Ricardo Jorge Duarte Ferreira

Condition-Based Maintenance Framework
Development for Several Applications

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Universidade do Minho
Escola de Engenharia

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Dissertação de Mestrado
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Trabalho efetuado sob a orientação do
Professor Doutor José Mendes Machado

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DECLARAÇÃO

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Resumo

A manutenção preditiva ou baseada em monitorização de condições, centra-se na identificação de falhas antes que elas ocorram. Estes sistemas, incorporam a inspecção dos equipamentos em intervalos predeterminados para determinar a condição do sistema. Esta inspecção pode ser nada mais do que a aquisição de grandezas físicas do equipamento, por exemplo, as vibrações, som, temperatura, pressão, luz, tensão, corrente, etc. Um sistema de monitorização de condições é destinado a monitorizar o funcionamento de um sistema complexo e fornecer ao operador ou ao sistema de controle autónomo uma avaliação precisa da saúde actual do sistema. O documento proposto descreve o trabalho feito em monitorização de sistemas mecânicos exteriores de comboios e para análise de vibração em máquinas de rotação usando uma arquitectura baseada em *"Open System Architecture Condition-based Maintenance System (OSA-CBM)",* que é definido como uma arquitectura padrão para mover informações em sistemas de monitorização de condições.

Keywords: OSA-CBM, Análise de Vibração, Indicadores de Saúde.

Abstract

Predictive maintenance or Condition-based maintenance (CBM), focuses on identifying failures before they occur. CBM incorporates inspections of equipment at predetermined intervals to determine system condition. These inspections could be nothing more than continual data collection from the equipment about the vibrations, sound, temperature, pressure, light, voltage, current, field strength and so on. A CBM system is intended to monitor the operation of a complex system and provide the operator or the autonomous control system with an accurate assessment of the system's current health. The proposed document describes the work done for CBM of train exterior mechanical systems and for vibration analysis on rotation machines using the Open System Architecture Condition-based Maintenance System (OSA-CBM) which is defined as a standard architecture for moving information in a condition-based maintenance system.

Keywords: OSA-CBM, Vibration Analysis, Health Indicators.

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List of Acronyms

CSWT	*Critical Software Technologies*
CBM	*Condition-based maintenance*
OSA-CBM	*Condition-based Maintenance System*
MIMOSA	*Machinery Information Management Open Systems Alliance*
RFID	*Radio-Frequency Identification*
RUL	*Remaining Useful Life*
EMD	*Empirical Mode Decomposition*
IMF	*Intrinsic Mode Function*
PSD	*Power Spectral Density*
FFT	*Fast Fourier Transform*
TSA	*Time Synchronous Averaging*
CWT	*Continuous Wavelet Transform*
RMS	*Root Mean Square*
MCR	*Matlab Compiler Runtime*

CHAPTER 1

Introduction

1.1. Purpose

This report describes a research project conducted within Critical Software Technologies (CSWT) in Southampton. The objective of the thesis is to gain insights into the process of developing a conditioning-based maintenance monitoring system.

1.2. Scope

Maintenance, although requiring the expenditure of significant amounts of energy, is usually required in order to keep (or restore) facilities at an acceptable operation [1]. For most applications maintenance is predominantly based on routine-scheduled prevention as well as previously unanticipated reactions to overcome faults. For decades, conventional wisdom suggested that the best way to optimize the performance of physical assets was to overhaul or replace them at a fixed interval [2]. This was based on the premise that there is a direct relationship between the amount of time (or number of cycles) that equipment spends in a service and is likelihood to fail. In [3] is stated that this relationship between running time and failure is true for some failure modes, but that is no longer very productive as equipment are now much more complex than they were. It is also pointed that a fixed interval overhaul ignores the fact that overhauls are extraordinarily invasive undertakings that massively upset stable systems. As such, they are likely to induce premature failures, which were intended to be prevented.

Unless there is a dominant age-related failure mode, fixed interval overhauls or replacements do little or nothing to improve the reliability of equipment. There is no gain in overhauling a machine that has nothing wrong with it [3]. Predictive maintenance or Condition-based maintenance (CBM), focuses on identifying failures before they occur. CBM incorporates inspections of equipment at continuous time or predetermined intervals to determine system condition. These inspections could be vibration, sound, temperature, pressure, light, voltage, current, field strength and so on. Also, the appropriate interval time for measurement should be employed such that the lead time to failure is optimized with respect to the economic cost of taking and analyzing the measurements.

Depending on the outcome of the inspection, either a preventive or no maintenance activity is performed which ultimately will reduce the maintenance costs in respect to more traditional approaches and will increase asset availability. CBM may employ several fault or defect detection methods to make fault prognostics. In general most of the methods work by comparing inspection data with standardized reference data.

Today with the advent of machine learning cloud, and big data technologies, CBM has suddenly shot into the limelight once again.

The underlying architecture of the CBM process is fairly uniform, irrespective of the end applications. The Machinery Information Management Open Systems Alliance (MIMOSA) organization provides the open systems architecture for CBM, termed System Architecture Condition-based Maintenance System (OSA-CBM) which includes essential elements of such a system and communication protocols between the elements (Figure 1.1).

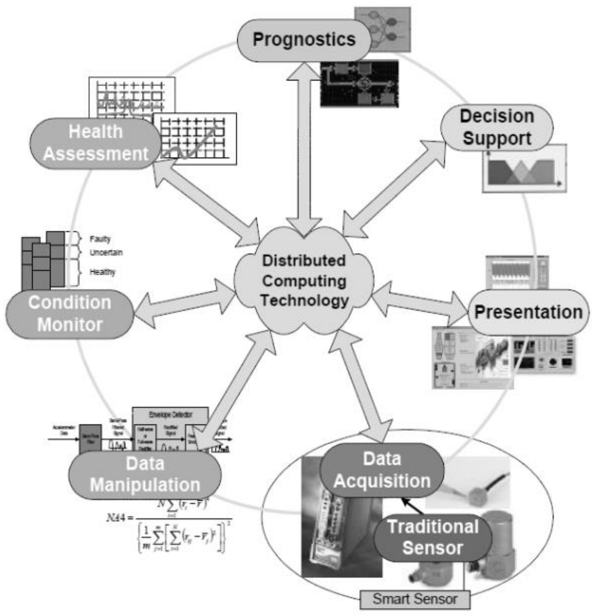


Figure 1.1 - OSA-CBM architecture [4].

The heart of the CBM system is prognostic which is basically predictive analysis or machine learning that uses component degradation and failure data from condition monitoring and trend analysis data monitored in health assessment to provide predictions about component failures. Predictive maintenance can utilize the advances in technology and the affordability which predictive analysis has brought to the market, and thus is going to be more relevant now than ever before.

1.3. Organization and Structure of the Thesis

In Chapter 1, a small introduction to what is CBM system and what is the problem that it tries to solve is presented showing also the used approach for implementation and why it was chosen.

In Chapter 2, a more detailed context to the industry reality regarding maintenance strategies and where the proposed framework is positioned is presented.

In Chapter 3, is presented all the work developed for Alstom in terms of software development to support the new monitoring hub for train inspection, which is being developed on site by them.

In Chapter 4, the work performed for *Arrive* which is a new project that will monitor rotational machines of maritime vessels and helicopters, presenting health indicators regarding asset condition is presented.

In Chapter 5, the developed algorithms for vibration diagnosis and the obtained values are presented.

CHAPTER 2

Maintenance Strategies

2.1. Introduction

Broadly speaking the maintenance of a critical asset may be divided into three separate approaches, namely: corrective or run to failure, preventative and predictive maintenance with the associated costs shown in Figure 2.1.

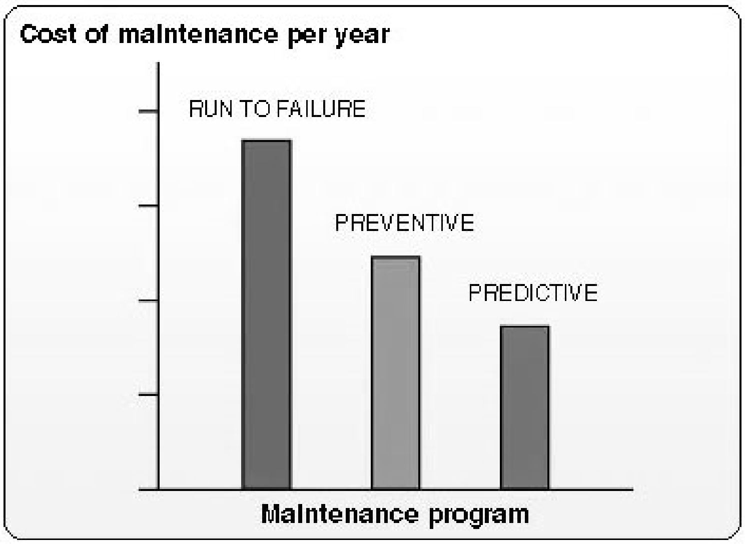


Figure 2.1 - Associated costs of maintenance plans.

A summary of these methods will be given in this chapter.

2.2. Corrective

Traditionally machines were run for the maximum length of time possible until they broke down. This has mainly two theoretical benefits:

Minimum planning - Because maintenance does not need to be scheduled in advance, the planning requirements are very low. Maintenance only needs to happen after breakdown has occurred.

Easy to Understand - Because of the plan's simplicity, this system is easy to understand and implement.

This is often not the best approach to maintenance due to some basic aspects such as:

- **Unpredictability** – Because most asset failures are unpredictable, it is difficult to anticipate when manpower and parts will be needed for repairs.

- **Inconsistency** – The intermittent nature of failures means the efficient planning of staff and resources can be difficult.

- **Costly** – All costs associated with this strategy need to be considered when it is implemented. These costs include production costs and breakdown costs, in addition to direct parts and labor costs associated with performing the maintenance.

- **Inventory Costs** – The maintenance team needs to hold spare parts in inventory, to accommodate for intermittent failures.

2.3. Preventive Maintenance

The preventive maintenance method uses an estimate for the mean time between failures of the particular machine to be maintained such that maintenance of key components may be undertaken at regular intervals shorter than the expected failure time. It is common to choose the intervals such that no more than 1-2% of the machines will experience failure within that time. This does mean that the vast majority could have run longer by a factor of two or three [5].

Preventive Maintenance Plans have the advantage when compared to less complex strategies. Unplanned, reactive maintenance has many overhead costs that can be avoided during the planning process. These costs of unplanned maintenance include lost production, higher costs for parts and shipping, as well as time lost responding to emergencies and diagnosing faults while equipment is not working. When maintenance is planned, each of these costs can be reduced. Equipment can be shut down to coincide with production downtime. Prior to the shutdown, any required parts, supplies and personnel can be gathered to minimize the time taken for a repair. These measures decrease the total cost of the maintenance.

Safety is also improved because equipment breaks down less often than for less complex strategies.

The disadvantage is that the majority of maintenance undertaken via this method is unnecessary, causing excessive cost of components and machine downtime because of unpredictable faults. The components to be replaced are often in perfect working condition and the unnecessary dismantling of a machine causes the risk of faults being introduced where previously none existed. This method does have its place, where the statistical spread about the mean failure time is small, hence the intervals may be organized in such a way to minimize cost, though this doesn’t work so well on components where the failure time less reliably predictable.

2.4. Predictive Maintenance

Predictive maintenance has two main objectives. Firstly, to predict when equipment failure might occur, and secondly, to prevent occurrence of the failure by performing any required maintenance. The task of monitoring for future failure allows maintenance to be planned before the failure occurs. Ideally, predictive maintenance allows the maintenance frequency to be as low as possible to prevent unplanned reactive maintenance, without incurring costs associated with doing too much preventative maintenance. Predicting failure can be done with one of many techniques. The chosen technique must be effective at predicting failure and also provide sufficient warning time for maintenance to be planned and executed.

Condition based maintenance uses measures of specific parameters of a machine to infer the current condition. This enables identification and diagnosis of faults and prediction of the remaining useful life (RUL) when compared to baseline results where the machine is inacceptable working order. This has distinct advantages when compared to other maintenance schemes, namely:

- **Increased asset availability**: Intelligent maintenance planning is enabled through the prediction and timely identification of incipient faults within equipment, thereby reducing the frequency and duration of unplanned maintenance events. This also supports improved spares management, reduced revenue losses from unplanned outages and optimal asset management.

- **Decreased maintenance costs**: Fewer maintenance events and fewer replacements of healthy components.

There are various methods used for obtaining knowledge of the internal condition of a machine, including vibration analysis**,** acoustic emission analysis, oil analysis, thermography, performance analysis, etc...

From all the existing methods, vibration analysis is by far the most used technique in condition monitoring. The prevalence is due to its quickness (nearly instantaneous) reaction to changes in machine condition when compared to other methods, such as thermography and oil analysis which will only show significant changes after the fault is sufficiently developed.

“Vibration has been proven to give the earliest indication of incipient mechanical defects that are growing slowly over time. If you measure temperature, for example, you will see a minute change in a bearing’s temperature about two minutes before you have a catastrophic failure. That’s no good to you.” Steve Boakes, business development director for General Electric Aviation Systems.

The vast archives of signal processing techniques developed over the past few decades enable the extraction of minute fault signals which are embedded in noise, or masked by more prominent signal components.

In an ideal world a CBM system would be able to identify, diagnose and provide prognosis for all possible faults that may occur with the system being monitored. This is unfortunately as impractical as it is uneconomical and hence the faults to be identified must be chosen in such a way to maximize the efficiency of the CBM program e.g. reduce maintenance costs and unscheduled down time as much as possible to increase productivity. Also a study needs to be made because sometimes the complexity of the algorithms and all the investment in data acquisition systems can be so high that isn’t economically viable.

2.4.1. **Permanent and Intermittent Monitoring**

There are two approaches to Condition Monitoring comprising of permanent and intermittent measurement and analysis. For a highly critical asset vibration sensors may be permanently mounted and the specific parameters being used as a measure of condition may be continuously monitored. Sudden changes in operating condition will therefore be recorded and monitored in real time, giving the maximum lead time available for maintenance planning and minimizing the risk of catastrophic or sudden break down.

The disadvantage of a permanent monitoring system is the initial cost of installation of such a system, and hence is usually only applied to the most critical assets. It is often beneficial to have the sensors built into the machines at the design stage as modification of existing machines can be prohibitive or impractical.

As permanent fit analyses the data in real time the signal processing techniques employed must use simple parameters such that the processing time is kept to a minimum. Hence parameters such as peak to peak, overall root mean square (RMS), crest factor and phase demodulation are employed rather than more advanced signal processing techniques. These simple parameters give a reduction in lead time before an impending failure compared to more complex techniques.

The more advanced techniques which may be employed for Condition Monitoring have a longer processing time than the simple parameters measured above, but give a far greater picture of the condition of the machine and hence may recognize the onset of a fault far sooner. Due to the long processing time such techniques are best suited to intermittent monitoring where the processing of the data is performed at set intervals in time, say once per month.

Offline CBM systems may be employed to take measurements for intermittent monitoring, negating the need for expensive permanently fitted transducers. These often come in the form of a compact console where the transducers are fitted in the desired location, the data is collected and the unit then performs the relevant processing techniques and outputs the inferred condition. This has the advantage of allowing time for the processing of more powerful techniques for greater lead time of diagnosis and also represents a more versatile method of monitoring as the unit is not fixed and hence may be employed on a range of machines. An appropriate interval time for measurement should be employed such that the lead time to failure is optimized with respect to the economic cost of taking and analyzing the measurements.

Therefore permanent monitoring is used on critical machines to shut them down in response to an impending failure before catastrophic break down occurs. It is relatively expensive to set up and gives short lead time before failure due to the monitoring of simple parameters necessitated by the processing of the data in real time. Intermittent monitoring employs more advanced signal processing techniques for the long-term advance warning and diagnosis of incipient faults. It is less expensive to employ than permanent monitoring, where the main cost occurs in the development of the analysis algorithms. It is also more versatile and may be used on a wider range of machines than permanent fit monitoring (due to economic feasibility).

For the most critical assets it is ideal to employ a combination of both permanent and intermittent monitoring. Unpredictable, sudden break downs may be avoided due to the application of the permanent fit monitoring, whereas the intermittent monitoring allows identification of incipient faults giving a greater lead time before break down, allowing adequate time for maintenance planning and component sourcing.

As stated, the architecture of the CBM process is fairly uniform, irrespective of the end applications so makes sense in developing a framework based on a known and acceptable architecture in the field. The focus of the OSA-CBM program is the development of an open standard for distributed CBM software components [6].OSA-CBM was developed in 2001 by an industry led team partially funded by the Navy through a Dual Use Science and Technology program. At the time, no framework or standard existed for implementing CBM systems. The team's participants covered a wide range of industrial, commercial, and military applications of CBM technology: Boeing, Caterpillar, Rockwell Automation, Rockwell Science Center, Newport News Shipbuilding, and Oceana Sensor Technologies. Other team contributors include the Penn State University / Applied Research Laboratory and MIMOSA. MIMOSA is a standard body that manages open information standards for operations and maintenance in manufacturing, fleet, and facility environments.

OSA-CBM simplifies the integration of a wide variety of software and hardware components by specifying a standard architecture and framework for implementing CBM systems. It describes the six functional blocks of CBM systems, as well as the interfaces between those blocks in conformity with the ISO-13374 (Figure 2.2).

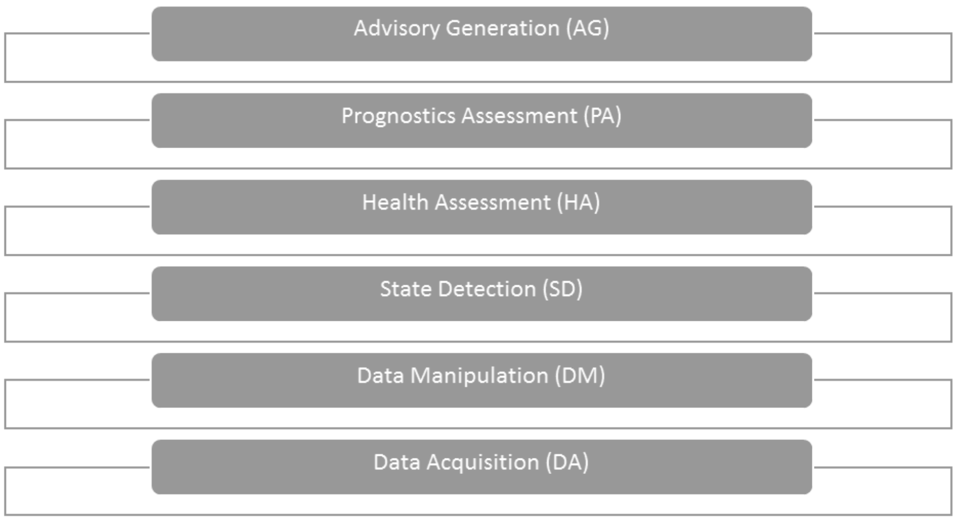


Figure 2.2 - OSA-CBM Functional Block [7].

The benefits from OSA-CBM consist in:

- **Cost** - OSA-CBM can provide significant cost savings because system integrators and vendors will not have to spend time creating new or proprietary architectures. Savings will also come from not being committed to single vendors developing entire CBM systems. Since the standard is broken into functional components, multiple vendors may compete to develop select blocks of functionality.

- **Specialization** - When vendors are not constrained to providing an entire CBM system, they can concentrate on one or few areas. The increase in specialization will allow for better algorithms and technology to be developed. Smaller companies that could not provide an entire CBM system can now specialize in one or more of the functional blocks.

- **Competition** - OSA-CBM allows all vendors to use the same input and output interfaces. The separation of functionality from how the information is presented to other applications allows direct comparison of the developed functionalities. Competition now can occur at a functional level, not a system or total solution level.

- **Cooperation** - Not only can competition increase, but cooperation can also. The sectioning of CBM into separate independent blocks will allow multiple vendors to each work on separate modules. Since the standard also defines the interfaces, each module will be able to communicate with the others seamlessly if developed using the same technologies.

CHAPTER 3

Alstom Health Hub Project

3.1. Introduction

The Alstom Health Hub (Figure 3.1) is an infrastructure that monitors asset health and uses advanced data analysis to predict their RUL and replace assets on a truly as-needed basis. It is supported by monitoring solutions which automatically capture condition data of rolling stock, infrastructure or signaling assets.

It is an innovative approach designed to shift from traditional mileage-based maintenance to predictive CBM, thus reducing the lifecycle cost for the operator [8].

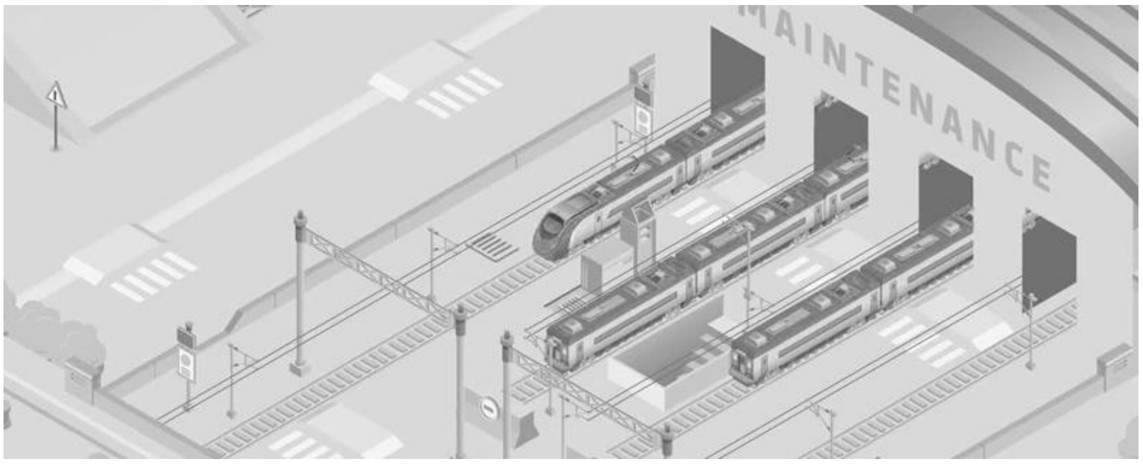


Figure 3.1 – Health Hub schematic [8].

The Health Hub is supported by various high technology data capture solutions allowing the measurement of the condition of three key consumables of a train as it moves through the portal: wheels, brake pads and pantograph carbon strips.

Figure 3.2 presents a simplified diagram which consists in the overall interaction between the monitoring systems and the health assessment systems.

Basically each train will have and Radio-Frequency Identification (RFID) which will firstly be identified in the Health Hub. After the measurement of the condition of the key consumables of a train, wheels, brake pads and pantograph carbon strips are acquired.

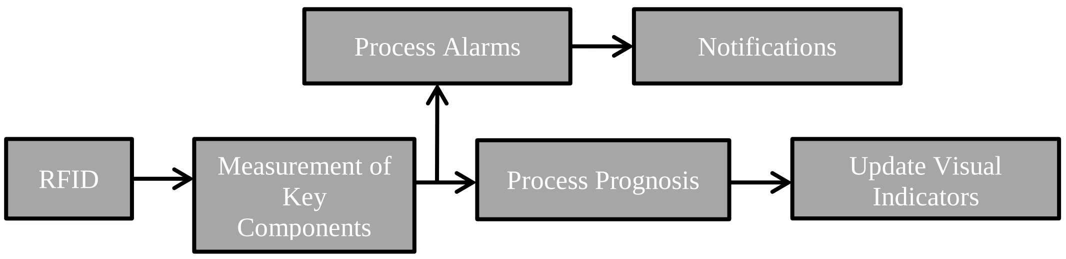


Figure 3.2 – Simplified flow of the health assessment.

The end of the acquisition will start two process in parallel, the process of the alarms for that specific train which basically consists in inspect if any of the components have passed the defined threshold and if that happened, a notification will be sent with a report by email/sms to the users. The other parallel process will be the process of the calculation of the prognosis. The prognosis is basically an algorithm to predict the future state of a given component i.e. its remaining useful life.

The algorithms use time-series of asset condition data combined with other data such as past maintenance history, track profile or even weather data.

Maintenance tasks for each asset are then anticipated accordingly and optimized.

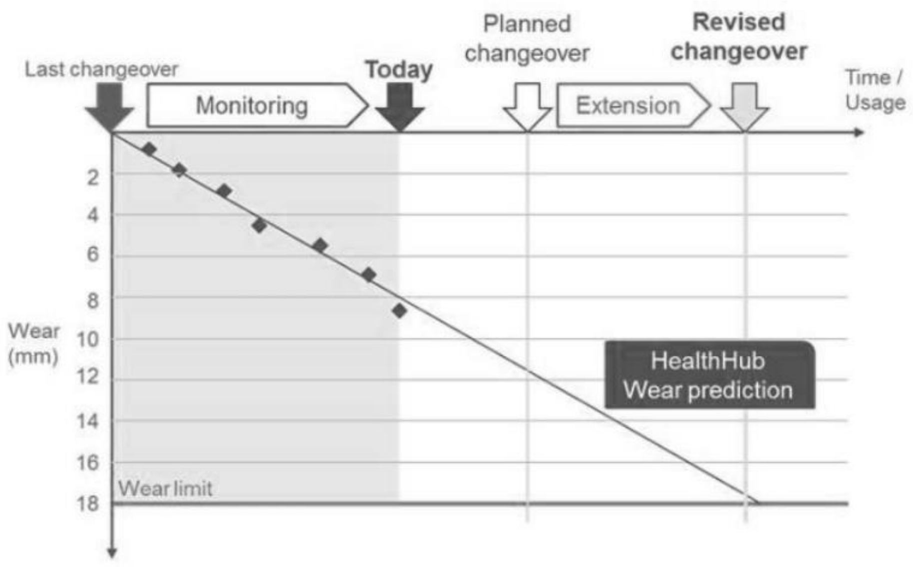


Figure 3.3 – Exemple of the prediction algoritm [9].

Annex A presents in a more detailed chart showing the exchange of data between the different modules that compose the system when a new train passes by a Health Hub.

3.2. Web Application

The web application allows the user to interact with the system and to access all of its functionalities allowing the user to view the status of the fleet and trains.

3.2.1. **Dashboard**

The train maintenance dashboard presents a view where one can easily see the status of all the trains in a fleet (Figure 3.4).

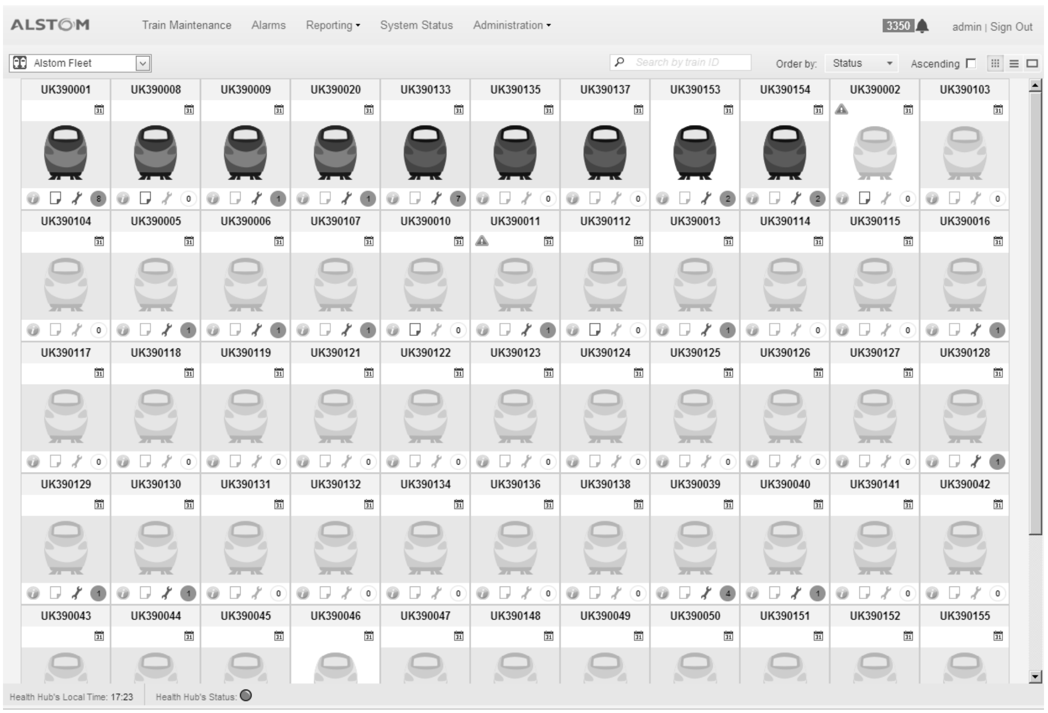


Figure 3.4 - Dashboard in grid view.

Each train is presented, with a cell similar to Figure 3.5.

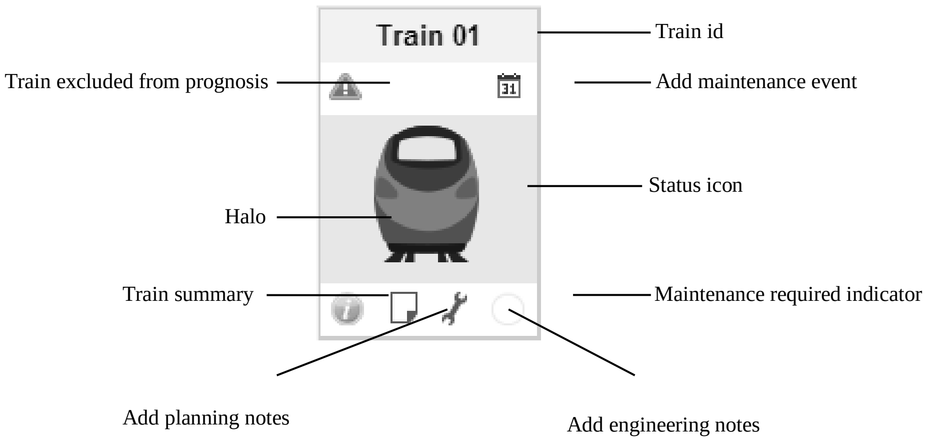


Figure 3.5 - Train Cell.

The items in this cell, show additional information when hovered, such as the number of engineering notes, planning notes and train state (based on the halo).

The information on the cell includes:

- The train id;

- Its last perceived status: the color of the train icon; it can be one of:
    - Grey: no data exists for the train; this should rarely, if ever, happen;
    - Green: everything seems to be OK with the train;
    - Amber: there may be some problems with the train, but nothing that requires immediate attention. This can occur when the scrap RUL warning distance of the train or one of its components is less than the distance to the train's next exam.
    - Red: some problems with the train require immediate attention. This can occur when the scrap RUL distance of the train or one of its components is less than the distance to the train's next exam.
- The train's halo can indicate a number of issues, dependent on its color. The color it takes can be one of:
    - White: everything is OK.
    - Blue: can mean that the train has not been measured since its last maintenance date, the train has not been measured for at least 3 days, or that the train has not been measured since the last time an alert was acknowledged for that train.
    - Red: action is required. This can indicate that there are unacknowledged alerts on the train; that the train is due for service; or that the train's expected RUL is less than or equal to zero.
- Whether the train has associated with it engineering notes, through a color scheme:
    - The train has engineering notes;

   - The train does not have engineering notes.

- Whether the train has maintenance notes:
   - The train has maintenance notes;
   - The train does not have maintenance notes.

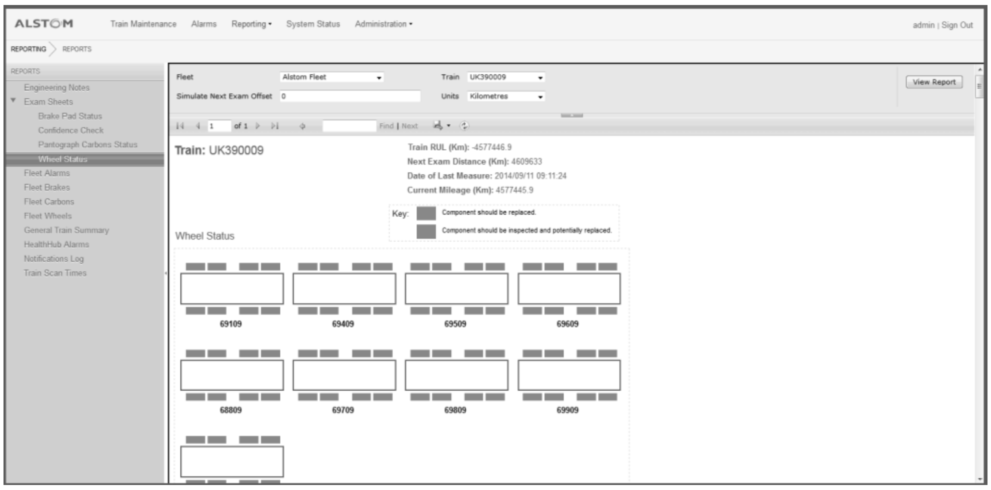
- Whether the train it has any anomalies:
   - The train has associated anomalies;
   - The train does not have any associated anomalies;

- If a train has been excluded from prognosis, indicated by a warning triangle ( )

Besides presenting this information, by clicking on the summary icon ( ) we are given a selection of information about the train.

3.2.2. **Reports**

The Reports module allows the user to generate the reports available in the SQL Server Reporting Server (Figure 3.6). These reports are also sent automatically when any anomaly is detected in the train.



Fleet: Alstom Fleet
Train: UK390009
Simulate Next Exam Offset: 0
Units: Kilometres
1 of 1

Train: UK390009

Train RUL (Km): -4577446.9
Next Exam Distance (Km): 4609633
Date of Last Measure: 2014/09/11 09:11:24
Current Mileage (Km): 4577445.9

Key:
▨ Component should be replaced.
▨ Component should be inspected and potentially replaced.

Figure 3.6- Exemple report.

3.2.3. **Dynamic and Wear Analysis**

These modules are basically modules that allow the user to display data over time (Dynamic Analysis) or over the train mileage (Wear Analysis). An example of the Wear Analysis module is presented in Figure 3.7.

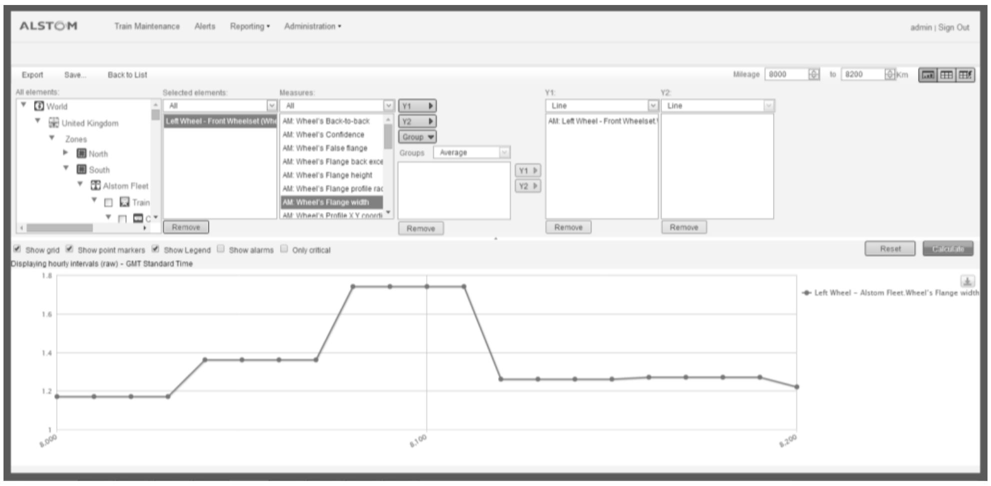


Figure 3.7 - Wear Analysis display example.

3.2.4. **Real-Time Status Information**

The module presents a display similar to that in Figure 3.8. The status of the Health Hub monitoring systems is indicated by the Red/Green indicators. The example in Figure 3.8 shows that the Health Hub is currently operating as expected.

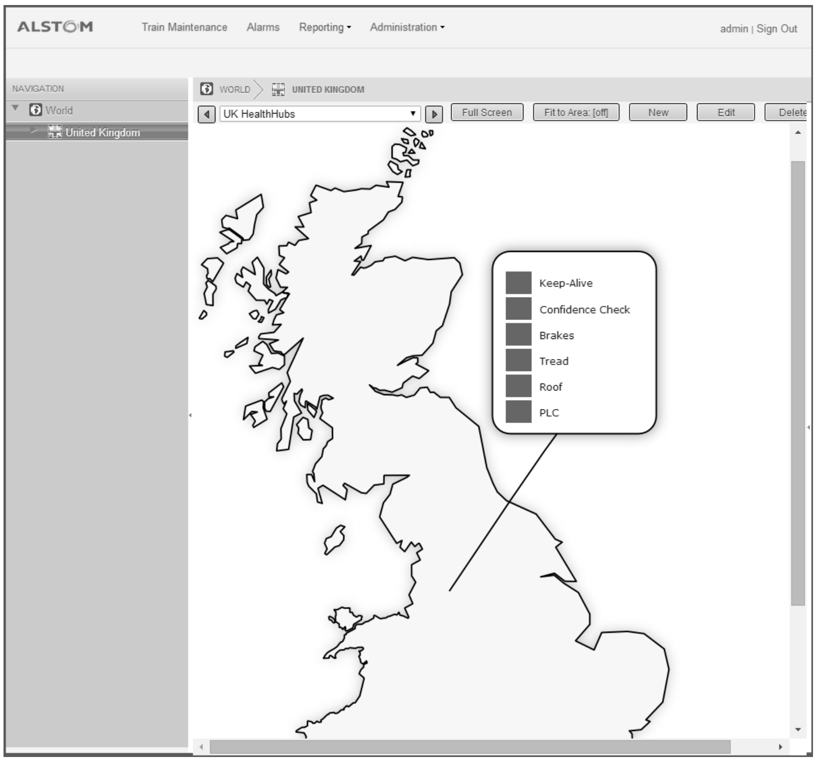
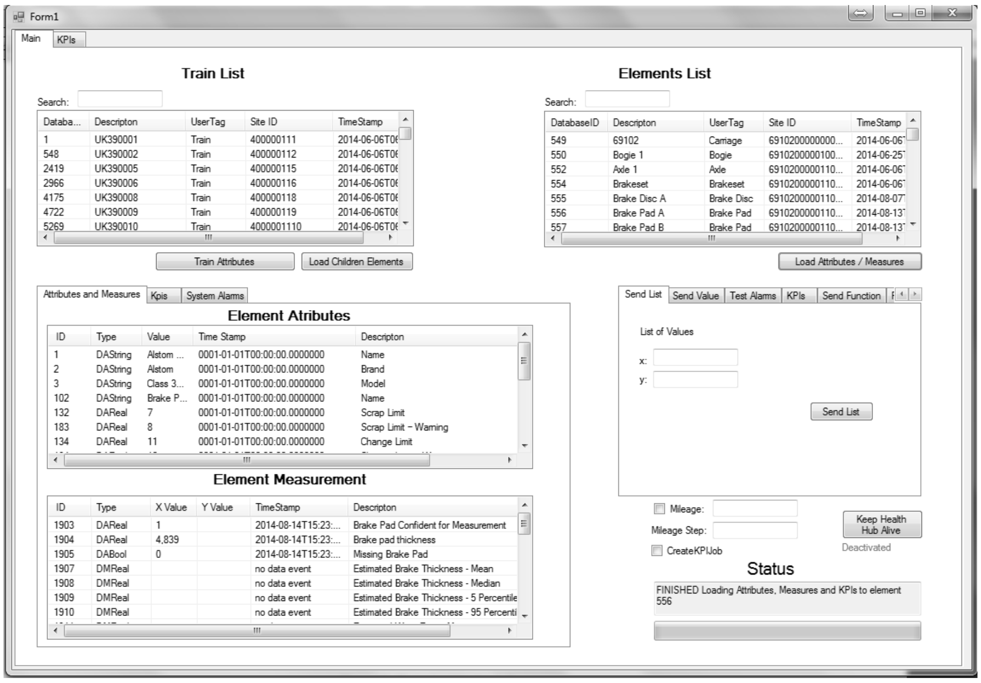


Figure 3.8 - The real-time view module.

The indicators in the real-time view are driven by the alerts received from the subsystems.

3.2.5. **Test Tool**

A request from the client was a tool to test all the features of web application that could be used by any person without vast software engineering knowledge. Regarding that a Gui was developed in C# [10] that test every features described in this document Figure 3.9.



Databa...	Descripton	UserTag	Site ID	TimeStamp
1	UK390001	Train	400000111	2014-06-06T0
548	UK390002	Train	400000112	2014-06-06T0
2419	UK390005	Train	400000115	2014-06-06T0
2966	UK390006	Train	400000116	2014-06-06T0
4175	UK390008	Train	400000118	2014-06-06T0
4722	UK390009	Train	400000119	2014-06-06T0
5269	UK390010	Train	4000001110	2014-06-06T0

DatabaseID	Descripton	UserTag	Site ID	TimeStamp
549	69102	Carriage	6910200000000...	2014-06-06T
550	Bogie 1	Bogie	6910200000100...	2014-06-25T
552	Axle 1	Axle	6910200000110...	2014-06-06T
554	Brakeset	Brakeset	6910200000110...	2014-06-06T
555	Brake Disc A	Brake Disc	6910200000110...	2014-08-07T
556	Brake Pad A	Brake Pad	6910200000110...	2014-08-13T
557	Brake Pad B	Brake Pad	6910200000110...	2014-08-13T

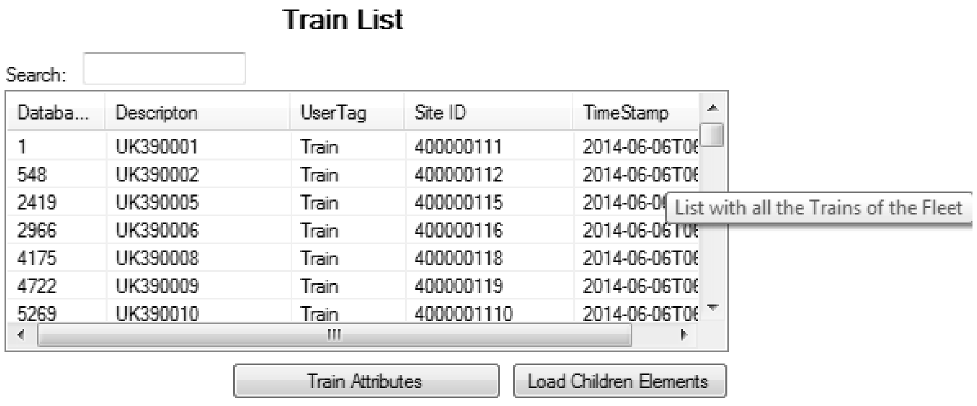
ID	Type	Value	Time Stamp	Descripton
1	DAString	Alstom ...	0001-01-01T00:00:00.0000000	Name
2	DAString	Alstom	0001-01-01T00:00:00.0000000	Brand
3	DAString	Class 3...	0001-01-01T00:00:00.0000000	Model
102	DAString	Brake P...	0001-01-01T00:00:00.0000000	Name
132	DAReal	7	0001-01-01T00:00:00.0000000	Scrap Limit
183	DAReal	8	0001-01-01T00:00:00.0000000	Scrap Limit – Warning
134	DAReal	11	0001-01-01T00:00:00.0000000	Change Limit

ID	Type	X Value	Y Value	TimeStamp	Descripton
1903	DAReal	1		2014-08-14T15:23:...	Brake Pad Confident for Measurement
1904	DAReal	4,839		2014-08-14T15:23:...	Brake pad thickness
1905	DABool	0		2014-08-14T15:23:...	Missing Brake Pad
1907	DMReal			no data event	Estimated Brake Thickness - Mean
1908	DMReal			no data event	Estimated Brake Thickness - Median
1909	DMReal			no data event	Estimated Brake Thickness - 5 Percentile
1910	DMReal			no data event	Estimated Brake Thickness - 95 Percenti

FINISHED Loading Attributes, Measures and KPIs to element 556

Figure 3.9 – Alstom Health Hub Test Tool.

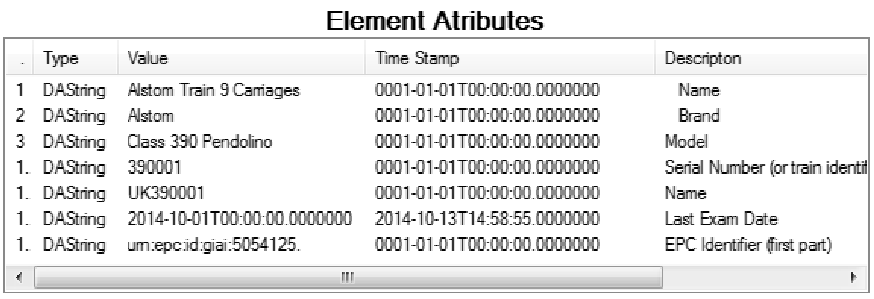
This tool basically interacts with developed framework in order to simulate the monitoring systems behavior and test the result in the developed front end. Initially the tool loads all the trains of the fleet and displays them in a list view.



Databa...	Descripton	UserTag	Site ID	TimeStamp
1	UK390001	Train	400000111	2014-06-06T0
548	UK390002	Train	400000112	2014-06-06T0
2419	UK390005	Train	400000115	2014-06-0
2966	UK390006	Train	400000116	2014-06-06T0
4175	UK390008	Train	400000118	2014-06-06T0
4722	UK390009	Train	400000119	2014-06-06T0
5269	UK390010	Train	4000001110	2014-06-06T0

Figure 3.10 – List with all the fleet trains.

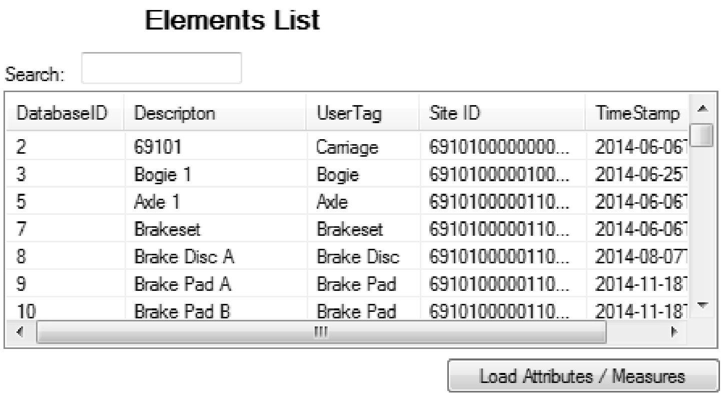
The user is then able to load the train attributes (Figure 3.11) and also load the train components (Figure 3.12).



Element Atributes

.	Type	Value	Time Stamp	Descripton
1	DAString	Alstom Train 9 Carriages	0001-01-01T00:00:00.0000000	Name
2	DAString	Alstom	0001-01-01T00:00:00.0000000	Brand
3	DAString	Class 390 Pendolino	0001-01-01T00:00:00.0000000	Model
1.	DAString	390001	0001-01-01T00:00:00.0000000	Serial Number (or train identi
1.	DAString	UK390001	0001-01-01T00:00:00.0000000	Name
1.	DAString	2014-10-01T00:00:00.0000000	2014-10-13T14:58:55.0000000	Last Exam Date
1.	DAString	urn:epc:id:giai:5054125.	0001-01-01T00:00:00.0000000	EPC Identifier (first part)

Figure 3.11 - Example of train attributes.



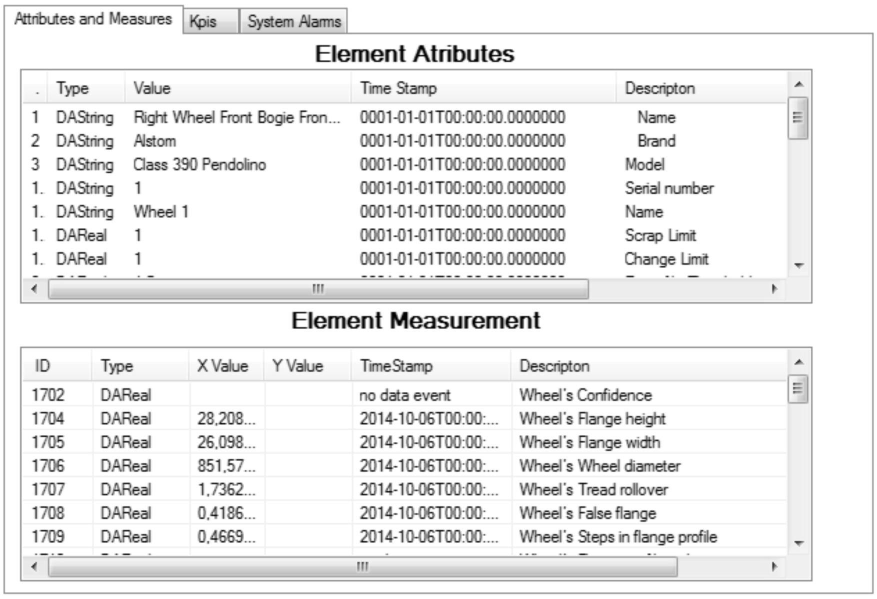
Elements List

Search:

DatabaseID	Descripton	UserTag	Site ID	TimeStamp
2	69101	Carriage	6910100000000...	2014-06-06T
3	Bogie 1	Bogie	6910100000100...	2014-06-25T
5	Axle 1	Axle	6910100000110...	2014-06-06T
7	Brakeset	Brakeset	6910100000110...	2014-06-06T
8	Brake Disc A	Brake Disc	6910100000110...	2014-08-07T
9	Brake Pad A	Brake Pad	6910100000110...	2014-11-18T
10	Brake Pad B	Brake Pad	6910100000110...	2014-11-18T

Figure 3.12 - List with all the train components.

For the wearable components is possible to test the associated measures to test the implemented alarms and abnormal end of life.



Element Atributes

.	Type	Value	Time Stamp	Descripton
1	DAString	Right Wheel Front Bogie Fron...	0001-01-01T00:00:00.0000000	Name
2	DAString	Alstom	0001-01-01T00:00:00.0000000	Brand
3	DAString	Class 390 Pendolino	0001-01-01T00:00:00.0000000	Model
1.	DAString	1	0001-01-01T00:00:00.0000000	Serial number
1.	DAString	Wheel 1	0001-01-01T00:00:00.0000000	Name
1.	DAReal	1	0001-01-01T00:00:00.0000000	Scrap Limit
1.	DAReal	1	0001-01-01T00:00:00.0000000	Change Limit

Element Measurement

ID	Type	X Value	Y Value	TimeStamp	Descripton
1702	DAReal			no data event	Wheel's Confidence
1704	DAReal	28,208...		2014-10-06T00:00:...	Wheel's Flange height
1705	DAReal	26,098...		2014-10-06T00:00:...	Wheel's Flange width
1706	DAReal	851,57...		2014-10-06T00:00:...	Wheel's Wheel diameter
1707	DAReal	1,7362...		2014-10-06T00:00:...	Wheel's Tread rollover
1708	DAReal	0,4186...		2014-10-06T00:00:...	Wheel's False flange
1709	DAReal	0,4669...		2014-10-06T00:00:...	Wheel's Steps in flange profile

Figure 3.13 - Example of wheel attributes and measures.

Several automated tests include activate train alarms, send measurements overtime to simulated usual train measures, simulated good and bad prognosis for a train, automated report generation and user notifications when alarms are generated and basically almost every developed functionality.

To improve traceability usually each test has a description of the implemented feature and a link to the client requirement to fundament why that feature was developed. An example of a test is presented in Figure 3.14

TEST CASE SPECIFICATION		
Test Case Identifier:	*ATHEHUVV-TCS-CSWT-0013*	
Responsibility:	*CSWT*	
Requirement:	*AHH-124 - ENG-REQ-011* *AHH-152 - ENG-REQ-028*	
Purpose:	*AHH-321 - Post-processing trigger (Alarms/KPI/Alerts)*	
Author(s):	*Ricardo Jorge Duarte Ferreira*	
Test Item(s):		
As the Post-Processing service, I want the common repository to alert me when new measurements are available, so that the various analysis processes can be run on the new data. (This is for the functionality covered within the DE Core). *AC-1: New measurement data triggers an alert to the Post-Processing service* *AC-2: KPI calculations must be calculated in a specific order* *NOTE: The trigger mechanism still needs to be agreed by all parties.*		
	Input Specifications:	**Output Specifications**
Step 1	• Go to "https://svn/engineering/projects/alstom-transport/ATHEHU-health-hub/work-products/test/GeneralApp" and open the OSACBMSimpleTest application. • Select the desired Train and click "Load Train Elements". Wait for the application load the elements for that train then select the desired element. • In the 'Several' tab, click on "Test Cranfield Algorithms"	• *New measures will be entered into the database for the selected train.*
Step 2	• *Run the following script in the database:* • `SELECT * FROM DYNAMIC_JOB` • `WHERE JOB_ID = 1` • `ORDER BY DJB_CREATION_TIMESTAMP DESC`	• *There will be a recently entered "CranfieldJobExecutor" job in the Dynamic_Job table.*
Environment Requirements:		
• *None*		
Special Procedural Requirements:		
• *To confirm that KPIs are working properly should also be confirmed that the log KPIDemandJob.txt in the scheduler should have no "ERROR" entries.*		
Inter-case Dependencies:		
• *None*		
Last execution date:		
05-Jul-2014 11:05:19		
Current status:		
PASSED		

Figure 3.14 – Test Example.

In the end, a test matrix was created (Figure 3.15) with the entire tests and the associated requirements that will then be used in the software acceptance tests.

Key	Summary	Test Identifier	Status	Comments
AHH-105	ENG-REQ-001.1	*ATHEHUVV-TCS-CSWT-0001*	**Passed**	
AHH-106	ENG-REQ-001.2	*ATHEHUVV-TCS-CSWT-0002*	**Passed**	
AHH-107	ENG-REQ-001.3	*ATHEHUVV-TCS-CSWT-0003*	**Passed**	
AHH-108	ENG-REQ-002.1	*ATHEHUVV-TCS-CSWT-0004*	**Passed**	
AHH-109	ENG-REQ-002.2	*ATHEHUVV-TCS-CSWT-0005*	**Passed**	
AHH-110	ENG-REQ-002.3	*ATHEHUVV-TCS-CSWT-0006*	**Failed**	
		ATHEHUVV-TCS-CSWT-0007	**Passed**	
AHH-111	ENG-REQ-002.4	*ATHEHUVV-TCS-CSWT-0008*	**Passed**	
AHH-112	ENG-REQ-003	--	--	*Deleted*
AHH-113	ENG-REQ-004	--	--	*These are not a software requirement, but a reflection of the expectation has been made clear to Alstom that this relates mainly to their system availability when in environment and IT support service.*
AHH-114	ENG-REQ-005.1	--	--	
AHH-115	ENG-REQ-005.2	--	--	
AHH-116	ENG-REQ-005.3	--	--	

Figure 3.15 – Test Matrix.

As the developed software can be reused for different applications with much less initial effort of implementation so does the test tool, that also can be reused in different software that uses the same framework with minor changes.

CHAPTER 4

Arrive Project

4.1. Introduction

The *Arrive* project is a new project that will monitor rotational machines and will present health indicators regarding asset condition.

The implemented system architecture is based on OSA-CBM similar to Alstom Health Hub Project. Figure 4.1 represents the interactions of all the intervenient in the proposed framework.

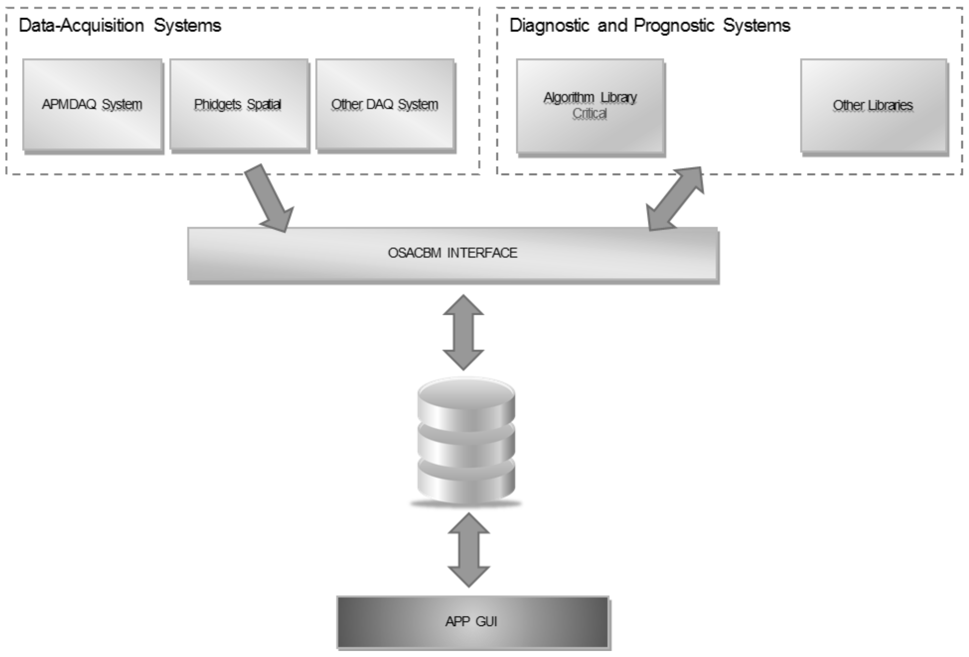
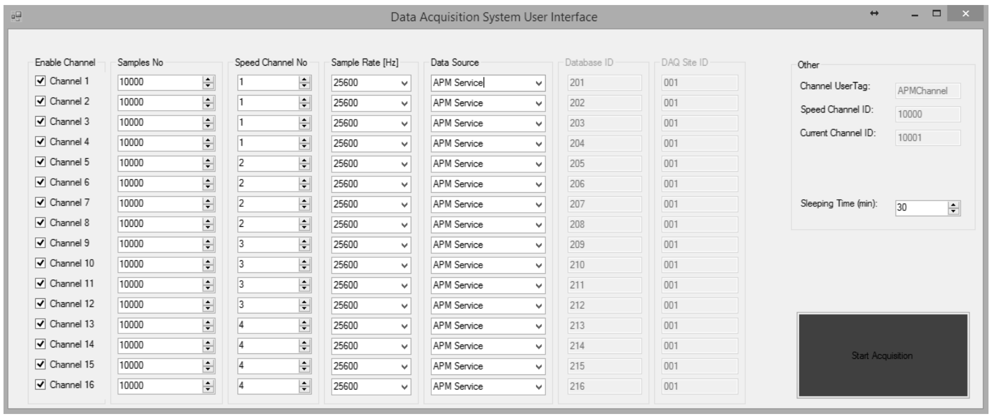


Figure 4.1 - Interface between the Systems and the Common Repository.

Basically two independent blocks were developed. The data acquisition system block (Figure 4.1) consists in a GUI (Figure 4.2) that was built in C# language and is main purpose is to send vibration data to the database. After the data is sent the diagnostic and prognostic system (Figure 4.1) is triggered. It consists in a web service that can be deployed on a server and it remains waiting until is triggered with an OSA-CBM request and is detailed in CHAPTER 5 of this document.

This web service consists in calculation of the entire developed algorithms based on the most recent signal and then the obtained values are sent to the database using OSA-CBM interface.



Data Acquisition System User Interface

Enable Channel	Samples No	Speed Channel No	Sample Rate [Hz]	Data Source	Database ID	DAQ Site ID
✓ Channel 1	10000	1	25600	APM Service	201	001
✓ Channel 2	10000	1	25600	APM Service	202	001
✓ Channel 3	10000	1	25600	APM Service	203	001
✓ Channel 4	10000	1	25600	APM Service	204	001
✓ Channel 5	10000	2	25600	APM Service	205	001
✓ Channel 6	10000	2	25600	APM Service	206	001
✓ Channel 7	10000	2	25600	APM Service	207	001
✓ Channel 8	10000	2	25600	APM Service	208	001
✓ Channel 9	10000	3	25600	APM Service	209	001
✓ Channel 10	10000	3	25600	APM Service	210	001
✓ Channel 11	10000	3	25600	APM Service	211	001
✓ Channel 12	10000	3	25600	APM Service	212	001
✓ Channel 13	10000	4	25600	APM Service	213	001
✓ Channel 14	10000	4	25600	APM Service	214	001
✓ Channel 15	10000	4	25600	APM Service	215	001
✓ Channel 16	10000	4	25600	APM Service	216	001

Other

Channel UserTag: APMChannel
Speed Channel ID: 10000
Current Channel ID: 10001
Sleeping Time (min): 30

Start Acquisition

Figure 4.2 - Implemented data acquisition system user interface.

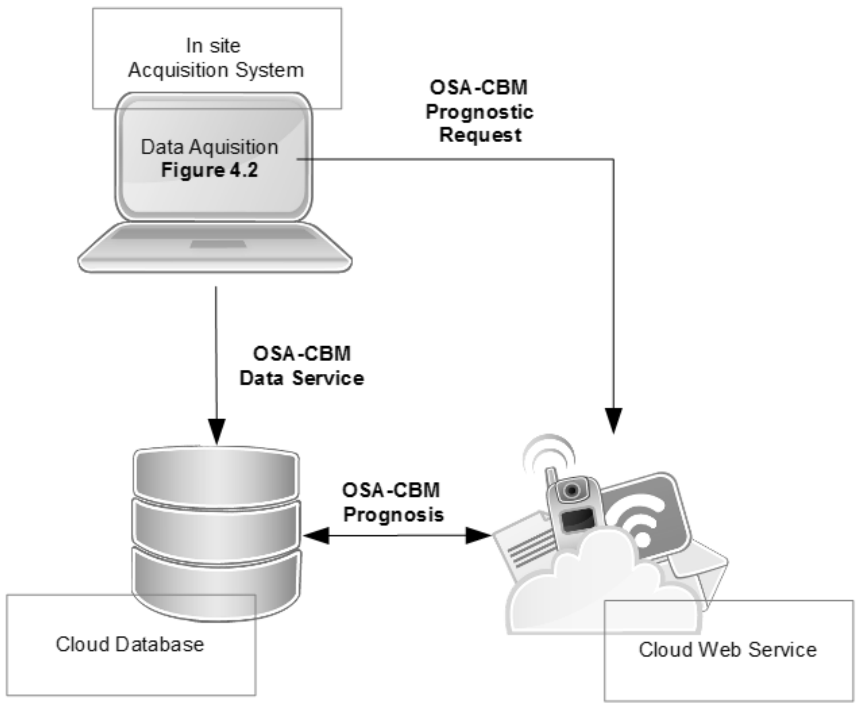


Figure 4.3 – Developed system architecture.

4.2. Technical Details

The technical purpose of vibration CBM is to analyze vibration data in both the time and frequency domain such that identification, diagnosis and prognosis of incipient faults may be inferred and the RUL of the asset or component estimated. In its simplest form this is accomplished by observing changes in specific parameters, such as the overall RMS value; when the value increases above a certain threshold relative to a baseline value the existence of a fault is implied. Various signal processing techniques may be employed to reduce background noise and separate out key features in the signal such that specific faults may be identified and diagnosed.

The CBM process consists of several stages:

- Data Acquisition - including the use of suitable transducers and ideal positioning/mounting;
- Data Storage - method of storing large data sets efficiently;
- Signal Processing - main body of CBM; Filtering, feature extraction, diagnosis/prognosis algorithms, etc;
- Data trending - Trend data over time such that anomalous conditions may be identified;
- Review- measurement intervals, threshold alarms etc.

A commonly used flowchart in this kind of applications is shown in Figure 4.4.

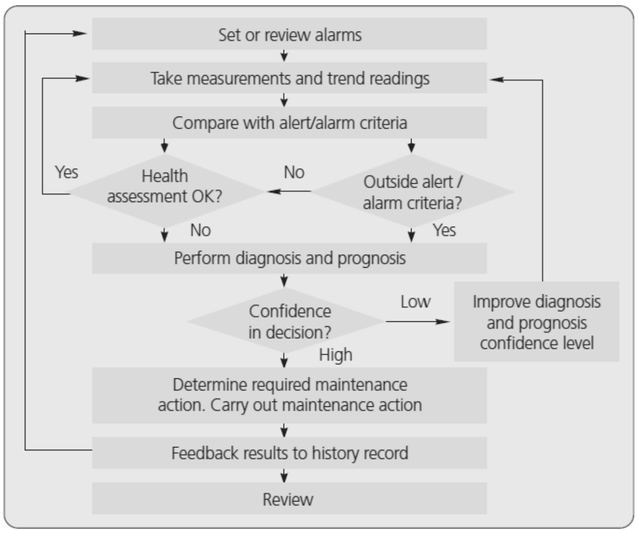

Set or review alarms
Take measurements and trend readings
Compare with alert/alarm criteria
Yes
Health assessment OK?
No
Outside alert / alarm criteria?
No
Yes
Perform diagnosis and prognosis
Confidence in decision?
Low
Improve diagnosis and prognosis confidence level
High
Determine required maintenance action. Carry out maintenance action
Feedback results to history record
Review

Figure 4.4 - ISO 17359 CBM flow diagram covering collection, analysis and assessment.

4.2.1. **Monitoring Equipment**

The choice of transducer is key to the effectiveness the subsequent CBM process has at identifying incipient faults. The bandwidth of a transducer defines the frequency range within which the transducer, usually an accelerometer, can operate within. The bandwidth is defined as half of the sample rate and the frequency response within this range is usually defined as flat within +/-3dB, therefore a sample rate must be chosen that is at least twice as large as the maximum frequency intended to be measured.

Attention must also be paid to the resonance frequency of the accelerometer as this will cause a marked deviation from the +/-3dB flat response. Most accelerometers are designed such that the resonant frequency is well above the maximum frequency to be measured, though insufficient mounting methods may cause this resonance to lower into the measurement range.

In the current project, two approaches were followed for the data acquisition. The first approach was done using a presented in Figure 4.5 which is a Phidgets Spatial.

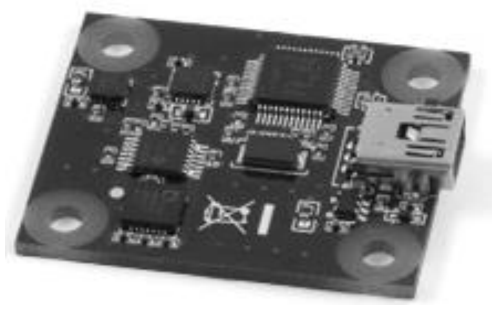


Figure 4.5 - Phidgets Spatial [11].

This is a relatively inexpensive accelerometer with a short bandwidth of 497Hz and a maximum acceleration measurement of +/-2g. A good advantage of this system is that it provides support for several programming languages with a simple search in the Internet. Due to the short bandwidth and small measurement range limitations are made on the type of fault which this accelerometer will be able to detect under given circumstances. Figure 4.6 is a typical trouble shooting table for vibration condition monitoring. As can be seen many faults occur within the first or second harmonics of the shaft rotational speed hence the bandwidth of the Phidgets accelerometer is adequate for those particular faults up to rotational speeds of approximately 15000 rpm such that the second harmonic is captured. The assets of interest in this project, namely marine craft rarely exceed rotational speeds of 2000RPM hence the Phidgets accelerometer has a broad band width enough to capture the first 14 harmonics (at 2000RPM).

Trouble arises when attempting to extract features specific to gear or bearing faults as they occur at frequencies many times above the rotational speed of the shaft. For instance the gear meshing frequency about which side bands occur which are indicative of the state of the gears occurs at a frequency equal to the number of gear teeth multiplied by the RPM of the gear wheel. Hence depending on the number of teeth on the gear wheel the meshing frequency could occur well outside the range of 500Hz, making the identification of gear faults impossible. For more detail on usual vibration faulty components see Figure 4.6.

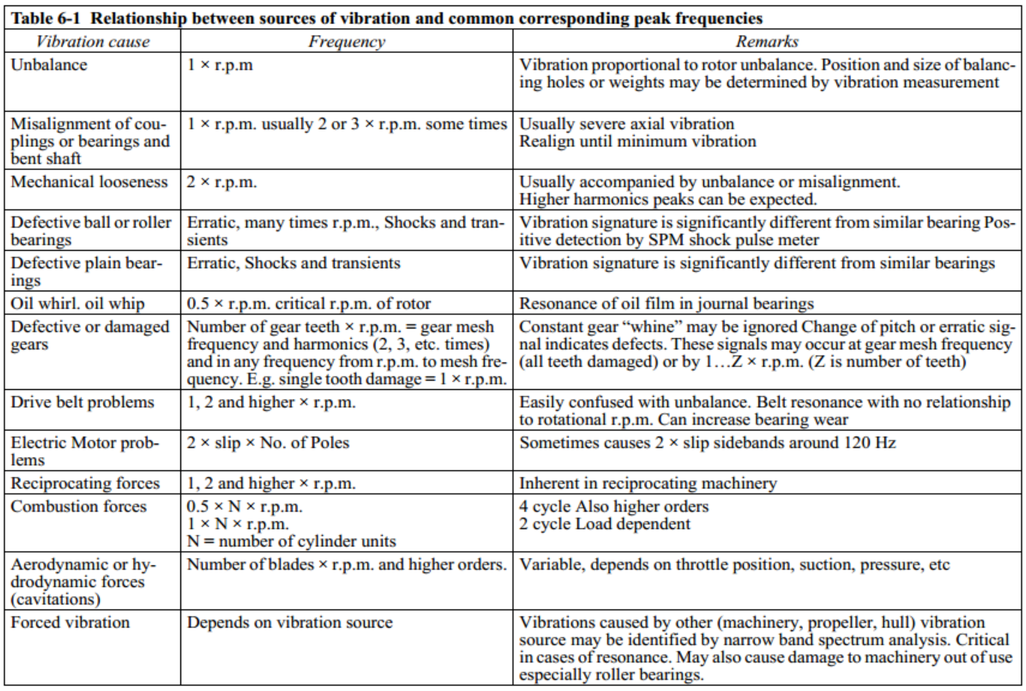


Table 6-1 Relationship between sources of vibration and common corresponding peak frequencies		
Vibration cause	*Frequency*	*Remarks*
Unbalance	1 × r.p.m	Vibration proportional to rotor unbalance. Position and size of balancing holes or weights may be determined by vibration measurement
Misalignment of couplings or bearings and bent shaft	1 × r.p.m. usually 2 or 3 × r.p.m. some times	Usually severe axial vibration Realign until minimum vibration
Mechanical looseness	2 × r.p.m.	Usually accompanied by unbalance or misalignment. Higher harmonics peaks can be expected.
Defective ball or roller bearings	Erratic, many times r.p.m., Shocks and transients	Vibration signature is significantly different from similar bearing Positive detection by SPM shock pulse meter
Defective plain bearings	Erratic, Shocks and transients	Vibration signature is significantly different from similar bearings
Oil whirl. oil whip	0.5 × r.p.m. critical r.p.m. of rotor	Resonance of oil film in journal bearings
Defective or damaged gears	Number of gear teeth × r.p.m. = gear mesh frequency and harmonics (2, 3, etc. times) and in any frequency from r.p.m. to mesh frequency. E.g. single tooth damage = 1 × r.p.m.	Constant gear "whine" may be ignored Change of pitch or erratic signal indicates defects. These signals may occur at gear mesh frequency (all teeth damaged) or by 1…Z × r.p.m. (Z is number of teeth)
Drive belt problems	1, 2 and higher × r.p.m.	Easily confused with unbalance. Belt resonance with no relationship to rotational r.p.m. Can increase bearing wear
Electric Motor problems	2 × slip × No. of Poles	Sometimes causes 2 × slip sidebands around 120 Hz
Reciprocating forces	1, 2 and higher × r.p.m.	Inherent in reciprocating machinery
Combustion forces	0.5 × N × r.p.m. 1 × N × r.p.m. N = number of cylinder units	4 cycle Also higher orders 2 cycle Load dependent
Aerodynamic or hydrodynamic forces (cavitations)	Number of blades × r.p.m. and higher orders.	Variable, depends on throttle position, suction, pressure, etc
Forced vibration	Depends on vibration source	Vibrations caused by other (machinery, propeller, hull) vibration source may be identified by narrow band spectrum analysis. Critical in cases of resonance. May also cause damage to machinery out of use especially roller bearings.

Figure 4.6 - Typical vibration trouble shooting chart for CBM .

Another approach for acquiring vibration was also tested using a high spec data acquisition system from Beran (Figure 4.7) that allows more focus on the signal processing techniques.

Figure 4.7 - Beran 720 Auxiliary Plant Monitor [12].

This is a much more advance acquisition system and its main features are:

Specifications:	
Dimensions (mm) 3	60 x 140 x 60
Measurement Inputs	16 channels of vibration or process inputs: accelerometer; velocity transducer; eddy current probe; process inputs, e.g. 4-20mA, 0-1V, 0-10V
Acquisition	Vibration/process: 24-bit A/D converters with 20kHz bandwidth per channel
Speed Inputs	4 channels including power output for transducers

Data Transfer	Via USB memory stick or Ethernet
Connectivity	Ethernet 10/100 BaseT RJ45 connector
Power Supply	10Vdc to 36Vdc <50W
Temperature Range	-20ºC to +60ºC (operating) -40ºC to +75ºC (storage)

Figure 4.8 – Beran main specifications [13].

4.2.1.1. Beran 720 Auxiliary Plant

The Beran 720 system when connected to Ethernet creates a web service that can be used to send data to any application.

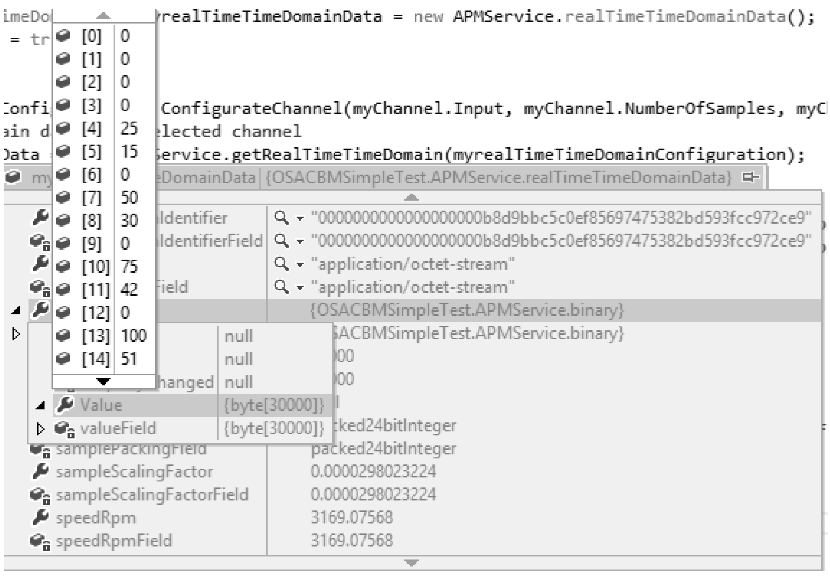
To acquire data from this service, it is necessary to add a service reference to the Microsoft Visual Studio Solution with namespace set to APMService and the desired IP.

The references in the code to APMService are references to the WCF automatically generated code created when the Service Reference is added. As an example of the ease of development with web services, the following code demonstrates a simple VB.NET application to acquire the data:

```
//Create new Service
var my720ApmService = new
APMService.ServicePortTypeClient("APMService","http://localhost:88");

//Get configuration
var my720ApmConfiguration = new APMService.apmConfiguration();

//Initialize Real Time Domain Configuration
var myrealTimeTimeDomainConfiguration = new
APMService.realTimeTimeDomainConfiguration();
//Initialize Real Time Domain Data

var myrealTimeTimeDomainData = new APMService.realTimeTimeDomainData();

// Configure Channel
myrealTimeTimeDomainConfiguration = ConfigurateChannel(myChannel.Input,
myChannel.NumberOfSamples, myChannel.SpeedChannel, myChannel.SampleRate);

// Get Real Time Domain data from selected channel
myrealTimeTimeDomainData =
my720ApmService.getRealTimeTimeDomain(myrealTimeTimeDomainConfiguration);
```

More info on the methods available on the APMService can be consulted using the “720 APM Open Interface Version 2 – Technical Note”.

The data is sent to the object “*myrealTimeTimeDomainData”* in binary packages and was necessary to convert it to an integer (Figure 4.9).



```
imeDo      realTimeTimeDomainData = new APMService.realTimeTimeDomainData();
 = tr
Confi      ConfigurateChannel(myChannel.Input, myChannel.NumberOfSamples, myC
ain d      elected channel
Data       Service.getRealTimeTimeDomain(myrealTimeTimeDomainConfiguration);
my         eDomainData | {OSACBMSimpleTest.APMService.realTimeTimeDomainData}

[0]  0                         lIdentifier       "0000000000000000000b8d9bbc5c0ef85697475382bd593fcc972ce9"
[1]  0                         lIdentifierField  "0000000000000000000b8d9bbc5c0ef85697475382bd593fcc972ce9"
[2]  0                                           "application/octet-stream"
[3]  0                         Field             "application/octet-stream"
[4]  25                                          {OSACBMSimpleTest.APMService.binary}
[5]  15                                          SACBMSimpleTest.APMService.binary}
[6]  0                                           00
[7]  50                                          00
[8]  30                                          l
[9]  0                                           ked24bitInteger
[10] 75    null            samplePackingField    packed24bitInteger
[11] 42    null            sampleScalingFactor   0.0000298023224
[12] 0     hanged  null    sampleScalingFactorField 0.0000298023224
[13] 100   Value      {byte[30000]}   speedRpm   3169.07568
[14] 51    valueField {byte[30000]}   speedRpmField 3169.07568
```

Figure 4.9 – Data Received from the APM Service.

Has the data is coming in pack of 3, first was necessary to combine all the packs in binary string. This was done using the following lines of code:

```
// Shift the data to 24 bits
int[] CurrentBinary = new int[3];
CurrentBinary[i] = 0;
CurrentBinary[i] = myrealTimeTimeDomainData.data.Value[refField] << 8;
CurrentBinary[i]              =              CurrentBinary[i]           +
myrealTimeTimeDomainData.data.Value[refField + 1] << 8;
     CurrentBinary[i]=CurrentBinary[i]+
myrealTimeTimeDomainData.data.Value[refField + 2];
```

After having the full value in a string, was necessary to convert it to a 32 bit binary string in order to use the method “Convert.ToInt32”. This was done using the following lines:

```
//Convert 24 bits to 32 bits signed and convert to scaling units
CurrentBinaryString[i] = Convert.ToString(CurrentBinary[i], 2).PadLeft(24,
'0');
CurrentBinaryString[i] = CurrentBinaryString[i].PadLeft(32,
CurrentBinaryString[i][0]);
     Current[i]=Convert.ToInt32(CurrentBinaryString[i],2)
      *myrealTimeTimeDomainData.sampleScalingFactor;
```

The corresponding Speed Channel is easily supplied using the simple method:

```
//Acquire Speed Value
RPMSpeed = myrealTimeTimeDomainData.speedRpm;
```

To send then the values to the Database, is necessary to build “OSACBMHealthHubDataService.Site”. An Example is shown below:

```
  var elementSite = new OSACBMHealthHubDataService.Site()
{
      //example of site constrution from DAPort (section 5.1.2.1)
      category = OSACBMHealthHubDataService.SITE_CATEGORY.SITE_SPECIFIC,
      siteId = DatabaseId,
      userTag = "APMChannel",
      regId = MIMOSA_REGID,
      systemUserTag = HEALTH_HUB_NAME
};
```

After build the site, is necessary to set send the data. As it's intended to send two different measures, the "OSACBMHealthHubDataService.DataEvent" is initialized like the following:

```
//now set the measure data values
var dataToSet = new OSACBMHealthHubDataService.DataEvent[2];

It is also necessary to define a timestamp for the data. This can be done
using the "OSACBMHealthHubDataService.OsacbmTime()":

  var measureTimestamp = new OSACBMHealthHubDataService.OsacbmTime()
            {
                time_type =
OSACBMHealthHubDataService.OsacbmTimeType.OSACBM_TIME_MIMOSA,
                time = DateTime.UtcNow.ToString("O")
            };
```

After it is possible to send the values for Speed and Current measures:

```
//Send Speed Measure to Database
SetDataEvent(ref dataToSet, ref pos, elementSite, measureTimestamp,
ANM_ID_Speed, currentvalue.SpeedValue);

// Send current Values to Database
SetDataEvent(ref dataToSet, ref pos, elementSite, measureTimestamp,
ANM_ID_Current, currentvalue.CurrentValue, currentvalue.Time);

var measureDataSet = new OSACBMHealthHubDataService.DataEventSet()
                    {
                        site = elementSite,
                        id = Convert.ToUInt32(elementId),
                        time = measureTimestamp,
                        dataEvents = dataToSet
                    };

var setDataResultStatus =
serviceDataProxy.serviceNotifyDataEventSet(measureDataSet);
System.Console.WriteLine("Set measure data return: [\n{0}\n]",
                        setDataResultStatus);
```

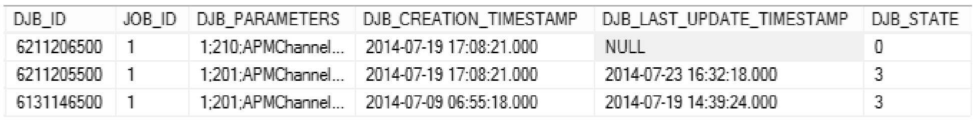
If the data was sent to the database successfully a message is displayed saying the transaction was "OK".

After sending all the values is necessary to inform the "Front End Interface" that new data is available in order to trigger the processing of the algorithms.

This is done using the following lines:

```
//finish indication
serviceProxy.epNotifyApp(
new OSACBMConfigurationLibraryService.Parameter[4] {
new
OSACBMConfigurationLibraryService.GeneralParameter(){datatype=OSACBMConfigura
tionLibraryService.XmlDataType.@string, name="MEASURESETFINISH",
value="ROOF"},
new
OSACBMConfigurationLibraryService.GeneralParameter(){datatype=OSACBMConfigura
tionLibraryService.XmlDataType.@string, name="RFID",
value=CurrentValues[0].Channel.ParentSiteId},
new
OSACBMConfigurationLibraryService.GeneralParameter(){datatype=OSACBMConfigura
tionLibraryService.XmlDataType.@string, name="HEALTHHUB",
value=HEALTH_HUB_NAME},
new
OSACBMConfigurationLibraryService.GeneralParameter(){datatype=OSACBMConfigura
tionLibraryService.XmlDataType.dateTime,name="TIMESTAMP",
value=measureTimestamp.time},  } );
```

This will insert in the table Dynamic_Jobs, a job indicating that new data was received for the selected Data Acquisition System like showed in Figure 4.10.



DJB_ID	JOB_ID	DJB_PARAMETERS	DJB_CREATION_TIMESTAMP	DJB_LAST_UPDATE_TIMESTAMP	DJB_STATE
6211206500	1	1;210;APMChannel...	2014-07-19 17:08:21.000	NULL	0
6211205500	1	1;201;APMChannel...	2014-07-19 17:08:21.000	2014-07-23 16:32:18.000	3
6131146500	1	1;201;APMChannel...	2014-07-09 06:55:18.000	2014-07-19 14:39:24.000	3

Figure 4.10 - Dynamic Job Exemple.

It is possible to see the last two jobs were already processed by the Algorithms, and the date that they were calculated is showed in "DJB_LAST_UPDATE_TIMESTAMP". The first job has the DJB_STATE = 0 and was not processed yet. As soon as the Scheduling System is installed on the System and his Started, we will try to connected to the Front End Application that there is a new job every time a DJB_STATE = 0.

4.2.2. **Fault Characteristics**

Within a complex machine such as a marine vessel engine, there are many sources of malfunction.

Faults may be identified by changes in the vibratory characteristics specific to the operation of the component in question under normal operation. For instance a shaft imbalance will cause an increase in out-of-balance forces and therefore cause an increase in the first harmonic of the shafts rotational speed. Some common faults can be:

- **Shaft imbalance** - manifests in the first harmonic of the shafts rotational speed. Out of balance forces are defined as follows:

$$F = me\omega^2$$

Where m is the unbalanced mass, e is the radius of eccentricity and ω is the angular velocity. Hence the out of balance force will increase proportional to the angular velocity squared, this may be utilized when order tracking.

- **Misalignment** - Commonly cited as a large twice running speed (2x) and/or running speed (1x) vibration component, though there is much debate as to the physical reason (Al-Hussain).

- **Mechanical Looseness** - Second harmonic of shaft speed.

- **Gear faults** - chipped/ cracked tooth, missing tooth, manifests as asymmetries in the side bands about the gear meshing frequency. The gear meshing frequency may be defined as follows:

$$f_{GM} = N \text{ x } f_r$$

Where f_{GM} is the gear meshing frequency (Hz), N is the number of gear teeth and f_r is the rotation speed of the gear (Hz). Side bands will then be spaced about the gear meshing frequency at frequency intervals equal to the shaft rotational speed.

- **Bearing faults** - many times the rotational speed of the shaft. Four generalized faults may be identified; ball damage, inner race defect, outer race defect and cage damage. Figure 4.11 shows a diagram of a typical rolling element bearing with relevant dimensions and frequencies [14].

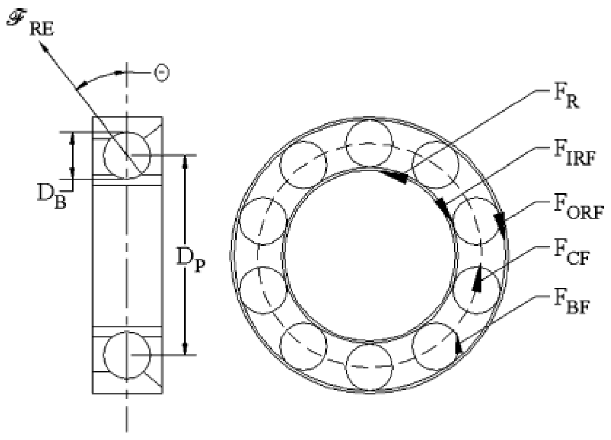


Figure 4.11 - Dimensions and fault frequencies of typical rolling element bearing [13].

The fault frequencies of interest are as follows:

$$F_{CF} = \frac{1}{2} F_R (1 - \frac{D_B}{D_P} \cos\theta)$$

$$F_{ORF} = \frac{N_B}{2} F_R (1 - \frac{D_B}{D_P} \cos\theta)$$

$$F_{IRF} = \frac{N_B}{2} F_R (1 + \frac{D_B}{D_P} \cos\theta)$$

$$F_{BF} = \frac{D_p}{2D_B} F_R (1 - [\frac{D_B}{D_P} \cos\theta]^2)$$

Where F_R is the shaft rotational speed (Hz), $F_{CF}$is the cage fault frequency (Hz), $F_{ORF}$is the outer race fault frequency (Hz), $F_{IRF}$is the inner race fault frequency (HZ), F_{BF} is the ball fault frequency (Hz), D_B is the ball diameter (m), D_P is the pitch diameter (m), N_B is the number of rolling elements and θ is the ball contact angle.

For more information on bearings see reference to [15]. For information on gear faults see references [16], [17], [18], [19], [20], [21].

4.3. Signal processing

The raw data gathered from the transducer, once stored adequately, yields very little information in terms of identification of key parameters indicative of the machines condition. Signal processing techniques must be employed to de-noise the raw data and extract key features specific to faults of interest.

Vibration signals are initially obtained as a series of digital values representing proximity, velocity, or acceleration in the time domain. This section reviews recent research on vibration techniques in the time domain for various types of rotating machinery and categorizes these techniques into the following groups.

4.3.1. **Time Domain**

Vibration signals are initially obtained as a series of digital values representing proximity, velocity, or acceleration in the time domain. This section reviews recent research on vibration techniques in the time domain for various types of rotating machinery and categorizes these techniques into the following groups (Figure 4.12).

4.3.1.1. Statistical parameters

Various parameters exist which may be used as indicators of a machines condition. The following whole vibration parameters are relatively simple to compute requiring little computing power. These have the benefit that they may be computed in real time and hence lend themselves well to on-line permanent fit CBM. The RMS value and crest factor have been applied in diagnosing bearings and gears [22]. The RMS of a vibration signal is a time analysis feature that measures the power content in the vibration signature. This feature can be very effective when detecting an imbalance in rotating machinery.

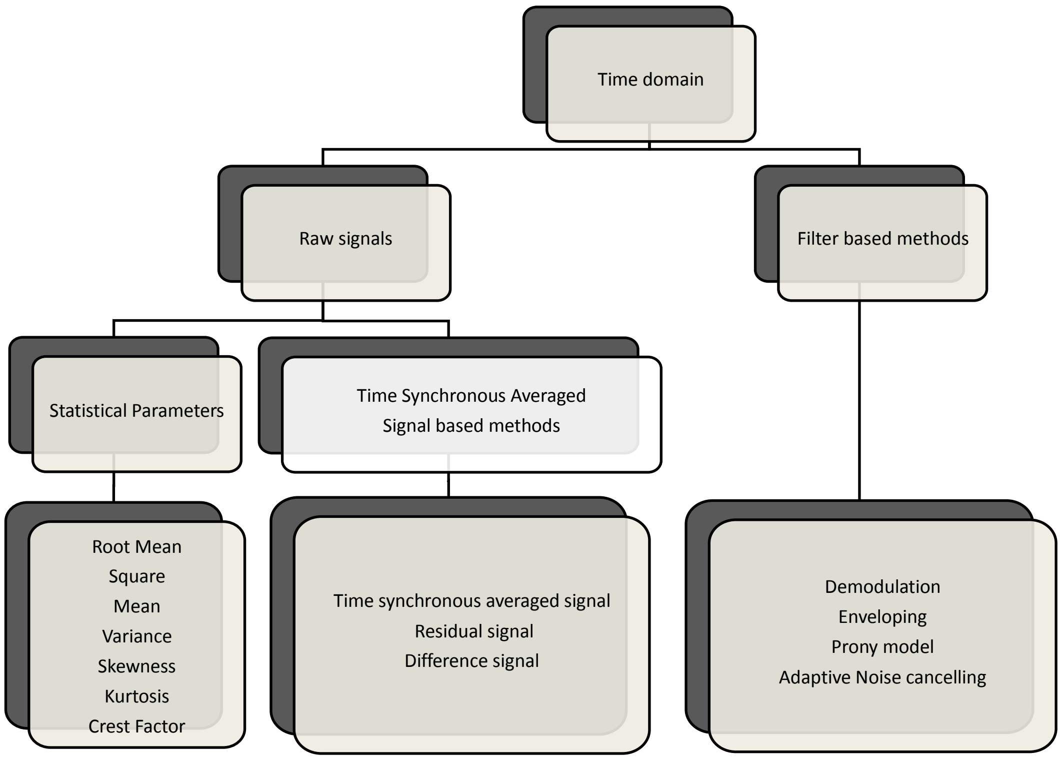


Figure 4.12 - Overview of time domain vibration feature extraction techniques.

The most basic approach for measuring defects in the time domain is to use the RMS approach which is often not sensitive enough to detect incipient faults in particular. Another measure is to use the "crest factor", defined as the ratio of the peak level of the input signal to the RMS level. Therefore, peaks in the time series signal will result in an increase in the crest factor value. This feature is used to detect changes in the signal pattern due to impulsive vibration sources such as tooth breakage on a gear or a defect on the outer race of a bearing.

Statistical analyses of vibration signals have proved to be useful in detecting machinery faults. In [22] is shown that the probability density function is correlated with bearing defects such as bearings in good condition have a gaussian distribution, whereas a damaged bearing results in non-Gaussian distribution with dominant tails because of a relative increase in the number of high levels of acceleration. Mean, variance, and skewness are the first moment, second moment, and the third moment of probability distribution respectively. Skewness is a measure of the asymmetry of the probability distribution of a real-valued random variable about its mean (Figure 20).

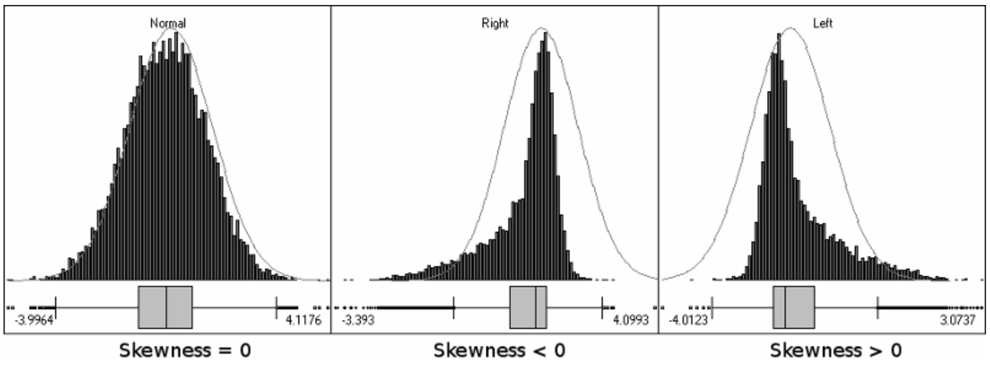


Figure 4.13 - Demonstration of Skewness Coefficient [23].

Kurtosis is defined as the fourth moment of the distribution and measures the relative flatness of a distribution as compared to a normal distribution. Kurtosis provides a measure of the size of the tails of distribution and is used as an indicator of major peaks in a set of data.

It is defined as the normalized fourth central moment of a distribution:

$$\beta_2 = \frac{\mathrm{E}[(X-\mu)^4]}{(\mathrm{E}[(X-\mu)^2])^2} = \frac{\mu_4}{\sigma^4}$$

Using this definition the value of kurtosis for a normal distribution is 3. A second definition maybe be that the value of kurtosis for the normal distribution is 0. This is defined as the fourth cumulant of the distribution divided by the second cumulant:

$$\gamma_2 = \frac{\kappa_4}{\kappa_2^2} = \frac{\mu_4}{\sigma^4} - 3$$

As the kurtosis of a distribution is a measure of the distributions peakness it may be used to identify impulsive components within a time signal. This applies particularly well to bearing faults where a defect will cause periodic impulsive impacts once per revolution. Hence kurtosis values of time series may be trended over time, where a significant increase will indicate the presence of a fault.

This technique can often become unstuck when the signals are highly embedded in noise as the kurtosis no longer captures the impulsive signature, causing a faulty signal to have similar kurtosis values as a healthy signal. This problem can be formulated as “detecting transient signals in strong additive noise”. Here kurtosis will generate high values in the presence of a fault provided the impacts are sufficiently well separated and the signal-to-noise ratio is sufficiently high [24]. As may be seen in Figure 4.14 showing a typical vibration signature of a rolling element bearing fault the presence of noise strongly affects the ability of kurtosis to identify the presence of the fault, yielding a value close to zero.

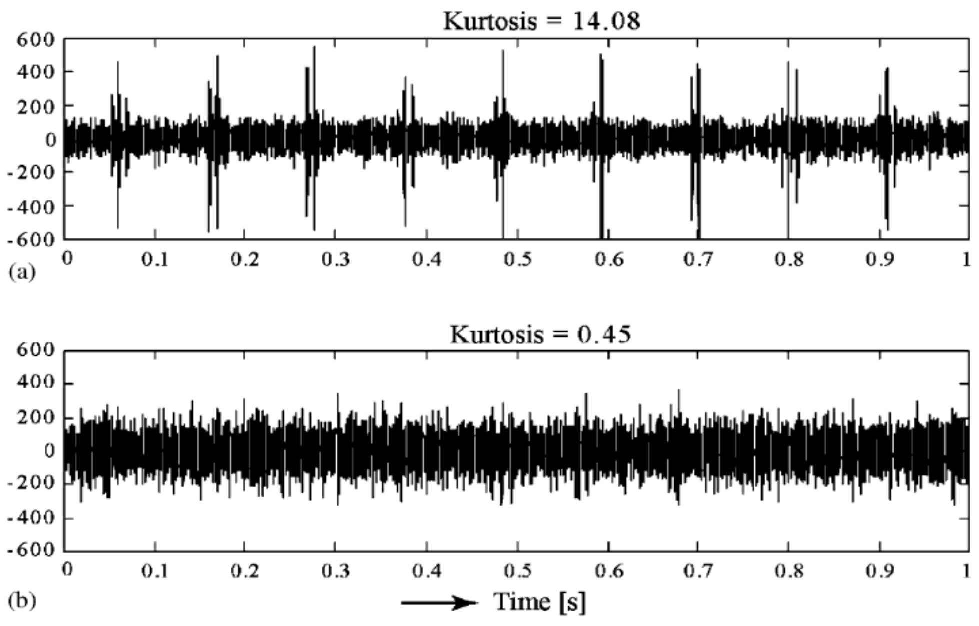


Figure 4.14 - Example of faulty bearing with little background noise (a) and in the presence of high back ground noise (b) [25].

Therefore the use of kurtosis as a global indicator of the entire time domain signal is inappropriate and is preferable to apply it locally in different frequency bands.

As rotating machinery faults present themselves, Kurtosis should signal an error due to the increased level of vibration. Kurtosis have been applied to diagnosing bearing, and gearbox faults [26].The Root mean square, peak value, kurtosis and crest factor have been combined with high frequency resonance techniques and an adaptive line enhancer to detect and localize damage in rolling bearings [27].

4.3.1.2. Time Synchronous Averaging

Time Synchronous Averaging is a method for improving the signal to noise ratio and recovering periodic signals which are embedded in noise. Assuming that the noise is randomly distributed throughout the signal the input signal may be sampled at fixed intervals corresponding to the period of the embedded wave form. This period may be inferred from tachometer data or through autocorrelation. The noise is then reduced by averaging the content of each interval. As the periodic waveform is constant each additional interval used in the average yields the same result, preserving the periodic waveform. As the noise is random the summation of the intervals will give positive and negative contributions, hence as the number of intervals increases the noise is reduced.

Let the input $f(t)$ be composed of a repetitive signal $s(t)$ and noise $n(t)$. Say the k_{th} repetition of $s(t)$begins at time t_k (where t_1=0) and that the sample are taken every T seconds. Then;

$$f(t) = s(t) + n(t)$$

This signal is then sampled, with sample values

$$\begin{aligned} f(t_k + iT) &= s(t_k + iT) + n(t_k + iT) \\ &= s(iT) + n(t_k + iT) \end{aligned}$$

It may be assumed that in a usual situation the average of the noise contributions is zero, with a constant RMS value σ. For the ith sample point the signal to noise ratio, S/N, may therefore be calculated as:

$$\frac{S}{N} = \frac{s(iT)}{\sigma}$$

After m repetitions the value stored in the i_{th} memory location is given by:

$$\begin{aligned} \sum_{k=1}^{m} f(t_k + iT) &= \sum_{k=1}^{m} s(iT) + \sum_{k=1}^{m} n(t_k + iT) \\ &= ms(iT) + \sum_{k=1}^{m} n(t_k + iT) \end{aligned}$$

Since the noise is random and the m samples are independent the mean RMS of the sum of the m noise samples is mσ^2, hence the RMS value is $\sqrt{m}\sigma$. Therefore the new signal to noise ratio is:

$$(\frac{S}{N})_m = \sqrt{m}(\frac{S}{N})$$

The signal to noise ratio is improved by a factor of $m^{1/2}$ [28].

In practice this principle is simple, usually consisting in placing the vibration sensor on the machine to be diagnosed and use a remote optical sensor or stroboscope with a trigger output to accurately determine the exact speed of the machine (Figure 4.15).

This external trigger will initialize the vibration data collector and with the use of a high number of averages can eliminate “cross-talk” signals and improve signal-to-noise ratio.

A simple example of the all process can be seen in Figure 4.16.

If this external trigger is unavailable a sync period may be found using several techniques (Autocorrelation, Fourier Transform, etc). Using these techniques a suitable period can be identified and can be used in the signal averaging technique.

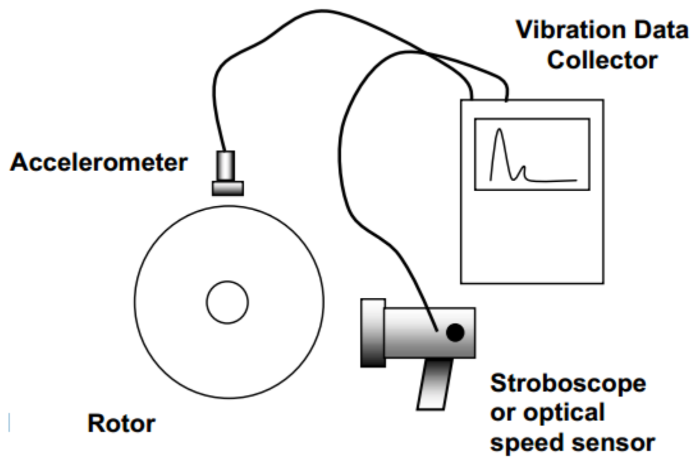


Figure 4.15 - Common Set-up for synchronous time averaging.

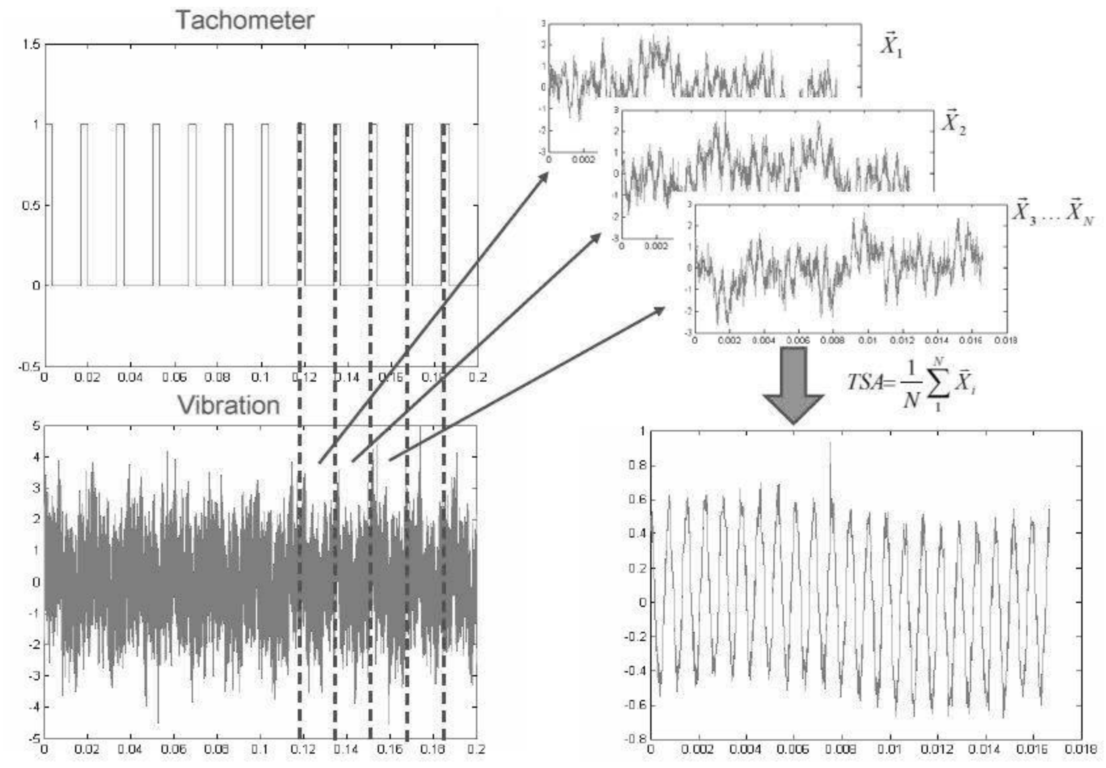


Figure 4.16 – Schematic of “Time Synchronous Averaging” algorithm [29].

4.3.1.3. Filter based methods

Demodulation including phase and amplitude demodulation is an important signal processing technique. The amplitude demodulation, also known as envelop, or resonance demodulation, or high frequency resonance demodulation techniques separates low-level, low-frequency signals from background noise, enabling them to be easily measured. In the application of gear faults detection, the amplitude demodulation focused on the fault-induced high-order modulation sidebands around the dominant gear meshing harmonic.

Many faults such as bearing and gearbox faults cause a modulation in the amplitude of the vibration signal. This is caused by impulsive strikes such as a missing tooth on a gear set or cracks in the inner race of a bearing cage. This impulsive strike will excite the natural resonance of the structure, but as the strike is of a very short duration the energy will be spread across many harmonics and hence will have low amplitude and the fault signal is always masked by noise and low frequency effects [30].

Envelope analysis enables the transient fault signals to be separated from any masking features such as background noise and frequency components due to other oscillatory forces (shaft rotation etc.).

A relatively simple processing method for envelope analysis may be seen in Figure 4.17 and may be described as follows. Firstly a high pass or band pass filter is applied to the raw time data as the transient faults are generally of high frequency corresponding, in the case of rolling element bearings. The filtered signal will be a modulated time waveform which is then rectified such that all negative amplitudes are made positive. The signal is then low pass filtered to output the enveloped signal which may then be frequency analyzed, the spectral content of which will signify the severity of the fault. For instance, a highly modulated signal once processed will produce large spectral content corresponding to the fault frequency and harmonics. A healthy signal will be minimally modulated producing little frequency content.

Figure 4.18 shows the enveloped vibration spectrum of a bearing in faulty and healthy condition. As can be seen there is far more frequency content attributed to the faulty bearing than there is to the healthy bearing. This may be used to indicate the bearings health and thresholds on the spectrum may be set at specific fault frequencies such that alarms may sound when the fault is sufficiently developed.

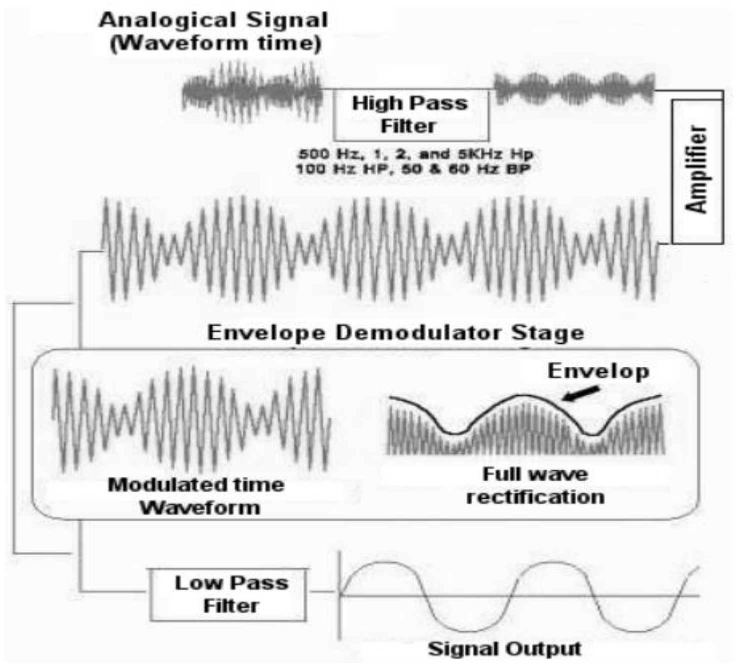


Figure 4.17 - Demodulation process [28].

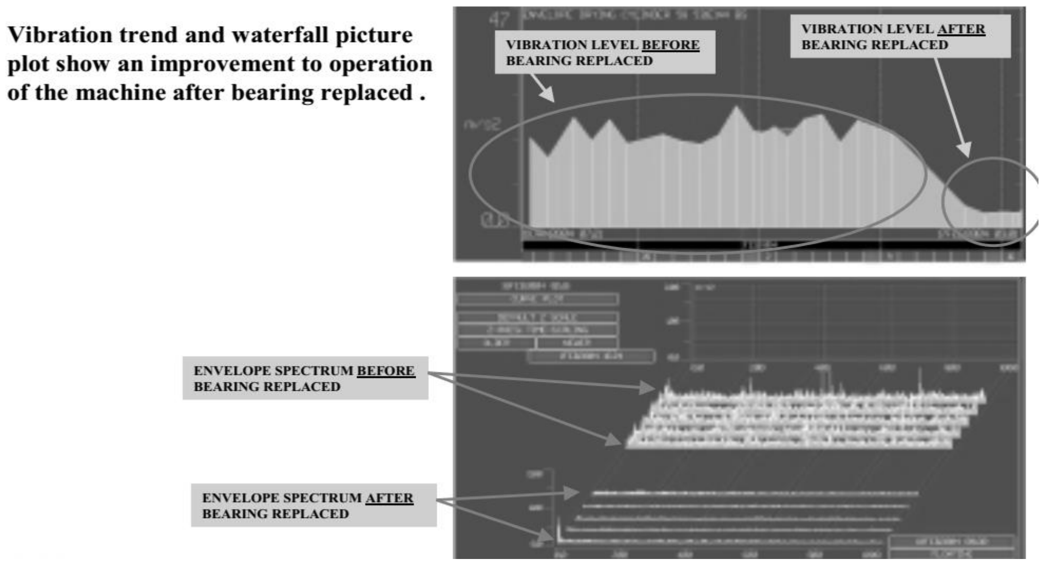


Figure 4.18 - Comparison of enveloped vibration spectra for faulty and healthy bearings [31].

There are several methods for the estimation of the signals envelope, the above being a more basic approach. Another method employs is the Empirical Mode Decomposition (EMD) algorithm. The implementation of this technique can be resumed in the following steps:

- Identify local maxima and minima in the signal;
- Deduce an upper and a lower envelope by interpolation (cubic splines);

  - subtract the mean envelope from the signal
  - iterate until extremes = zeroes +1

- Subtract the so-obtained Intrinsic Mode Function (IMF) from the signal;

- Iterate on the residual.

Figure 4.19 demonstrates an example of the iteration steps on the EMD algorithm which is called “Shifting”. In the end of the process a signal decomposition is achieved and is expected that the number of extreme will decrease as the procedure continues, so that the signal is sequent decomposed into the highest frequency component “imf_1” to the lowest frequency component “imf_n”, for some finite n and a residue signal r [32].

Finally, for the signal shown above the decomposition signals are shown in Figure 4.20.

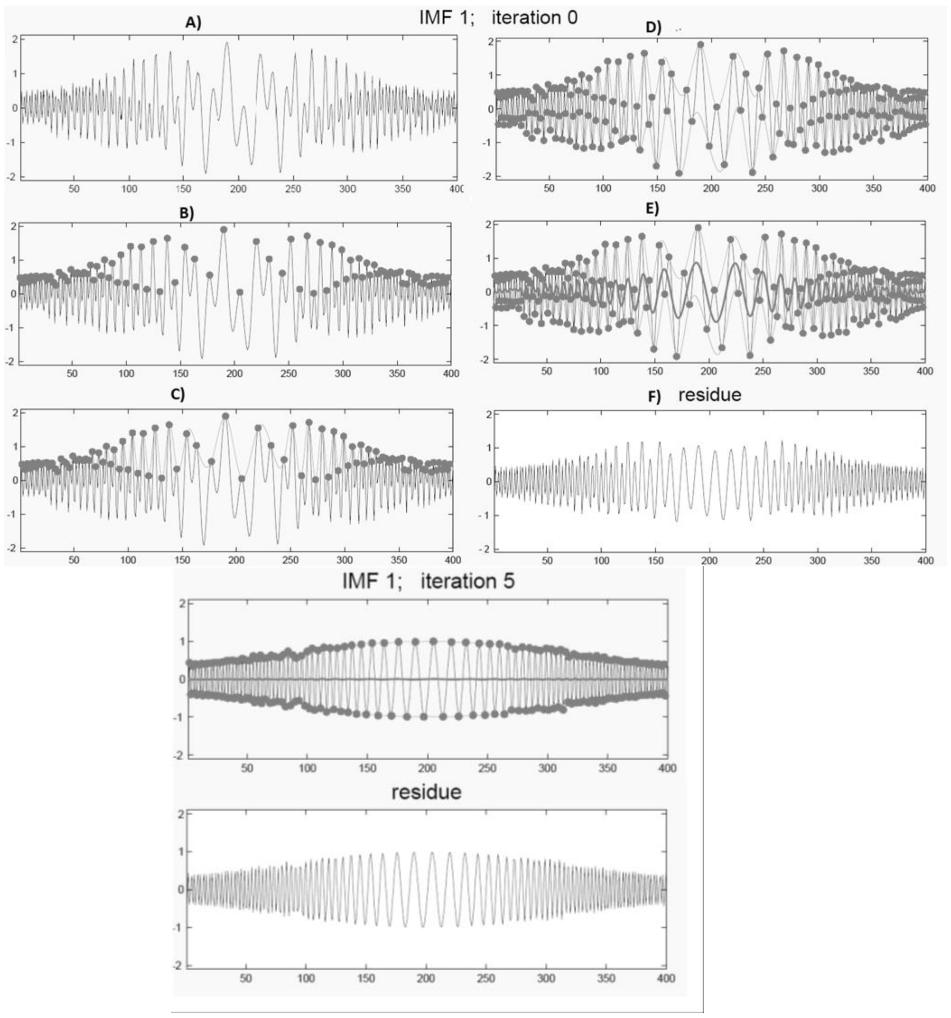


Figure 4.19 - Empirical Mode Decomposition Iteration [33].

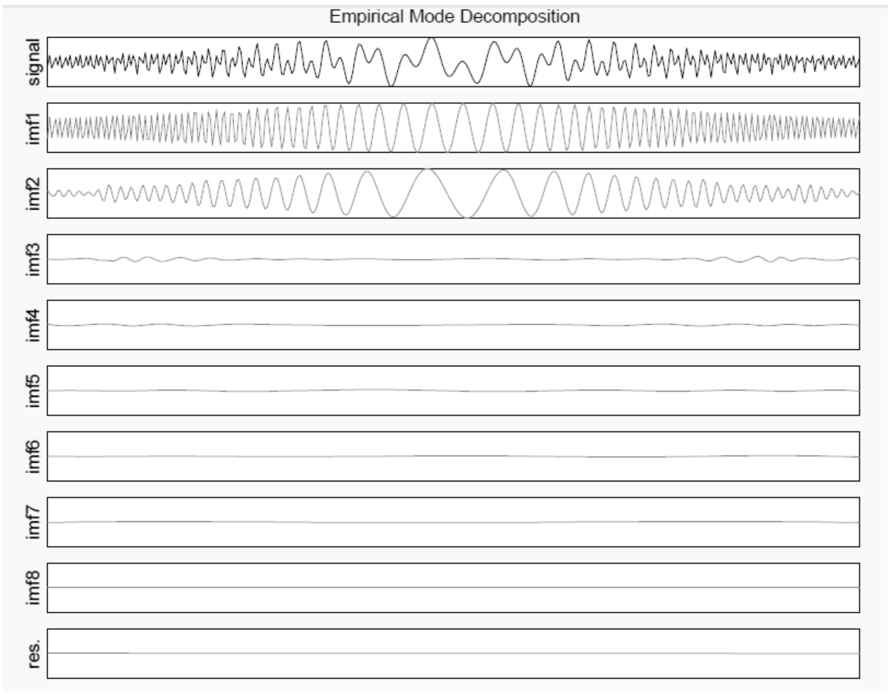


Figure 4.20 - Empirical Mode Decomposition Signals [33].

4.3.2. **Frequency Domain and Time Frequency Domain Feature Extraction Techniques**

Features regarding frequency information such as frequency domain features and time frequency domain features are being widely investigated at present. These features can generally indicate machinery faults better than time domain vibration features because characteristic frequency components such as resonance frequency components or defect frequency components can be relatively easily detected and matched to faults.

4.3.2.1. Fast Fourier Transform

The Fast Fourier Transform (FFT) is the most conventional diagnosis technique and has been widely used to identify the frequency features of signals. These signals can be raw signals or processed signals.

There are vast amounts of literature covering the technical details of the Fourier transform and FFT, so technical details will be omitted here.

Mathematically, the process of Fourier analysis is represented by the Fourier transform:

$$F(\omega) = \int_{-\infty}^{\infty} f(t)e^{-j\omega t}dt,$$

This means that FFT is the sum over all time of the signal $f(t)$ multiplied by a complex exponential.

The results of the transform are the Fourier coefficients, which when multiplied by a sinusoid of appropriate frequency, yield the constituent sinusoidal components of the original signal (Figure 4.21).

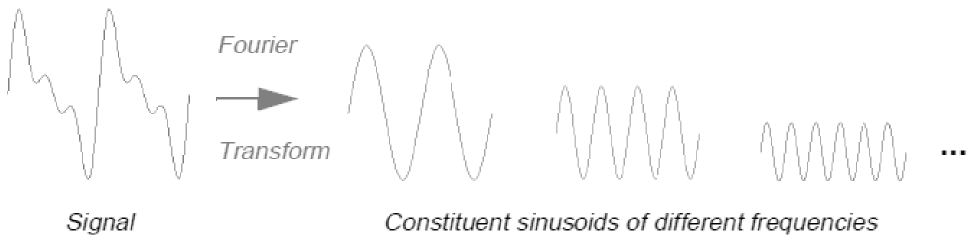


Figure 4.21 - Fourier Transform Principle [34].

In the case of analysis it is often useful to calculate the power spectral density (PSD) rather than an FFT as this yields data proportional to the energy within the signal. Once the data has been transformed into the frequency domain, specific features should be present relating to frequencies of interest such as the shaft rotational speed and harmonics thereof. The fundamental frequency of the engine will also be present (relating to number of pistons etc.) again with harmonics.

Frequency content due to gear meshing and bearing related components will also be present but is often embedded in noise or masked by other components. Therefore pre-processing may be required to denoise the input signal or filter it into the relevant frequency bands such that the fault feature is extracted (see Time Synchronous Averaging (TSA), digital filtering and enveloping).

Once in the frequency domain it is possible to track specific features and trend them over time. For instance tracking the amplitude of the frequency component relating to the rotational speed of the shaft will give an indication to the extent of which the shaft is out of balance relative to a baseline value. Tracking such things as the gear meshing frequency and corresponding side bands will give indications to the health of the gears. This overcome the issues with whole vibration parameters in that changes to the energy content of specific frequencies can be isolated when trending.

The main difficulty with frequency analysis is the pre-processing necessary to extract the feature to be monitored.

Frequency analysis is also useful when dealing with variable speed machines. For a variable speed machine whole vibration parameters will indicate little about the state of the machine as the amplitude of vibration will increase with engine speed.

4.3.2.2. Wavelet Transform

Compare wavelets with sine waves, which are the basis of Fourier analysis. Sinusoids do not have limited duration —they extend from minus to plus infinity. And where sinusoids are smooth and predictable, wavelets tend to be irregular and asymmetric (Figure 4.22).

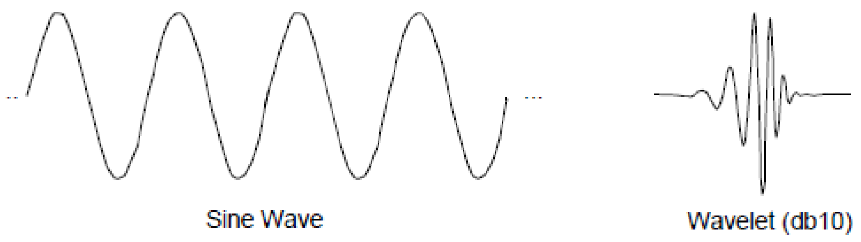


Figure 4.22 - Comparison between a Sine Wave and a Wavelet [32].

Fourier analysis consists of breaking up a signal into sine waves of various frequencies. Similarly, wavelet analysis is the breaking up of a signal into shifted and scaled versions of the original (or mother) wavelet.

A wavelet is a waveform of effectively limited duration that has an average value of zero.

Just looking at pictures of wavelets and sine waves, you can see intuitively that signals with sharp changes might be better analyzed with an irregular wavelet than with a smooth sinusoid. It also makes sense that local features can be described better with wavelets, which have local extent.

Similarly to the FFT, the continuous wavelet transform (CWT) is defined as the sum over all time of the signal multiplied by scaled, shifted versions of the wavelet function Ψ:

$$C(scale, position) = \int_{-\infty}^{\infty} f(t)\psi(scale, position, t)dt$$

The result of the CWT is many wavelet coefficients C, which are a function of scale and position (Figure 4.23).

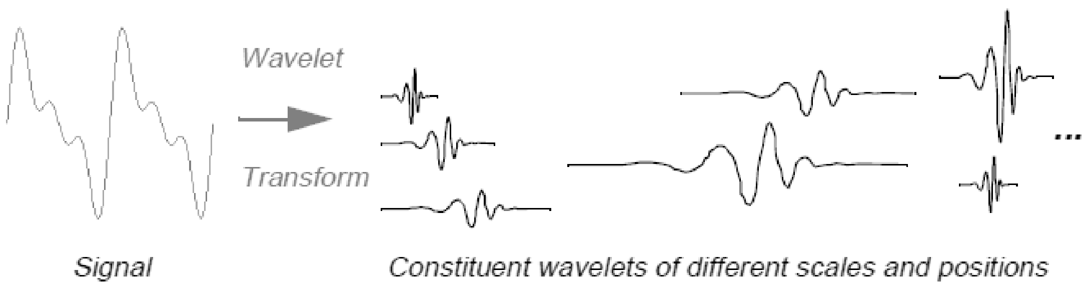


Figure 4.23 - Wavelet Transform Principle [32].

This process can be resumed in 5 steps described below:

1. Take a wavelet and compare it to a section at the start of the original signal.

2. Calculate a number, C, that represents how closely correlated the wavelet is with this section of the signal. The higher C is, the more the similarity. Note that the results will depend on the shape of the chosen wavelet (Figure 4.24).

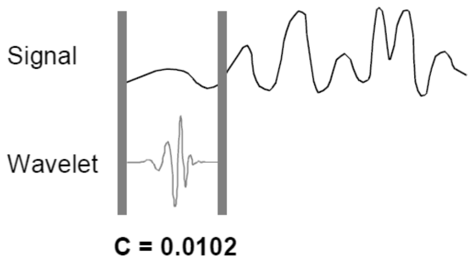


Figure 4.24 – 2nd step of Wavelet Transform Algorithm [32].

3. Shift the wavelet to the right and repeat steps 1 and 2 until covering the whole signal (Figure 4.25).

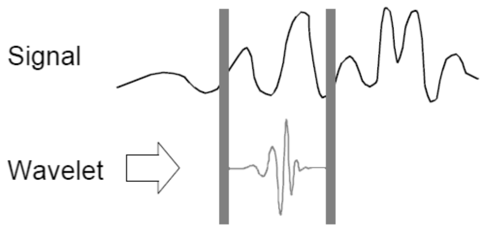


Figure 4.25 – 3rd step of Wavelet Transform Algorithm [32].

4. Scale (stretch) the wavelet and repeat steps 1 through 3 (Figure 4.26).

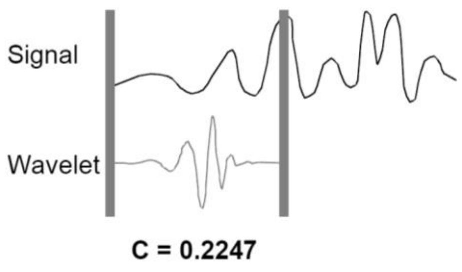


Figure 4.26 – 4th step of Wavelet Transform Algorithm [32].

5. Repeat steps 1 through 4 for all desired scales.

As described, the continuous wavelet transform is the sum over all time of the signal multiplied by scaled, shifted versions of the wavelet. This process produces wavelet coefficients that are a function of scale and position.

In the end coefficients at different scales by different sections of the signal are produced. The coefficients constitute the results of a regression of the original signal performed on the wavelets. A common approach to make sense of this coefficients is to plot them using x-axis representing position along the signal (time), the y-axis representing scale, and the color at each x-y point represents the magnitude of the wavelet coefficient C (Figure 4.27).

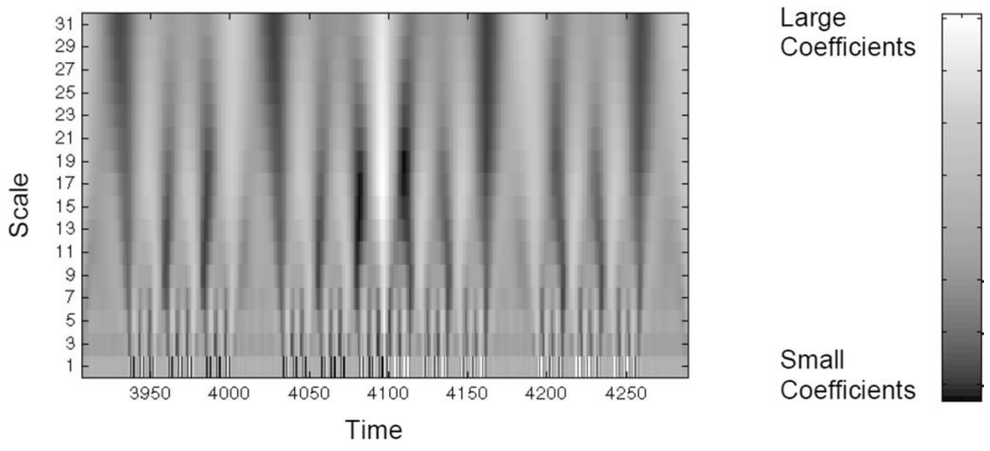


Figure 4.27 – 2d Plot of Continuous Wavelet Transform [32].

3d plots are also another option to visualize the Continuous Wavelet Transform (Figure 4.28).

The continuous wavelet transform coefficient plots are precisely the time-scale view of the signal processed. It is a different view of signal data than the time-frequency Fourier view, but it is not unrelated.

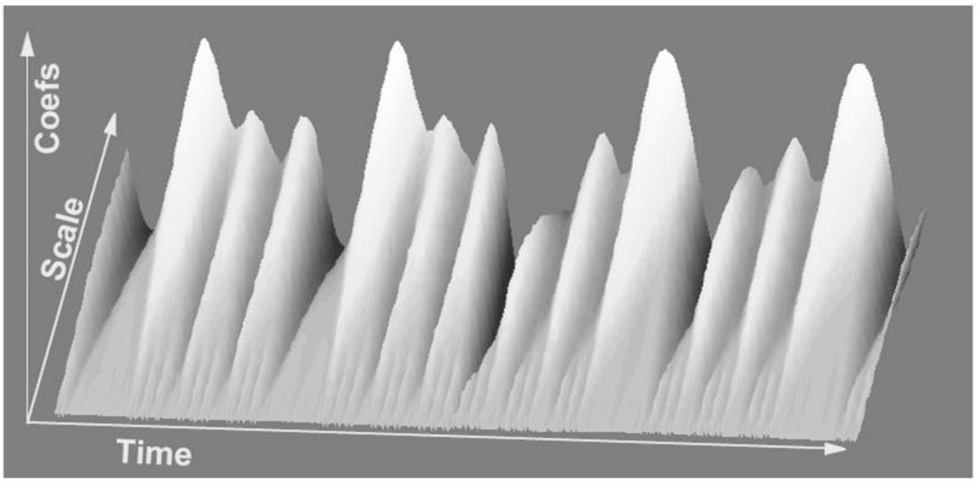


Figure 4.28 –3d Surface Plot of Continuous Wavelet Transform [32].

4.3.2.2.1. Wavelet Transform

As seen in Figure 4.27, y-axis labels run from 1 to 31. Recall that the higher scales correspond to the most “stretched” wavelets. The more stretched the wavelet, the longer the portion of the signal with which it is being compared, and thus the coarser the signal features being measured by the wavelet coefficients.

Thus, there is a correspondence between wavelet scales and frequency as revealed by wavelet analysis:

Thus, there is a correspondence between wavelet scales and frequency as revealed by wavelet analysis:

- Low scale a $\Rightarrow$Compressed wavelet

  $\Rightarrow$ Rapidly changing details

  $\Rightarrow$ High frequency ω.

- High scale a $\Rightarrow$ Stretched wavelet

  $\Rightarrow$ Slowly changing, coarse features

  $\Rightarrow$ Low frequency ω.

The fact that wavelet analysis does not produce a time-frequency view of a signal is the strength of the technique. Not only is time-scale a different way to view data, it is a very natural way to view data deriving from a great number of natural phenomena.

4.3.2.2.2. One-Stage Filtering: Approximations and Details

For many signals, the low-frequency content is the most important part. It is what gives the signal its identity. The high-frequency content, on the other hand, imparts the details. Consider the human voice. If the high-frequency components are removed, the voice sounds different, but is still possible to tell what's being said. However, if enough of the low-frequency components are removed, gibberish is heard. It is for this reason that, in wavelet analysis, often refers to the terms of approximations and details.

The approximations are the high-scale, low-frequency components of the signal. The details are the low-scale, high-frequency components. The filtering process, at its most basic level is presented in Figure 4.29.

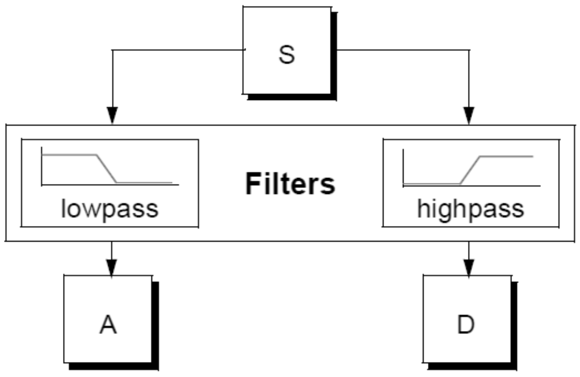


Figure 4.29 - One-Stage Filtering schematic [32].

The original signal, S, passes through two complementary filters and emerges as two signals.

Unfortunately, when actually performing this operation on a real digital signal, twice as much data as started is generated. Suppose, for instance, that the original signal S consists of 1000 samples of data. Then the approximation and the detail will each have 1000 samples, for a total of 2000 (Figure 4.30).

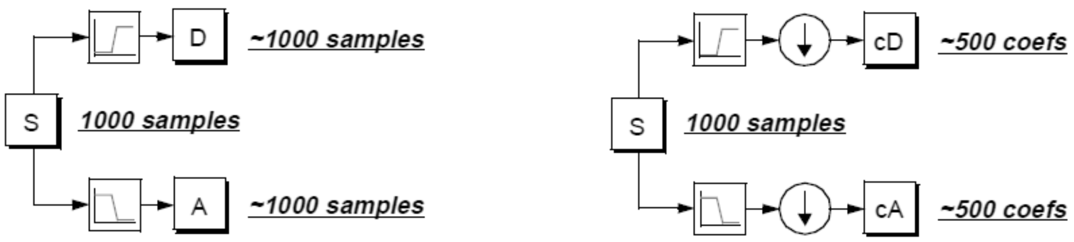


Figure 4.30 - One-Stage Wavelet Filtering schematic [32].

The process on the right, which includes down sampling, produces DWT coefficients. To gain a better appreciation of this process, a one-stage discrete wavelet transform of a signal will be presented. The used signal will be a pure sinusoid with high-frequency noise added to it.

Using the following code on matlab:

```
s = sin(20.*linspace(0,pi,1000)) + 0.5.*rand(1,1000);
              [cA,cD] = dwt(s,'db2');
```

The schematic of the process will be shown in Figure 4.31.

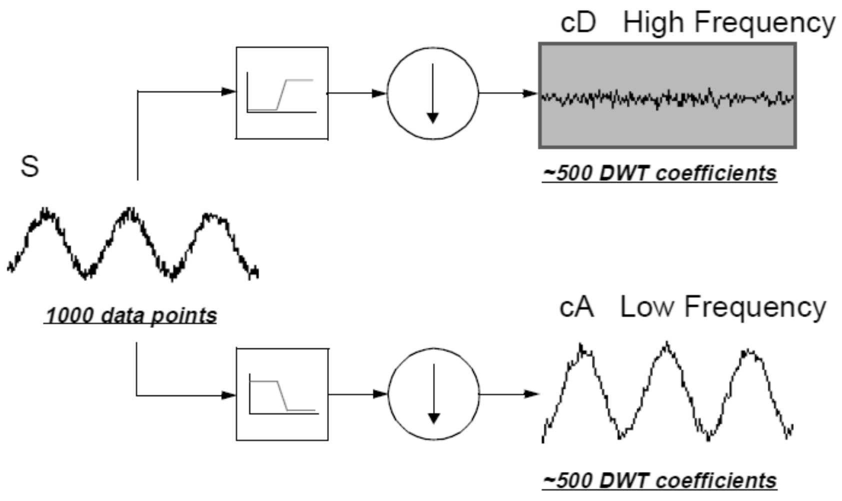


Figure 4.31 – One-Stage Wavelet Filtering example [32].

Notice that the detail coefficients cD consist mainly of the high-frequency noise, while the approximation coefficients cA contain much less noise than does the original signal.

It may observe that the actual lengths of the detail and approximation coefficient vectors are slightly more than half the length of the original signal.

This has to do with the filtering process, which is implemented by convolving the signal with a filter. The convolution "smears" the signal, introducing several extra samples into the result.

4.3.2.2.3. Multi-Level Decomposition

The decomposition process can be iterated, with successive approximations being decomposed in turn, so that one signal is broken down into many lower-resolution components. This is called the wavelet decomposition tree (Figure 4.32).

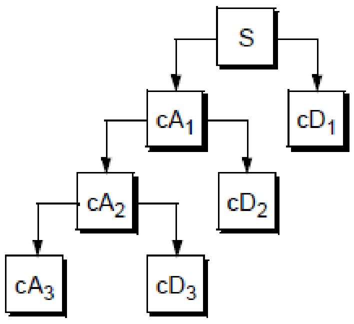


Figure 4.32 - Multi-Level Decomposition Schematic [32].

4.3.2.2.4. Wavelet Reconstruction

It has been shown how the discrete wavelet transform can be used to analyze, or decompose, signals and images. Another useful concept is how those components can be assembled back into the original signal with no loss of information. This process is called inverse discrete wavelet transforms (IDWT) (Figure 4.33).

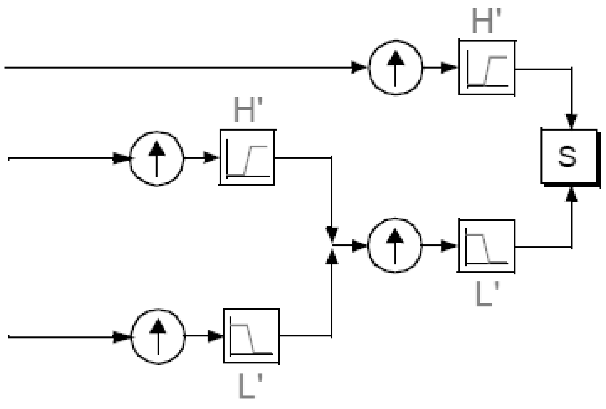


Figure 4.33 – Inverse Discrete Wavelet Transform schematic [32].

Where wavelet analysis involves filtering and down-sampling, the wavelet reconstruction process consists of up-sampling and filtering. Up-sampling is the process of lengthening a signal component by inserting zeros between samples (Figure 4.34).

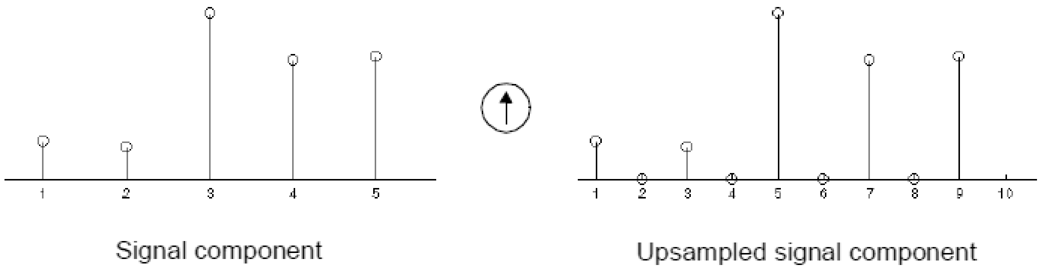


Figure 4.34 – Up-sampling step used on IDWT [32].

This process is mandatory in order to analyze the signal using FFT as will be presented in the next chapter.

CHAPTER 5

Implemented Algorithms and C# Libraries

5.1. Introduction

All the following algorithms were developed in matlab and then compiled to C# and deployed in a web service that performs the calculation of the algorithms every time new data is available. The proposed algorithms were developed based in reviews of recent research of vibration techniques for various types of rotating machinery stated by literature. Also matlab was opted as main algorithms development based platform because is the standard platform used for these applications, ease of use, and internal knowledge that the company already have in this environment.

The method used for running the matlab code in a C# environment is the matlab Compiler Runtime (MCR) which enables royalty-free deployment to users who do not have matlab.

It is possible to package the MCR with the developed application or have your users download it during installation.

To compile the matlab code to C#, though, it is necessary to have the matlab Compiler that compiles the libraries and applications that then can be used in C#. A detailed guide on how to compile matlab code to C# can be found in [35].

5.2. Signal Generator

The performance of the implemented methods is demonstrated using a computer–generated simulated signal [15]. The signal was built with a sampling frequency of 8 kHz. The major components include a 60/(Simulated Speed) Hz component considered as slow shaft relative amplitude 1.0, 30/(Simulated Speed) Hz fast shaft (relative amplitude 0.6), 34/(Simulated Speed) Hz gear meshing frequency relative amplitude 0.3, and a 10/(Simulated Speed) Hz characteristic frequency, carried on a modulated 2.0 kHz wave, with a random jitter (max. 3%), simulating for instance a rolling–element–bearing outer race fault; the signal has initial amplitude of 0.1, decaying with a time constant of 2 ms.

The referred signal is presented in Figure 5.1.

Also a signal considered as a good condition signal was used which consisted in changing the Rolling Element component to only a 10/(Simulated Speed) Hz characteristic frequency (Figure 5.2).

In the end summing all the compositions of the signal components shown in Figure 5.1 the signal presented in Figure 5.3 is achieved.

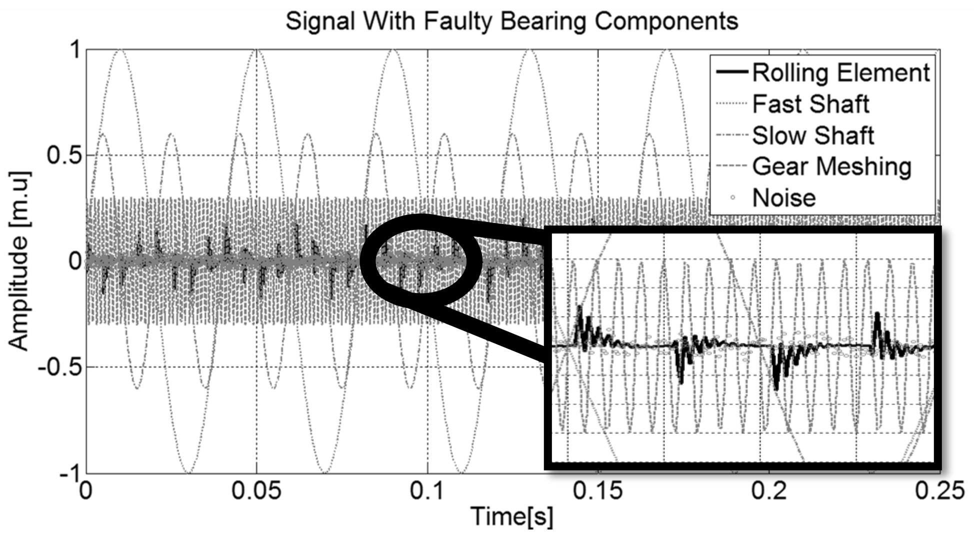


Figure 5.1 - Simulated faulty signal using matlab for Input “(Simulated Speed)” = 1500 rpm.

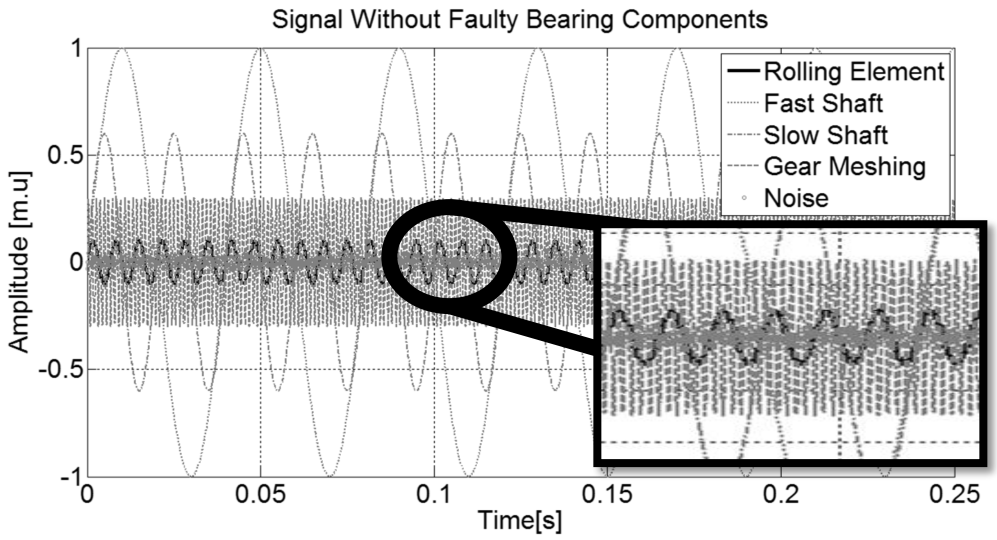


Figure 5.2 -- Simulated good signal using matlab for Input “(Simulated Speed)” = 1500 rpm.

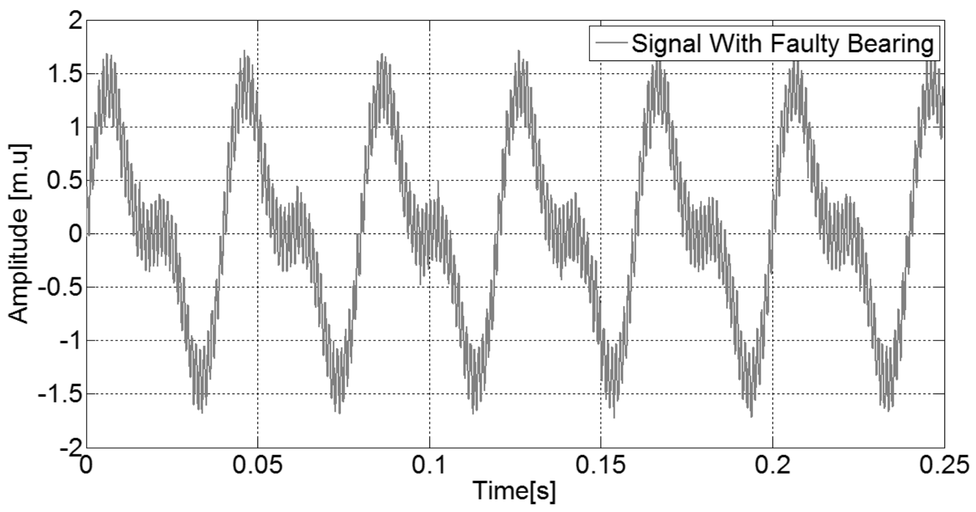


Figure 5.3 - Overall Signal with Faulty Bearing Components.

These simulated functions can be generated in matlab using the function:

```
[t,YGood, YFaulty, Fs]=Generate((Simulated Speed));
```

In which is the referred "(Simulated Speed)" is the value correspondent to the desired Simulated Speed.

In C# by adding the reference "GenerateSignals.dll" to the project and adding the following lines to the code:

```
// Initialize GenerateSignals

GenerateSignals.BearingFault SignalObj = new GenerateSignals.BearingFault();
//Generate Simulated Signals
double Speed = 1500;       //Speed of Motor
SignalClass  Signal  =  new  SignalClass(  SignalObj.Generate(4,  Speed));    //Call
Matlab Function to generate signals
```

Signal Class was created to help handling the values and consists in a simple class:

```
   public class SignalClass
    {
        public MWArray t;
        public MWArray YGood;
        public MWArray YFaulty;
        public MWArray Fs;
        public SignalClass(MWArray[] MWArray)
        {
            t = MWArray[0];
            YGood = MWArray[1];
            YFaulty = MWArray[2];
            Fs = MWArray[3];
        }
```

5.3. Indicators

As shown in “Statistical parameters” section, there are several Time based Indicators that can be used in Condition Monitoring. For the presented project some indicators were implemented and the library for using those Indicators in a C# project was generated.

On matlab environment following (assumed that the signal was simulated with the previous function), the developed indicators can be calculated as shown:

```
%Calculate Mean of Signal
Mean = mean(YSignal);
%Calculate Crest Factor of Signal
CrestFactor = crest(YSignal);
%Calculate Kurtoisis of Signal
Kurtosis = kurtosis(YSignal);
%Calculate Standard Deviation of Signal
Std = std(YSignal);
%Calculate Variance of Signal
Var = var(YSignal);
%Calculate Mean and Standard Deviation of Peak 2 Peak
frame = Speed/60;
YFaulty.meanp2p = meanp2p(YSignal, frame, Fs);
YFaulty.stdp2p = stdp2p(YSignal, frame, Fs);
```

A small description can be added on this last function “meanp2p” and “stdp2p”. To calculate the value of the Mean Peak to Peak, as input is needed the desired frame of the signal, which an example can be the Speed / 60 (which will give the Fundamental Component Mean Peak to Peak) and the Signal Frequency. With this the Peak to Peak value in the desired frame can be calculated and also the Standard Deviation of the Peaks.

For the Simulated Signal at the Speed of 1500 rpm the detected peaks are shown in Figure 5.4 and Figure 5.5.

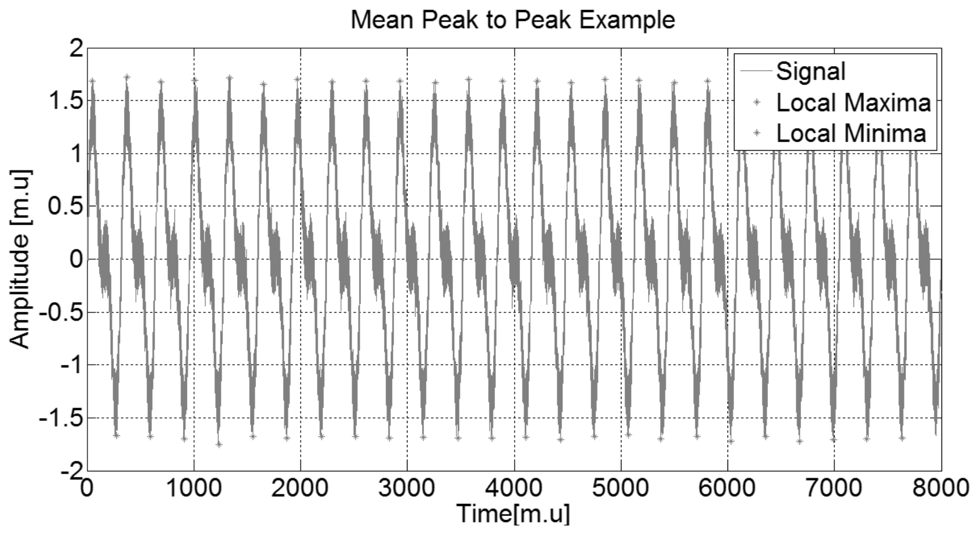


Figure 5.4 - Graphic of Mean Peak to Peak Calculation.

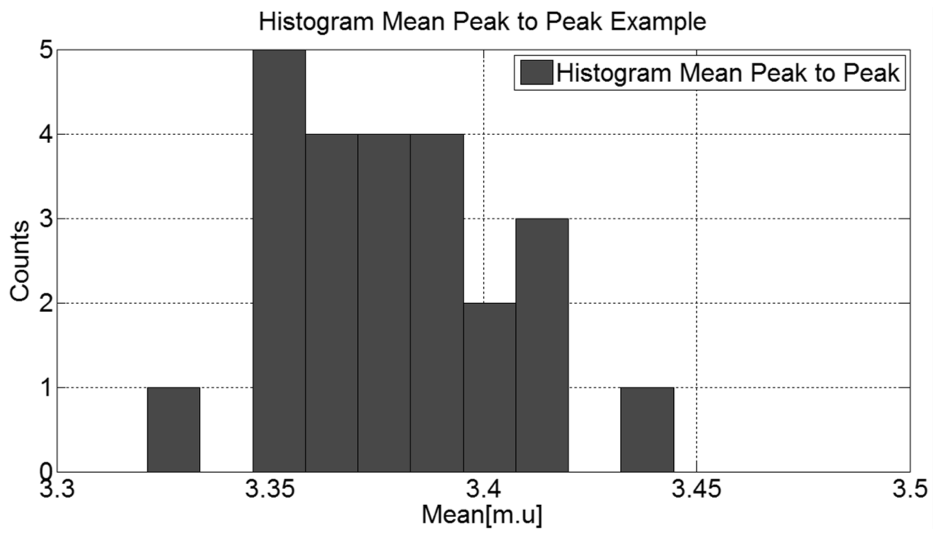


Figure 5.5 - Histogram of Mean Peak to Peak Calculation.

Using this, the mean value of peak to peak and the standard deviation are calculated.

In C# by adding the reference “Indicators.dll” to the project and adding the following lines to the code, the algorithms can be calculated.

```
// Initialize Indicators
IndicatorClass Indicators = new IndicatorClass();//Generate Simulated Signals

var Mean = IndObj.mean(YSignal);
var CrestFactor = IndObj.crest(YSignal);
var Kurtosis = IndObj.kurtosis(YSignal);
var Std = IndObj.std(YSignal);
var Var = IndObj.var(YSignal);
var Meanp2p = IndObj.meanp2p(YSignal, Speed/60, Fs);
var Stdp2p = IndObj.stdp2p(YSignal, Speed/60, Fs);
```

5.4. Complex Functions

Theory behind the implemented complex functions is presented in several chapters of the section “Signal processing”.

5.5. Fast Fourier Transform and Peak Detection

FFT function can be called from matlab using the following command:

```
[time, power, FFTMax, PowerMax]=FFT(YSignal, Fs);
```

FFT when used with “LocatePeaks” is a powerful tool. After using FFT, user can use the “LocatePeaks” function in order to take information of the Peaks found in the FFT.

As there is some noise within the FFT is necessary to use Thresholds in order to minimize the information returned by the function “LocatePeaks”. These Thresholds were manually chosen and may/should be changed when applied on a real application.

To use the function “LocatePeaks” the user is asked to use 3 parameters:

- **Threshold** - Minimum height difference. Specify the threshold height difference between a peak and its neighboring values as a positive real number. “LocatePeaks” only returns peaks that exceed their neighbors by at least the value of the Threshold.
- **MinPeakHeight** - Minimum peak height. Specify the minimum peak height as a real-valued scalar. “LocatePeaks” only returns peaks that exceed the MinPeakHeight.
- **MinPeakDistance** - Minimum peak separation. Specify the minimum peak distance, or minimum separation between peaks as a positive integer. User can use the MinPeakDistance option to specify that the algorithm ignore small peaks that occur in the neighborhood of a larger peak. When user specifies a value for MinPeakDistance, the algorithm initially identifies all the peaks in the input data and sorts those peaks in descending order. Beginning with the largest peak, the algorithm ignores all identified peaks not separated by more than the value of MinPeakDistance.

One example of implementation after previous using FFT can be:

```
%Defining the parameters
Threshold = 0.00001;
MinPeakHeight = FFTMax*0.0000001;
MinPeakDistance = 10;

%Find Peaks
[Xpeaks, Ypeaks] = LocatePeaks(YSignal, Threshould, MinPeakHeight,
MinPeakDistance);
```

For the implement simulated function using Speed = 1500 rpm, the output of this function for the faulty signal and good signal is shown in Figure 5.6 respectively.

As expected the “Good Signal” don’t present the high frequency components that are seen in the “Faulty Signal” and presents much less harmonics. This is due to the complexity of the Bearing Faulty Simulated Signal.

Also adding the reference “ComplexFunctions.dll” to the project and adding the following lines to the code, the algorithms can be calculated.

```
//Inicialize Complex Functions
ComplexFunctions.ComplexFunctions CompFunctObj = new
ComplexFunctions.ComplexFunctions();
//Calculate FFT
var FFT = CompFunctObj.FFT(4, YSignal, Fs);

//Find FFT Peaks
MWArray Threshould = 0.000001;
MWArray MinPeakHeight = FFT[2] * 0.0001;
MWArray MinPeakDistance = 1;

var   FFTPeaks   =   CompFunctObj.LocatePeaks(2,   FFT[0],   FFT[1],   Threshould,
MinPeakHeight, MinPeakDistance);
```

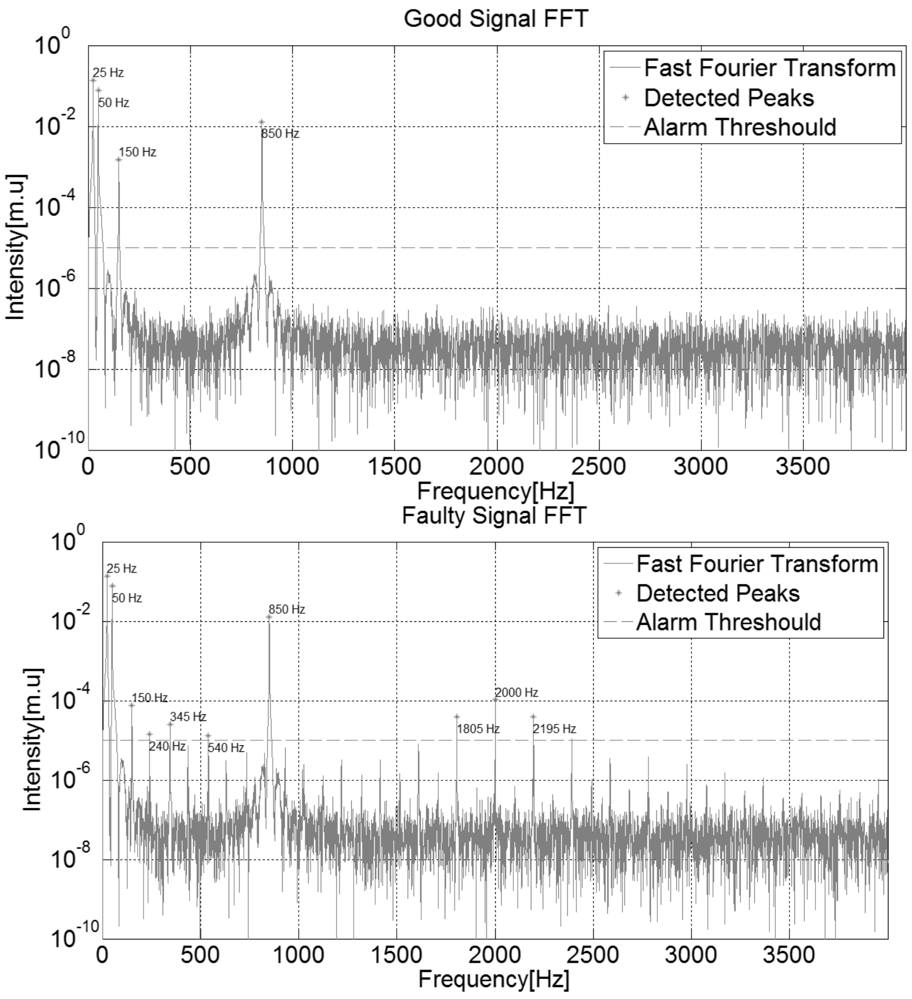


Figure 5.6 - On top picture FFT of “Faulty Signal” is shown and on bottom picture FFT of “Good Signal” is shown.

5.6. Filtering

The implemented filter consists in a Butterworth Filter. This filter is implemented in a two-step process using the following functions:

```
%Constructing the Filter
[a,b]=butter(order,Wn,ftype);
%Applying the filter to the signal
Signal = filter(a,b,Signal);
```

Where:

- order – Order of the filter;
- Wn – Is the cut-off frequency of the filter which is a value if ftype is “high” or “low” or a vector if ftype is “stop” or ”bandpass”.
- Ftype – Is the type of filtering implemented and can be: “high”, “low”, “stop” or “bandpass”.

The stop band and the band pass filters were used. One example of implementation can be:

```
FreqBand = 200;        %Window for the filter
CutOffFrequency = 2000 %Wanted Cutt-Off Frequency
WnS = ((CutOffFrequency+FreqBand)/(Fs/2)); %Lower Limit for the Filter
WnI = ((CutOffFrequency-FreqBand)/(Fs/2)); %Upper Limit for the Filter

%Construction of the Frequency Vector
Wn =[WnI WnS]

%Filter Band Signal
[a,b]=butter(15,Wn,'bandpass');
PassBandSignal = filter(a,b,YFaulty);


%High pass Filter
[a,b]=butter(15,Wn,'stop');
StopBandSignal = filter(a,b,YFaulty);
```

For the implement simulated function using Speed = 1500, the output of this function for the Faulty Signal using has input of the filter the Faulty Frequency of 2000 Hz (Figure 5.7).

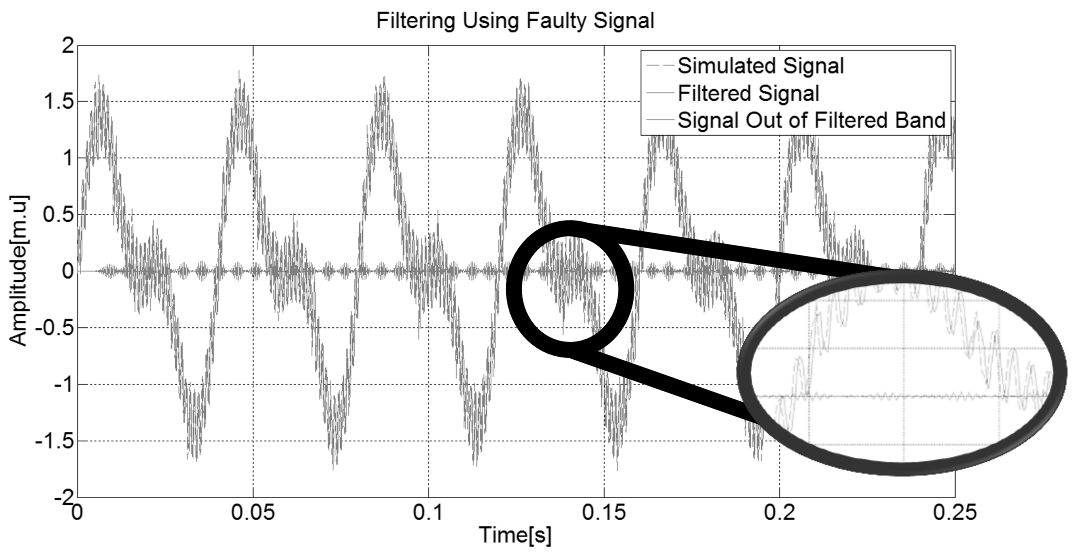


Figure 5.7 – Output of Butterworth Filter applied to Faulty Signal using as input 2000 Hz Cut-Off Frequency.

It is possible to see that the filtering can actually take valuable information about the Faulty Frequency. If “FFT” is on filtered signals, the effectiveness of the implemented filter can be seen and is shown in Figure 5.8.

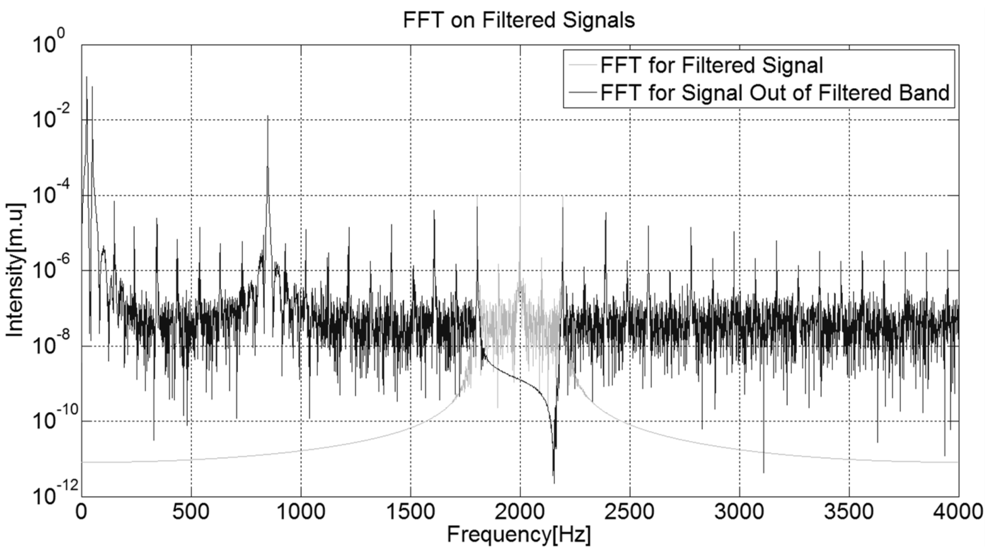


Figure 5.8 – FFT on Filtered Signals.

Clearly is seen that filter Cut-Off slope is very high. That is due to the selected order of the filter of 15. If a lower order filter was chosen the filter wasn’t so accurate.

Also in “ComplexFunctions.dll” library, the Filtering functionality can be used in the project by adding the following lines to the code:

```
//BandPass Signal using Butterworth Filter with frequency 2000Hz

double[] aux = new double[2] { 2.00 * 2000 / Fs * 0.90, 2.00 * 2000 / Fs * 1.10
};
MWNumericArray Wn = new MWNumericArray(aux);
MWArray FilterOrder = 15;          //Order of the filter
MWArray FilterType = "bandpass";   //Band pass type filter
//Create Butterworth Filter
MWArray[] Filter = CompFunctObj.butter(2, FilterOrder, Wn, FilterType);

//Apply BandPass Filter to Signal

MWArray PassFreqSignal = CompFunctObj.filter(Filter[0], Filter[1], YSignal);
FilteredSignalPassComp = ConvertToDouble(HighFreqSignal);

//Apply StopBand Filter to the Signal using same Filter
FilterType = "stop";   //Band pass type filter
//Apply Filter to Signal
MWArray StopFreqSignal = CompFunctObj.filter(Filter[0], Filter[1], YSignal);
     FilteredSignalStopComp = ConvertToDouble(StopFreqSignal);
```

5.7. Enveloping

There are some techniques regarding Signal Enveloping. One of the easiest one and implemented using the function “envelop” basically consisted in reutilizing some parts of the code used for the calculation of the EMD imf$_s$. It consists on a two-step process:

- Identify local maxima;
- Deduce an upper interpolation (cubic splines);

The “envelop” function is called using the following command:

```
envelopSignal = envelop(Signal);
```

In comparison to this simple Enveloping technique, a more complex approach described in the literature was also used, the “Hilbert Envelop” and can be called using the function “hilbertenvelop”.

The “hilbertenvelop” function is called using the following command:

```
HilbertSignal = hilbertenvelop(PassBandSignal);
```

Using this simple enveloping in the Stop Band Filtered Signal is a good application of this kind of enveloping and the result is shown in Figure 5.9.

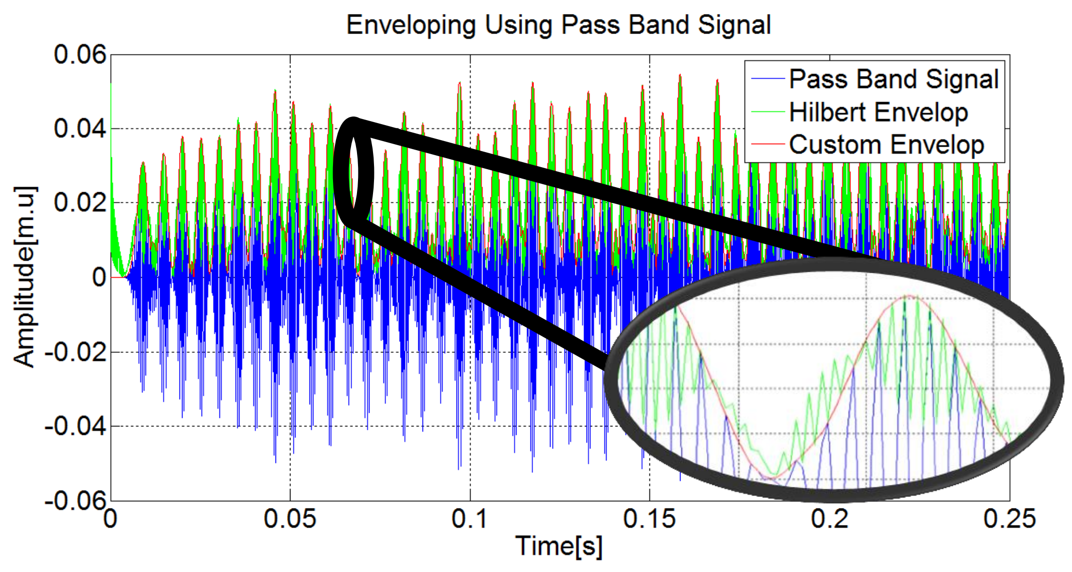


Figure 5.9 – Simple Enveloping and Hilbert Enveloping applied to the Stop Band Filtered Signal.

Using the FFT on the Envelop Signals, some new unknown information about the signal can be seen.

In Figure 5.10 the FFT of the Simple Enveloping and of the Hilbert Enveloping is presented.

Both Enveloping techniques detect a peak at 195 Hz which clearly is a signature of the Faulty Bearing Component. The Hilbert Enveloping also shows a peak at higher frequency but possible this has another interpretation that was not studied in enough detail to take conclusions.

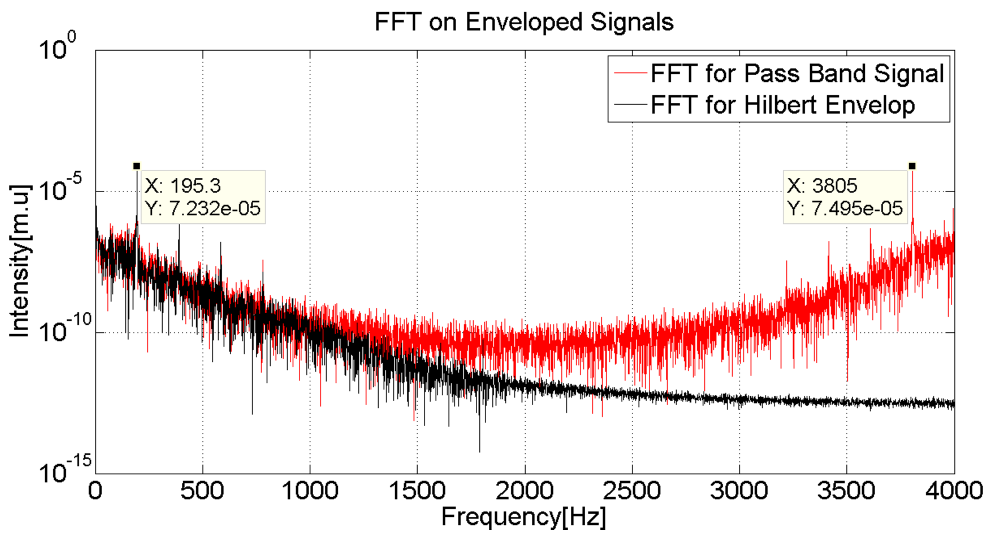


Figure 5.10 – Signal eveloping using “envelop” function(Red) and using “hilbertenvelop” function (Black).

Both this enveloping techniques are available in the “ComplexFunctions.dll” library:

```
//Envelop Signal
MWArray Envelop = CompFunctObj.envelop(YSignal);
//Envelop Signal
MWArray HilbertEnvelop = CompFunctObj.hilbertenvelop(YSignal);
```

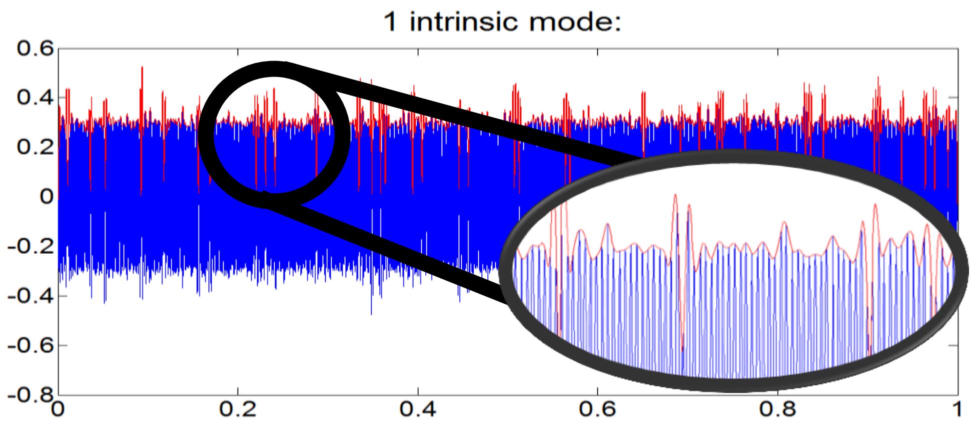
5.8. Empiricial Mode Decomposition

EMD can be considered a more complex Enveloping technique as described in the “Technical Details” Section. The EMD generates on its outputs the called imfs that contain information about several frequency components on a signal. The EMD function can be used on matlab like the example shown:

```
%Calculate Signal Empirical Mode Decomposition
imf = EMD(YSignal);
```

Using this EMD function all the imf$_s$ are calculated, and an example using the Faulty Signal shown in Figure 5.11.

It is clearly seen that the Imf$_s$ shows valuable information about the signal. As usual the EMD can then be combined with the FFT to examine the predominant frequency component on each the Imf and will be obtained result will be shown on Figure 5.12.



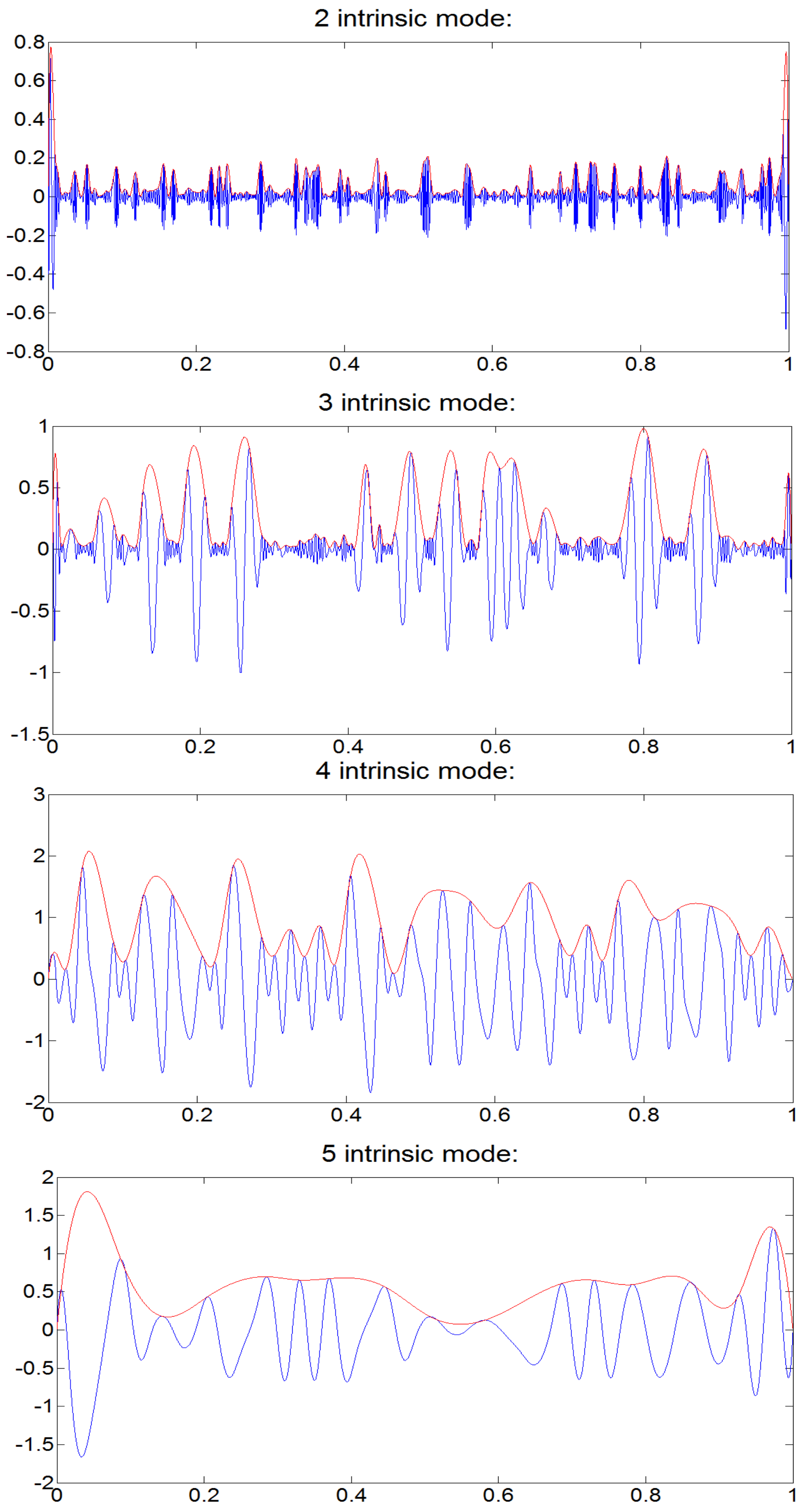
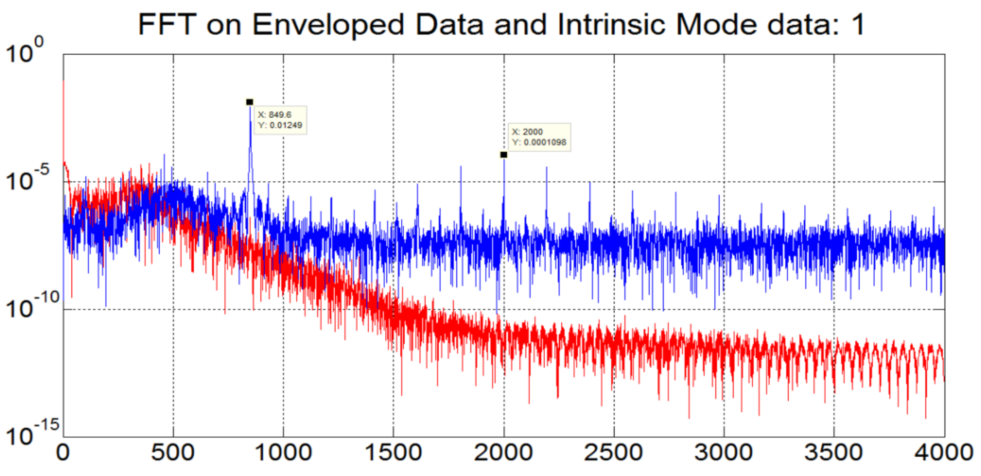
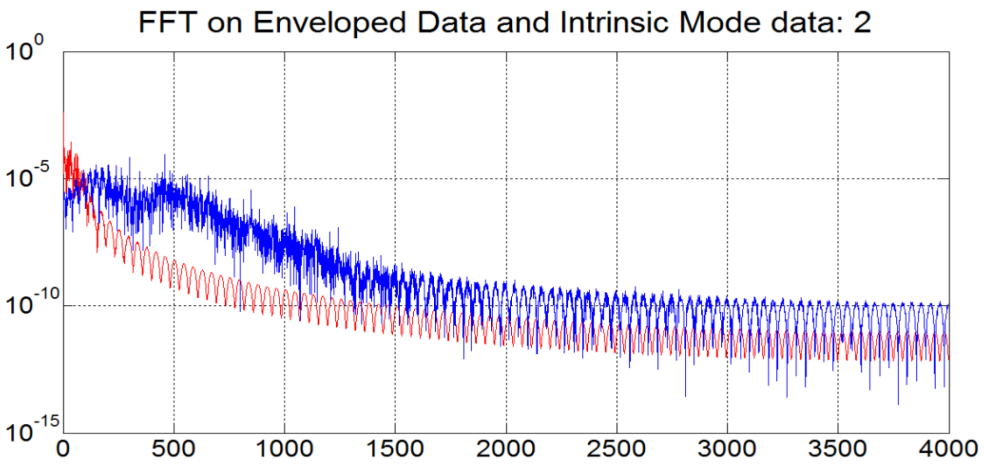
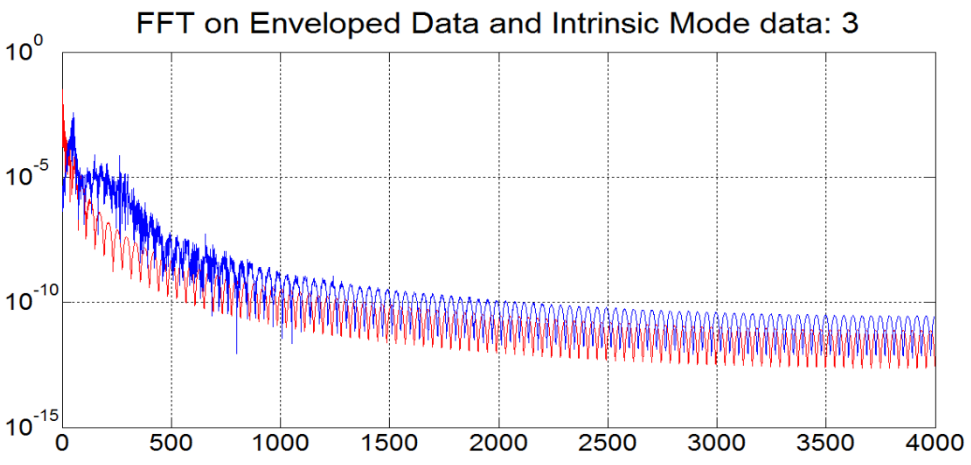
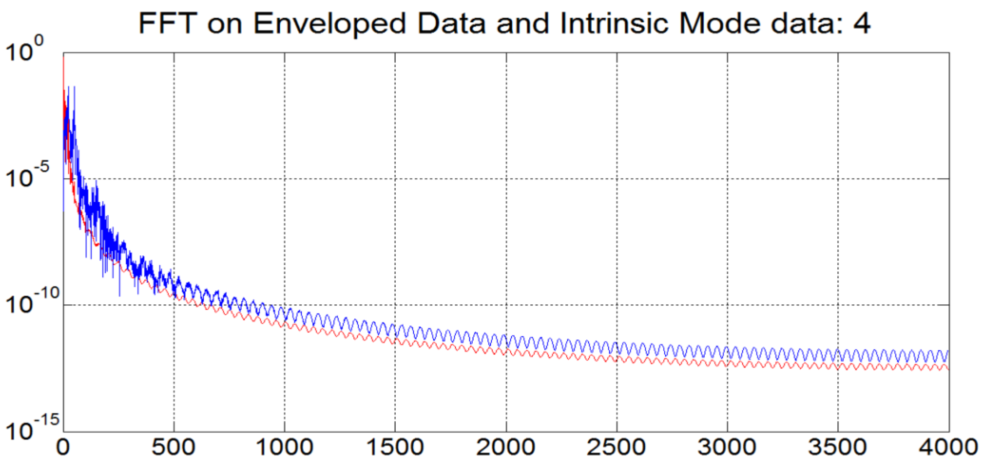


Figure 5.11 –Imfs(Blue) and Simple Enveloping(Red) on Faulty Signal.


FFT on Enveloped Data and Intrinsic Mode data: 1
X: 849.6
Y: 0.01249
X: 2000
Y: 0.0001098
10^0
10^-5
10^-10
10^-15
0
500
1000
1500
2000
2500
3000
3500
4000


FFT on Enveloped Data and Intrinsic Mode data: 2
10^0
10^-5
10^-10
10^-15
0
500
1000
1500
2000
2500
3000
3500
4000


FFT on Enveloped Data and Intrinsic Mode data: 3
10^0
10^-5
10^-10
10^-15
0
500
1000
1500
2000
2500
3000
3500
4000


FFT on Enveloped Data and Intrinsic Mode data: 4
10^0
10^-5
10^-10
10^-15
0
500
1000
1500
2000
2500
3000
3500
4000

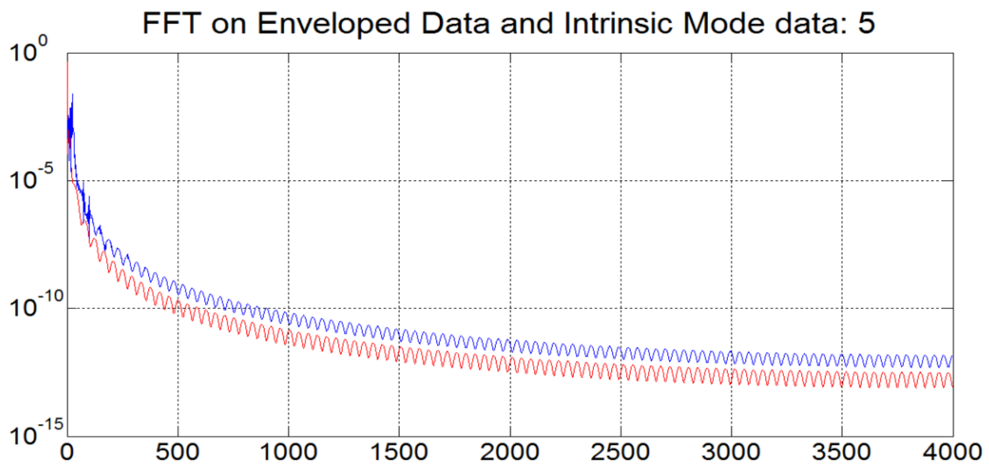


Figure 5.12 – FFT on calculated Imf$_s$ (Blue) and on Enveloped Imf$_s$ (Red).

Supported by the theory and looking at the plots, can be concluded that the first Imf has as main component the higher frequency components and on each iteration the slow components of the signal raise. As a title of curiosity, if the faulty bearing component is raised to double of the amplitude, the envelop of the 1rst Imf component shows a clear peak at 195 Hz which is compatible to the pick found in the envelop of the filtered signal as shown in Figure 5.13.

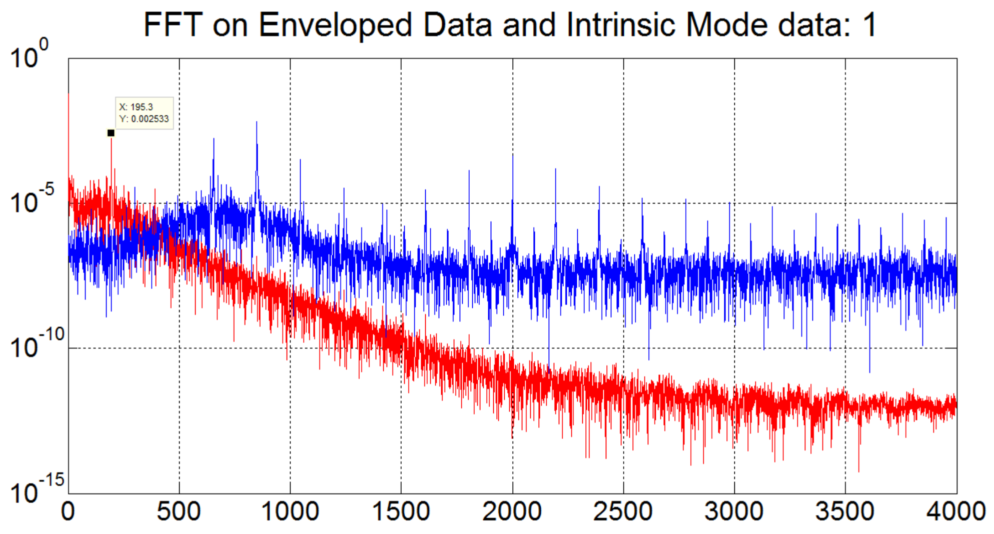


Figure 5.13 – 1rst imf component on faulty signal with amplitude of the faulty component increased to double.

This translates that if the faulty components increase, the IMF can successfully detect their signature without requiring an active filtering.

The EMD function is available in the “ComplexFunctions.dll” library calling the following method:

```
//Envelop Signal
MWArray Imfs = CompFunctObj.EMD(YSignal);
```

5.9. Time Synchronous Averaging

TSA is a technique that is very used and known throw the literature. Unfortunately at the time of the creation of this report, only simulated data was used so no trigger from a tachometer was provided. This means that another approach was used. On matlab environment, when calling the function "TSA", the user needs to use the following function:

```
%Perfom time Syncronous Average base on Fundamental frequency input
frame = Speed/60;
[Time,SyncronousSignals]=tsa(YSignal, frame, Fs);
```

Basically this inputs consist in the same as the ones used for the calculation of the Mean Peak to Peak. The output of this function is a vector of time and another with all the detected synchronous signals. In the case of our faulty signal, the output of this function can be seen on Figure 5.14.

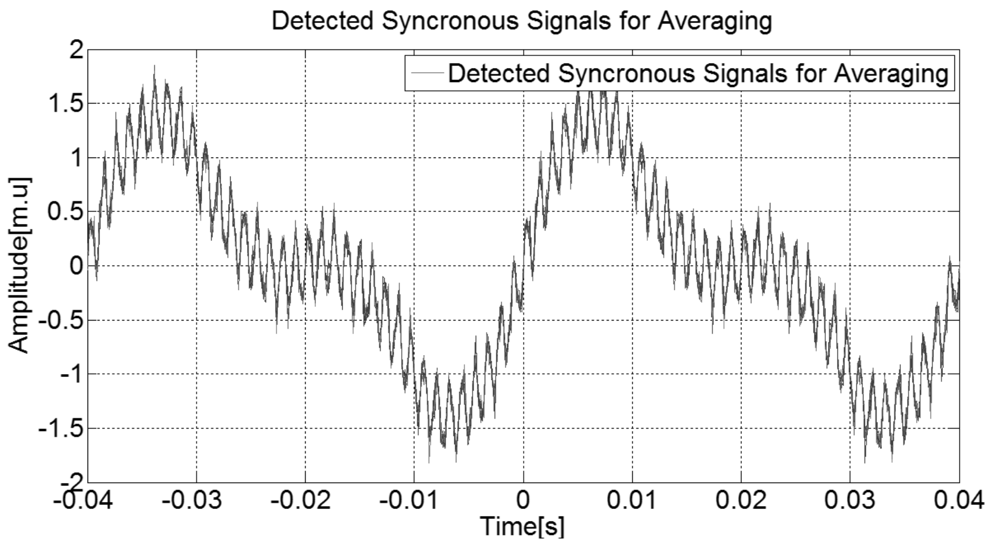


Figure 5.14 – Detected Synchronous Signals using TSA function on Faulty Signal.

A common approach now would be calculating the mean signal of all the synchronous signals. This is easily achieved with the simple command:

```
%Calculate mean of Syncronous Signals
TSaSignal = mean(SyncronousSignals);
```

The result of this function can be seen on Figure 5.15.

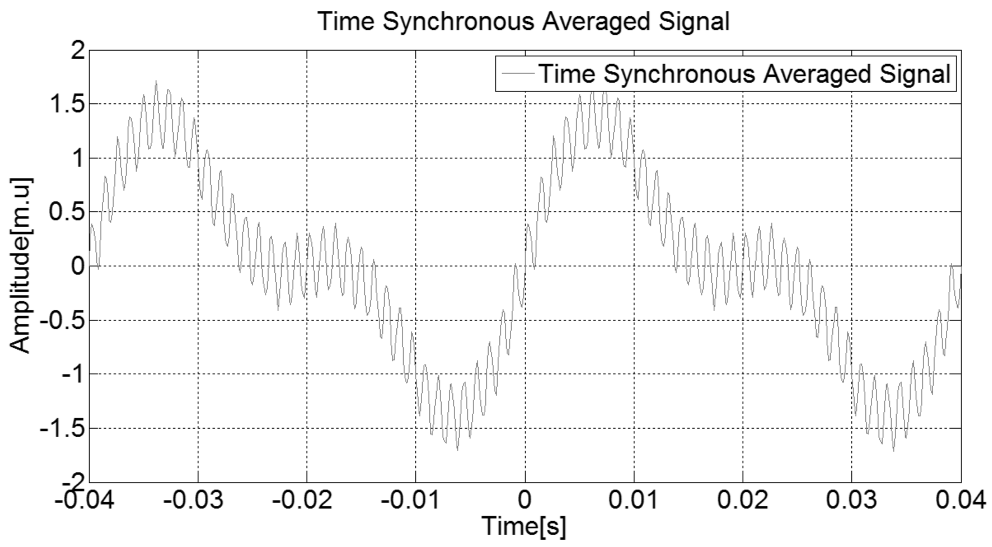


Figure 5.15 – Time Synchronous Averaged Signal.

Again, the user can has now some options to use this signal. A common procedure is to calculate the indicators on the Time Synchronous Averaged Signal and monitor them over time. It is also possible to calculate the FFT and detect the peaks of this Signal (Figure 5.16).

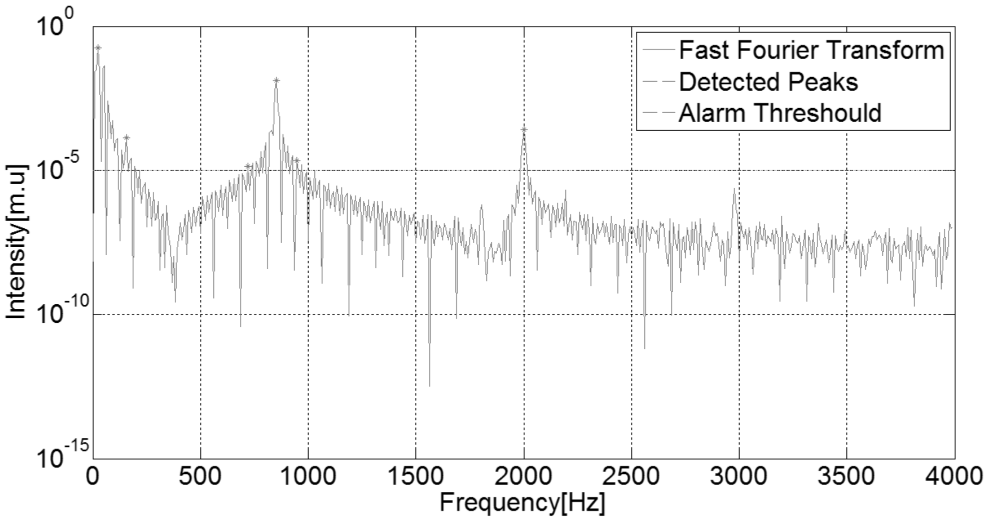


Figure 5.16 – FFT on Time Synchronous Averaged Signal.

Clearly this FFT has less noise that the raw Signal as expected.

Another approach can be applying the so called Short Time Fast Fourier Transform using each of the Detected Synchronous signals. Using the vector of the Synchronous Signals a simple code to calculate the Short Time Fast Fourier Transform. This function output is shown in Figure 5.17.

```
%Calculate Short Time Fast Fourier
[Timer,Power,Count]= STFFT(Time,SyncronousSignals, Fs);
```

```
%Plot the result
plot3(Timer, Count, Power);
```

This is implemented and is possible for the user to use this function. Still more study needs to be done in order to validate the possibility of the extraction of some valuable indicators from output of this function.

All the referred functions are also implemented in the “ComplexFunctions.dll” library as shown below:

```
//Calculate Time Synchronous Averaging
MWNumericArray frame = new MWNumericArray(Speed / 60);
MWArray[] TSA = CompFunctObj.tsa(2,Signal, frame, Fs);

//Mean value of TSA signal
Indicators.Indicators IndObj = new Indicators.Indicators();
MWArray TSASignal = IndObj.mean(TSA[1]);

//FFT of Tsa Signal
MWArray[] TSA_FFT = CompFunctObj.FFT(4, TSASignal, Fs);

//STFFT of Tsa Signal
MWArray[] TSA_STFFT =CompFunctObj.STFFT(3, TSA[0], TSA[1]);
```

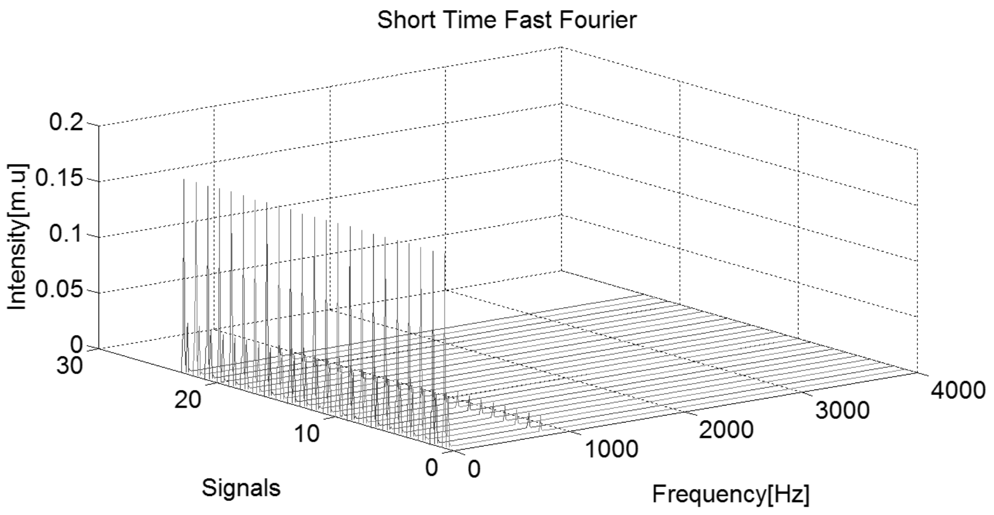


Figure 5.17 – Short Time Fast Fourier on Detected Synchronous signals.

5.10. Wavelet Decomposition

Wavelet Decomposition is a powerful algorithm vastly described in the literature. One implemented function based on this concept is “WaveletDecomposition” and it can be used like shown below:

```
%Define Wavelet
wname ='db8';
DecompositionNumber =5;
```

```
%Define Wavelet Decomposition
[Time,LowFreq, HighFreq, Fs]=WaveletDecomposition(Ysignal, Fs, wname,
DecompositionNumber);
```

The output of this function can then be plotted and is show in Figure 5.18.

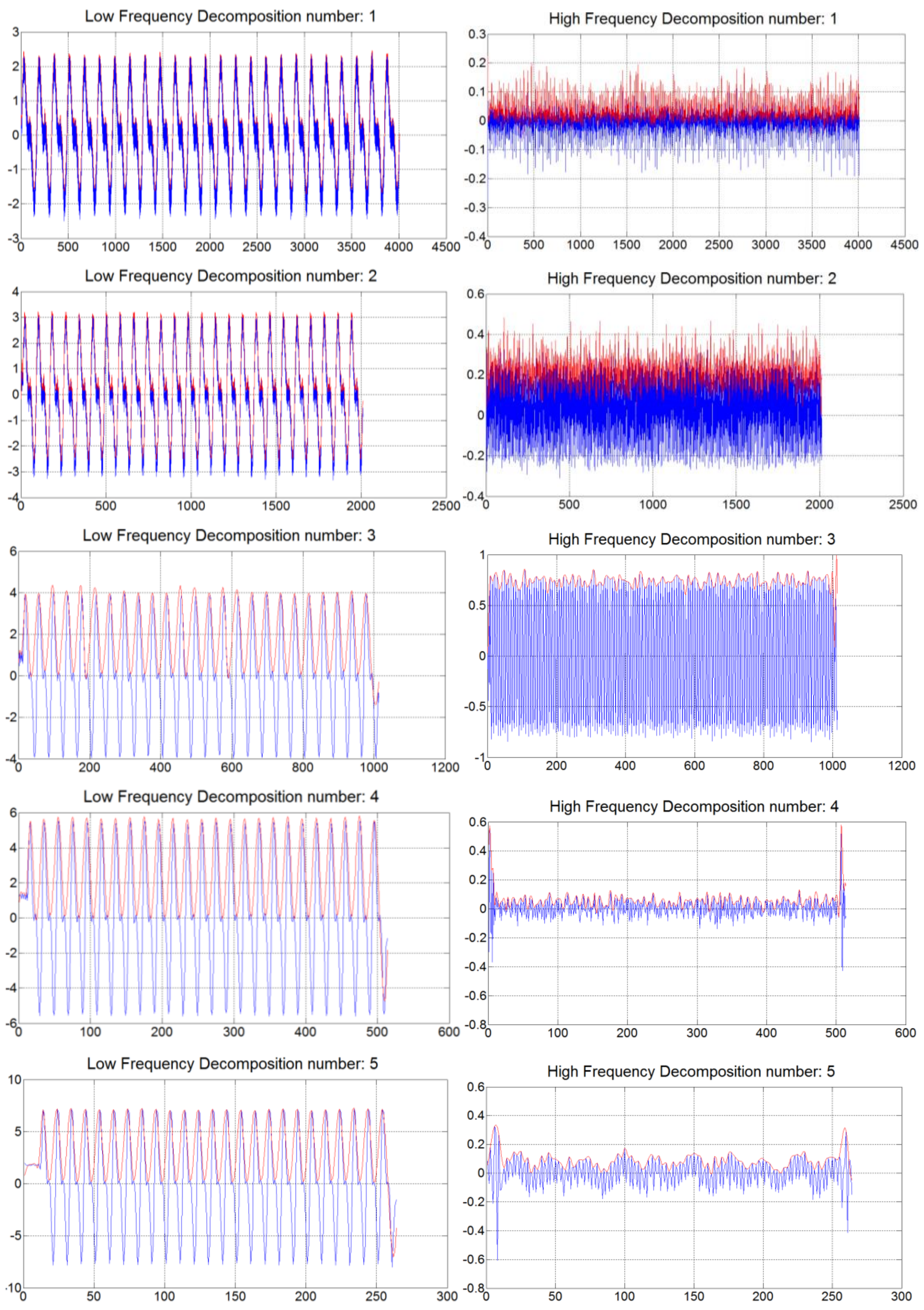


Figure 5.18 –Wavelet Decomposition on Faulty Signal (Blue) and Simple Enveloping Signal (Red).

Notice that in the plots shown above, the x-axis refer to sample number. Each time a wavelet decomposition is made the number of samples decrease. This results in a lower sample rate meaning that a correction needs to be done in the sampling rate in order to calculate the FFT.

As expected each decomposition acts like a filter on the signal. FFT can then be calculated to take some conclusions (Figure 5.19).

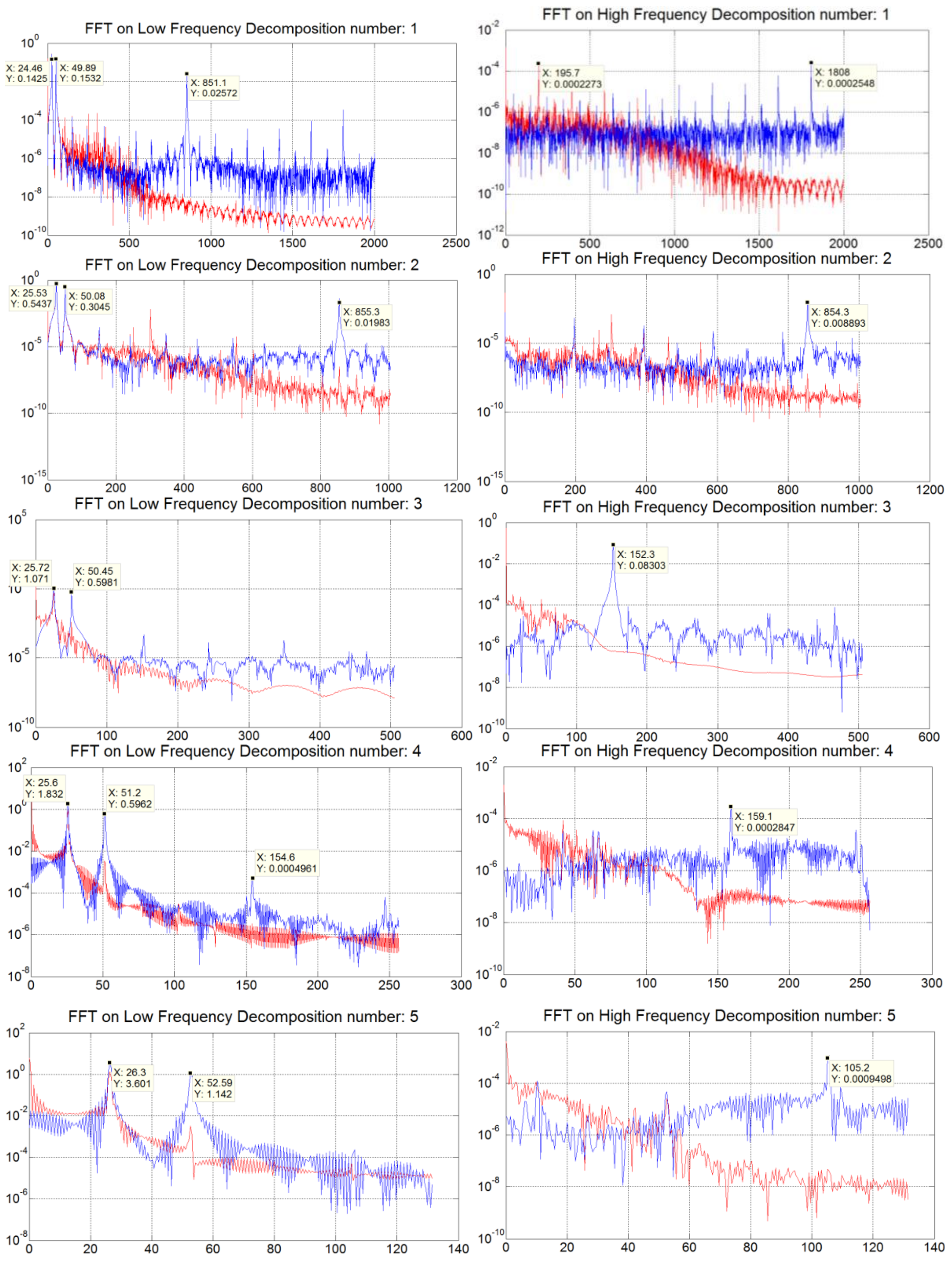


Figure 5.19 – FFT on Wavelet decomposition (Blue) and Simple Enveloping Signal (Red).

Using FFT on the Wavelet decomposition signals a very important conclusion could be taken. Looking to the FFT on the High Frequency Decomposition 1, we can see that the Higher Peak is the Peak close to the Faulty Bearing. Also the envelop peak shows a similar signature to the Faulty Bearing.

Whoever, has the sampling rate was decrease by half when performing wavelet decomposition (from 8000 Hz of the original signal to 4000 Hz), there was not enough sampling rate to successfully detected the exact frequency of the faulty signal. To prove this theory the sampling rate of the original signal was increased from 8000 Hz to 10 000 Hz and the results are presented on Figure 5.20:

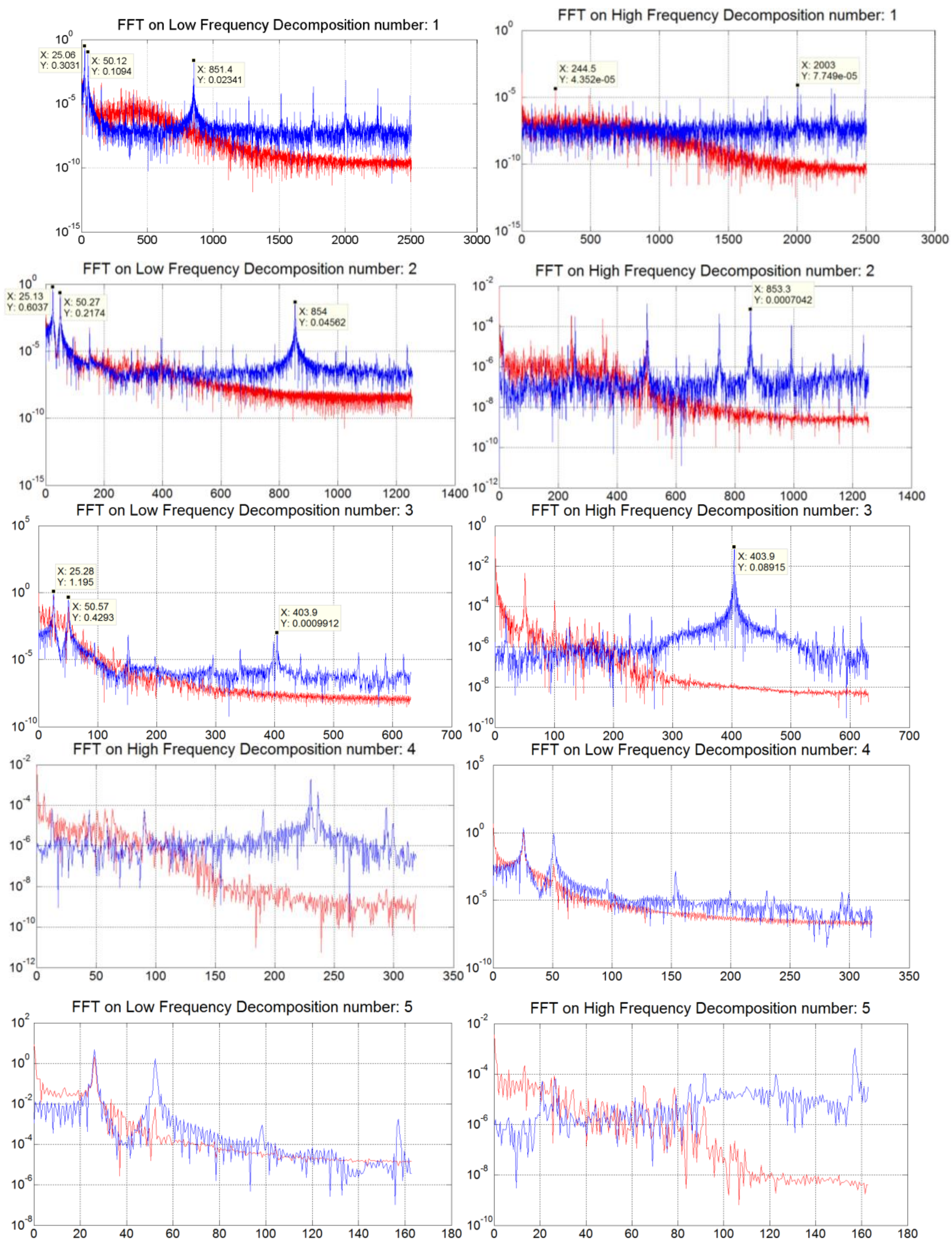


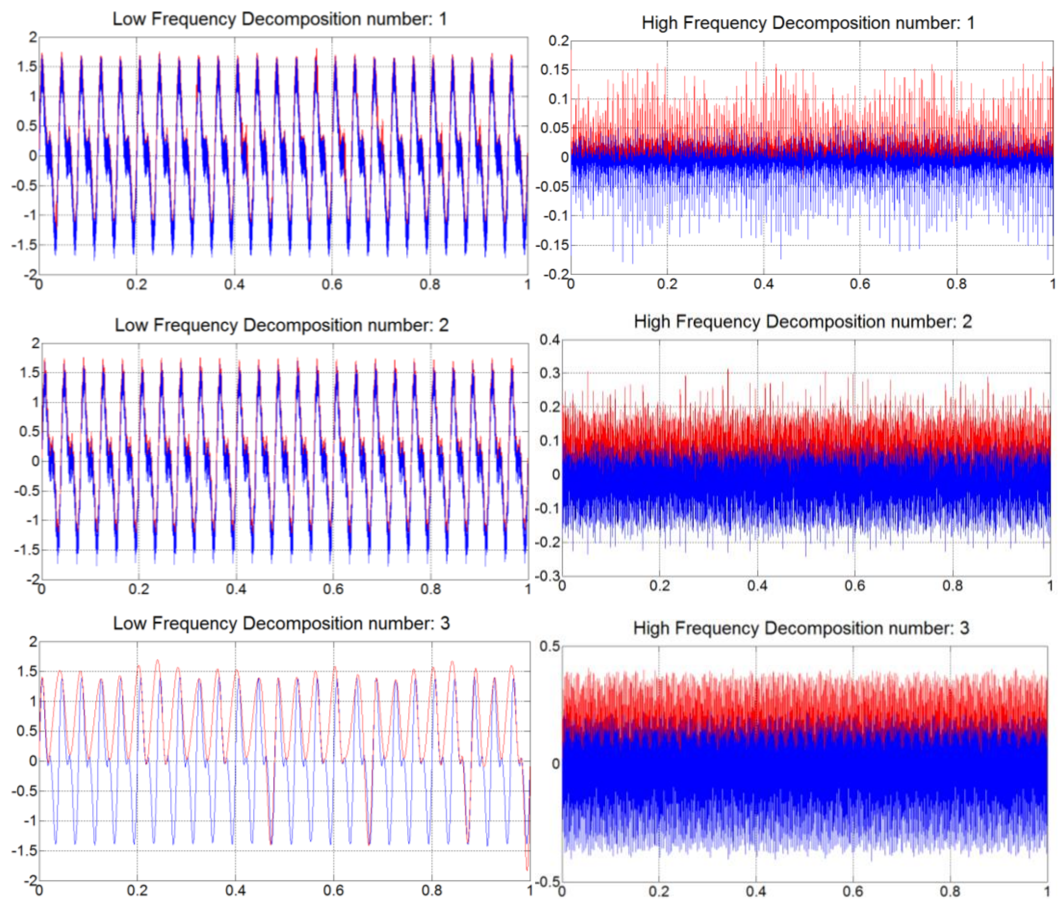
Figure 5.20 - FFT on Wavelet decomposition (Blue) and Simple Enveloping Signal (Red).

With the increase of the original signal, it can be seen that High Frequency Decomposition 1, successfully detected a Peak corresponding to the Faulty Bearing proving also that a sample rate limitation was causing the frequency distortion. Also the envelop peak keeps showing a similar signature to the Faulty Bearing.

In some applications increasing the Sampling Rate can have big drawbacks and sometimes also mean buying an expensive Acquisitions Systems. Some research was made around the possible solutions regarding this problem and it was discovered that using Inverse Wavelet on the Decomposed Signals restored the Sampling rate on the Signals. This was implemented using the function “WaveletDecompositionWithReconstruction”.

```
%Define Wavelet
wname ='db8';
DecompositionNumber =5;

%Define Wavelet Decomposition with Reconstruction
[LowFreq, HighFreq]=WaveletDecompositionWithReconstruction(Ysignal, wname, 
DecompositionNumber);
```

The output of this function can be seen in Figure 5.21.



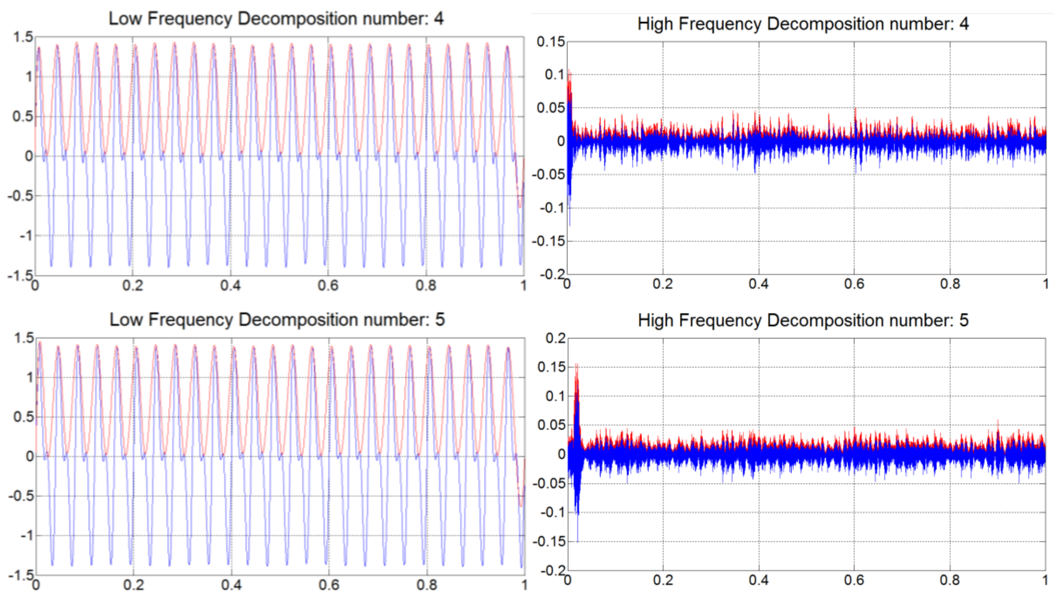
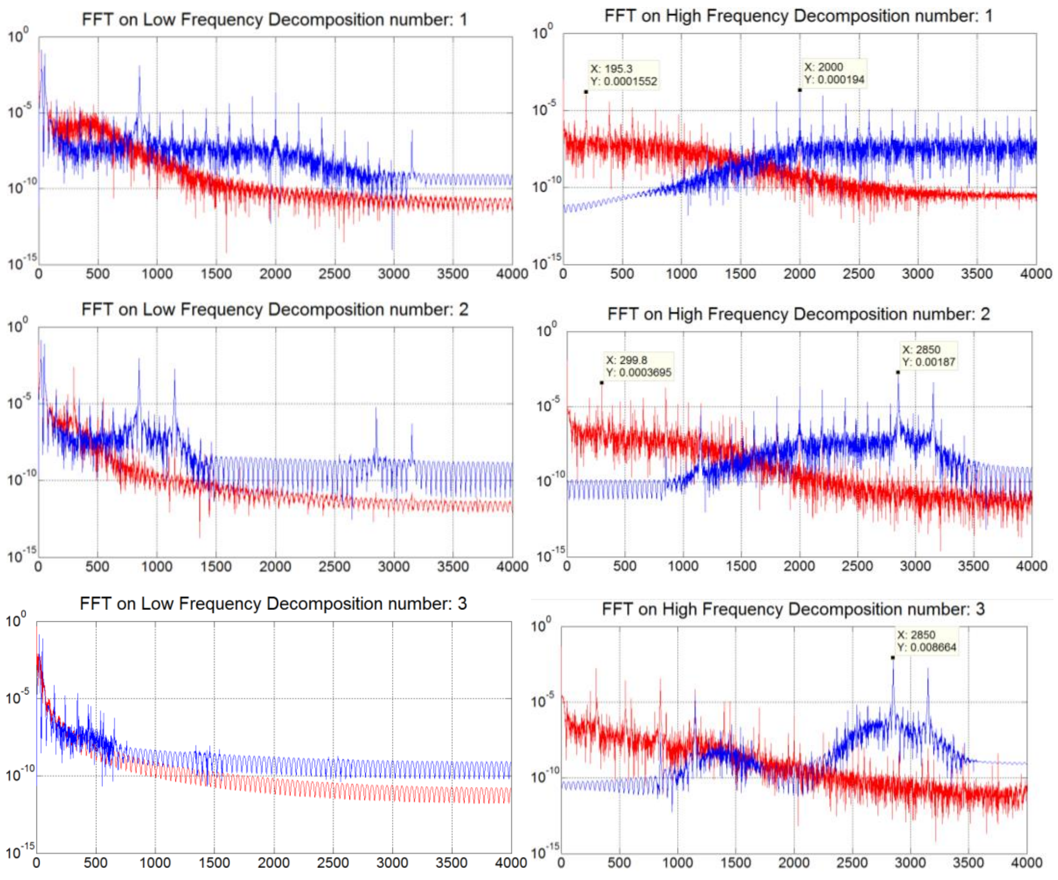


Figure 5.21 –Wavelet Decomposition on Faulty Signal (Blue) and Simple Enveloping Signal (Red).

As expected each decomposition acts like a filter on the signal. FFT can then be calculated to take some conclusions (Figure 5.22).



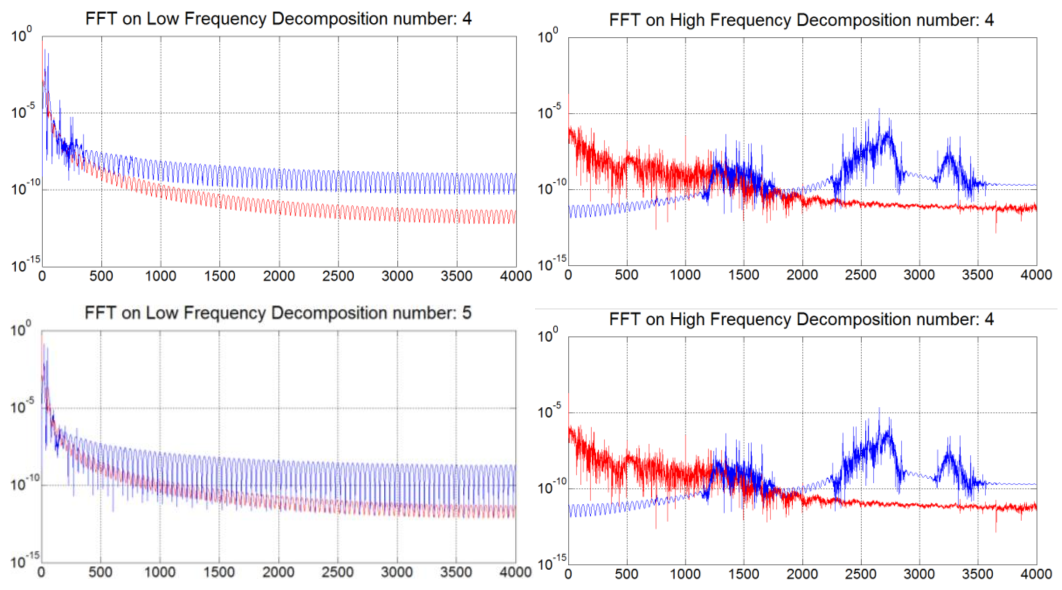


Figure 5.22 – FFT on Wavelet decomposition (Blue) and Simple Enveloping Signal (Red).

Using FFT on the Wavelet Decomposition with Reconstruction signals, a very important conclusion could be taken. Looking to the FFT on the High Frequency Decomposition 1, we can see that the Higher Peak is the Peak characteristic of the Faulty Bearing. Also the envelop peak shows a similar signature to the Faulty Bearing. This means that this technique can be used for diagnosis which makes this functionality very interesting.

Wavelet Decomposition with Reconstruction is also accessible using "ComplexFunctions.dll" library as shown below:

```
//Wavelet Decomposition with Reconstruction
MWArray wname = "db8";
MWArray DecompositionNumber = 5;
MWArray[] WaveDec = CompFunctObj.WaveletDecompositionWithReconstruction(2,
YSignal, wname, DecompositionNumber);
```

Continuous Wavelet Transform, referred in "Signal processing" of this report, was also implemented during this work. It is a very complex function not a lot of interest was given to it whoever for further studies /applications this technique can be useful and is also worthy to talk about in this document. This function can be accessed on matlab using the function "ContinuousWaveletTransform" like shown in the example below:

```
%Calculate Continuos Wavelet Transform
[wave, period, scale, coi, dj,paramout, k] = ContinuousWaveletTransform
(YSignal, Fs);
```

After that the result can be plotted on 2d like the following example:

```
freq = 1./period;
power = abs(wave).^2;
contour(t,freq,log(power));
```

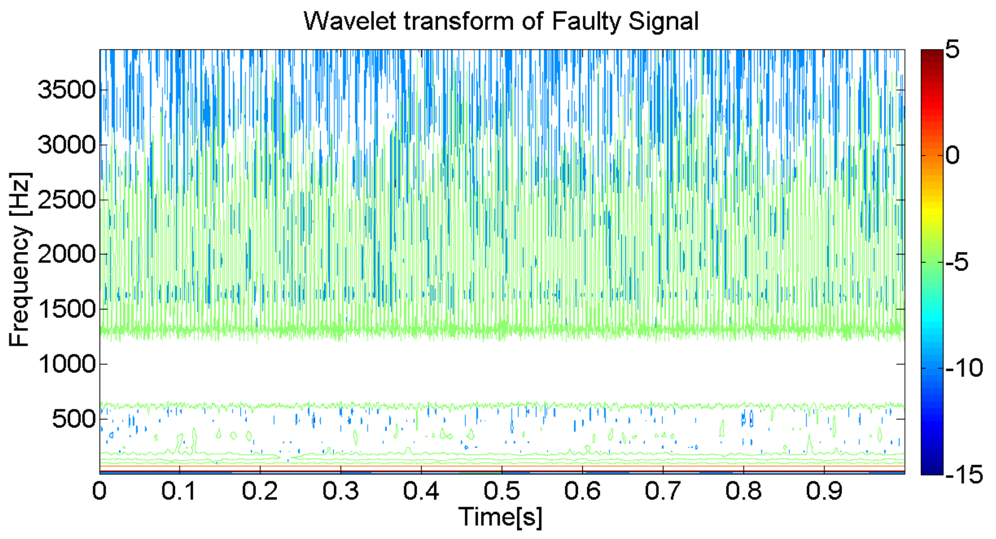


Figure 5.23 – Continuous Wavelet Transform on Faulty Signal.

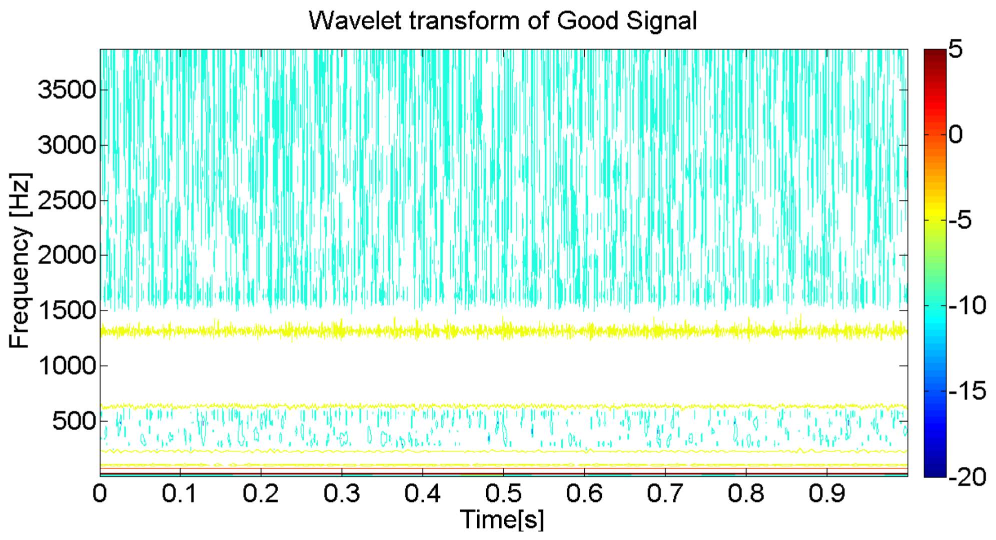


Figure 5.24 – Continuous Wavelet Transform on Good Signal.

It can be seen that the Continuous Wavelet Transform on Faulty Signal (Figure 5.23) shows higher Power Spectrum on High Frequencies than the Continuous Wavelet Transform on Good Signal (Figure 5.24). Whoever as this signals are continuous this algorithm suits better to detect any discontinuity has referred.

5.11. Diagnoses Library

The diagnoses library consists in a web service that can be deployed on a server and remains waiting for receiving a OSA-CBM request that is sent using the scheduler every time the a job is created in the database.

Basically this web service consist in calculate all the developed algorithms on the triggered signal and send the obtained values to the database using OSA-CBM interface. A basic flowchart of the implemented algorithm is shown in Figure 5.25.

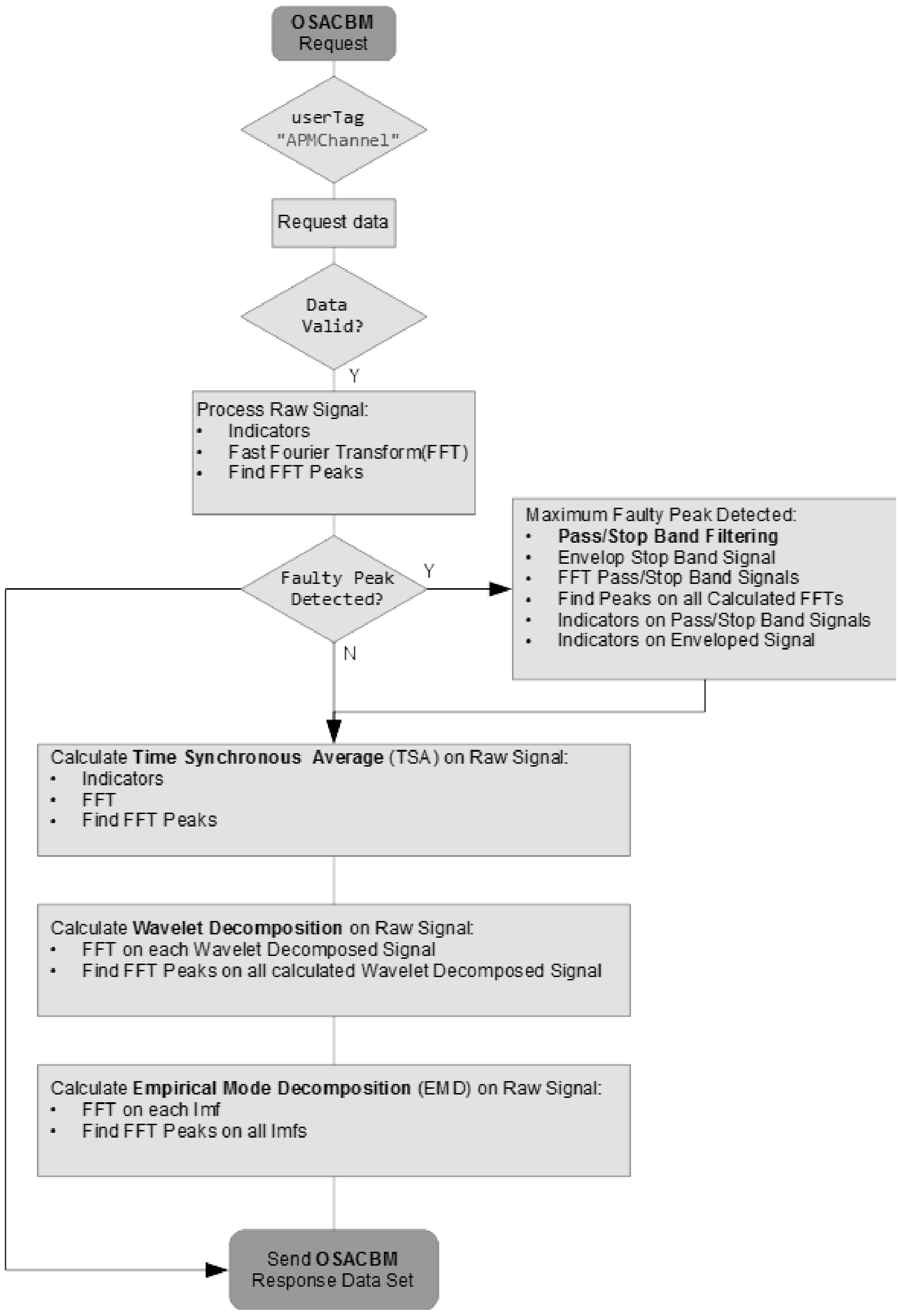

OSACBM Request
userTag "APMChannel"
Request data
Data Valid?
Y
Process Raw Signal:
• Indicators
• Fast Fourier Transform(FFT)
• Find FFT Peaks
Faulty Peak Detected?
Y
N
Maximum Faulty Peak Detected:
• Pass/Stop Band Filtering
• Envelop Stop Band Signal
• FFT Pass/Stop Band Signals
• Find Peaks on all Calculated FFTs
• Indicators on Pass/Stop Band Signals
• Indicators on Enveloped Signal
Calculate Time Synchronous Average (TSA) on Raw Signal:
• Indicators
• FFT
• Find FFT Peaks
Calculate Wavelet Decomposition on Raw Signal:
• FFT on each Wavelet Decomposed Signal
• Find FFT Peaks on all calculated Wavelet Decomposed Signal
Calculate Empirical Mode Decomposition (EMD) on Raw Signal:
• FFT on each Imf
• Find FFT Peaks on all Imfs
Send OSACBM Response Data Set

Figure 5.25 – FlowChart of the diagnoses library.

CHAPTER 6

Conclusions

In this work, several the work performed during the Internship in Critical Software Technologies is presented. In a first approach was needed to understand the problems that a CBM system tries to solve and it's place in modern industry. That was presented in Chapter 1 and developed in detail in Chapter 2 contextualizing with other common approaches for maintenance.

In Chapter 3, is presented a system for train conditioning-based monitoring that was improved during this internship and it's features. Through the work in this project, knowledge related to key components of a train and common measures on a system was developed and a framework where is possible to test all the features of a conditioning monitoring system is presented.

Chapter 4 presents the work done for *Arrive* project. This project is very recent and aims to monitor rotational machines present health indicators regarding assets condition. The developments on this project were done slowly because most of the improvements were firstly done in Alstom and then adapted. Here firstly insights on common faults were studied and common approaches suggested by the literature are presented.

Chapter 5 finally presents the results obtained with the developed algorithms. Although the code is not presented, it is intended for this chapter to be a starting point for anyone who wants to develop algorithms for CBM systems.

The environment developed by Critical Software Technologies regarding conditioning-based monitoring system is a very powerful framework. The overall architecture is made in a way that is easily adaptable to other applications. At this points more work needs to be done in order to build a truly adaptable structure that lower the costs in terms of future developments to become more compatible in the field.

In order to prove the concept for both the framework and applicability in vibration analysis, several algorithms were developed but much more work needs to be done in order to validate obtained results.

Unfortunately the algorithms were only tested using a simulated signal and that is a less strong point regarding this work.

Alstom project is finishing and is now on acceptance tests by the client and was the first project in the field done by Critical Software Technologies. *Arrive* Project at the moment only back end developments were done which were developing an interface to communicate with the data acquisition systems and develop the web service that calculate the diagnostic algorithms.

Much more work need to be done by Critical in order to become a major player in the conditioning monitoring market. Critical lacks expertise in technical domain and this thesis is a solid starting point in order for Critical start developing it's own library of functions regarding this topic.

Further work with real signals of known faulty vessels and healthy vessels needs to be done in order to evaluate what algorithms are useful and afterwards a machine learning algorithms would be the next step in order to successfully evaluate the health condition of the machines.

Developments regarding front end visualization of data and automatically generated alarms need to be done also. As during this internship only simulated signals were developed, more study needs to be done in order to test the system performance for bigger and more vibration samples acquired at same time.

Prior to this internship, I had no knowledge and experience working with web development and web applications. I also had no experience in vibration analysis. I had a basic introductory course in C# and same thing for SQL. During my internship I developed a lot of skills in C#, algorithm integration, user interface developing using windows forms and making SQL queries. Technically I learn a lot about conditioning monitoring systems and algorithm developing related to vibration analysis which was very interesting. The internship was a huge challenge with all the lack of background, but looking for what I have accomplished in the end I am really happy for everything I did and learn.

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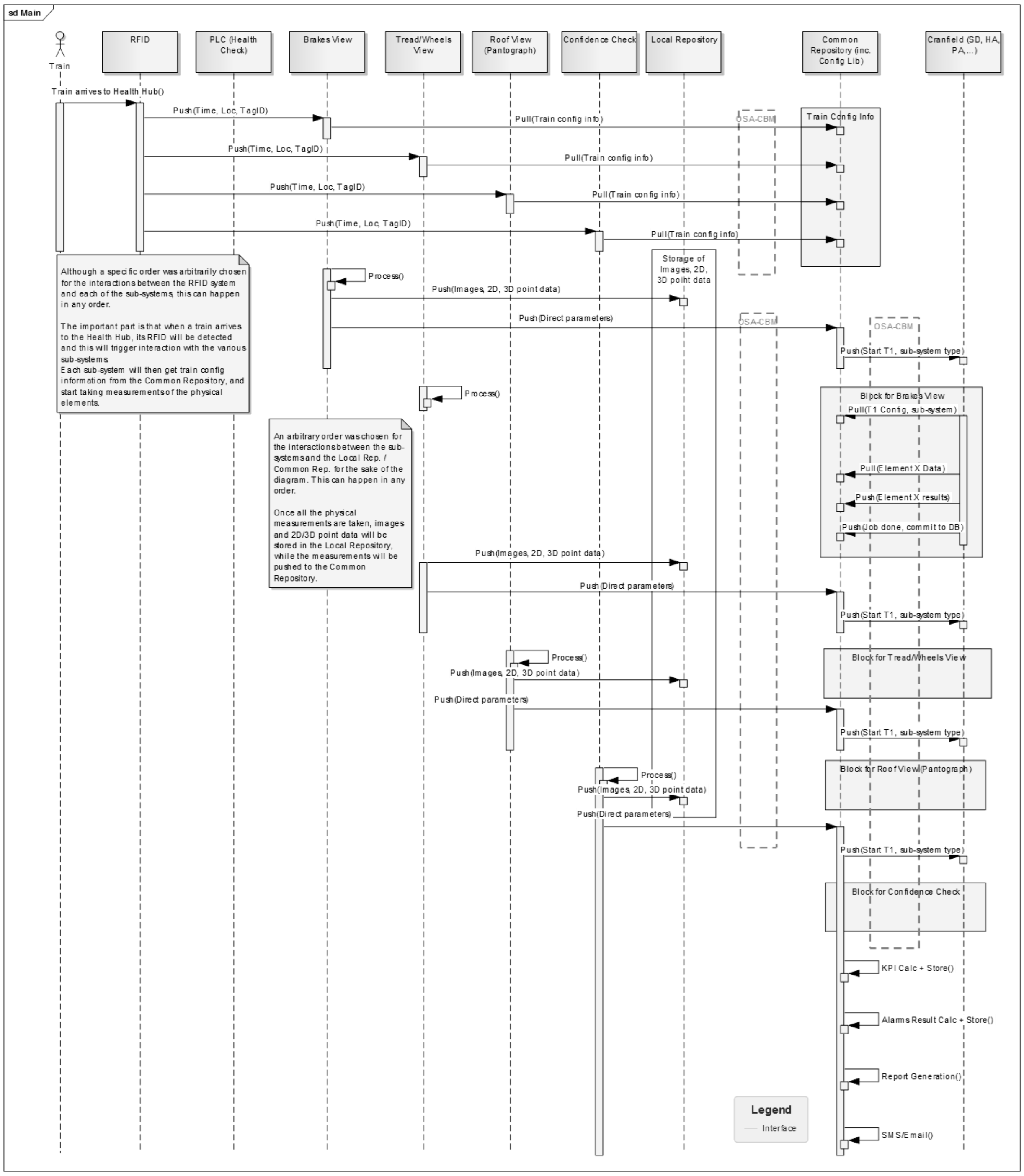
Annex

Annex A - Test Log Report

The following chart presents in a general way the exchange of data between the different modules that compose the system when a new train passes by a Health Hub.


sd Main
Train
RFID
PLC (Health Check)
Brakes View
Tread/Wheels View
Roof View (Pantograph)
Confidence Check
Local Repository
Common Repository (inc. Config Lib)
Cranfield (SD, HA, PA,...)
Train arrives to Health Hub()
Push(Time, Loc, TagID)
Pull(Train config info)
OSA-CBM
Train Config Info
Storage of Images, 2D, 3D point data
Process()
Push(Images, 2D, 3D point data)
Push(Direct parameters)
Push(Start T1, sub-system type)
Block for Brakes View
Pull(T1 Config, sub-system)
Pull(Element X Data)
Push(Element X results)
Push(Job done, commit to DB)
Block for Tread/Wheels View
Block for Roof View(Pantograph)
Block for Confidence Check
KPI Calc + Store()
Alarms Result Calc + Store()
Report Generation()
SMS/Email()
Legend
Interface

Although a specific order was arbitrarily chosen for the interactions between the RFID system and each of the sub-systems, this can happen in any order.

The important part is that when a train arrives to the Health Hub, its RFID will be detected and this will trigger interaction with the various sub-systems.
Each sub-system will then get train config information from the Common Repository, and start taking measurements of the physical elements.

An arbitrary order was chosen for the interactions between the sub-systems and the Local Rep. / Common Rep. for the sake of the diagram. This can happen in any order.

Once all the physical measurements are taken, images and 2D/3D point data will be stored in the Local Repository, while the measurements will be pushed to the Common Repository.