [46].

6.2.1 Vibration analysis in gearboxes

In order to apply the vibration analysis to a gearbox, it should be known that this method can measure meshing frequencies of gears in order to diagnose a fracture or gear pitting fault.

The common gear faults generate a frequency spectrum that that extends from frequencies below the shaft rotating frequency up to multiples of the gear mesh frequency.

The meshing frequency of a gear should be referenced to the rotation speed of the machine, so it is calculated by the product of the number of teeth of the gear, and its respective rotating characteristic frequency, as is described by:

$$G_{meshf} = number\ of\ teeth\ on\ gear\ x\ gerar\ rpm(f)$$

This mesh frequency is normally surrounded by other lower harmonics located in two sidebands (usually at a frequency multiple of the rotating speed). Gear defects cause an alteration in the number and amplitude of these sidebands.

The most used methods to detect a gear fracture using vibrations signals are based on the calculation of statistical features to the vibration spectrum as discussed in detail by W. Wang *et al.* in 2001 [48].

One example of a methodology to perform a vibration analysis is based on the envelope method. This method is a widely used method to identify defects on rolling elements like gears or bearings. The main steps for applying this method are shown in **Figure 24**.

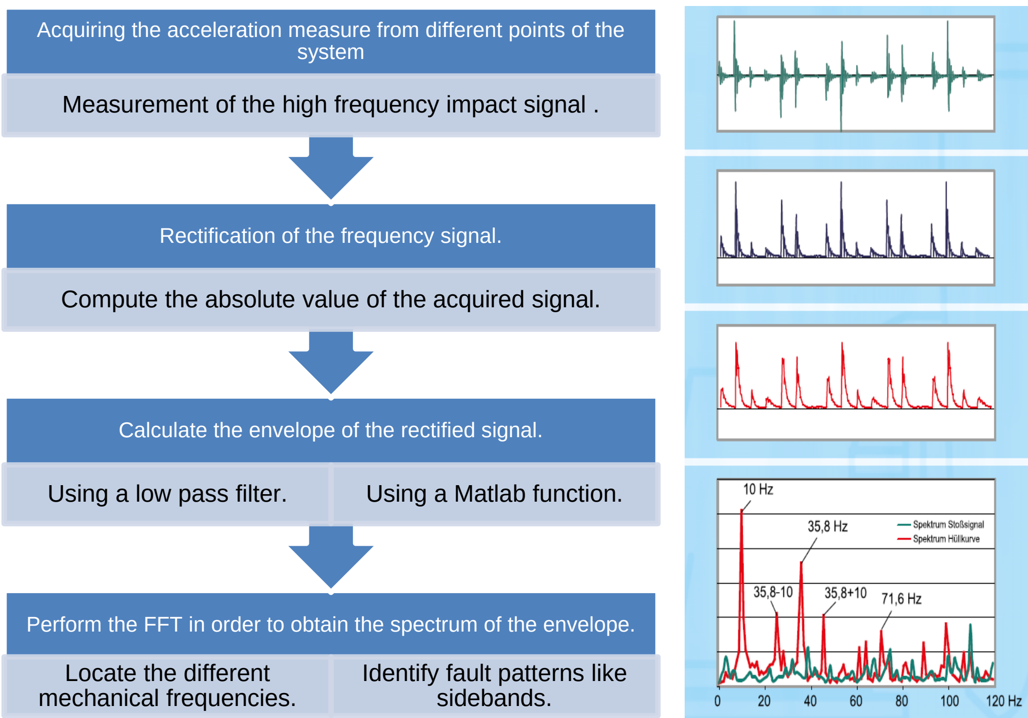


Figure 24 Envelope analysis methodology for vibration analysis

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This method is based on the fact that the defects generate impacts with very high frequency vibration components. The low frequency impact which is relevant for the fault diagnosis is really difficult to identify if no signal processing is made. In this sense, the envelope analysis demodulates the high frequency impact signal allowing the mechanical impact frequency to be measured [47].

6.3 Acoustic emission analysis on fault diagnosis

Acoustic emissions signals in condition monitoring have been evolving the last decades. A nowadays AE signal represents a trusted method to detect and prevent the failures in the specific systems (as pumps or construction). But it is also a young technology in the world of electromechanical systems preventive maintenance.

6.3.1 Introduction and historical background

Acoustic Emission technology (AE) on testing began to be investigated in the early middle of the 20th Century. But the first article that studies the phenomena of acoustic emissions was in the 1940s; this article was related to the problem of predicting rock bursts in mines in order to keep the workers safe. So the main field of the AE was geology [19].

AE history started in 1950s with publication of Kaiser’s dissertation made by J. Kaiser in 1950. It was the first significant study about AE applied on analysing the data from metals (steel, zinc, aluminium, copper, and lead). The most significant observation extracted from this investigation was the denominated Kaiser Effect.

Basically, it says that no relevant acoustic emission could be detected until the pressure applied over the material under test surpassed the previously highest level applied. It was used in a first instance to provide useful information about irreversible processes in a particular rock.

The Kaiser effect applies to deformation processes like plastic deformation and crack growth. Whereas frictional motion between the flanks of existing cracks may generate repeated acoustic emission by stick slip processes during repeated loading of a specimen. This effect is to be seen also during repeated unloading of specimens containing cracks.

Based on this article from Kaiser, B.H. Schofield re-examine it and published his work as entitled “Acoustic Emission” in 1961. This is the first use of the terminology of AE in history.

Then in the 1960s the study turns around the concrete engineering. J. Kaiser studied the noise emitted during application of compressive load in concrete; this is the first study about the Kaiser effect in real engineering materials. He found that the Kaiser effect was observed up to around 75% load level of failure load (from 70 to 85%) , and reported that generating behaviour of AE signals was closely related with the volumetric change and the absorption on ultrasonic waves [14]. In 1965, G.S Robinson [50] used more sensitive equipment and shows that the acoustic emission happens in lower levels of load.

In 1970s D. Wells [51] built a still more sensitive apparatus, with which he could monitor Acoustic Emissions in the frequency range from about 2 to 20 kHz. Green A.T was the first to obtain data from more than 100 kHz. Also he was the first to show that AE from concrete are related to failure process within the material and using source location techniques he was able to determine the location of the defects.

These were the most important papers in the beginnings of the AE analysis. In order to demonstrate the evolution in the acoustic emission research ambit and the fact that nowadays is a forefront topic, a search inside the IEEE database was performed.

As a result in 1988 there were at least 90 articles about AE around the world and the publication rate was about 7 articles each year, nowadays there are more than 500 articles around the world and each year more than 40 articles in this topic are published. The **Figure 25** shows the progression of the study in the Acoustic Emission field.

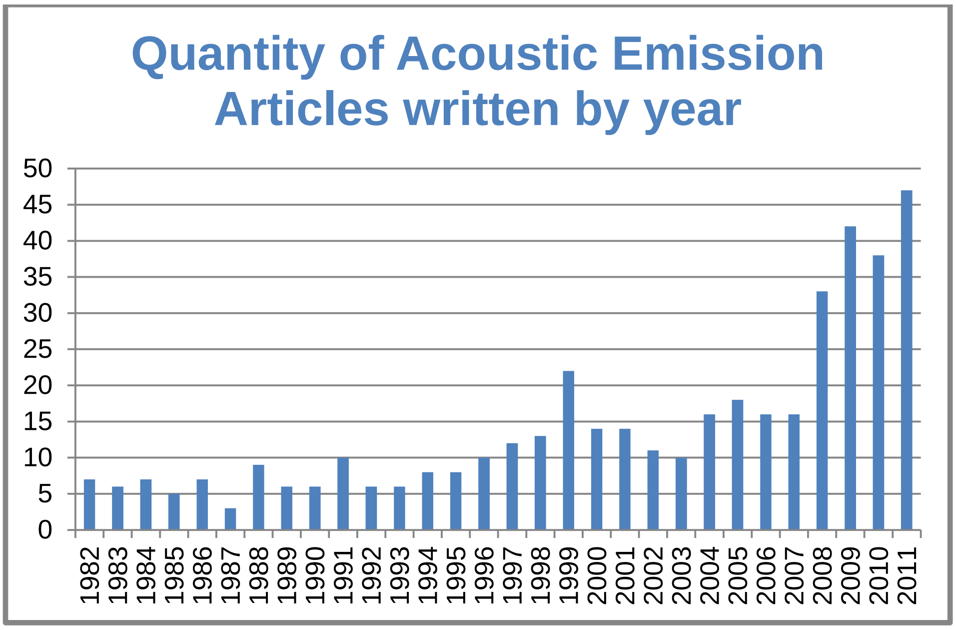


Figure 25 Evolution of the Acoustic Emission Articles in IEEE

This factor shows that AE applied on EMS testing is a young technology which is in the practical stage. It has to improve and evolve to become a trusty standard method to identify and test engineering pieces, machines and mechanisms.

6.3.2 Methodology to perform a fault diagnosis with AE signals

The methodology to find the best features for detecting the fault by means of AE analysis can be divided in 4 stages:

- Stage 1: Collection of AE signals in different experiments.
- Stage 2: Observation of AE signature and trend of the series of simulation defects.
- Stage 3: Establishing correlation between the AE activity and seeded defects. Compare faulty and healthy condition test.
- Stage 4: Actualisation in diagnosis and prognosis of the defects/faults using AE technology.

This will be the methodology applied in the practical part of the project. It should be noticed that stages 2 and 3 are very close in terms of processing. The raw data collected does not offer as much direct information about the defects as is desired.

In order to match AE activity with defects is necessary a previous signal processing that ends in the *feature extraction*. These features can be calculated from the temporal signal like have been the trend in the last decades. Once the features are calculated for different cases (types of defect, fault severity, load and speed conditions, etc.) is time to observe the evolution or trends of them in function of the defects. So the main problem

6.3.3 Extracting fault information from an AE signal

In order to find the faults with AE signals, the most used technique is the parameter analysis method [14]. In these kinds of techniques, first of all, an AE signal has to be acquired from the component, and then analysed in order to extract several features to identify the failure.

Feature extraction is an important but also one of the most difficult steps, mainly because the processed data contains irrelevant information. The main objective is to extract features from the AE signal that are related to the faults. This is the point where signal processing techniques should be used, because they eliminate the unnecessary information and avoid misleading

It is important to consider that all these features are not only related to the failure, **they can be attached to the test conditions** (like the rotatory speed of the machine, the load applied to the shaft or the defect size).

So it's important to do first an experiment with healthy components to see if the results are affected or not by the characteristics of the test, and then use a deteriorated bearing to contrast the obtained results.

In this project, only time domain and frequency domain features have been considered. There is no feature extraction in time-frequency domain, despite this technique is useful in a first approach to detect the frequencies where the AE signal has significant content in order to focus the study on this sections.

6.3.3.1 Which features should be extracted?

As was explained in section 5.1, time domain techniques are very good tools for analysing temporal acquired data. They are best suited for when the component is analysed under stationary conditions, but are also helpful for non-stationary conditions. The **Table 2** shows a summary of the art state about the temporal techniques methods to analyse an AE signal

Mechanical Component: Fault	Features from AE signal	Researchers
Bearings & Gears: Diverse Faults	RMS	*J.J. Holroyd et al.[33]*
Shaft: Misalignment Gear: Tooth Breakage	AE amplitude RMS Standard Deviation Duration	*E. Siores et al.[34]*
Gear: Pitting	AE amplitude	*A.Singh et al. [35]*
Gear: Pitting (size)	Peak Amplitude Ringdown County Energy	*N. Tandon et al. [36]*
Gear: Pitting	Energy	*H. Sentoku et al.[37]*
Shaft: Misalingment Gear: Natural Pitting	Peaks Energy	*T. Toutounzakis et al. [38]*
Gear: Wear state	Ringdown Counts	*M. Markovic et al. [39]*
Gear: grinding process (Wear State)	Ringdown Counts Amplitude	*J.R. Wilson et al. [40]*
Gear: teeth meshing fault	Amplitude Distribution Change	*M.P.Spencer et al. [41]*
Gear: Pitting	Crossover count Energy	*K.H Pedersen et al.[42]*
Bearing: wear	Energy RMS Kurtosis	*M. Abdullah et al. [43]*

Table 2 Summary with the latest papers using AE testing with Temporal Techniques

The statistic characteristics are the most important ones, because they easily show the general condition information, parameters as the Kurtosis, the RMS value , are directly related to the AE generation source, and thus with the failure.

The AE technique of detecting fault is relatively new so that the most practical and understandable features have been extracted. Further analysis on these signals is needed in order to find more tools to do a better correlation with the state of the mechanical components studied.

Mathematical tools like Fast Fourier Transform can give more information, maybe, about the size or severity of the fault, also the spectrum given by the FFT could be used in order to apply a posterior statistical analysis on in and calculate features like the RMS value.

6.3.4 How to correlate the features with the fault

In this sense, a very interesting study was developed X. Zhang et al. in 2009 [8], where they used a primary motor to give movement to a rotating machine unit, ant this mechanism was connected to a loading unit. The relations between the parameters of the test and the features extracted from can be summarized to determinate the most important features concretely in mechanical component condition monitoring.

In the study, it is compared the influence of the test parameters in the main features of the signal. The conclusions have been extracted and classified by the feature involved. The study is carried on with bearings, but it could be extrapolated to other mechanical elements with some particularities. The results are showed below.

The counts of the AE signal

An AE count is defined as the number of times the amplitude of the signal exceeds a threshold value. The counts are related to the oscillating frequency of the AE signal.

- **The influence of the rotating speed:** When the speed increases, also the counts do. So there is a direct relation with the counts and the rotatory speed of the machine. But the numbers of counts increases with and without the defect, so it can be affirm that AE counts are very sensitive to the speed. In fact this is a logical behaviour since with the increase of speed, more mechanical impacts will take place, and then, more AE burst signals will be generated.
- **The influence of the defect size:** AE counts are not influenced by small or incipient defects, but are specially influenced with larger defects.

Therefore, AE counts are not sensible to the load applied to the system, and they are highly influenced by the rotating speed and larger defects. Also it was noticed, that the AE counts were closely related to the test conditions, a modification in any parameter such as the geometrical shape of the element, the position of the sensor inside the experiment, the threshold voltage set by the user or others will influence the number of counts extracted from the AE signal with or without the presence of defects.

The explanation of this phenomenon is that the counts are related to the activity level of the source, this activity depends of the physical properties of the material (a stress wave produced by an iron source is not equal propagated that one produced by an iron material) and the working conditions of the test.

So it might be difficult to detect failures in mechanical components using only the number of the AE signal's counts because the result can be influenced by the experimental conditions.

2.2.3.2 The amplitude of the AE signal

The amplitude is related directly with the deformation mechanism and the strength of the AE source [52]. Also like the AE counts, it can be affected by the conditions of the test and especially by the sensor's characteristics.

- **The influence of the rotatory speed:** The amplitude of the AE signal is highly affected by the rotatory speed of the machine. If the bearing is under failure, the amplitude of the signals significantly increases with the rotatory speed.
- **The influence of the defect size:** The amplitude of the AE signal highly increases with the presence of the defect. So it's a very good feature to determinate if a defect exists. Although, once this defect exists, the AE amplitude is not sensitive to the defect's magnitude so the amplitude could not be used to estimate the size of the defect and then its severity.

The conclusions extracted from the analysis indicate that if there is no defect, the AE amplitude will be only influenced by the speed applied to the mechanical system. **Once the defect exists, the amplitude could detect that defect, but it has not a constant or obvious relation with the defect size.**

The physical explanation under this phenomenon is that when a defect appears, it changes the deformation dynamics of the defect area. That dynamic is not affected by defect size or the load. In the other hand, the rotating speed modifies the deformation mechanism changing the strength and the impact frequency around the defect area of the mechanism. , so it seems logical some kind of changes

2.2.3.3 The AE signal's energy

The energy of an AE signal is defined generally as the root mean square (RMS) of the signal. This feature is important because it is not sensitive to the electronic system gain and eliminates the coupling between the machine and the AE transducer. It gives an accurate and more objective measure from the status of the mechanical element.

- **The influence of the rotatory speed:** The energy is related to the AE area. If the speed increases, the AE signal will do more counts, and also the amplitude will increase. So if the energy is the area under the signal's envelope, the energy would highly increase with the variation of the speed. It should be noticed that the increase will take place with or without the defect. As it has been mentioned before, the increase of speed implies an increase in the number of generated bursts in a same period of time.
- **The influence of the defect size:** The energy increases when a defect is detected, but it's not directly related with the defect's expansion. So the defect can be detected, but not its severity.

The AE energy is less affected by the mechanical load, but is more affected by the varying conditions of the test. As happens to the AE amplitude, an increase of the speed in an electromechanical system will affect the impact frequency and the strength in the defect point and would highly increase the energy of the signal. Despite of this fact, **is one of the most useful indicators in order to detect the failure presence inside a system if compared with the RMS in healthy condition**, because is a quantification about the energy in the acoustic emission wave.

2.2.3.4 The AE Kurtosis value

Kurtosis is a fourth order statistics which measures the crest shape of the probability density function of the sample. It can give an estimation of the probability to generate periodical impulses with large amplitude**. This is important because a train of periodic impulses in an AE signal is a clear feature of failure.**

There are different research works, as the performed by F. Chu *et al.* in 2005 [54] that use the kurtosis feature to evaluate the working condition of electromechanical actuators.

When a defect appears, maintaining the same speed in the system, it will generate a train of periodic impulses, that will increase the kurtosis value indicating that the systems is moving from its normal distribution.

With the increase of the defect size and the rotating speed, the kurtosis value would greatly increase. Furthermore, there is so far no evidence of the influence of the load applied to the kurtosis value.

2.2.3.5 Conclusions

This section could be summarized emphasizing that the parameter of the experimental configuration which most affects the features extracted from the AE signal is the speed of the electromechanical system. However, it modifies the features in any working conditions, with or without the failure. –for that reason it is necessary to be careful with the speed set point of the experimental conditions if do not want to extract misleading conclusions.

Another important conclusion extracted from [8] is that **the influence of the mechanical load does not affect the results of the test.** For this reason, in this project when performing the real analysis, no different loads have been considered.

According to the different studies performed in the field of acoustic emission analysis for fault diagnosis, **the more suitable features to consider are the RMS value of the signal, the amplitude of the AE signal and the frequency components of the spectrum.** All these consideration are summarized in the Figure 26 as a global conclusion of the AE method for fault diagnosis

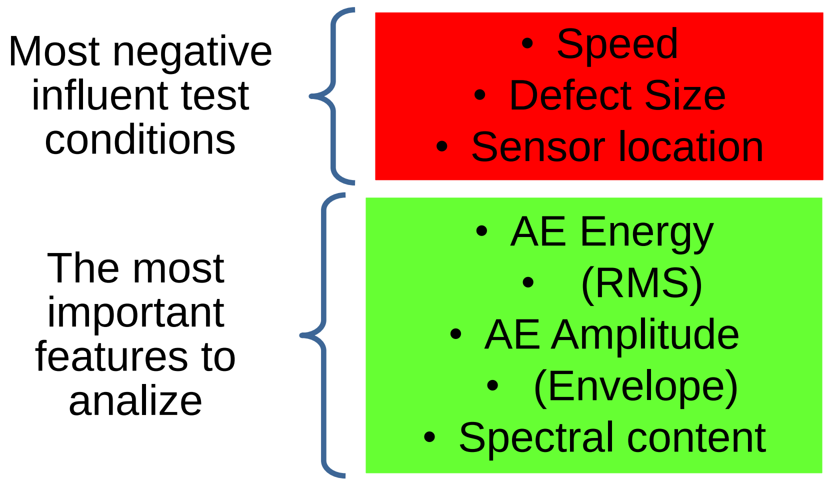


Figure 26 Main test parameters to consider and main features to analyse in AE signals

6.4 Comparative between Vibration and AE analysis

This section wants to do a review about the main differences between the vibrations and the AE analysis in fault diagnosis. The main advantages and drawbacks of each method would be exposed in order to justify why to use AE Signals in mechanical condition monitoring and fault detection.

One of the most important properties of condition monitoring based on Acoustic Emissions is the fact that these signals are very sensitive to incipient defects. The failure could be detected just when it appears.

The failure process begins with small cracks and wears in the material. By their own nature, these initials degradations cause waves of high frequency and low amplitude. When the failure, the wave frequency decreases amplitude tends to grow. Vibration sensors are very useful, but detection involves some progress in the degradation of the component. In AE, higher frequency signals could be detected so the failure could be earlier seen.

Otherwise, with the vibration signals, the failure can only be detected when it's in a critical state, sometimes too late to repair the mechanism. As a result, Acoustic Emission (AE) is being proposed as a firm substitute for the vibration techniques [8].

A weak point about the vibration analysis is closely related to one his analysis fundamental premise, the fact that each component or failure vibrates in a specific frequency. This is a key factor in order to recognize the different fundamental frequencies in the vibration spectrum. There are many variables that could affect the behaviour of the machine like the load applied to the system, non-lineal elements (like saturations), electrical noise, etc. **These phenomena can mask the important frequencies in the vibration spectrum; causing with this misleading results in the posterior diagnosis**.

This problem happens because **vibration analysis works in a low frequency range (1-30 kHz)**. Working with these frequencies can be a problem because they are similar to the frequency order of the mechanical noise. This noise appears in the rotating machines due to mechanical problems such as misalignment or imbalances and is very difficult to completely remove.

Otherwise, acoustic emission signals work in a range of frequencies from 20 kHz to 1 MHz. This range is bigger than the mechanical noise so the noise is not overlapped with the acquired signal. As a result, AE signals are practically unaffected by the general mechanical noise giving cleaner information than the vibration signals. To summarize all these properties, the advantages of the acoustic emission analysis can be enumerated as follows:

- They are insensitive to mechanical background noise.

- They can detect the faults at the very beginning and follow all the defect process.
- The information given is more consistent and can better represent the state of the element.

In the other hand, one of the main limitations of the acoustic emission method is based on its passive nature; it only is able to “listen” or detect energy wave propagated throughout the machine. This fact implies that signals acquired have very low amplitude and are highly influenced by the properties of wave propagation, which depend on the elements shape and materials characteristics about all the components inside the electromechanical system.

Having a low amplitude is also another important drawback, because in combination of the high characteristic frequency of this signal makes it very vulnerable to suffer EMC problems. So a proper grounding and shielding is always required in combination with an amplifying stage.

Another problem found in vibration analysis, regarding to the present project, is the efficiency of this method to detect faults when it’s applied to gears. According to W. Wang *et al.* in 2001 [48], due to missed hits and false alarms, only the 40% of the faults could be found.

It should be said that nowadays the research in both methods is focused on the same objective, increasing the effectiveness of the fault detection. Regarding to this fact, some authors like H. D. Ruoyu *et al.* in 2010 [49] talk about obtaining a performance of the 97% with acoustic emission analysis and a 78% using vibration analysis at detecting and classifying failures in gears. It should be noticed the great performance achieved from the AE analysis.

6.4.1 Conclusions

This conclusion section tries to shows a Vibration and Acoustic emission analysis overview, making emphasis in the relation between the main electro-mechanical faults and Vibration and Acoustic possibilities applied to diagnose them.

For this reason, it is shows two tables, for vibration analysis (**Table 3**) and Acoustic emission analysis (**Table 4**), which collect faults and experimental conditions in order to show which of these combinations is more suitable than the others for Vibration or Acoustic emission application.

As can be seen in these tables, the AE analysis has several problems detecting faults from the engine. For example it is no suitable for detecting demagnetization in the engine and faults in the Stator windings.

In the other hand, the vibration is able to detect those faults, but has a reduced performance in gear fault detection under varying load or torque.

Faults \ Condition	Constant speed and torque	Variable speed and/or torque	Incipient failure independently of the conditions
Bearings			
Stator windings			
Eccentricity			
Gears			
Jamming			
Demagnetization			

Table 3 Main faults, experimental conditions and Vibration Signal.

Faults \ Condition	Constant speed and torque	Variable speed and/or torque	Incipient failure independently of the conditions
Bearings			
Stator windings			
Eccentricity			
Gears			
Jamming			
Demagnetization			

Table 4 Main faults, experimental conditions and Acoustic Signal.

With this conclusion, the theoretical comparison between both diagnosis methodologies is over, but it will be resumed in the last part of the project in order to perform a real one.

To conclude this section, a summary with all the particular differences between the vibrations and the acoustic emission method is given in Table 5.

Function	Vibration	Acoustic emissions
Provides nonintrusive monitoring capability at a location remote from the equipment.	NO	NO
Provides useful diagnostic information at very incipient degradation levels.	NO	YES
Able to detect a variety of mechanical faults.	YES	YES
Able to detect a variety of electrical faults.	YES	NO
Offers means for separating one form of disorder from another.	YES	YES
The computational cost of acquisition and fault parameters extraction is not high.	YES	NO
High Signal Noise ratio.	NO	YES
Detecting the characteristic frequencies of some faults in the motor current is difficult even when the corresponding fault is prominent.	YES	NO
The effects of some machine faults can be reflected in the physical signal with similar characteristics masking the diagnosis between them.	YES	YES

Table 5 Main advantages and drawbacks of vibration and AE methods

7. Definition of the experimental Setup

Before this section, all the theoretical fundaments of the fault diagnosis in electromechanical systems have been explained. In addition, the main bases of vibration and acoustic emission analysis for condition monitoring have been presented.

From now on, the following sections cover the practical application of this project. Regarding to the different objectives presented in the introduction, in order to achieve three different objectives this practical application could be divided in three different parts, which are:

- The analysis and characterization of the acoustic emission signals obtained from the experimentation under a laboratory test bench. With the intention to obtain a suitable methodology that could be converted into a pseudo automatic fault diagnosis algorithm.
- The conversion of this methodology into an informatics code that could be implemented with an embedded platform, such as a µC based board.
- A comparison between the main techniques for fault condition monitoring applied to the same.

In this section the laboratory test bench used to carry out the experiments will be explained. It can be divided in two different parts:

- The electromechanical system and the control: formed by the power supply, the power cabinet, the inverters and the motor based test bench.
- The Acquisition system: formed by the AE sensor system, the vibration sensor (accelerometer) and the NI-PXI system.

Also, all the software used in the experiments will be briefly mentioned.

7.1 Experimental Set Up

The next section defines all the elements used in this experimental part of the project. The electromechanical system is the same in either experiments, but the acquisition system changes depending on the element used to acquire the data, the commercial acquisition system PXI or the Keil microprocessor board.

For this reason, in this section only the power scheme will be shown. In order to define the different parts of the experimental test bench, a general diagram of the global system (electromechanical power) is shown in

There are two PMSM motors in the test bench, the first one is used as the main motor over which the speed set point is defined, and the other one will be used as a resistive load by a torque set point.

Both motors are connected to the input and the output of the gearbox. Two ABB ACSM1 Inverters are controlled with a PC and connected to both motors in order to transmit the speed and load set points.

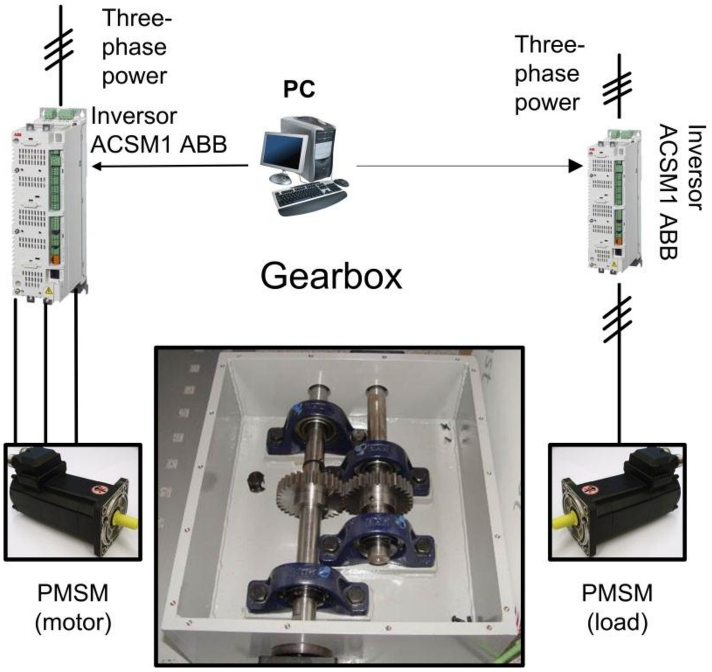


Figure 27 Global scheme of the power system of this project

Inside the gearbox, there is an Acoustic Emissions sensor connected to an amplifying system. The AE sensor is connected to a NI PXI-6115 board which is connected to a National Instrument PXI or to the MCBSTM32F400 Keil board.

7.2 Definition of the power System

In this section, the characteristics of the power electronics system, the PMSM motors and the power cabinet will be specified. The power supply is a three-phase voltage of 400V. There is also available a 24 V supplied by a parallel connected DC-source.

7.2.1 The power cabinet

The power cabinet contains all the power supply elements needed to control the electromechanical systems, the security switches, the filters to improve the voltage quality and the chokes.

7.2.2 Control switches

There are two switches connecting the power voltage with the inverters. They are controlled by two knobs at the outside of the cabinet. In the middle, there is another switch, which connects the three phases with each switch. The last one is connected with the emergency stop on the outside of the cabinet.

7.2.3 The Chokes

There are two chokes, one for inverter. The reactors have three coils, one for every phase. When they are in series connection with the supply, they are used to filter the harmonics and high frequency disturbances. This happens because the impedance of a coil will increase when the frequency increases, thus making it harder for these signals to come through.

7.2.4 The EMI Filters

Next the power signal will go through the filters. They are made by a connection of coils and capacitors. The utility of the filter is divided in two different tasks. It will provide a clean and better signal to the convertor, and make sure that the high frequency disturbances created in the inverter will not affect the net. In other words, it will eliminate the high order harmonics and reduce the signal's THD. The used filters are Ultra-compact EMC/RFI Filter for Three-phase Systems and Motor Drives from SCHAFFNER. The component model is FN-3258-16-44.

Characteristic	Parameter Value
Maximum continuous operating voltage:	3x 480V 277VAC
Rated currents:	16 A with 50ºC
Typical power rating:	7,5 kW
Power loss at 25ºC /50Hz	6,1 W
Operating Frequency Range	150kHz-30MHz
Overload:	4x rated current at switch on. 1.5x rated current for 1 minute, once per hour.

Table 6 FN-3258 Filter main characteristics

The system is designed to prevent and eliminate the common mode noise and filter the higher frequency harmonics. It gives good attenuation performance as low pass filter with a cut frequency of150 kHz. Chokes with exceptional saturation resistance are used, so they provide and excellent thermal behaviour. The main characteristics of the filter are given by **Table 6**.

7.2.5 The Motor Drive

Two ABB ACSM1 Inverters are used to control the motors. The ACSM1 can control with or without feedback. It implements a DTC (direct torque control) motor control technology to guarantee high performance.

The main characteristics are:

- Input Current 4.7A.
- Input Voltage - 380/440V three phase +-10% at 50/60Hz.
- It can resist an overload of 150% along 60 seconds.
- Speed Control Range - 0/500Hz.
- 2 x Analog Inputs,
- 2 x Analog outputs (one Voltage, one Current),
- 6 Digital Inputs,
- 1 Relay Contact set.
- Programmable from a pc with additional software.

In the **Figure 28** it is possible to see the Inverter and identify all of its different parts. It is a key component in the system because the speed and the torque applied will define the experimental conditions, and as it has been mentioned, it affects greatly to the test result when working with Acoustic Emission sensors.

Figure 28 also shows how the motor drive is divided in four modules. It has an Analog and digital I/O extension module, a feedback interface in order to control the motors and receive the speed from the resolver, and a communication interface.

The system operation will be as follows:

First the AC-supply will go through the chokes and the filter straight to the ABB inverter. When the voltage signal enters through the inverter, the current will be rectified to achieve a signal closer to a normal DC signal. The next step is the DC/AC conversion by an inverter and it's here where the actual control of the motor takes part.

The DTC system will generate a waveform in order to activate the IGBT placed at the inverter. The IGBT's are controlled by a PWM (Pulse Width Modulation). In order now to control the speed of the motors, the IGBT's will be closed or opened for specific time. The time they remain open divided by the PWM's modulation period is called the duty cycle.

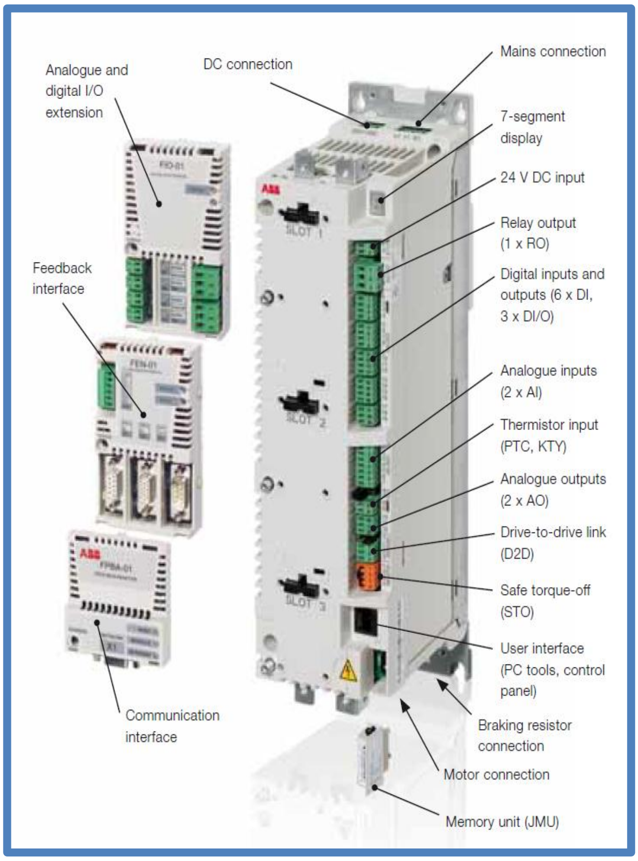


Figure 28 Identification of the different parts of the ABB ACSM1

7.2.6 The Brake Resistors

Close to the inverter there is a braking chopper. This is used to extract the energy that is generated when the motors are braking. It is also used to extract the energy that the motor for the load is generating because it is constantly acting as a generator, so it is needed to dissipate the generated energy.

The brake resistors used in this project are the model ALPHA CAR 155 DT 415 from the company DANOTHERM. The component is shown in **Figure 29**.

They are specially constructed for high pulse loads compared to the average load. The resistors comply with IP20 giving electrical and thermal protection. The resistors are silicone free. The is about 145W in steady state load and pulse loads of 60 times compared to the nominal load (8700 W) in one second each 120s. Definition of the motor bench

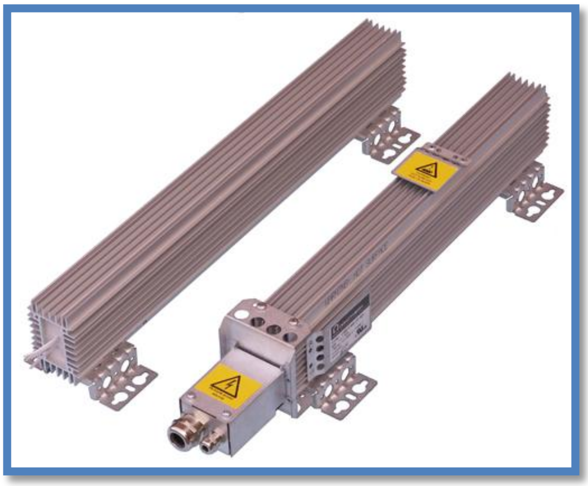


Figure 29 Alpha aluminium housed compact brake resistor model 155 DT 415

The Figure 27 has showed the power configuration of the experimental setup, it is composed by two Permanent Magnet Synchronous Machines (PMSMs). One acting as a speed drive and the other as a load (both are from the same motor model). The bearing supports for the external shaft and gears are located inside the gearbox. The Figure 30 shows an image of the selected engine.

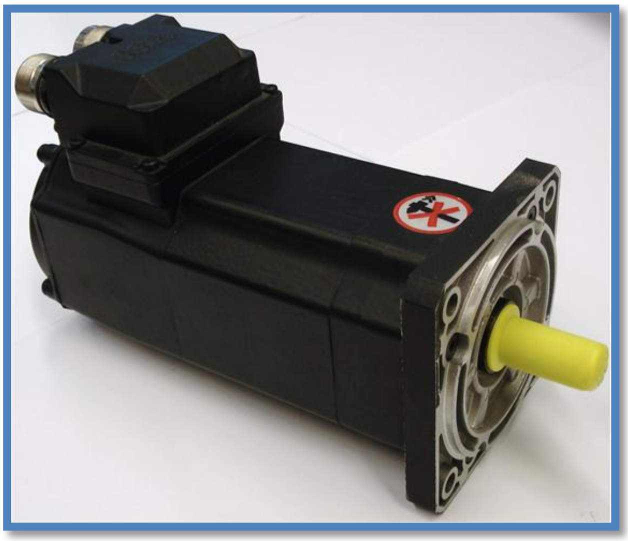


Figure 30 The ABB PMSM selected

Both motors have the same characteristics which are showed in the Table 7 . There are two wires connected on the top of the engine. One for delivering the three phase voltage to the stator of the motor, the other one is to connect the resolver of the electrical motor with the converter. This resolver determines the absolute position of the rotor as it’s explained in section 7.4.1 The Resolver.

PMSM Motors	
Nominal power [P_n]	1.57kW
Nominal Speed [N_n]	6000rpm
Nominal Torque [T_p]	2.5Nm

Table 7 Main characteristics of the PMSM Motors

7.3 Definition of the gearbox

The gearbox is a customized metallic box which contains the bearing supports for the shaft and the gear transmission system. It is needed to preserve and at the same time lubricate the engines to conserve their mechanical conditions, so all the mechanical components of the gearbox were treated with grease.

The Figure 31 shows a close up image of the gearbox with the shafts, the bearings and the gears inside.

Figure 31 Image of the gear box used in this project

Two gears form the gearbox in a simple 1:1 stage, it should be noticed that the shaft that support the under test gear is drilled in order to allow the pass of the sensor wire toward the preamplifier.

7.3.1 The Gears used in the project

The gear is made of carbon steel and has 31 teeth as showed in Table 8. It should be noticed that the indicated characteristics are common for all.

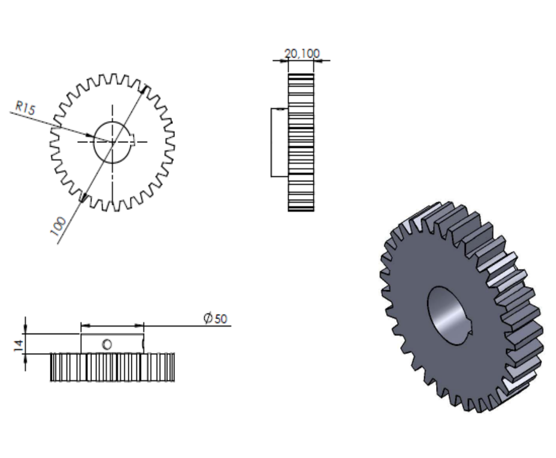
Standard Gears Characteristics	
Nº of teeth 31 **D_SIDES= 2mm** **D_TEETH= 10.25 mm**	
Tooth type Spur	
Steel Carbon steel (**EU** 1015 **DIN** C-15(1.0401) **AFNOR** XC 8 **IHA** F-111)	

Table 8 Standard characteristics of the gears used in this project

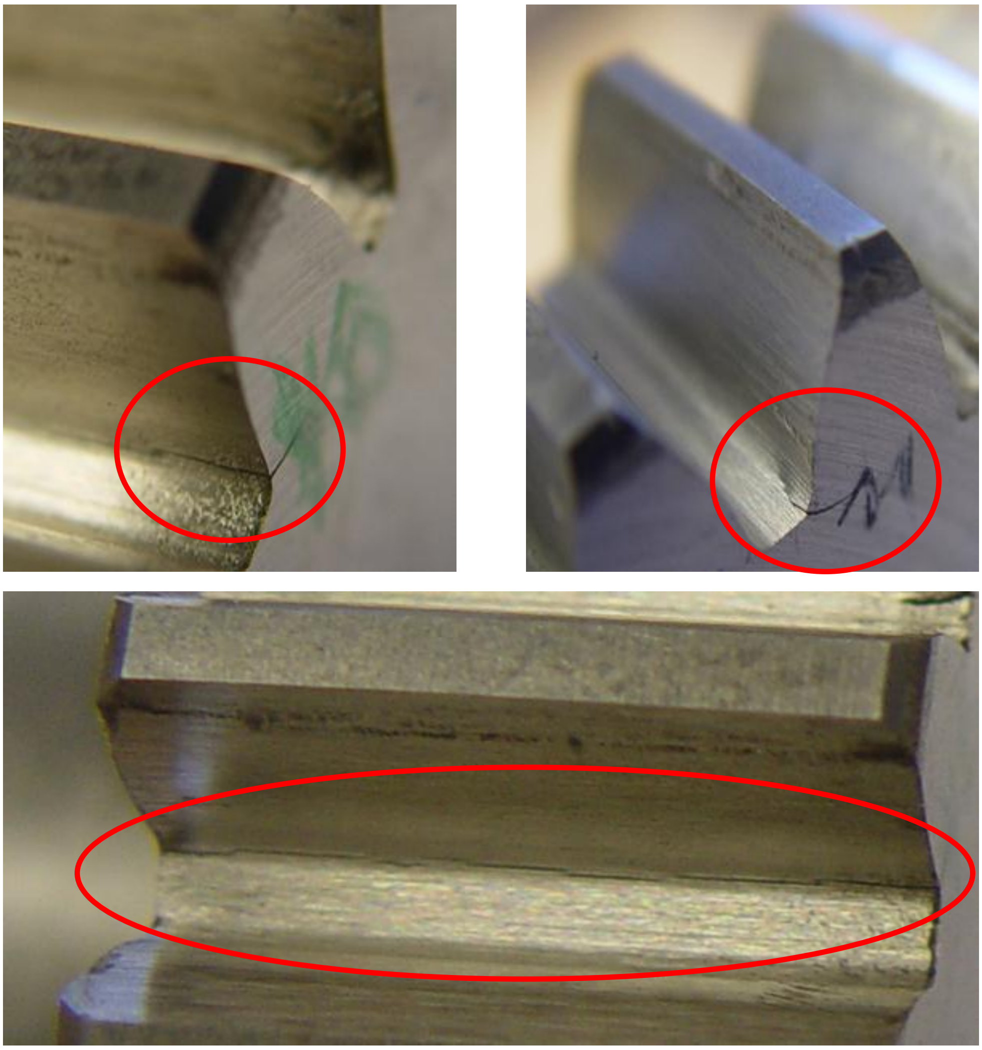


Figure 32 Detail images of the 7 faults gear

There are only three different gears used in this project. All have the same mechanical characteristics, but differ in the severity of the failure. There is a completely healthy gear that is used in a first step of the experiments. The second one has only a little failure in two uncial teeth. And the third one has de highest failure that is divided in seven different tooth fractures along the gear.

This gear has been subjected to fatigue test (during the material's characterization experiments), resulting in the generation of a serial of cracks in different teeth, concretely seven different tooth fractures has been made. These cracks present different severity degree as it can be seen in **Figure 32**.

This gear has the highest number of failures considered in this experiment. It is used always in the AE analysis, as the first gear to be compared with the healthy one. Due to these seven faults, all the acoustic emission events could be highlighted and be better detected by the AE sensor.

7.4 Definition of the Acquisition System

Next, the acquisition system is defined. This system can be divided in three parts.

- The first one includes all the sensors to read and visualize the mentioned physical magnitudes of the electromechanical system.
- The second one includes the additional electronic necessary to successfully send the sensor’s signal to the acquisition system.
- The third part is composed by the PXI acquisition system and the integrated acquisition boards.

7.4.1 The Resolver

The motors come with an integrated resolver in order to determinate the exact position of the rotor which is a crucial factor in the PMSM control, so with the resolver the flux vector can be estimated, and with it the exact position of the rotor.

Resolver is composed by three main parts as shown in **Figure 33**. There is one primary winding, called the ‘Reference winding’, and two secondary windings, the ‘SIN’ and ‘COS’ winding. The rotary transformer shown is used to make the energy supply of the reference winding brushless.

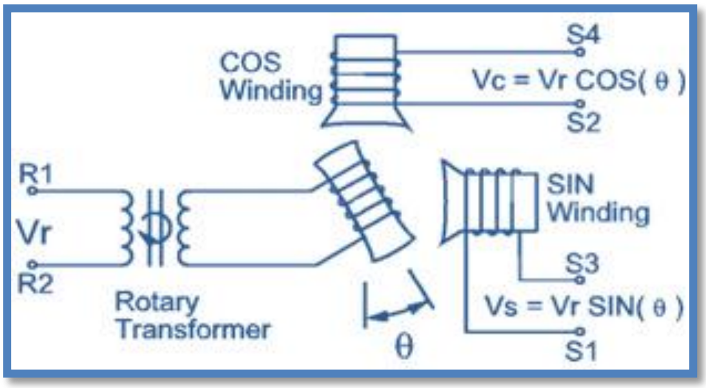


Figure 33 How a resolver works and its schema

In general, reference winding is excited by an AC voltage (V_r). The moving magnetic field will induce a voltage V_S and V_C in respectively the SIN winding and the COS winding. The magnitude of these voltages equals V_r multiplied by the sinus and cosines of the angle that the rotor made. With these parameters it is possible to determine the angle (θ).

The ABB resolver's seize is 15 and has 2 poles. It is integrated with the rotor and connected to the motor's external port shown in Figure 34. It is connected by the green wire directly to the ABB's ACSM1 motor drive.

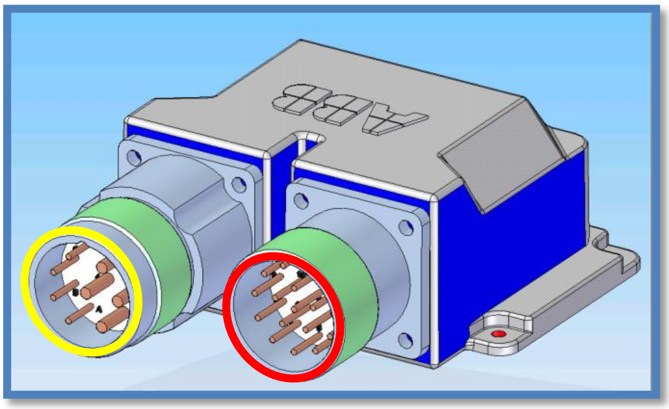


Figure 34 The ABB signal connector of the resolver (red) and the power supply (yellow)

7.4.2 The Acoustic Emission acquisition system

In this section, the AE acquisition system is defined. Before the components were defined, the main problems of the AE sensors will be redefined.

It is known that this kind of sensors had signal attenuation problems due to the low output amplitude that gives the AE transducer [14]. So in this kind of applications, a pre-amplification stage is very important.

In the proposed application, the AE sensor is placed in direct contact with the surface of the gear to enhance the diagnosis information contents of the signal. Generally, AE sensors are applied over the chassis in critical places of the machine. However, in this laboratory application the sensor is placed on the gear. As it was explained, the signal measured is very different depending on the position of the sensor [14]. But fixing the sensor is not easy because the gears will be rotating as obvious and in contact with the lubrication oil. So a component to eliminate the rotatory movement of the shaft is needed. This component is called slip-ring, and will be explained later in this section.

So the AE sensors acquisition system will consist of:

- The National instrument acquisition system PXI to acquire the data, explained in section 7.4.3.
- The AE Sensor to acquire the signals value from the test bench.
- A slip- ring to connect the stationary part of the system with the components under rotatory speed.
- A pre amplifier to increase the low value of AE signal's amplitude.
- A supply to power the preamplifier and extract the signal's properties.
- An external DC voltage source to power the preamplifier and the supply.

7.4.2.1 The amplification stage

Because the AE deals with the detection of mechanical degradation in its initial stages, one of the main problems is the low amplitude of the signal. Therefore, it needs some kind of preamplification in order to preserve the sensed information until the acquisition.

There exist AE probes with the preamplification stage incorporated in the same probe chassis; however, this option is normally more expensive than the regular probes without preamplification stage. The preamplification stage used in this project consists on a Vallen Systems AEP4 preamplifier and a self-made signal demoduler. This stage has been designed in order to increase the AE sensor's amplitude in 40dB.

The AEP4 preamplifier is shown in **Figure 35**. It is a compact preamplifier optimized for the Vallen AE systems sensors; it has a wideband response from 2,5 kHz to 3 MHz. This preamplifier supports single ended sensors and is equipped with a calibration bypass. The gain of the component is configurable by jumper and can be set to 34 or 40 dB. In the experiments performed, the gain will be always set to 40dB.

Figure 35 Frontal image of the Vallen Preamplifier AEP4

As can be seen in Figure 35, the AEP4 has two BNC terminals, one output for the sensor and one input/output for the supply. The amplifier needs to be connected to a 28 VDC supply font. So it uses the input/output connector to receive the power signal from the supply and, at the same time, it sends the sensor's data modulated trough the same wire to the supply. Then the supply will isolate the data signal from the DC power voltage and send it to the National Instruments PXI.

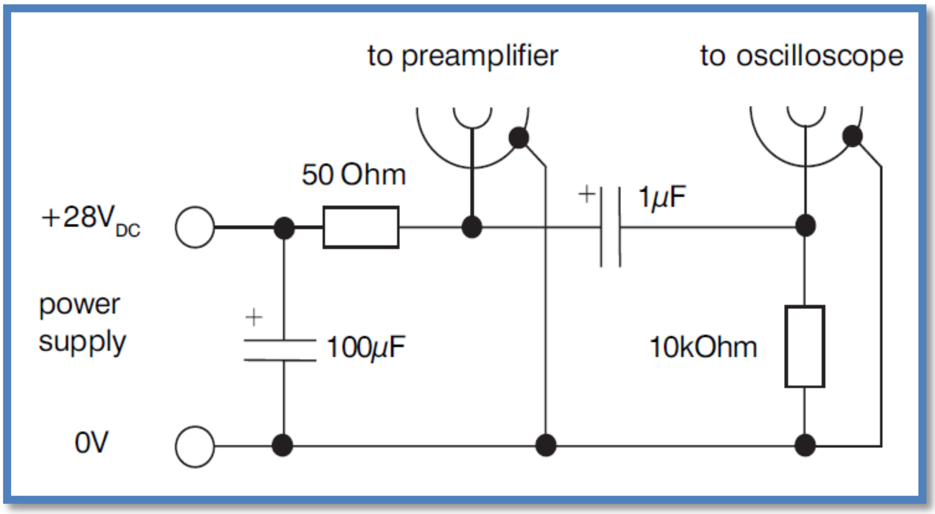


Figure 36 Power supply schematic in order to filter the acquired signal

The supply function its simple, it has to provide the 28VDC power supply signal trough the preamplifier and demodulate the signal inside the same port which contains the lecture of the sensors. Then, it has to send the isolated signal through its output port to the acquisition system. The Isolation scheme is shown in Figure 36.

So the 28VDC and the GND ports will be connected to the laboratory's DC power supply; the preamp port, as its name indicates, will be connected to the Vallen preamplifier AEP4.

7.4.2.2 The Slip-Ring

A Slip-Ring is a rotary coupling used to transfer electric current from a stationary unit to a rotating unit [53]. It is used to connect the electronics components, which are rotating inside the gearbox, to the stationary one outside the gearbox.

The used Slip-Ring is a Mercotac Model 430-SS shown in **Figure 37**. The main electric characteristics are shown in **Table 9** . It has four conductor contacts. This is a special kind of Slip-Ring which connection is made through a pool of liquid metal molecularly bonded to the contact, which provides a low-resistance, stable connection. During rotation the fluid maintains the electrical connection between the contacts without any wear.

This kind of Slip-Ring is specially made for low amplitude signal transmission as it has no brushes. Brush Slip-Rings, are usually composed of a rotating metal ring upon which a metal brush rubs and transfers the electrical signal or current. While brushed Slip-Rings are technically simple in operation, this rubbing interface is fraught with problems that include wear, high electrical resistance, oxidation, and resistance fluctuations which cause electrical noise.

Figure 37 The Mercotac 430-SS Slip-Ring

So the benefits from this Slip-Ring are:

- The Slip-Ring's connectors produce near zero electrical noise due to their brushless design.

- The resistance through the rotating contact is less than one milliohm, which is much lower than the resistance of a Slip-Ring. The lower resistance, the less attenuation of the signal.
- As no direct contact exists, the signal is not degraded over time. It does not require any kind of maintenance.

Model	**430-SS**	**Ampere rating at 240VAC**	**2@4/2@30**
Conductors	4	**Max Freq. MHz**	100 MHz
Voltage AC/DC	0-250V	**Contact Resistance**	<1mΩ
Max Op RPM	1200 Rpm	**Temperature:**	60 to -29 ºC

Table 9 Main Electrical Characteristics of the Slip-Ring

The Slip-Ring uses to attenuate the sensor signal's amplitude. A test was performed in order to extract the attenuation characteristic of the Slip-Ring. In this test, a 50mV amplitude sinusoidal signal with was generated with the Oscilloscope and introduced to the Slip-Ring. The output of the Slip-Ring was measured in order to obtain the attenuation of the signal. The test was made from 20 kHz to 4 MHz.

From the results of the test, no attenuation indices were found. The amplitude of the output signal was approximately constant in all the range of frequencies analysed. The test could be concluded by saying that this slip-ring has no signal attenuation in steady conditions, without rotation.

When the Slip-Ring rotates, the amplitude and the frequency of the signal were constant, but some noise appears in the output signal. So it should be considered in the real test with the motors.

The Slip-Ring should be correctly fixed to the gearbox in order to preserve the wire's integrity. With this modification, the slip ring is forced to rotate by him and not by the action of the cable connected to it.

7.4.2.3 The Acoustic Emission Sensors

In this section, the AE sensor used in this project will be defined. It should be noticed that the explanation about how an acoustic emission sensor works is given in section 4.5, so this concept is not explained here.

A sensor was selected from the Vallen Systems Company, more concretely the VS900-M. This sensor presents a large frequency response and properties which will be defined. In order to select the sensor and identify its properties, the company gives the frequency response curves.

The VS900-M covers a wide frequency range as shown in Figure 38. But it can be seen that it present a non-constant frequency response at 200 kHz and 400 kHz. In these frequencies it has some amplitude fluctuations which could introduce some misleading results to the test. So the frequencies of 200 and 400 kHz of this sensor would have to be specially analysed or an equalization process should be applied.

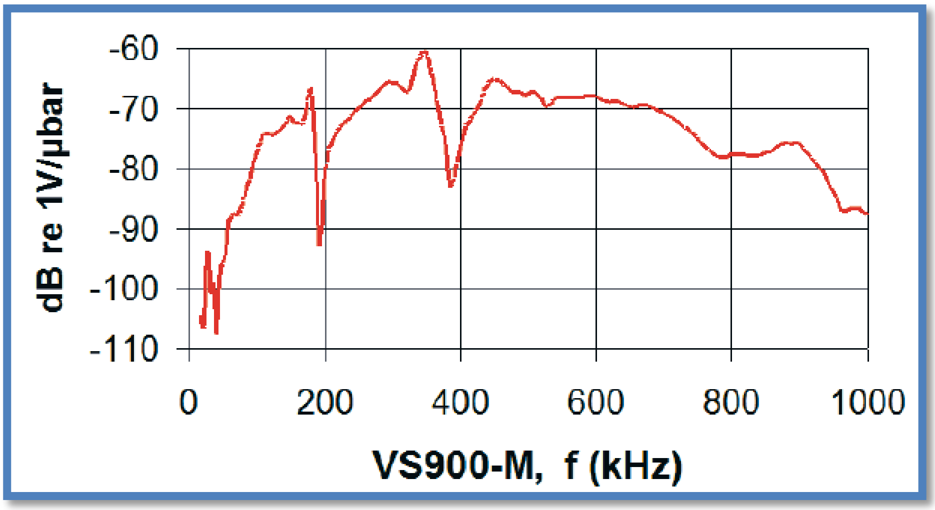


Figure 38 Frequency response curve of the VS900-M

Those curves are obtained applying a method based on ASTM standard E976. It is an experimental test where the AE sensor is excited by a wideband ultrasonic emitter. The sensor under test is placed face-to-face with the emitter; then the emitter is then stimulated with a continuous sine wave, which frequency is swept over the range of interest.

The RMS signal level of the sensor under test is plotted in dB versus frequency, whereby 0 dB refers to a sensor output of 1V at an excitation of 1 µbar.

So a good AE sensor is the one who presents the maximum number of dB (greater amplitude on its output) and nearly constant amplitude in all the frequency range. The selected sensors are:

Most of the transducers from the Vallen Systems (including the vs900) have a 10 - 32 Microdot output as can be shown in Figure 39. Microdot is a company who designs special wires for Nano coaxial connectors. The wire is shielded and the connectors are made of gold. It should be noticed that the length of the wire, which connects the sensor to the amplifier stage, should be less than 1,2m. If this length is exceeded, more than 6 dB of attenuation may affect the sensor's signal amplitude.

To correctly coupling the sensor to the gear, some kind of vacuum element is needed. This element has to transmit the stress signal from the gear without producing a change of the medium impedance. So the most commonly used element to connect the AE sensors to the material are silicone grease or Vaseline.

Figure 39 Different AE sensors from Vallen Systems

With this, all the acoustic emission acquisition system has been defined. It should be noticed that only the components and the base configurations have been defined. In the next sections, in every test performed, the sensor used and the system configuration specific for the test will be explained.

Now, the AE signal is acquired by the sensor, amplified with the pre-amplifier and isolated by the supply. So the last step to this signal is to be acquired by the by a specific board.

7.4.3 The Signal Acquisition System

All the instrumentation is based on National Instrument equipment [11]. All the sensed signals will be acquired from different acquisitions boards from NI. The boards will be connected to the acquisition chassis, NI PXIe-1O61Q shown in Figure 40.

Figure 40 The National Instrument Acquisition PXIe (Full configured)

This chassis has eight slots as can be seen in the picture. In this case four slots are used, the numbers 1,2,5,7.

- The first slot is always used by the central unit. This slot contains an embedded PC of the reference NI PXIe-8106.
- The second slot contains the high frequency acquisition card, the NI PXI-6115, which acquires the data from the AE sensor and a pinout interface model SCB-68.
- The eighth slot contains a NI PXI-4472B a special acquisition card where the triaxial accelerometer will be connected.

7.4.3.1 The NI PXI-1062Q Acquisition Chassis

This component is the acquisition chassis which support all the installed boards and the CPU of the system. It provides also the power supply from the 220 VCA

The NI PXIe-1062Q 8-slot chassis, designed for a wide range of test and measurement applications. It is very flexible because it can allocate up to 8 different acquisition boards from NI. It provides a high-bandwidth communication to all the boards connected, it gives up to 1 GB/s per-slot dedicated bandwidth.

The NI PXIe-1062Q chassis operates over a 0 to 55 ºC temperature range and holds acoustical noise as low as 43.6 dBA at temperatures below 30 ºC. The chassis features a built-in 10 MHz reference clock, a built-in 100 MHz reference clock. It can provide more than 3 GB/s total system bandwidth. The maximum power at nominal conditions (from 0 to 55 ºC) is 354 W.

The Table 10 shows the available slots and the compatibility with other National Instruments boards and peripherals. So any peripheral compatible from national instruments could be connected to this chassis.

NI PXI-1062Q	
Available slots	4 PXI slots, 1 PXI Express system timing slot, and 2 PXI Express hybrid slots
Compatibility	Compatible with PXI, PXI Express, CompactPCI, and CompactPCI Express peripheral modules

Table 10 Available slots and compatible peripherals of the PXI-1062 Acquisition Chassis

All the boards are allocated inside the chassis. The final appearance of the chassis is shown in **Figure 40**. It should be noticed that every board has a specific type of bus and properties to communicate, so there is a specific slot for every kind of target.

7.4.3.2 The NI PXI-8106 Embedded Controller board

The NI PXI-8106 PXI/CompactPCI embedded computer is a high-performance system controller board. This board is the “CPU” of the PXI. It connects all the other boards to the same system and makes them accessible from the operative system of the PXI. Also it provides the communication interface with the user and other generic computer peripherals providing 4 USB ports, two screen outputs and other control functions as can be seen in **Figure 41**.

So as a result, it converts the PXI in a fully computer system compatible with Windows and all the National Instruments software. In the PXI could acquire the data from the instrumentation system, visualize and process the data in order to give the first results to the user. The characteristics of the PXI-8106 CPU are a 2.16 GHz Intel Core 2 Duo T7400 dual-core processor with 2 GB DIMM dual-channel 667 MHz DDR2 RAM standard.

It should be noticed that the control unit of the PXI will always be allocated in the first slot. In the project, a TFT monitor, a keyboard and a mouse are connected to this target, also the USB ports of this board are used to collect the generated data.

The PXI has an own Windows 7 Operative System and it contains the software Signal Express in order to perform the acquisitions, which is explained in the next section.

Figure 41 General view of the NI PXI-8106 Embedded controller

7.4.3.3 The NI PXI-6115 high sampling rate acquisition board

PXI-6115 is a high frequency acquisition board for applications up to 4 MS/s. It is used due to the high working frequency of the Acoustic Emission signals. This board is the element responsible for collecting the data from the AE sensors.

It is a dedicated analog to digital converter but can also provide the inverse function, so half of the on-board memory is dedicated to analog input and the other half to analog output. The main features of this board are:

- 4 high-speed analog inputs, 10 MS/s per channel, 12 bits of resolution equipped with on-board antialiasing filters.
- Deep on-board memory (32 or 64 MS) and extended input ranges from ±0.2 to ±42 V.
- Two 12-bit analog outputs, 4 MS/s single channel.
- 2.5 MS/s dual channel.
- 8 digital I/O lines; two 24-bit counters; analog and digital triggering.

A can be noticed in the **Figure 42**, the 6115 board does not have any inputs or outputs in the target, so it need a pinout interface module in order to read and write the data. So for this application a NI SCB-68 pinout module is used.

The SCB-68 module is an interface between the AE generated signal and the acquisition board. It will read the sensor signals and send it to the specific AI channel of the PXI-6115 board.

Figure 42 NI PXI-6115 High Frequency Acquisition Board

The module is shown in Figure 43, and consists of analog inputs and outputs. The outputs are in order to generate signals with the board's two 12-bit analog outputs. The analog outputs will not be used in this project at the moment. For every analog input there is a ground connection.

Figure 43 NI SCB-68 Pinout Module

Combined with the shielded cables, the SCB-68 provides a very low-noise signal termination. It is compatible with single- and dual-connector NI X Series and M Series devices with 68-pin connectors. It should be noticed that if a shielded wire is used, the shield should be connected to a GND port of the SCB-68 module.

In this project, the exit of the supply is connected to the SCB-68 module.

7.5 Software

Briefly, all the software used in this project will be explained. Including the software to control the motors and the software to acquire process and monitorize data. Also the software to program the embedded system would be defined.

7.5.1 DriveSPC

The SPC in DriveSPC stands for Solution Program Composer and is the place where the actual running program of the inverters is configured / programmed. The programming happens with the use of function blocks, which are connected with each other.

There is a set of different tab as shown in **Figure 44,** one for each group of parameters to configure. It should be noticed that the blocks to control and communicate with the motor are already implemented. The user only can add some secondary bloc to operate and fix the value of the signals the implemented blocks works with.

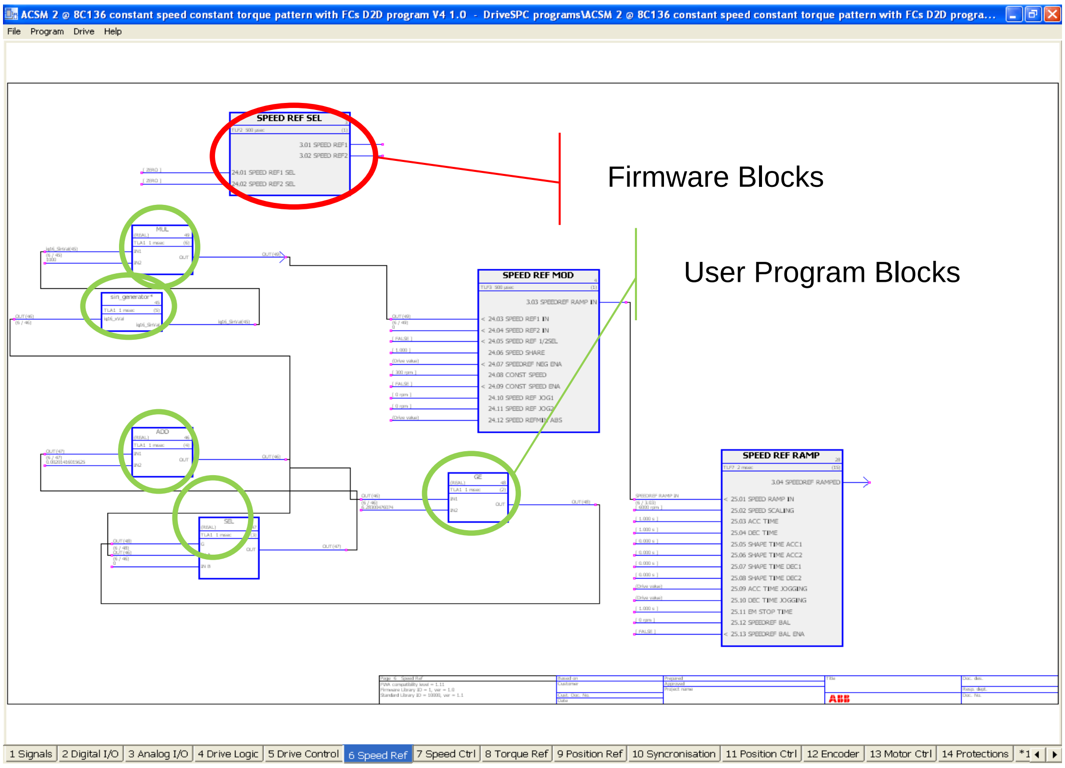


Figure 44 Example of the Speed Ref Tab in the DriveSPC.

The big blocks (marked in red), called firmware blocks, are the default configuration of the DriveSPC. If the user wants to make his own configuration, he has to use normal blocks (green).

When the program is finished it can be downloaded into the converter and afterwards the motor can be run using the DriveStudio. This program allows a deeply and more flexible configuration of the motor. User can implement different load or speed set points of any kind. In this first project, the configuration of the motor will be the given by defect and it will be configured with DriveStudio.

7.5.2 DriveStudio

DriveStudio is the first program that has to be used after the ABB motor drive is installed. With this program all the information, about the motor used, is set. This information is needed for the DriveSPC. As can be seen in **Figure 45**, in the main screens are all the parameters that can be configured.

So it provides a simple and easy way to communicate with the drive and also it can send simply speed set points to the motor using the buttons under the yellow rectangle in **Figure 45**. The speed set point could be introduced and by clicking in the green button it can be sent to the motor. The red button stops the motor.

In this project, is the program used to communicate and excite the motor.

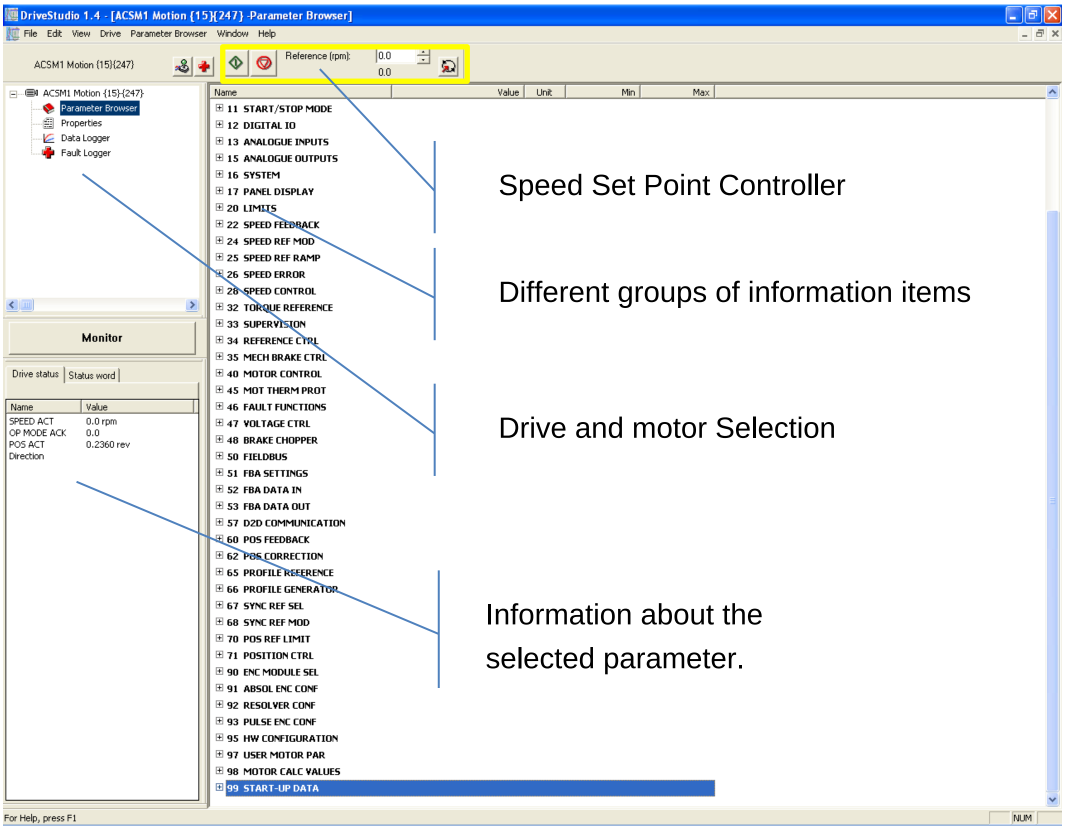


Figure 45 Main Screen of the Drive Studio Software

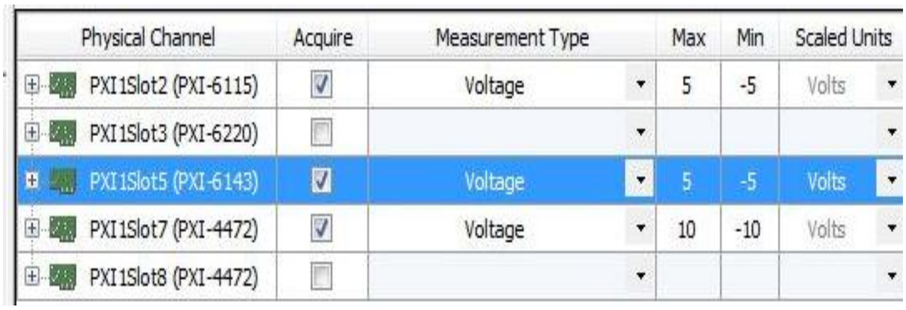
It should be noticed that this block works as an OPC server so the items are organized by devices and groups. So there is a set of 99 groups which contains different items about some specific motor information.

All the drivers connected to the COM port with this computer will appear in this program as a selectable device.

7.5.3 Signal Express

Signal Express is interactive measurement software for quickly acquiring, analysing and presenting data. This software runs inside the National Instruments PXI and automatically detects all the boards installed to the PXI, as it can be seen in Figure 46.

The left panel shows all the active acquisition signals from the board. The signals and the boards to acquire are selected in the inferior panel (Chanel View). This software helps to configure and select the amplitude range of the signal and the kind of measurable variable. It should be noted that it automatically adapts the options for each different board.



Physical Channel	Acquire	Measurement Type	Max	Min	Scaled Units
PXI1Slot2 (PXI-6115)	☑	Voltage	5	-5	Volts
PXI1Slot3 (PXI-6220)	☐				
PXI1Slot5 (PXI-6143)	☑	Voltage	5	-5	Volts
PXI1Slot7 (PXI-4472)	☑	Voltage	10	-10	Volts
PXI1Slot8 (PXI-4472)	☐				

Figure 46 Main window of the Signal Express Software

The central panel is used to monitorize all the selected variables. It can be divided in displays or tabs in order to visualize the data from one or more channels. It provides some basic functions to save and export the data as image or as plain text data in order to make the posterior signal processing.

7.5.4 MATLAB

MATLAB® is a high-level language and interactive environment for numerical computation, visualization, and programming. Matlab is one of the most famous mathematical software for all kind of research fields. The functioning of Matlab is based on the toolboxes. A toolbox is a set of instructions and functions with a specific purpose.

All the data of this project has been processed and analysed using different toolboxes from Matlab.

8. Analysis and characterization of the AE signal

In this section, the experiment to analyse and characterize the acoustic emission signals is explained. First of all the definition of the experiment would be given involving the global scheme of the different components involved and the configuration of all the acquisition system.

As a reminder, the objective of this experiment is the analysis and characterization of the acoustic emission signals obtained from the experimentation under a laboratory test bench.

All the properties of different elements used in this project were explained in the previous section, so only the specific configuration of them for this experiment will be explained. As a result the explanation will lead directly to the global scheme of the test bench used in this test.

8.1 Configuration of the experiment

The test bench configuration used for the analysis and the characterization of the AE signals is shown in **Figure 47**.

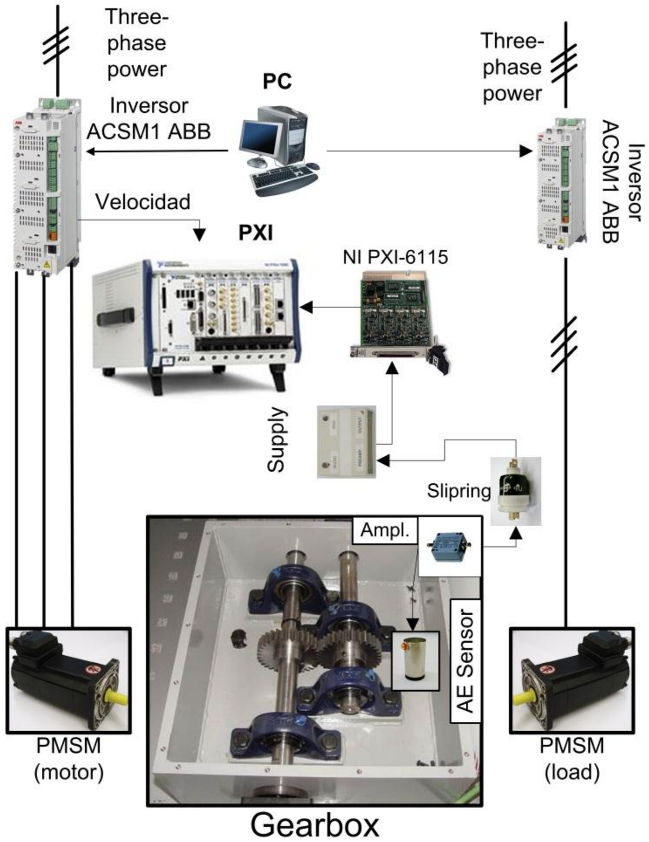


Figure 47 Global scheme of the test bench used in the AE signal analysis (First part)

The main particularization of this configuration is the position of the AE sensor for obtaining the maximum information from the failure of the gear. The sensor is located as close as it could be to the fault.

This means that the sensor should be attached to the gear surface. The attaching mode has to permit the transmission of the stress signal from the gear without producing a change of the medium impedance The solution provided for attaching the sensor is using a glue-based fixation method. The glue which fit the specifications is the Cyanoacrylate.

The Cyanoacrylate is specially designed to fix all kind of materials in a short lapse of time, and has a medium viscosity near to the silicone grease. The main disadvantage of this glue is its low resistance to impacts when it’s dried. It forms a crystalline layer around the sensor which could be broken easily, but not in the direction of the vibrations it would receive, so the sensor will not disengage.

In addition, as could be seen in **Figure 47**, the AE sensor is located inside the gearbox, so the utilization of the slip-ring, in order to obtain the signals for the rotatory sensor is required. The slip ring is connected to the sensor (the moving part) and the static part to the amplifier. The amplifier is connected to the supply and this to the 6115 high speed acquisition board of the National Instruments PXI.

8.1.1 Configuration of the acquisition system

Once the elements involved in the elements that require a configuration is only the acquisition board from the PXI. In this board, as explained in the previous section, the experiment parameters such as the sampling frequency, the number of the samples, the voltage range of the signal acquired and the scaling factor should be defined.

As was defined in the theoretical part of this project, the selected sampling frequency of the acoustic emission signals was set to 5 MHz. In order to achieve a spectral resolution of 2 Hz in the frequency spectrum, 2.5 MS (samples) are acquired. This means that the signal acquired would have a total time length of 2 seconds. This is more than the necessary because in the lowest speed (150 Rpm) the shaft performs a complete revolution in 0.4 seconds, so 5 complete revolutions would be captured.

The voltage range of the signal is set at -10 to 10 V in order to detect the burst signals characteristics of the acoustic emission.

This board also gives the possibility to perform a low pass filter in order to prevent aliasing effect. This filter is configured at 500 kHz which are higher than 5 times the maximum frequency that wants to be analysed in the test.

8.1.2 Methodology for the experiment

The experiments will be performed in diverse conditions. The Gears used, will be the previously explained in section 7.3.1. The gears used in this project are a healthy gear, a gear with a fault in one tooth, and a gear with several faults. In the experiment they will be working in with several conditions of speed (150 Rpm, 250 Rpm and 450 Rpm). The process of research will follow these steps:

- **Selection of a gear with a specific defect.** The piece will be damaged with a specific setup. This stage allows controlling and knowing exactly the state of the piece in the beginning of the experiment. So that facilitates the correlation of the severity or type of defect with the extracted features. The way the gears are specifically damages, is not involved with this project.
- **Experiment performance**. The motors of the test bench will follow diverse patterns of speed programmed on the inverter. Consequently, different conditions in the Gear internal structure will be forced. At the same time AE acquisitions will be stored. In this experiment, only one position is considered, the sensor attached to the gear surface.
- **Analysis of AE signals.** This step concern all the process explained in the following sections and ends with the correlation between faults and features.

In order to prevent that the acquired data could be particularly altered, each acquisition would be repeated three times. So a tree diagram with all the acquisitions can be made and is shown in Figure 48.

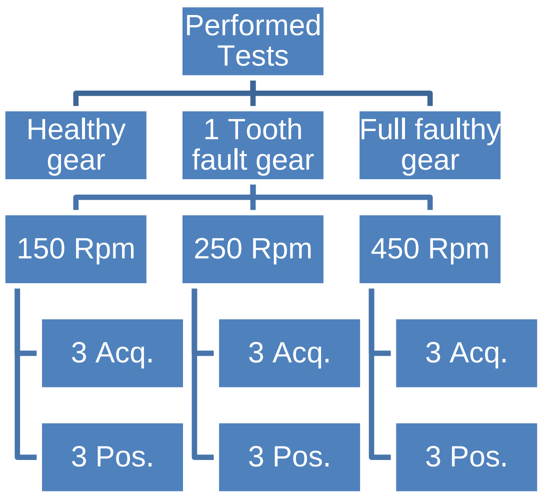


Figure 48 Diagram of the different tests performed to the system

8.2 Pre-Processing the acquired data

The acquired signal is wideband and subjected to the non-flat sensor response. Vibrations generate the lowest part of the spectrum in the mechanical system and it is not desirable for the study on this project. Other effect to be considered is the response of the sensors used in the experiments. Also the signal will be affected by white noise that can be supressed. Considering these effects the following signal pre-processing algorithm is applied:

Firstly a FIR hi-pass filter with a cut frequency of 50kHz and a rejection in 0Hz of 0.001 have been implemented in order to eliminate all vibration and other components due to misalignment of the shaft or the bearing.

This compensation try to equalize the signal taking in account the response of the sensor that is obtained from the specifications of the sensor, which could be seen in **Figure 38 Frequency response curve of the VS900-M**.

The equalization consist in multiply by a variable factor every frequency component in order to get a flat response of the acquisition system. Fixing certain sensitivity (-60dB in these experiments) on the algorithm this calculates the necessary factor for each frequency that brings the sensitivity of the real sensor to this level and apply them. After this the signal is anti-transformed to get back it in the time domain. Once the different data has been processed, the analysis of the AE signals could be performed.

8.3 Analysis of the results

This section covers the analysis of the obtained results.

8.3.1 Time domain analysis

Once the experiments have been made, a time analysis would be made to see if the results could be related in some measure with the expected values of an electromechanical actuator.

8.3.1.1 Validating the obtained data

It should be assured that, during the whole process of acquiring the AE signal, from the test bench and pre-processing, the data represents the actual condition of the machine. In other words, in order to perform a further analysis, the data collected from the machine should be validated.

The acquired signal represented in the whole acquisition time its more similar to a continuous AE signal, as can be seen in **Figure 49**. Although as has been said in the acoustic emission theory to characterize the signals, only burst signals has been considered.

This happens because the considered sampling time represents more than 5 complete revolutions, but if only one revolution is sown (Figure 50), the d AE events are related to the different gear collision could be appreciated. It should be considered that the revolution time depends on the speed of the test.

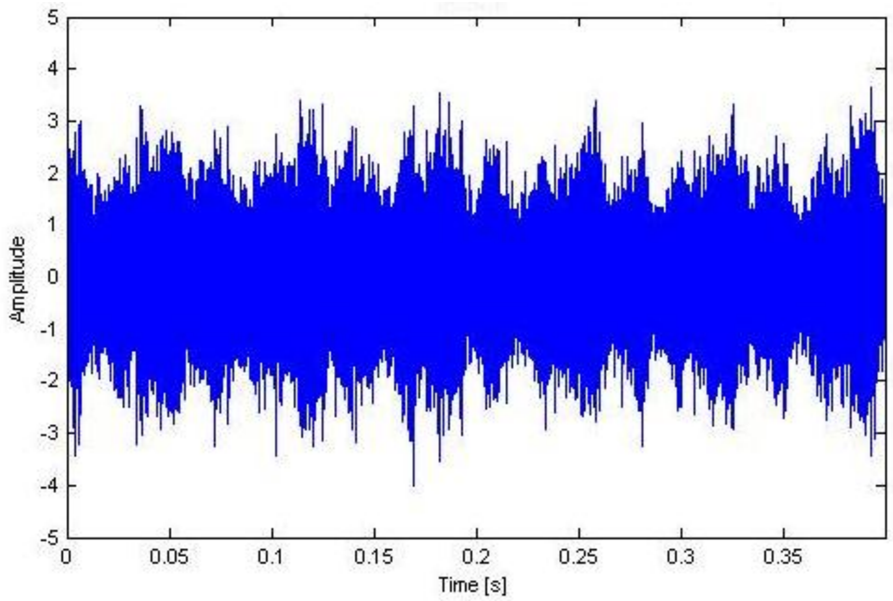


Figure 49 Temporal behaviour of AE signal in complex gearbox test bench.

The first step is recognizing which is the pattern of each burst (or event), in the time-domain analysis. This could be helpful in order to validate the data obtained from the experiment.

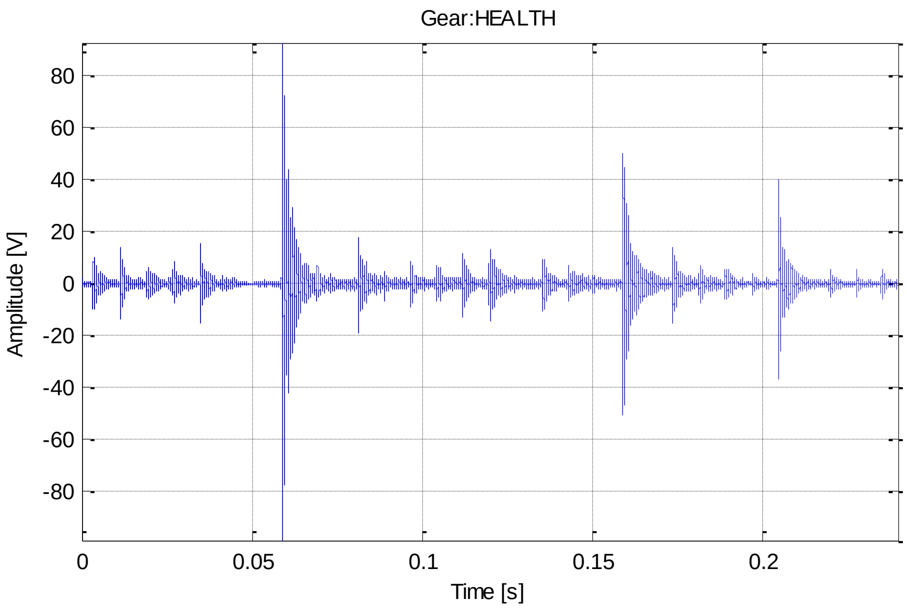


Figure 50 A representation of a single revolution in a healthy gear.

In the **Figure 50** most of the 31 gears collisions of one revolution could be characterized, due to the constant proximity of the AE burst, but in order to properly detect if the burst signals corresponds to each collision the following calculations has been made.

In case of gears system, the time between two collisions (T_{TEETH}) could be easily calculated by the examination of the temporal AE signals, taking into account which is the speed of rotation and the number of teeth (Z) the T_{TEETH}, using the following equation:

$$T_{TEETH} = \frac{60\,[s]}{Z * v\,[rpm]}$$

For example, for the previous figure performed in the healthy gear at a speed of 250 rpm:

$$T_{TEETH} = \frac{60\,[s]}{31 \cdot 250\,[rpm]} = 7.74\,ms$$

As can be seen in **Figure 51**, the other time evaluated between consecutive peaks are 7.8 which perfectly fits to the estimated value, so every single burst represents a collision between the two gears.

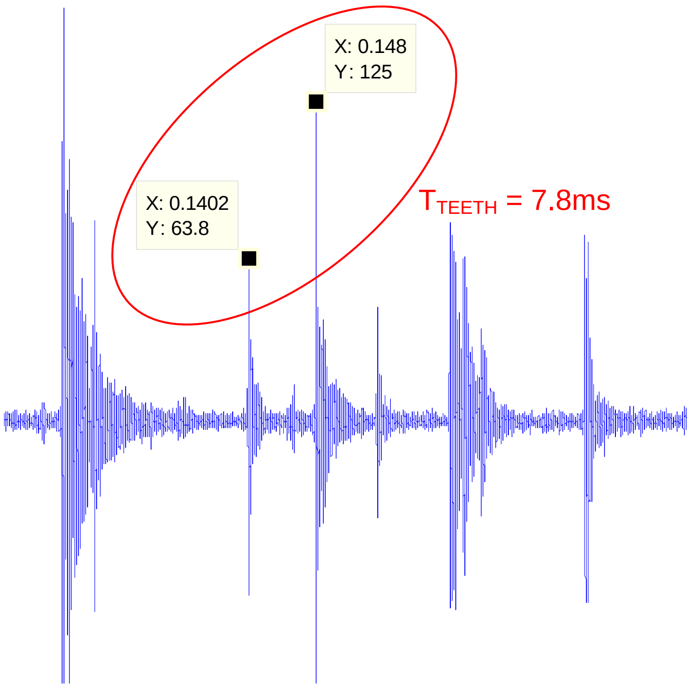


Figure 51 Detail of the Figure 50 where the calculated T_{Teeth} value could be seen

If the different bursts are observed, when the maximum amplitude of the burst is reached, it decreases but short time later it makes a second peak. In each collision there is a first impact when the gears engage; later a second collision is made when the two teeth are separated.

It is confirmed by comparing distances between the same side of 2 teeth and the distance between both sides of same teeth.

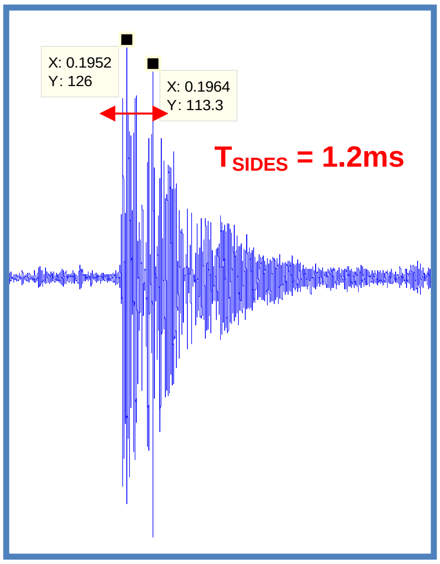


Figure 52 Detail of Figure 50 to identify the T_{SIDES} value

Considering this last case with a speed of 250 rpm and a T_{TEETH} of 7.74ms this value could be calculated as:

$$T_{SIDES} = \frac{D_{SIDES}}{D_{TEETH}} \cdot T_{TEETH}$$

Considering the specific value of D_{SIDES} and D_{TEETH} in the gears used in this project, the obtained T_{SIDES} is:

$$T_{SIDES} = \frac{2\ mm}{10.25\ mm} \cdot 7.74ms = 1.51ms.$$

This time could be perfectly seen in Figure 52, where a detail from the first figure is given. With these few test, has been check that the data obtained from the test bench fits with the estimated result from a electromechanical actuator that uses a gearbox. So the data obtained and pre-processed has been validated.

8.3.1.2 Influence of the test condition

It has been said in previous theoretical sections, that the test condition are a factor to consider, because the influence for example of the rotating speed or the defect of the fault to the result. In order to illustrate this fact, a graph (Figure 53) is shown with the same healthy gear but at the three different speeds (150, 250 and 450 RPM).

It can be seen how when the speed is low (150 RPM) the amplitude of the main peak is over 19.14 V, when the speed is increased to 250 RPM, the value of the main peak changes to 64,71 V, and when the high speed test is performed (450RPM), this amplitude rises up to 88V. So it is demonstrated that the speed of the test is one of the most important factors to consider, as it has been said in [8].

The next factor to consider is the influence of the severity of the failure. In order to perform this comparison, a figure with the same speed test performed under three different severities would be shown, concretely, in Figure 54.

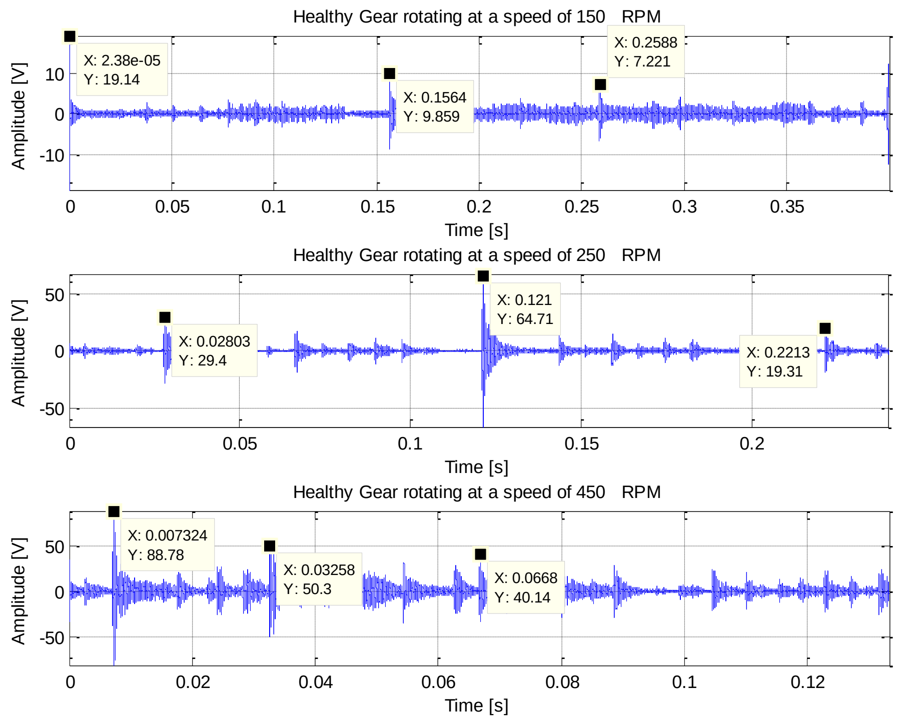


Figure 53 Comparison between the same test at 3 different speeds 150, 250 and 450rpm)

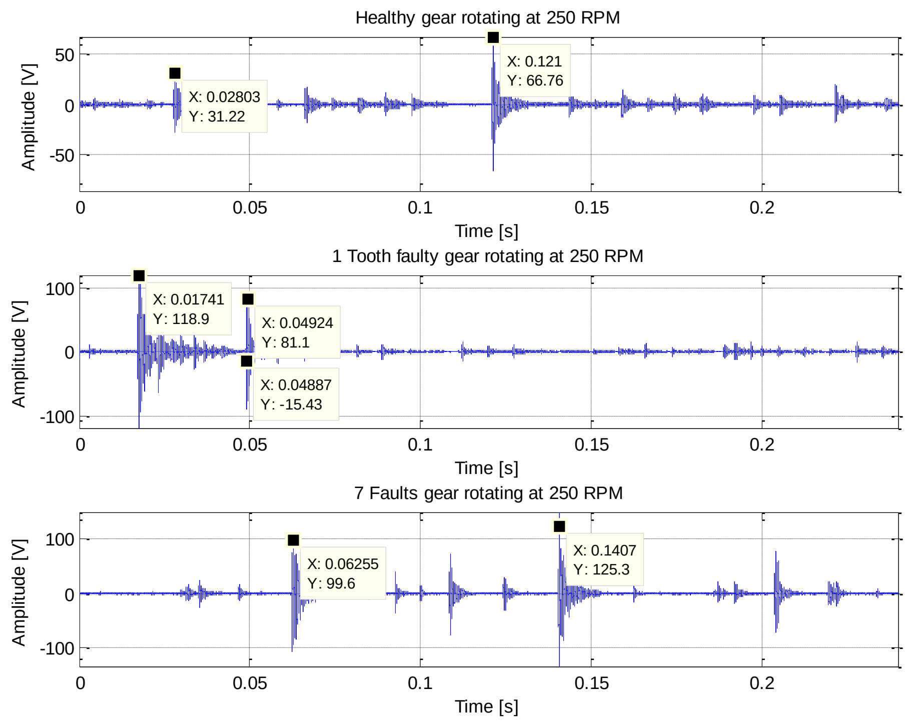


Figure 54 Comparison between the same tests at 3 different failures (at 250rpm)

In section 6.3.4How to correlate the features with the fault, was said: *"Once the defect exists, the amplitude could detect that defect, but it has not a constant or obvious relation with the defect size".* The results show exactly this fact, it can be seen how the amplitude of the main peak increases when a defect is located at the gear , it goes from 66.76 V in healthy condition to 118.9 V in 1 tooth fault, and to 125.3 V in the gear with the seven failures. So between the two kinds of failures, the amplitude of the AE signal is approximately equal.

So the two considerations made when talking about the most influence parameters of the test performed in the acquired data has been proved.

8.3.2 Frequency domain analysis

These same AE signal has been analysed in frequency-domain by means of a DFT algorithm explained in section 5.2.1 Discrete Fourier Transform. This new signal is plotted in the range of operation of the sensor (previously equalized bandwidth seen in section 8.2).

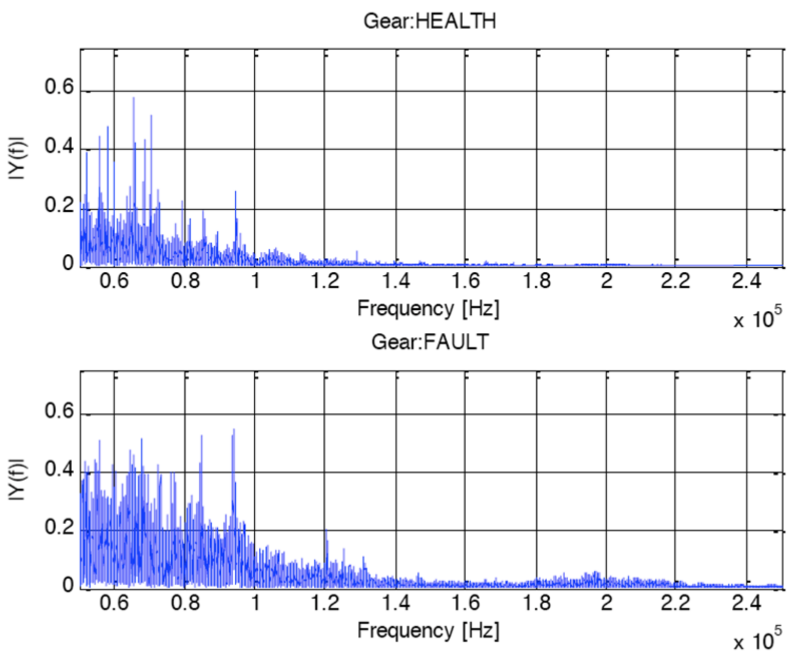


Figure 55 FFT of AE signal at the same speed (450rpm), in with healthy and 7 faults gear

The frequency-domain analysis will allow the inspection of the spectral contents of the acquired signals, and the identification of the AE signal behaviour depending on the speed and fault. Some initial results reveal the displacement of the AE signal spectral content to higher frequencies in presence of mechanical degradation in the system.

As it can be seen in Figure 55, under faulty conditions, the main frequency components are moved towards 100 kHz zone in the "low-frequency range", but also, a new frequency band around 200 kHz appear in the "high-frequency range". This frequency amplitude is low versus the original one, but if a zoom in this area is made, hence this increase could be perfectly seen. As shown in Figure 56.

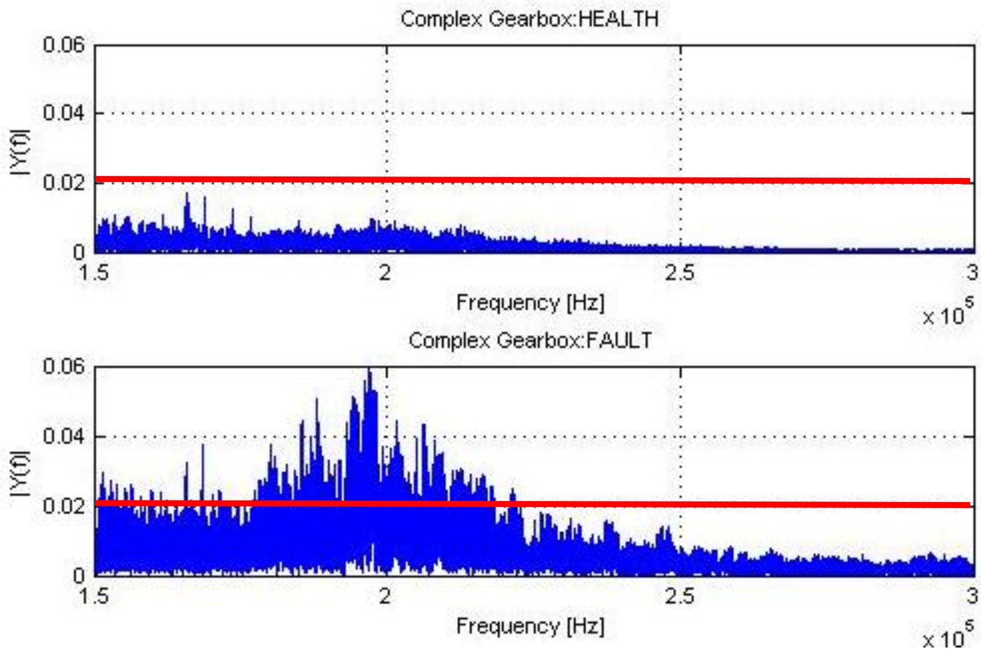


Figure 56 Detail of the FFT of AE signal of Figure 58

The increase of the frequency content over the band of 200 kHz is very interesting, because these frequencies could be isolated in time domain using basic digital filtering. But before performing that time domain analysis, the STFT would be used to validate the appearance of this spectral content in the 200 kHz band.

8.3.3 Time-Frequency analysis

The time-frequency-domain allows the analysis of the evolution of AE spectral contents in regard with time. The use of these techniques imply high computational cost, however, it allows obtaining additional information helpful to understand the AE patterns. In this sense, the time-frequency domain analysis is out from the study in this project, it is only used to justify the appearance of spectral content in the band of 200 kHz when a fault occurs.

As it can be observed, the AE burst can be distinguished in time-domain, however, it can be confirmed that all of the observed bursts corresponds to degraded conditions due to the spectral contents analysis. An important spectral content around 200 kHz is present in all the AE en events.

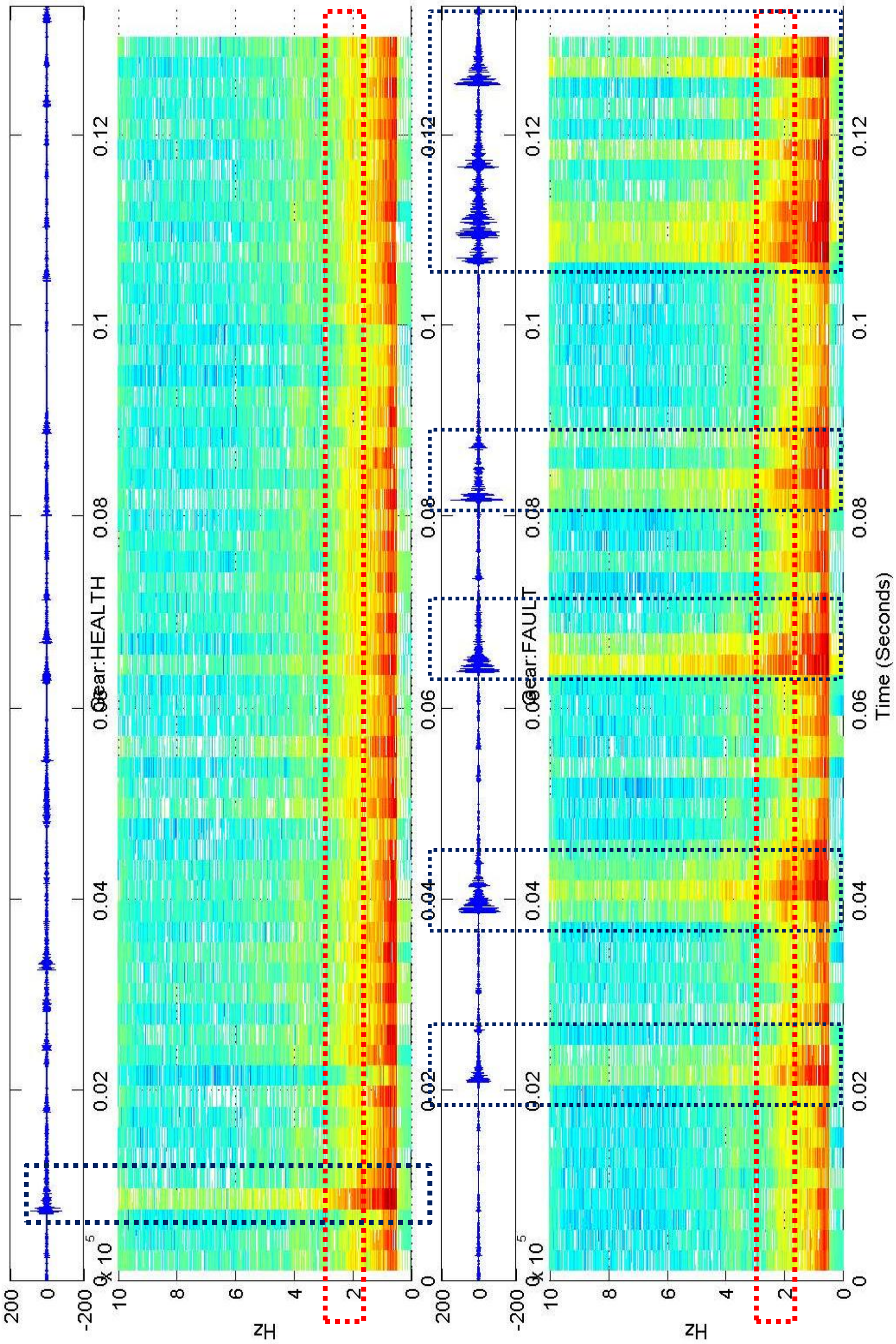


Figure 57 Comparison between the STFT of the healthy gear and the faulty one at 450 rpm

8.4 Detecting the failures

Due to this displacement of the spectral contents of the AE signal under faulty conditions, and the identification of the 200 kHz zone as a significant region for early fault detection, different filters have being applied

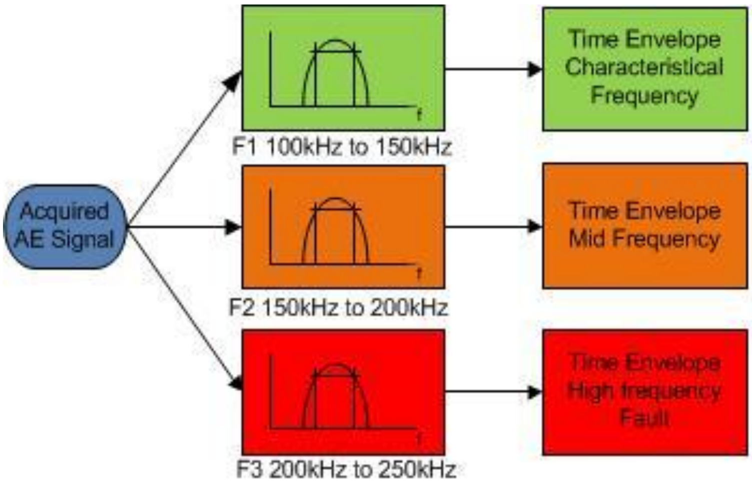


Figure 58 Proposed algorithm for fault detection

In order to detect the different failures, and based on the analysis performed before, time domain analysis is proposed for identifying the different failures in the test. In this sense, due to the information seen in the STFT of the Figure 57, the considered as interesting frequency bands are: The frequency band from 100 kHz to 150 kHz, the frequency band from 150 kHz to 200 kHz, and the frequency band from 200 kHz to 250 kHz

The proposed method is to apply a set of three band filters, based on a FIR structure, and then a Time envelope to highlight the data, In this sense, a set of figures show this analysis carried out over the test bench, more concretely, from [Figure 59 to Figure 64].

The nomenclature of the graphical performed are: (a) Temporal AE acquisition. (b) Time-envelope and pass-band filter between 100 and 150 kHz. (c) Time-envelope and pass-band filter between 150 and 200 kHz. (d) Time-envelope and pass-band filter between 200 and 250 kHz. The axes magnitudes are: the y axis is Amplitude (V) and x axis is time (sec).

The filters are configured to focus the analysis around the 200 kHz in order to observe the spectral contents variation under faulty conditions. Once the filter is applied, the remaining data is processed by an envelope function.

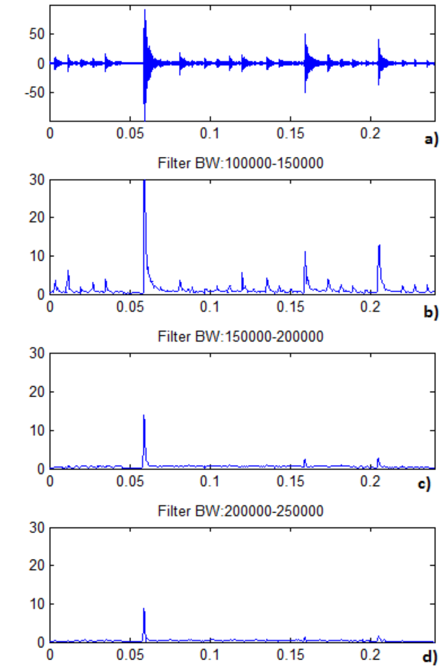


Figure 59 Acquired AE signal from the healthy gear at a speed of 250 RPM

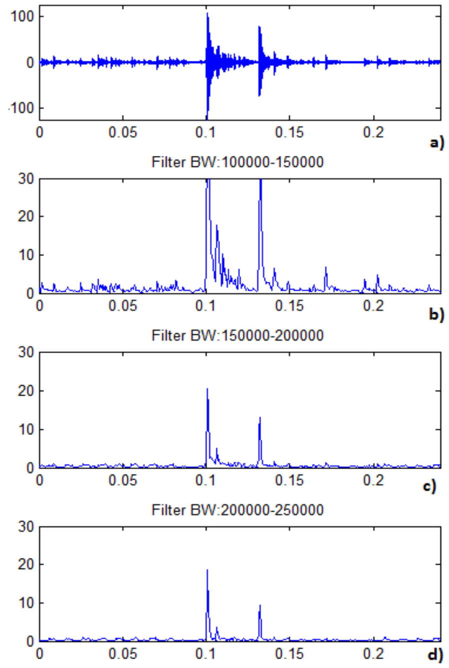


Figure 60 Acquired AE signal from the 2 Tooth (1 Tooth) gear at a speed of 250 RPM

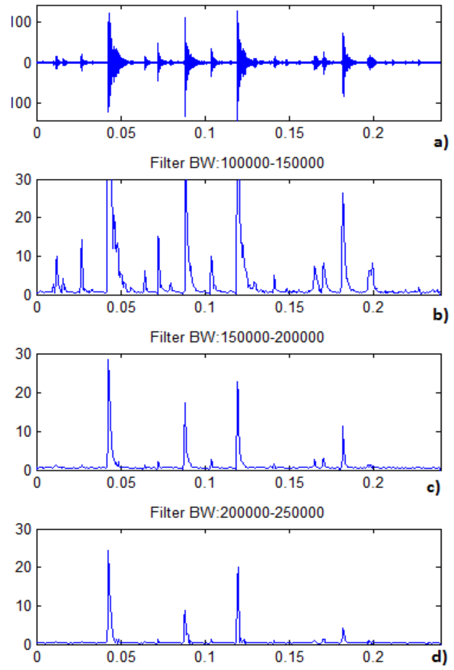


Figure 61 Acquired AE signal from the 8 Tooth (7 Tooth) gear at a speed of 250 RPM

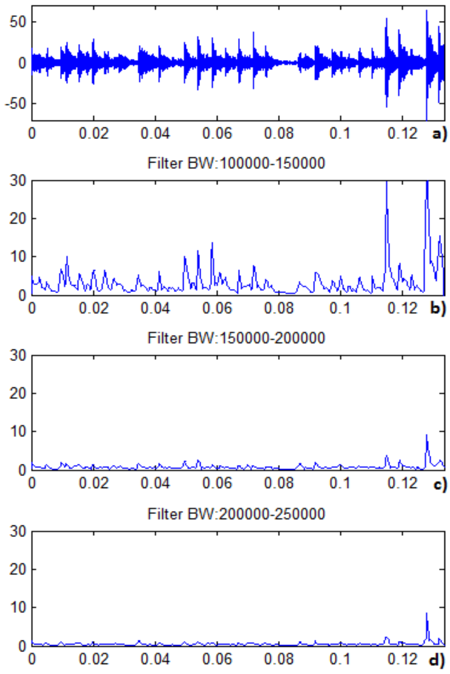


Figure 62 Acquired AE signal from the healthy gear at a speed of 450 RPM

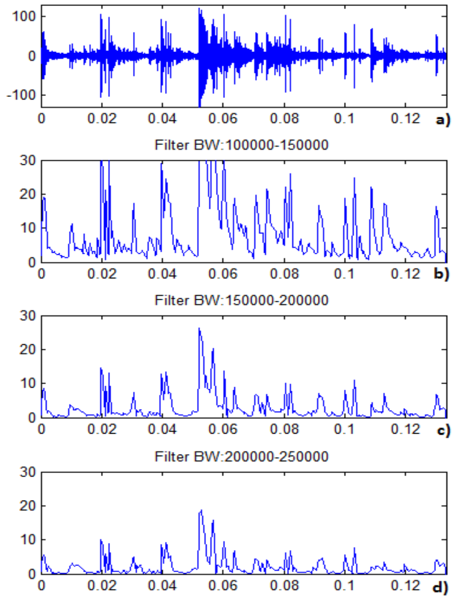


Figure 63 Acquired AE signal from the 2 Tooth (1 Tooth) gear at a speed of 450 RPM

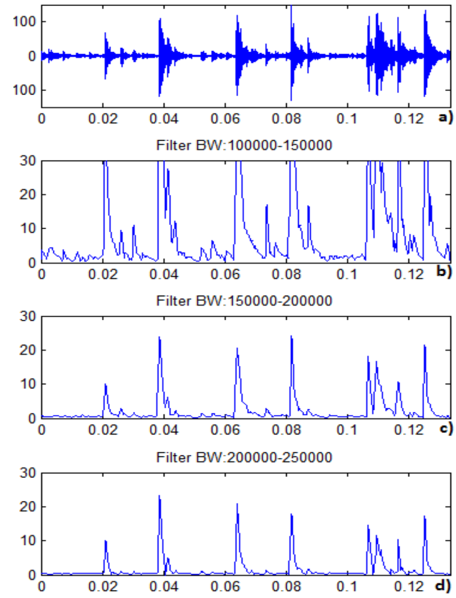


Figure 64Acquired AE signal from the 8 Tooth (7 Tooth) gear at a speed of 450 RPM

8.5 Conclusions

So analysing the results, can be seen in Figure 59 , with the test performed at speed of 250 rpm, and Figure 62 (450 rpm) are shown the fact that with this methodology, **when the system is in healthy condition, there is no frecuencial content in the second and the third band, so the high frequency band is not influenced by the rotating speed of the machine.**

Despite of this fact, there is always content in the frequency band of 100 to 150 kHz. This is the characteristic operating frequency of the acoustic emission signals. And it is always visible in every test performed.

When a gear with a failure is used, a number of peaks equal to the number of the tooth with a fault are obtained. For this reason, the gear considered as a single tooth fail shows two different peaks, after analysing the gear, a second fracture under the opposite teeth has been discovered, the same result has been obtained with the 7 tooth gear. This fracture could be due to the degradation process of the performed experiments.

The conclusions from the previous analysis are that with this method, can be used to detect not only the presence of a fault, but also its severity. It could be seen, how with the proposed method, the spectral content from each band could be directly related with the failure in the gear.

9. Embedding the fault diagnosis system

In this section the process of embedding the diagnosis algorithm is treated. The aim of this algorithm is to apply the acquired knowledge of the section 8 for characterizing and analysing an acoustic emission signal acquired from an electromechanical system.

In order to implement this operation, a STMicroelectronics STM32F407IG microcontroller is used integrated with the MCBSTM32F400 board from Keil.

As has been explained in this project, working with acoustic emission signals means to work with very high frequency signals, from 30 kHz to 1 MHz. In order to correctly acquire this kind of signals, the Nyquist criteria should be considered, so the analogue to digital converter of the acquisition board should be able to acquire samples at a minimum rate of 2 MHz.

There is not very common characteristic in commercial embedded microprocessors. According to this fact, the STM32F407IG microcontroller has an ADC with a maximum sampling frequency of 7.2 MHz that fits perfectly the specifications.

In the other hand, one of the most important limitations of this processor is the internal RAM. With only 192+4 Kbytes of SRAM if a single AE signal is captured, most of his RAM will be filled. If a resolution of 12 bits is chosen, only 49000 samples could be obtained (sampling at 2MHz).

This problem could be solved, due to the utilization of the DMA peripheral. This peripheral could take the data from the buffer of the ADC and helps the CPU to move the data to the external RAM of 2MB.

Regarding to the algorithm for fault diagnosis implemented, the main objective of it is the analysis of the AE signal acquired directly by the microcontroller, in order to obtain condition status information in regard with the mechanical degradation of the machine under monitoring.

In the first part, a definition of the embedded platform and the different peripherals involved and their characteristics are given. Then, the main procedure of the algorithm performed is defined, and thus the block diagram of the performed C code is shown.

Once the structure of the program is known, the different peripheral configuration is shown. And at the end, a test is performed in the real system in order to test the obtained results.

9.1 Definition of the embedded platform

In this section the main characteristics of the different elements of the MCBSTM32F400 board are commented. This information is based on the technical information and the partner's information [55]. It should be said that this STM32F407IG microcontroller is integrated in a development kit made by Keil, so it is not specific for signal processing, so it is has general porpoise external peripherals located in the MCBSTM32F400 board.

A general image of the board and its peripheral is shown in **Table 11**.

Parameter	Description
Supply Voltage	5 Volts DC (provided by the USB bus of a PC), or
	8-12 Volts DC power from an external power supply.
Supply Current	300mA typical, 375mA maximum
XTAL Frequency	25 MHz
Microcontroller	STMicroelectronics STM32F407IG (MCBSTM32F400)
Peripherals	1 × RS232 Interface,
	1 × CAN Interface,
	2 × USB Device, Host and OTG Interfaces (Full-speed and high-speed),
	1 × Ethernet Interface,
	1 × Wireless Near Field Communication (NFC) Interface,
	1 × 3-axis accelerometer,
	4 × Push buttons (Reset, Wake Up, Tamper, User),
	1 × Analog Input (connected to potentiometer),
Board Size	124mm x 170mm (4.875" x 6.69").

Table 11 Main components of the MCBSTM32F400

9.1.1 STMicroelectronics STM32F407IG

The STM32F407xx family is based on the high-performance ARM® Cortex™-M4 32-bit RISC **core operating at a frequency of up to 168 MHz**. The Cortex-M4 core features a Floating point unit (FPU) single precision which supports all ARM single precision data processing instructions and data types. It also implements a full set of DSP instructions and a memory protection unit (MPU) which enhances application security.

The STM32F407IG operates in the –40 to +105 °C temperature range from a 1.8 to 3.6 V power supply. The supply voltage can drop to 1.7 V when the device operates in the 0 to 70 °C temperature range.

9.1.2 Internal and external memories

The STM32F407iG incorporates high-speed embedded memories, a Flash memory up to 1 Mbyte, and a SDRAM of 192 Kbytes, up to 4 Kbytes of backup SRAM. This area is accessible only from the CPU. Its content is protected against possible unwanted write accesses, and is retained in Standby or VBAT mode.

In addition to the Flash and RAM internal of the STM32F407IG MCU, the MCBSTM32F400 board contains extra RAM memory in order to help in applications like the performed in this project where additional RAM memory for storing the data acquired is needed.

So this board is provided by:

- 2 MB External SRAM (Which will be used in this project as a complement to the 192 kB SDRAM to locate the full signal acquired).
- 8 MB External NOR Flash.
- 512 MB External NAND Flash
- 8 KB EEPROM with NFC (wireless near field communication).

9.1.3 The system clock

As has been said, in this application, the ADC is one of the most important peripherals to use. The sampling rate of this peripheral is related with the system clock divided by an assigned preescaler, so the properties of the clock should be briefly mentioned. Three different clock sources can be used to drive the system clock:

- High speed internal clock (HIS): It’s an up to 16 MHz oscillator clock.
- High speed external clock (HSE) from 4 MHz to 26 MHz oscillator clock.

- Main phase-locked loop (PLL) clock with a PLL voltage-controlled oscillator (PLLVCO), up to 2 MHz.

The 16 MHz internal RC oscillator is factory-trimmed to offer 1% accuracy over the full temperature range. The application can then select as system clock either the RC oscillator or an external 4-26 MHz clock source.

Several prescalers allow the configuration of the three AHB buses, which are the buses where the peripheral are connected, the high-speed APB (APB2), where the ADC is attached, and the low-speed APB (APB1) domains.

The maximum frequency of the three AHB buses is 168 MHz while the maximum frequency of the high-speed APB domains is 84 MHz. The maximum allowed frequency of the low-speed APB domain is 42 MHz.

9.1.4 General-purpose DMA

Direct memory access (DMA) is used in order to provide high-speed data transfer between peripherals and memory and between memory and memory. Data can be quickly moved by DMA without any CPU action. This keeps CPU resources free for other operations [55].

In the STM32F4071IG there are two different DMA controllers, where each controller has 8 different streams and can response to petitions from 8 different channels.

The configuration of the DMA is made by software and transfer sizes between source and destination are independent. All the configuration of the DMA will be explained in section 9.1.4.

The DMA could work transferring data from one source to a destination, the available source-destination possibilities are:

- Peripheral-to-memory
- Memory-to-peripheral
- Memory (internal)-to-memory(external)

The selected configuration of this project is peripheral to memory, so only this configuration would be explained, further information on DMA could be found in [55].

When the peripheral-to-memory mode is enabled in the software configuration, each time a peripheral makes a request, in this case the ADC when finishes an acquisition. The DMA could work using a FIFO buffer that stores the data until the peripheral finishes. When the request is made, the stream initiates a transfer from the source to fill the FIFO buffer. When the data threshold level of the FIFO is reached, the contents of the FIFO are drained and stored into the destination.

But in this program, the DMA will be working in direct mode, so all the data will be saved in the ADC buffer and when the conversion finishes, the DMA will attend the peripheral's request. This mode is restricted to transfers where the source and destination transfer widths are equal.

9.1.5 Analog to digital converter

The 12-bit ADC is a successive approximation analog-to-digital converter. It has up to 19 multiplexed channels. The result of the ADC is stored into a left or right-aligned 16-bit data register.

The A/D conversion of the channels can be performed in single, continuous, scan or discontinuous mode. In single mode the ADC only performs a unique acquisition if it asked to do it. In continuous conversion mode, the ADC starts a new conversion as soon as it finishes one. Also it could work in single channel conversion, where each channel converts one single signal, or in multichannel where different ADCs are combined in order to convert a single signal.

It has a software configurable maximum resolution of 12 bits, from 0 to 4094 values, but other options could be selected like 10 bits, 8 bits and 6 bits.

The ADC is directly connected with the DMA if it is enabled. If enabled, after each conversion of a regular channel, a DMA request is generated. This allows the transfer of the converted data from the ADC_DR register to the destination location selected by the programm126.

9.2 Definition of the diagnosis algorithm selected

Once the development platform has been defined, the algorithm that wants to be implemented will be explained. This algorithm is selected in base at the acquired knowledge in section 8. Analysis and characterization of the AE signal.

In this section has been explained, that the acoustic emission signal always have the main part of the spectral content over 100 kHz. In this sense, in the previous section, concretely in (8.3.2) could be seen how, if the gear is healthy, the main spectral content of the signal is located over the frequency range of 100 kHz. In addition, as can be seen in the same previous figure, when a fault was introduced in the system, appears new frecuencial content over the frequency band of 220 kHz.

In this sense, the proposed methodology, considering the calculation power of an embedded platform, is to perform a set of three band pass digital filter (FIR) in order to isolate the spectral content of the signal in a concrete frequency band, but in time domain, reducing with this the complexity of the signal processing.

The global structure for the proposed algorithm is shown in **Figure 65**. The main steps of this algorithm would be explained.

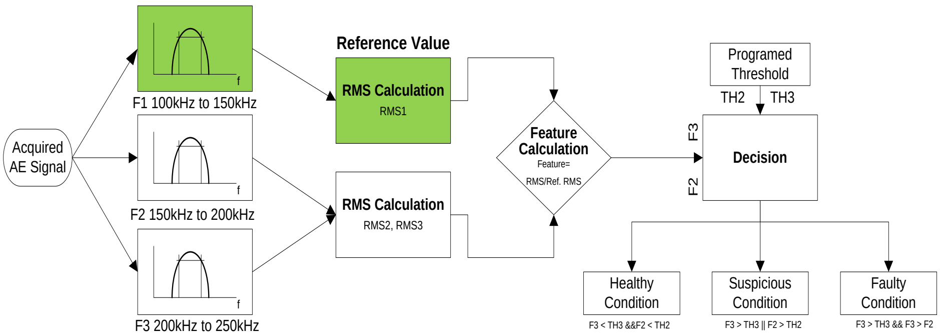


Figure 65 proposed algorithm for fault diagnosis by means of AE signals

First of all, the AE would be acquired with the ADC of the board. Once acquired, the three band pass filters would be applied to the acquired signal in order to obtain the temporal content of each frequency band. Then, the RMS value would be calculated from the data of each filter. The F1 RM value (RMS1) would be used as a reference value, and the other two RMS would be used for the feature calculation.

The utilization of the RMS1 as a reference value is due to the influence of the test condition in the RMS. As can be seen in section 8.3.1.2 Influence of the test condition, the operating speed of the machine has always a strong influence over the amplitude of the signal, and with this the RMS value. In order to isolate the results from the speed of the experiment, the RMS2 and RMS values are referenced to the RMS1, giving with this the two features used in this algorithm which are:

$$Feature\ 2\ (F2) = \frac{RMS2}{RMS1}$$

$$Feature\ 3\ (F3) = \frac{RMS3}{RMS1}$$

Then these features are compared with two thresholds (TH1, TH2) values which have been previously introduced. These thresholds are the same features, but when the system is in healthy condition. So they are a reference of the spectral content in each frequency when the system is in healthy condition.

The feature who gives a certain information about the failure is F3, but at in very low speed, the spectral content of the signal does not arrives to the frequency band of 200 kHz (filter3).

So in function of the features and the programmed thresholds the conditions that could be achieved are:

- **Healthy condition:** Is given when none of the features exceeds the threshold programmed level. This involves that logical condition:

  $$Healthy\ if\ F2 < TH2\ AND\ F3 < TH3$$

  This means that the high spectral content is lower than in healthy condition, so the system has no signs of failure.

- **Suspicious condition:** Is given when one of the features exceeds the threshold programmed level. This involves that logical condition:

  $$Suspicious\ if\ F2 > TH2\ OR\ F3 > TH3$$

  This means that high frecuencial content has been found in filter 2 and filter 3, and this spectral content is significant compared to the first reference filter, and also it is bigger than the programmed threshold.

- **Faulty condition:** Is given when the feature 3 is bigger than the feature 2 and at the same time the feature 3 exceeds the threshold value. This involves that logical condition:

  $$Faulty\ if\ F3 > TH3\ AND\ F3 > F2$$

  This means that all the significant spectral content is located over the frequency band of 200 kHz, which means that the system is in faulty condition.

The result of the comparison is directly the diagnosis of the fault inside the system using the acoustic emission signal analysis. In the following section, the design of the band pass filters is briefly commented.

9.2.1 Band pass filters design

Three different band pass filters are used in this project. All these filters are implemented as a finite input response filter, due to its simplicity and assured stability, as seen in section 5.1.2.1.

The filters are designed with Matlab's Filter design & analysis tool, the filter template that must be filled, is shown in **Figure 18 Band pass filter schema applied to acquired data**. The frequencies that must be selected are the Fstop 1, Fpass1, Fpass2 and Fstop2. The Fpass1 and Fpass2 of each filter is the defined from each frequency band, [100, 150] kHz for the first filter, [150, 200] kHz for the second filter, and [200, 250] kHz. The frequency stop of each filter is the previous mentioned filter plus a frequency offset of $\pm\ 50\ kHz$.

The order of the filters is 79 (80 coefficients) and has been equally selected for all the filters. The different filters response could be seen in **Figure 66** the first filter; in **Figure 67** the second band pass, and the last one in **Figure 68**.

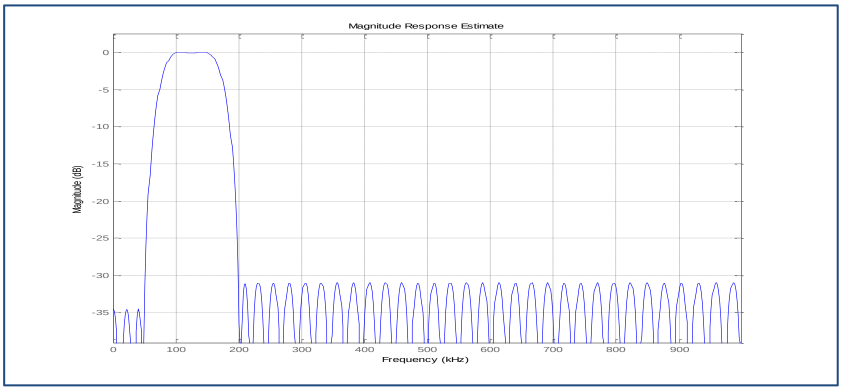


Figure 66 Frequency spectrum of the first filter from 100 to 150 kHz

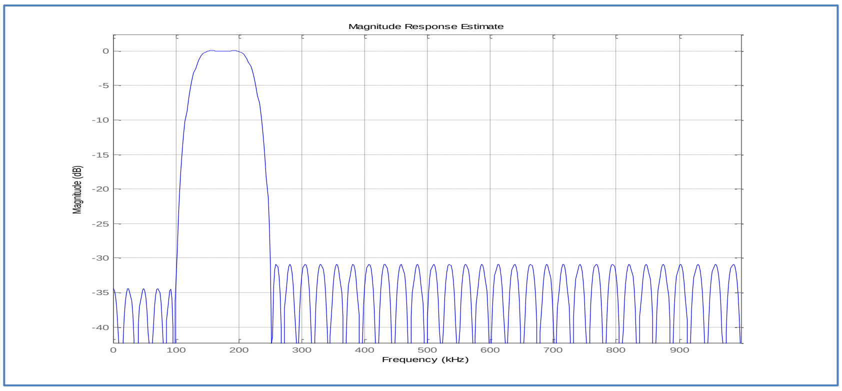


Figure 67 Frequency spectrum of the second filter from 150 to 200 kHz

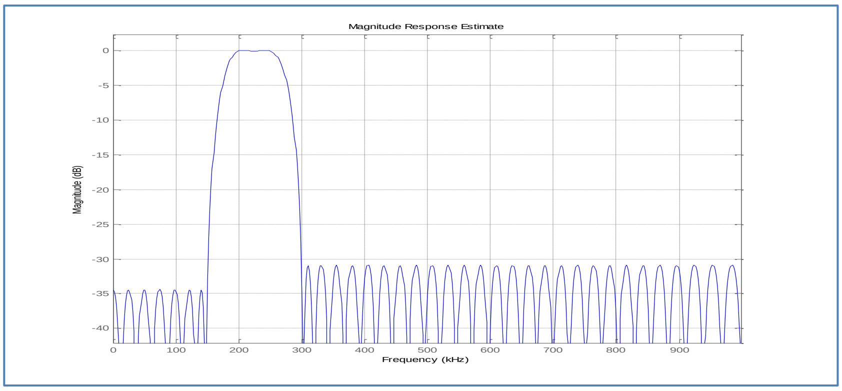


Figure 68 Frequency spectrum of the first filter from 200 to 250 kHz

9.3 Software Implementation

9.3.1 Main structure of the program

This section covers the structure of the computer code generated in the Keil board. This code is made in order to perform a first approach of the fault diagnosis algorithm. The first step is to identify the block diagram of the program which could be seen in Figure 69.

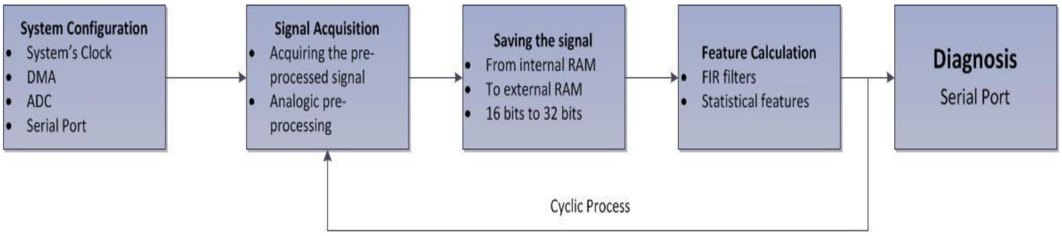


Figure 69 Flow diagram of the computer code

According to this diagram, the first step the program should do is to set the whole system configuration. In order to perform the fault diagnosis, the peripherals to be configured in this program are:

- **The system's clock:** The clock of the system should be configured because the ADC, as will be explained in the following section, uses this value in order to set the maximum and minimum available sampling rates.
- **The data memory access (DMA):** The DMA is needed in this application due to the limitations of the internal RAM memory of this microcontroller. The DMA will move the data between the ADC and the internal RAM memory.
- **The ADC:** This is the fundamental peripheral in order to acquire the acoustic emission signal from the test bench. It should be said that before arriving to the ADC, in order to adapt the signal to the board voltage range, the signal should be previously pre-processed.
- **The serial port** will be used for transmitting the calculated features to the computer by a connection RS232. The configuration of the transmission parameters should be set in the first step.

The main operative diagram of this software is shown in Figure 70.

Once the whole system is correctly configured, the next step is acquiring a signal from the test bench. The signal is acquired (from the AE sensor after external electronic conditioning), digitalized and stored in the microprocessor. Due to the memory storage constraints, **the acquired signal corresponds to 20.000 samples of 12 bits acquired at a sampling frequency of 2MHz. This is equivalent to a sampling time of 10 ms.**

Figure 70 Flow diagram of the software developed

It should be considered that in this project, the acoustic emission signal at the supply's exit has amplitude over $\pm 10\ V$, but the used board could only work in a voltage range of $[0,\ to\ 3.3]V$. In order to adjust the polarity and the voltage range, an adequation board between the supply and the ADC has been used. This board performs a conversion of the input signal into a [0 3.3] V signal with a resolution from [0 to 4096]. Later when the signal has been acquired, it will be reconverted in order to obtain the real value.

The main problem here is the fact that the ADC is connected directly to the microcontroller, so it uses the internal RAM memory to save the data acquired. However, the acoustic emission phenomena have a very high frequency, so a elevate resolution is required. If the converted is set to 12 bits of resolution, but by its internal configuration, it converts this value to a 16 bits float variable.

One Float is equal to 4 bytes of information, so if 20.000 samples are acquired, the amount of memory used is:

$$20.000\ samples \cdot 4\ B = 80\ KB\ \cong 196\ KB$$

This 80KB of data are very close to the maximum capacity of the internal ram that is 192 KB, so considering other values stored in the ram, a second acquisition could not be performed. So the data is needs to be moved at the external RAM 2MB.

The operation of moving the data could represent a high load for the µC, so the utilization of the DMA peripheral is required. This peripheral could help to move the 80 KB of data captured with the ADC and move it to the internal RAM without consuming CPU capacity.

When the data is moved from the internal to the external RAM, the 16 integers are converted into floats with a total length of 32 bits. This is made in order to fit to the type specification of the posterior applied mathematical functions from the CMSIS libraries commented in section 9.3.3.

When the data is saved in the external memory, it should be adjusted in this sense; the following equation has been used:

$$testInput\_f32[index] = \ (testInput2\_f32[index] - 2046) * 8.05/10000$$

Where the 2046 value is in order to set the 0 level of the original signal, and the (8.05/10000) value is set in order to convert the acquired value scaled from 0 to 3.3 value into the original voltage.

Once the data is stored in the external ram, the signal processing and the feature extraction could be made. For this algorithm, a frequency band decomposition using a set of three band pass FIR filters is used.

These filters are digitally implemented in C, but they are designed with the data filtering toolbox (fdatool) from Matlab. In Matlab, the filter response and the filter order is selected and the Float32 coefficient matrix is retrieved.

The three filters cover the bands from 100 to 150 kHz, from 150 to 200 kHz and from 200 k Hz to 250 kHz. The time response of these filters is analysed in order to obtain the RMS value from it. The RMS value of each band would be stored in order to calculate the features explained in the previous section.

Once the features have been calculated, the diagnosis algorithm explained in section 9.2, would be applied in each band RMS value and the result, together with the value of each feature would be send trough the serial port to a computer.

It should be noticed that this process will be repeated every 10 ms. In the next section, each configuration of the peripherals is given, also the configuration sentences are commented. In addition, the section of the program code that configures that peripheral is mentioned.

9.3.2 Main peripheral and µC configuration

In this section the most important configuration of the critical peripherals involved in this project is shown. The most important peripherals considered are:

- The system clock.
- The ADC for acquiring the AE signal.
- The DMA for moving the acquired signal to the external RAM memory.

9.3.2.1 Clock configuration

Configuring the clock of the system is a key factor because all the clocks of the internal peripherals of the microprocessors work in a frequency related to the main clock. This clock source is input to a PLL thus allowing increasing the frequency up to 168 MHz where several preescaler that affects the peripheral configuration should be chosen.

In order to easy configure the different clocks, an excel file to automatically fill the configuration file is provided. The global scheme of this file is shown in **Figure 71.**

In order to configure the clock of the ADC peripheral, some considerations should be taken into account. As was previously said, the peripheral clock directly deepens of the global system clock divided by a preescaler, the preescaler that affects the ADC clock is the APB2 preescaler.

In order to know the frequency that should be configured in function of the sampling frequency selected, a simple formula is applied, which is:

$$f_{sample} = \frac{ADC_{Clock}}{Nº\ Cycles\ to\ perform\ a\ conversion}$$

Where f_{sample} is the desired sampling frequency of the ADC (in this case 2 MHz), the number of the cycles to perform a conversion is considered as the number of *the resolution bits of the ADC plus 3 cycles (time to perform an acquisition),* ADC_{clock} *is the oscillating frequency of the clock that is wanted to know.*

In this programme, the selected frequency is:

$$ADc_{clock} = 2MHz \cdot (12b + 3b) = 30\ Mhz$$

The selected frequency should be 30 MHz, but the minimum preescaler configurable in the APB1 bus is 2, as a result the selected clock frequency is 60 MHz.

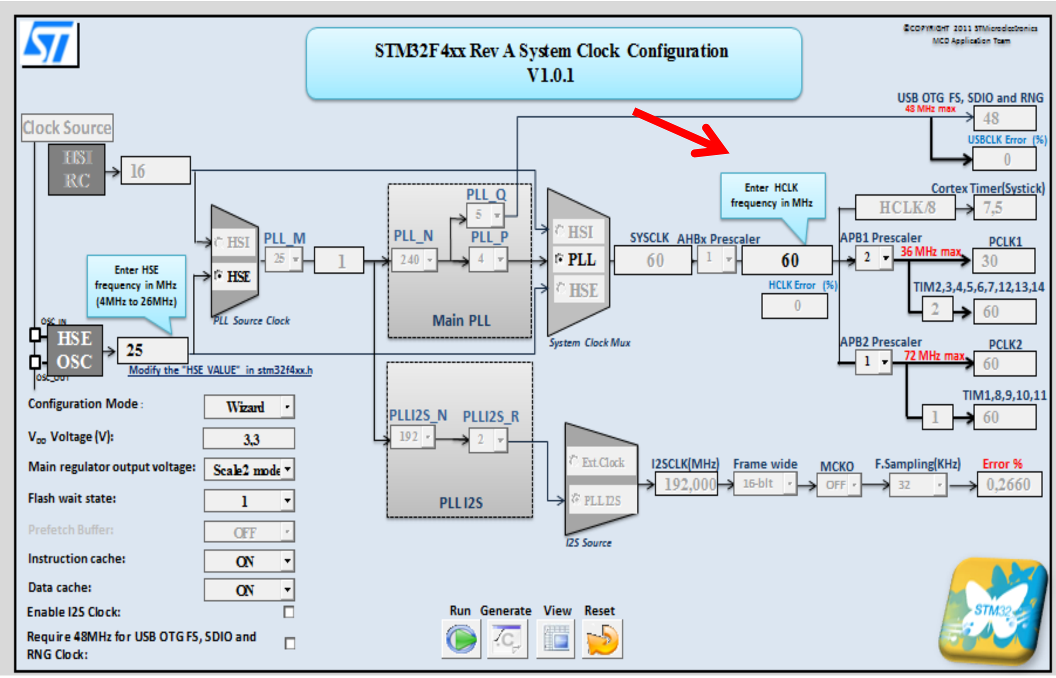


Figure 71 System clock configuration diagram for the STM32F4xx family

The excel file generates the C configuration file named system_stm32f4xx.c where the parameter that contains the selected frequency is uint32_t System Core Clock = 60000000.

9.3.2.2 ADC configuration

Once the configuration of the system clock has been made, the ADC could be configured. The ADC instructions are obtained from the STM32F4xx DSP and Standard Peripherals Library.

First of all a general configuration of the ADC peripheral should be made. In this sense, the ADC_CommonInitStructure should be defined. In this structure, the ADC mode, the clock preescaler, the sampling delay and the buffer behaviour should be defined. The chosen configuration is:

- **ADC mode:** The ADC mode is set to independent, because only ADC is used. Regular conversions can be performed on one or all ADCs. In that case, they are independent of each other and are interrupted when an injected event occurs.

- **ADC clock preescaler:** This parameter has been explained in the previous section. IT is given by the clock configuration and is actually set to 2 (60MHz 7 2= 30MHz ADC clock).
- **DMA Access Mode:** This parameter says if the DMA should wait for the buffer of the ADC to be completely filled in order to collect the data.
- **Initial Delay:** An initial delay should be configured because the ADC requires a short among of time to arrive at its steady-state. In this sense, the first 5 samples are discarded.

The code performed to do this configuration is shown in Figure 72.

```
/* ADC CommonInit****************************************/
  ADC_CommonInitStructure.ADC_Mode = ADC_Mode_Independent;
  ADC_CommonInitStructure.ADC_Prescaler = ADC_Prescaler_Div2;
  ADC_CommonInitStructure.ADC_DMAAccessMode =
ADC_DMAAccessMode_Disabled;
  ADC_CommonInitStructure.ADC_TwoSamplingDelay =
ADC_TwoSamplingDelay_5Cycles;
  ADC_CommonInit(&ADC_CommonInitStructure);
```

Figure 72 ADC common initialization code

Once the common configuration for the entire ADC has been performed, the specific configuration of the channel used is made. The parameters to configure are the ADC resolution, the number of different channels that want to be scanned, the conversion mode, the channel activation, the data alignment and the number of conversion to make each cycle.

- **The ADC resolution:** is set to 12 bits (the options for the resolution are 8, 10 and 12 bits).
- **Scanning different channels:** Gives the option of scanning consequently more than one ADC channel. This option is not used in this program.
- **The conversion mode:** In this sense, the ADC supports different operation modes, in this application, the ADC is configured in a continuous operation mode, because one a conversion of 20.000 samples is performed, the ADC keeps this data in his buffer, and when the DMA is free, it automatically takes the data to the external RAM.
- **Activation of this ADC channel:** Is set to internal because is activated by the clock itself every 10 ms.
- **The data alignment:** The data in the ADC could be aligned in several ways because it involves two different registers; in this application the selected alignment is right.
- The number of **consecutive conversions** is set to 1.

The code performed to do this configuration is shown in Figure 73.

```
/******************* ADC3 Init ***********************/
  ADC_InitStructure.ADC_Resolution = ADC_Resolution_12b;
  ADC_InitStructure.ADC_ScanConvMode = DISABLE;
  ADC_InitStructure.ADC_ContinuousConvMode = ENABLE;
  ADC_InitStructure.ADC_ExternalTrigConvEdge =
ADC_ExternalTrigConvEdge_None;
  ADC_InitStructure.ADC_ExternalTrigConv =
ADC_ExternalTrigConv_T1_CC1;
  ADC_InitStructure.ADC_DataAlign = ADC_DataAlign_Right;
  ADC_InitStructure.ADC_NbrOfConversion = 1;

  ADC_Init(ADC3, &ADC_InitStructure);

/* Enable DMA request after last transfer (Single-ADC mode)*/

ADC_DMARequestAfterLastTransferCmd(ADC3, ENABLE)
```

Figure 73 ADC concrete channel initialization code

In addition, in order to continuously activate the ADC when it's finished, the instruction `ADC_DMARequestAfterLastTransferCmd` should be used with the ADC channel selected (in this program, the ADC channel selected is 3).

9.3.2.3 DMA configuration

Once the ADC has been configured, the DMA could be defined, and with this all the main peripherals configuration would be made. In order to directly collect the data from the ADC buffer, some parameters should be defined. The code performed to set this configuration to the DMA is shown in Figure 73.

First of all, the channel of the DMA used is selected, in this program the used channel is DMA channel 2. Each DMA channel is related to different peripheral, so according to [55] the DMA channel related to the ADC3 is the channel 2.

```
/* DMA2 Stream0 channel2 configuration  *****************/
  DMA_InitStructure.DMA_Channel = DMA_Channel_2;
  DMA_InitStructure.DMA_PeripheralBaseAddr =
(uint32_t)ADC3_DR_ADDRESS;//source adress
  DMA_InitStructure.DMA_Memory0BaseAddr = (uint32_t)&testInput2_f32; //
destination adress
  DMA_InitStructure.DMA_DIR = DMA_DIR_PeripheralToMemory;
  DMA_InitStructure.DMA_BufferSize = 20000;
  DMA_InitStructure.DMA_PeripheralDataSize =
DMA_PeripheralDataSize_HalfWord;
  DMA_InitStructure.DMA_MemoryDataSize = DMA_MemoryDataSize_HalfWord;
  DMA_InitStructure.DMA_Mode = DMA_Mode_Normal;
  DMA_InitStructure.DMA_Priority = DMA_Priority_High;
  DMA_InitStructure.DMA_FIFOMode = DMA_FIFOMode_Disable;
  DMA_InitStructure.DMA_FIFOThreshold = DMA_FIFOThreshold_HalfFull;
  DMA_InitStructure.DMA_MemoryBurst = DMA_MemoryBurst_Single;
  DMA_InitStructure.DMA_PeripheralBurst = DMA_PeripheralBurst_Single;
  DMA_Init(DMA2_Stream0, &DMA_InitStructure);

  DMA_Cmd(DMA2_Stream0, ENABLE);
```

Figure 74 DMA concrete channel main part of initialization code

Once the channel is defined, first the peripheral address hold be given, in this case the ADC3 base address, and secondly the destination address. In this program the destination address of the DMA is a 32bits Float variable from the external RAM, so a pointer to this memory address is given.

The function mode of the DMA is set to peripheral to memory, because it takes the data from the ADC3 peripheral and saves it into the internal memory. This data would be later converted from the integer (16 bits) to the float (32 bits). Each time a peripheral request occurs, the stream initiates a transfer from the source to fill the FIFO. When the threshold level of the FIFO is reached, the contents of the FIFO are drained and stored into the destination [55].

The DMA buffer size is equal to the number of data acquired, 20000 samples. The data collected is saved in an array, so there is a unit increase in the direction of the DMA for each data.

In addition, all the format and the number of the packages that has to be transmitted is configures, in particular, the format is half word (16 bits) and thus, the number of packages of 16 bits sent each time is 1.

9.3.3 Signal processing functions

In order to perform the different mathematical operations, the library CMSIS is used. This library provides different mathematical and signal processing functions for this specific microprocessor. But all the data should be converted into floats with a total length of 32 bits. One of the main reasons from this conversion is that Matlab coefficients are given in this format.

Two different functions from this library have been used, the first one includes the FIR filtering function, and the function is the RMS calculation over a data vector.

9.3.3.1 Filter function

The used filter function, according to the data format used in this program (Float 32) should be **arm_fir_f32 ( )**. The header of this function is shown **in Table 12.** But before using the filtering function, the structure of the filter should be selected. In this sense, the function arm_fir_init_f32 is used. The variables that should be used as arguments in this function are:

- ***S**: points to an instance of the floating-point FIR filter structure. Is a vector which contains the selected filter structure configured by this function.
- **numTaps:** Number of filter coefficients in the filter. In this application is set to 80 (Filter order +1).

- ***pCoeffs:** points to the filter coefficients buffer. It is a pointer to the stored Matlab coefficients. There are three different coefficients, one for each filter.
- ***pState:** points to the state buffer.
- **blockSize:** Number of samples that are processed per call. It is the data window where the filter is applied. For this reason, it should be bigger than the number of coefficients (numtap).

Once the filter structure has been defined, the filter should be applied in a for structure from 1 to the length of the numBlocks. The used function to apply the filter is **arm_fir_f32 ( )**. The parameters of this function are:

- ***S:** points to an instance of the floating-point FIR filter structure. Is the filter previously configured structure.
- ***pSrc:** points to the block of input data. Is the Float32 AE signal that wants to be filtered.
- ***pDst:** points to the block of output data.
- **blockSize:** number of samples to process per call. Is the external memory variable where the output data wants to be stored.

9.3.3.2 RMS Function

Calculates the Root Mean Square of the elements in the input vector. The underlying algorithm is used:

Result = sqrt(((pSrc[0] * pSrc[0] + pSrc[1] * pSrc[1] + ... + pSrc[blockSize-1] * pSrc[blockSize-1]) / blockSize));

The parameters used in this function are:

- ***pSrc:** points to the input vector
- **blockSize:** length of the input vector
- ***pResult:** rms value returned here

Filter function
arm_fir_init_f32 (arm_fir_instance_f32 ***S**, uint16_t **numTaps**, float32_t ***pCoeffs**, float32_t ***pState**, uint32_t **blockSize**). void arm_fir_f32 (const arm_fir_instance_f32 *S, float32_t *pSrc, float32_t *pDst, uint32_t blockSize)
RMS function

Void arm_rms_f32 (float32_t ***pSrc**, uint32_t **blockSize**, float32_t ***pResult**).

Table 12 Selected mathematical functions from the library CMSIS

9.4 Final Test performed

In order to demonstrate the correct operating of this program, an experimental test has been performed. The conditions of the test are shown below (Figure 75).

The only difference between the other tests is the fact that the previous acquisition system, the PXI from national instruments has been substituted for the Keil microprocessor board. In this sense, the acquisition board used for the signal adequation are also shown in the diagram.

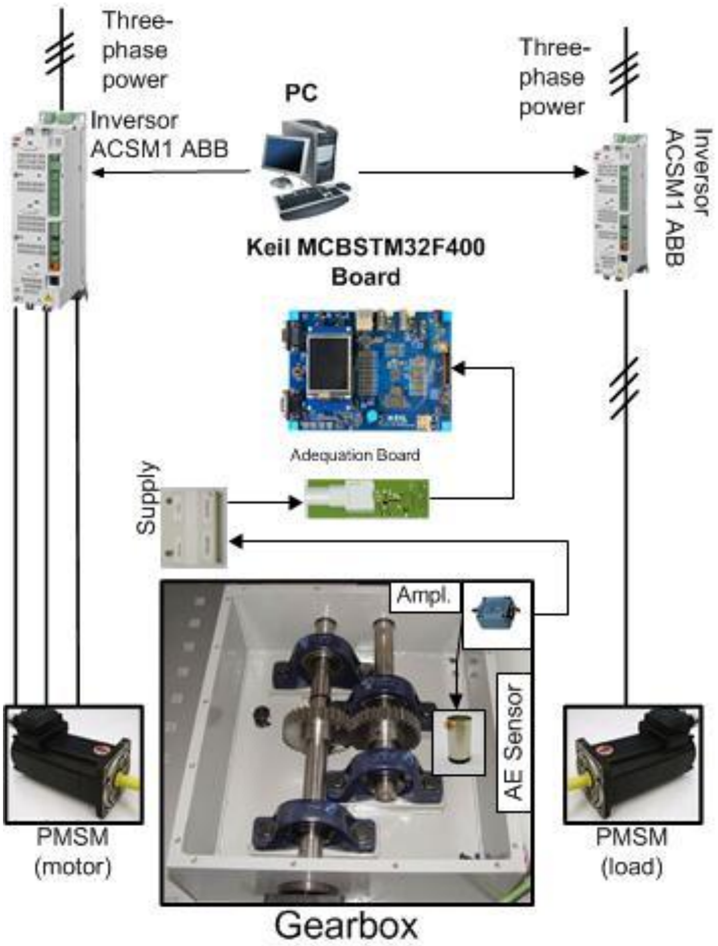


Figure 75 Global scheme for the test performed with the Keil board

Several tests under different conditions have been performed, first of all with the healthy gears, in order to extract the threshold values for the posterior tests. After performing different test, the selected value for the two thresholds has been set as:

- Threshold 2: 0.6
- Threshold 3: 0.6

It should be reminded that this value is the division between the RMS value of the mid frequency and high frequency filters, and the RMS value of the low frequency filter (where the main spectral content when the gear is healthy is located).

Once the threshold value has been set, another test in healthy conditions is performed in order to validate the program. The result of the information given by the serial port is shown in **Figure 76**.

```
                DATA PROCESSING

Here the Results:
-- Original Signal--
                  RMS: 0.75589

 -- Filtered Signal1 From 100KHz to 150KHz --

                        RMS: 0.65000

 -- Filtered Signal2 From 150KHz to 200KHz --
                        RMS: 0.12704

-- Filtered Signal3 From 200KHz to 250KHz --

                        RMS: 0.00703

-- Fault Diagnosis --

-- Fature Calculated From 150KHz to 200KHz Band--
             Programmed Threshold: 0.60000
             Feature Actual Value: 0.19545

-- Fature Calculated From 200KHz to 250KHz Band--
             Programmed Threshold: 0.60000
             Feature Actual Value: 0.01082

                 System Condition: H

Where:
              'H' is healthy condition
              'S' is suspicious condition
              'F' is faulty condition
```

Figure 76 Results from the performed test in healthy conditions

It could be seen in this results how the spectral content of the signal in healthy conditions, because the most part is located in the first filter. RMS of the original signal is RMS= 0.75589, the RMS in the first filter is RMS1 =0.65. The features are F2= 0.19545 and F3= 0.01082. So considering the specified logical conditions the value that should be obtained is Healthy.

The second test is performed with the seven failures gear, in order to verify if it could detect the fault condition in a really damaged gear. The results of the test are given in **Figure 77**.

```
              DATA PROCESSING

Here the Results:
-- Original Signal--
                 RMS: 0.92103

 -- Filtered Signal1 From 100KHz to 150KHz --

                       RMS: 0.73029

 -- Filtered Signal2 From 150KHz to 200KHz --
                       RMS: 0.68762

-- Filtered Signal3 From 200KHz to 250KHz --

                       RMS: 0.91385

-- Fault Diagnosis --

-- Fature Calculated From 150KHz to 200KHz Band--
                       Programmed Threshold: 0.60000
                       Feature Actual Value: 0.94158

-- Fature Calculated From 200KHz to 250KHz Band--
                       Programmed Threshold: 0.60000
          Feature Actual Value: 1.25135

                       System Condition: F

Where:
                        'H' is healthy condition
                        'S' is suspicious condition
                        'F' is faulty condition
```

Figure 77 Results from the performed test in faulty conditions

The results shows the appearance of spectral content in higher frequency band when the gear fault is under failure. It can be seen how the Feature value F· is bigger compared with the acquired one in healthy conditions (F3=0.01082) which indicates that the performed algorithm is able to detect the failure of the gear.

The increment of the Feature 3 is one of the most significant conditions of the feature appearance. It should be noticed that there is a common part of pass band between the second and the third filter, this is the main reason for the elevate value on the feature F2.

In addition, a third test has been performed in order to see if the algorithm could detect a gear with a minor defect (only a small crack in one tooth). The test has been performed and it could be seen how spectral content appears in the second filter and the suspicious condition could be achieved, but the algorithm is not able to detect such a small fracture. The results of this test are given in

```
                 DATA PROCESSING

Here the Results:
-- Original Signal--
                      RMS: 0.80953

 -- Filtered Signal1 From 100KHz to 150KHz --

                              RMS: 0.71890

 -- Filtered Signal2 From 150KHz to 200KHz --
                              RMS: 0.80267

-- Filtered Signal3 From 200KHz to 250KHz --

                              RMS: 0.35876

-- Fault Diagnosis --

-- Fature Calculated From 150KHz to 200KHz Band--
                              Programmed Threshold: 0.60000
                              Feature Actual Value: 1.11653

-- Fature Calculated From 200KHz to 250KHz Band--
                              Programmed Threshold: 0.60000
             Feature Actual Value: 0.49904

                              System Condition: S

Where:
                               'H' is healthy condition
                               'S' is suspicious condition
                               'F' is faulty condition
```

Figure 78 The results of the test performed under one teeth condition

It should be said that this algorithm is only a first approximation of a real diagnosis system; it has been implemented in an embedded system in order to demonstrate that the features extracted from the first analysis could be simplified and applied to a real diagnosis problem.

Also it could be seen how the RMS amplitude of the original signal increases with the defect of the gear, as can be seen in the different RMS value of each experiment,

The algorithm works well under health and severe fault condition, but it requires a more accuracy when the gear is only affected by one small failure. With this conclusion, the section of the embedded code is over. It should be noticed that the full program code is available in the Annexed part to the memory.

10. Conclusions of the project

At the end of the project, all the objectives have been successfully completed, including the objectives from the first, and the second part. The conclusions of this project are divided in two different parts.

10.1 Conclusions of the first part of the project

At the first part of the project, there is a complete description about what fault diagnosis system for electromechanical actuators is and what the different steps to apply it. According to this fact, a complete description from the diagnosis problem, from the initial fracture to the final diagnosis has been made.

Defect diagnosis could be seen as a solution for the failures in gearboxes. It has not the same cost to repair a gearbox than buying a new machine instead moreover, the cost of unexpected plant stops can be unaffordable. This problem could be avoided by making a good preventive maintenance based on condition monitoring and defect diagnosis.

Regarding to the analysis of the acoustic emission signals, a revision of the Acoustic Emission on concrete Testing has been made. Starting with the generation of the acoustic emission event, and ending with the correlation between the characteristics of the AE signal and the failure of the gear.

As a conclusion, the analysis of the acoustic emission signals from a electromechanical actuator, is very useful technique to detect incipient failures, using this method, a preventive maintenance and to correctly recognize the failure inside the component.

Despite of this fact, it is a young technology which is improving each day, the main drawback from this method is the fact that there is not a defined methodology for applying it.

The first part of the project has been ended with a comparative between the actual used method for diagnosis (vibration analysis) and the acoustic emission method. The differences between the two methods have been exposed in a comparative table, which resumes all the conclusions extracted from this theoretical comparative.

10.2 Conclusions of the second part of the project

Regarding to the practical part of the project, an acquisition system in order to correctly acquire data from the acoustic emission sensors has been implemented and validated with the characterization of the acoustic emission signals acquired in the different tests.

Referencing the NI-PXI, it has been found that the high frequency acquisition board (6115) is very sensitive to the EMI presents in the laboratory; in particular, it has several problems with the influence of the inverter used to control the motors. In this sense, it could also be said that one of the problems of the acoustic emission signals are their low amplitude and high frequency. This leads to the fact that all the acquisition system should be properly grounded and shielded.

Regarding to the AE analysis, it has been checked that two main kinds of AE signals can be acquired: continuous and discrete signals. The continuous signal is more related to a healthy behaviour, however, the complexity of the mechanical components, or the increase of the speed will leads to the generation of a continuous AE composed by continuous AE bursts.

in general, the AE acquired signal shows a continuous noise level (in continuous and discrete signals). The fault apparition or the speed increase modulates the AE bursts amplitude significantly, but not the AE noise level.

One of the most important conclusions is the fact that mechanical degradation implies a displacement of the AE spectral content to higher frequencies. Two main frequency bands have been detected: around 100 kHz and around 200 kHz. The analysis of the spectral contents around 200 kHz represents the most reliable approach for fault detection and degradation quantification.

In this sense, the decomposition of the signal in three different bands can be used to detect not only the presence of a fault, but also its severity. It could be seen, how with the proposed method for analysing the acoustic emission signal, the spectral content from each band could be directly related with the failure in the gear.

Regarding to the embedded platform, the STM32F407IG microcontroller has been achieve a great performance at acquiring the acoustic emission signal due to its high frequency analog to digital converter.

A simple algorithm for fault detection could have been implemented based on the previous mentioned method. In this sense, this algorithm is able to detect the faulty condition when the gear has been highly degraded, but it only gives suspicious condition when applied to a one tooth gear fault. So a further calibration of this algorithm should be done.

As a further work, an experimental comparative between the acoustic emission methods should be done in order to validate all the theoretical premises.

Finally, I would like to thank at the group MCIA for the possibility to collaborate in this project ant the supervision they have made to my work.

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