# Design and validation of a methodology for wind energy structures health monitoring

By

**EKHI ZUGASTI URIGUEN**

Thesis submitted for the degree of PhD from the Polytechnic University of Catalonia

Supervised by

DR. LUIS EDUARDO MUJICA
DR. JAVIER ANDUAGA

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DOCTORAL THESIS
Departament de Matemàtica Aplicada III
Universitat Politècnica de Catalunya Barcelona, Spain
September, 2013

# Preface

I would like to thank all of the people who encouraged and supported me during the execution of this research. Firstly I would like to thank Prof. Dr. José Rodellar and Dr. Fernando Martinez for introducing me to this very interesting field of research and the opportunity they have provided to in it. I would also like to thank my supervisors, Dr. Luis Eduardo Mujica and Dr. Javier Anduaga for the patience and guidance that they have generously provided throughout the extended period of this research project. More than just being my supervisors, they have been friends who have been always there to help me at any time when I needed assistance in any matter.

I owe special thanks to Miguel Angel Arregui and Ana Gomez for their dedication, encouragement, advice and assistance for the successful completion of the project. I would like to thank as well the other members of Ikerlan and UPC who were always very unconditionally to help me at any time with my enquiries for the proceeding of this project.

My greatest debt is to my Parents and Sister (and my new nephew!), who have provided inspiration, confidence and firm support throughout my life and studies.

Also to you, person who is reading these lines, friend, referee, person of the jury, student... Thank you for your interest in this work.

*Hitz gutxitan: ♡ Iñaki, Arantza, Hiart eta Harri ♡*

*"Benetako arrakasta lortzeko hurrengo galderak egin zure buruari: Zergatik? Zergatik ez? Zergatik ez ni? Zergatik ez oraintxe bertan?"* **James Allen**

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# Nomenclature

**Roman Symbols**

| | |
|---|---|
| AE | Acoustic Emission |
| ANN | Artificial Neural Network |
| AR | Auto-Regresive |
| AS | Auto Scaling |
| AU | Acoustic Ultrasonics |
| BMU | Best Matching Unit |
| CBR | Case Based Reasoning |
| COMAC | Coordinate Modal Assurance Criterion |
| CS | Continuous Scaling |
| DI | Damage Indicator |
| DOFs | Degree Of Freedom |
| DP | Data Preprocessing |
| E | Expected vavlue |
| EOC | Environmental and Operational Conditions |
| FBG | Fiber Bragg Gratings |
| FE | Finite Element |
| FEA | Finite Element Analysis |
| FRF | Frequency Response Function |
| GA | Genetic Algorithm |
| GPR | Ground Penetrating Radar |
| GS | Group Scaling |
| HDPE | High Density Poly-Ethylene |

| | |
|---|---|
| IBDD | Impedance-Based Damage Detection |
| LDV | Laser-Doppler Vibrometer |
| MAC | Modal Assurance Criterion |
| MI | Mutual Information |
| MREU | Minimum-Rank Elemental Update |
| NDT | Non-Destructive Testing |
| OF | Optical Fiber |
| OMA | Operational Modal Analysis |
| OSS | Offshore Support-Structure |
| PCA | Principal Component Analysis |
| PSD | Power Spectral Density |
| RFV | Residual Force Vector |
| SEAMAC | Sensor Elimination by Modal Assurance Criterion |
| SFD | Sensor Fault Detection |
| SHM | Structural Health Monitoring |
| SOM | Self Organizing Maps |
| SSI | Stochastic Subspace Identification |
| STD | Standard Deviation |
| UmRMR | Unsupervised minimum Redundancy Maximum Relavance |
| WES | Wind Energy Structures |
| WT | Wavelet Transform |

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# RESUM

## Disseny i validació d'una metodologia per a la monitorització i detecció de danys en estructures d'energia eólica

per EKHI ZUGASTI URIGUEN

*DIRECTORS:*
DR. LUIS E. MUJICA
DR. JAVIER ANDUAGA

Octubre, 2013
Barcelona, Catalunya

L'objectiu de la Monitorització de la salut estructural (SHM) és la verificació de l'estat o la salut de les estructures per tal de garantir el seu correcte funcionament i estalviar en el cost de manteniment. El sistema SHM combina una xarxa de sensors connectada a l'estructura amb monitoratge continu i algoritmes específics. Es deriven diferents beneficis de l'aplicació de SHM, on trobem: coneixement sobre el comportament de l'estructura sota diferents operacions i diferents càrregues ambientals , el coneixement de l'estat actual per tal de verificar la integritat de l'estructura i determinar si una estructura pot funcionar correctament o si necessita manteniment o substitució i, per tant, reduint els costos de manteniment.

El paradigma de la detecció de danys es pot abordar com un problema de reconeixement de patrons (comparació entre les dades recollides de l'estructura sense danys i l'estructura actual, per tal de determinar si hi ha algun canvi) . Hi ha moltes tècniques que poden gestionar el problema. En aquest treball s'utilitzen les dades dels acceleròmetres per desenvolupar aproximacions estadístiques utilitzant dades en temps per a la detecció dels danys en les estructures. La metodologia s'ha dissenyat per a una turbina eòlica off - shore i només s'utilitzen les dades de sortida per detectar els danys. L'excitació de la turbina de vent és induïda pel vent o per les ones del mar.

La detecció de danys no és només la comparació de les dades. S'ha dissenyat una metodologia completa per a la detecció de danys en aquest treball. Gestiona dades estructurals, selecciona les dades adequades per detectar danys, i després de tenir en compte les condicions ambientals i operacionals (EOC) en el qual l'estructura està treballant, es detecta el dany mitjançant el reconeixement de patrons.

Quan es parla del paradigma de la detecció de danys sempre s'ha de tenir en compte si els sensors estan funcionant correctament. Per això és molt important comptar amb una metodologia que comprova si els sensors estan sans. En aquest treball s'ha aplicat un mètode per detectar els sensors danyats i s'ha insertat en la metodologia de detecció de danys.

Aquesta estratègia de detecció de danys s'ha validat en diferents models i estructures reals: en un model de turbina que s'executa en un programa de verificació, i en una torre de laboratori simulant un aerogenerador marí, a més d'alguns models estructurals simples. En aquesta tesi es presenten resultats prometedors per a certs estats d'error predefinits i funcions dels danys.

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# ABSTRACT

## Design and validation of a methodology for wind energy structures health monitoring

by **EKHI ZUGASTI URIGUEN**

*ADVISORS:*
DR. LUIS E. MUJICA
DR. JAVIER ANDUAGA

October, 2013
Barcelona, Catalonia

The objective of Structural Health Monitoring (SHM) is the verification of the state or the health of the structures in order to ensure their proper performance and save on maintenance costs. The SHM system combines a sensor network attached to the structure with continuous monitoring and specific, proprietary algorithms. Different benefits are derived from the implementation of SHM, some of them are: knowledge about the behavior of the structure under different loads and different environmental changes, knowledge of the current state in order to verify the integrity of the structure and determine whether a structure can work properly or whether it needs to be maintained or replaced and, therefore, reduce maintenance costs.

The paradigm of damage detection can be tackled as a pattern recognition problem (comparison between the data collected from the structure without damages and the current structure in order to determine if there are any changes). There are lots of techniques that can handle the problem. In this work, accelerometer data is used to develop statistical data driven approaches for the detection of damages in structures. As the methodology is designed for wind turbines, only the output data is used to detect damage; the excitation of the wind turbine is provided by the wind itself or by the sea waves, being those unknown and unpredictable.

The damage detection strategy is not only based on the comparison of many data. A complete methodology for damage detection based on pattern recognition has been designed for this work. It handles structural data, selects the proper data for detecting damage and besides, considers the Environmental and Operational Conditions (EOC) in which the structure is operating.

The damage detection methodology should always be accessed only if there is a way to probe that the sensors are correctly working. For this reason, it is very important to have a methodology that checks whether the sensors are healthy. In this work a method to detect the damaged sensors has been also implemented and embedded into the damage detection methodology.

This kind of damage detection strategies are validated in different models and real structures. Turbine models running in a Wind Turbine verification software, and a laboratory tower simulating an offshore wind turbine are used to validate the methodologies, among simpler structural models. Promising results for certain predefined error states and damage functions are shown in this thesis.

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# RESUMEN

## Diseño y validación de una metodología para la monitorización y detección de daños en estructuras de energía eólica

por **EKHI ZUGASTI URIGUEN**

*DIRECTORES:*
DR. LUIS E. MUJICA
DR. JAVIER ANDUAGA

Octubre, 2013
Barcelona, Catalunya

El objetivo de la Monitorización de la salud estructural (SHM) es la verificación del estado o la salud de las estructuras con el fin de garantizar su correcto funcionamiento y ahorrar en el costo de mantenimiento. El sistema SHM combina una red de sensores conectada a la estructura con monitorización continua y algoritmos específicos. Se derivan diferentes beneficios de la aplicación de SHM, donde encontramos: conocimiento sobre el comportamiento de la estructura bajo diferentes operaciones y diferentes cargas ambientales, el conocimiento del estado actual con el fin de verificar la integridad de la estructura y determinar si una estructura puede funcionar correctamente o si necesita mantenimiento o sustitución y, por lo tanto, reduciendo los costes de mantenimiento.

El paradigma de la detección de daños se puede abordar como un problema de reconocimiento de patrones (comparación entre los datos recogidos de la estructura sin daños y la estructura actual, con el fin de determinar si hay algún cambio). Hay muchas técnicas que pueden manejar el problema. En este trabajo se utilizan los datos de los acelerómetros para desarrollar aproximaciones estadísticas utilizando datos en tiempo para la detección de los daños en las estructuras. La metodología se ha diseñado para una turbina eólica off-shore y sólo se utilizan los datos de salida para detectar los daños. La excitación de la turbina de viento es inducida por el viento o por las olas del mar.

La detección de daños no es sólo la comparación de los datos. Se ha diseñado una metodología completa para la detección de daños en este trabajo. Gestiona datos estructurales, selecciona los datos adecuados para detectar daños, y después de tener en cuenta las condiciones ambientales y operacionales (EOC) en el que la estructura está trabajando, se detecta el daño mediante el reconocimiento de patrones.

Cuando se habla del paradigma de la detección de daños siempre se debe tener en cuenta si los sensores están funcionando correctamente. Por eso es muy importante contar con una metodología que comprueba si los sensores están sanos. En este trabajo se ha aplicado un método para detectar los sensores dañados y se ha metido en la metodología de detección de daños.

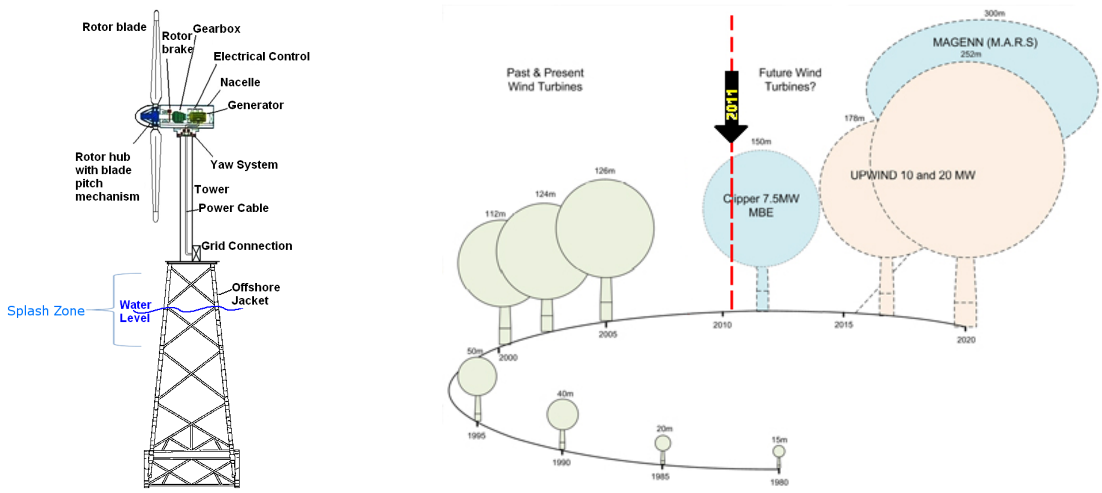
Esta estrategia de detección de daños se ha validado en diferentes modelos y estructuras reales: en un modelo de turbina que se ejecuta en un programa de verificación, y en una torre de laboratorio simulando un aerogenerador marino, además de algunos modelos estructurales simples. En esta tesis se presentan resultados prometedores para ciertos estados de error predefinidos y funciones de los daños.

# Chapter 1

# Introduction

## 1.1 Motivation

The world energy crisis has made the humanity find new energy sources. The development of renewable energy sources is a key research driver as the greenhouse effect is affecting the global warming problem. Among the renewable energy technologies, the wind energy is thought to be a cheap and clean energy source. Wind turbines are doing the job of creating energy from wind, and the maturity, and cost competitiveness makes the wind energy one of the best clean energy sources nowadays.




**(a)** *Configuration of an offshore turbine* **(b)** *Size evolution of Wind Turbines*

**Figure 1.1.** *Wind turbines information [25]*

In Fig. 1.1a it can be seen a typical configuration of an offshore wind turbine system. In order to harvest more energy through higher efficiencies and due to cost-effective considerations, the size of the wind turbine has increased over the years ( Fig. 1.1b). The size is not the only thing that has changed, nowadays the wind farms are moving towards the sea. Taking into account the height of the turbine and the rough sea conditions, the wind industry is now facing new problems. Among these new problems, we can find:

1. It is difficult to perform inspection and maintenance work considering the height and location of the turbine. This can be difficult for the maintenance worker, and quite risky.
2. The marine sea conditions, and the durability of the structure in the water, and specially the substructure.
3. How to transport the energy to the shore.

To improve safety considerations, to minimize down time, to lower the frequency of sudden breakdowns and associated huge maintenance and logistic costs and to provide reliable power generation, the wind turbines must be continuously monitored to ensure that they are in good condition.

Among all the monitoring systems, a Structural Health Monitoring (SHM) system is of primary importance because structural damage may induce catastrophic damage to the integrity of the system. A reliable SHM system, low cost and integrated into the wind turbine system may reduce wind turbine costs and make wind energy more affordable. The SHM information gathered could be used in a condition - based maintenance program to minimize the time needed for inspection of components, prevent unnecessary replacement of components, prevent failures and it allows utility companies to be confident of power availability.

This idea also exist to other types of structures too. In civil engineering, this idea is applied to bridges for example, or also to important buildings, such as historical buildings, or buildings in risky places, near plate tectonics edges.

## 1.2 Structural Health Monitoring

Structural Health Monitoring aims to give, at every moment during the life of a structure, a diagnosis of the "state" of the constituent materials, different parts, and the full assembly of these parts constituting the structure as a whole [6]. The state of the structure must remain between the limits specified, but this domain can be changed by the structure getting older and usage, or by the environment and operational conditions. Monitoring has the advantage of saving the data in different times, and the full history of the state of the structure is stored in a database. This can also provide a prognosis (evolution of damage, residual life, etc.). SHM objectives can be classified in four levels, as can be seen in Figure 1.2 [149]:

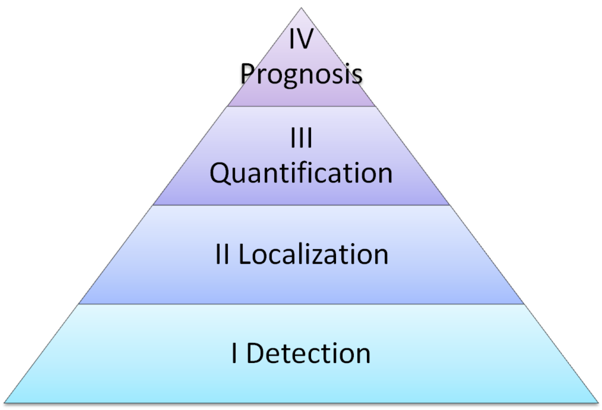



**Figure 1.2.** *SHM Levels*

SHM involves the integration of sensors, data transmission ability inside the structures. It makes possible to reconsider the design of the structure and the full management of the structure itself. If only the first level is considered (Figure 1.2), the damage detection, it could be estimated that Structural Health Monitoring is a new and improved way to make a Non-Destructive Testing (NDT).

SHM approaches include sensors and computational intelligence. The computational intelligence processes sensors information during the lifetime of the structure. That way, it tries to mimic the biological system, composed of a nervous system (sensing), muscles (actuation) and a brain (processing, storing and recalling information). An illustration of this mimic can be seen in Figure 1.3 [147].

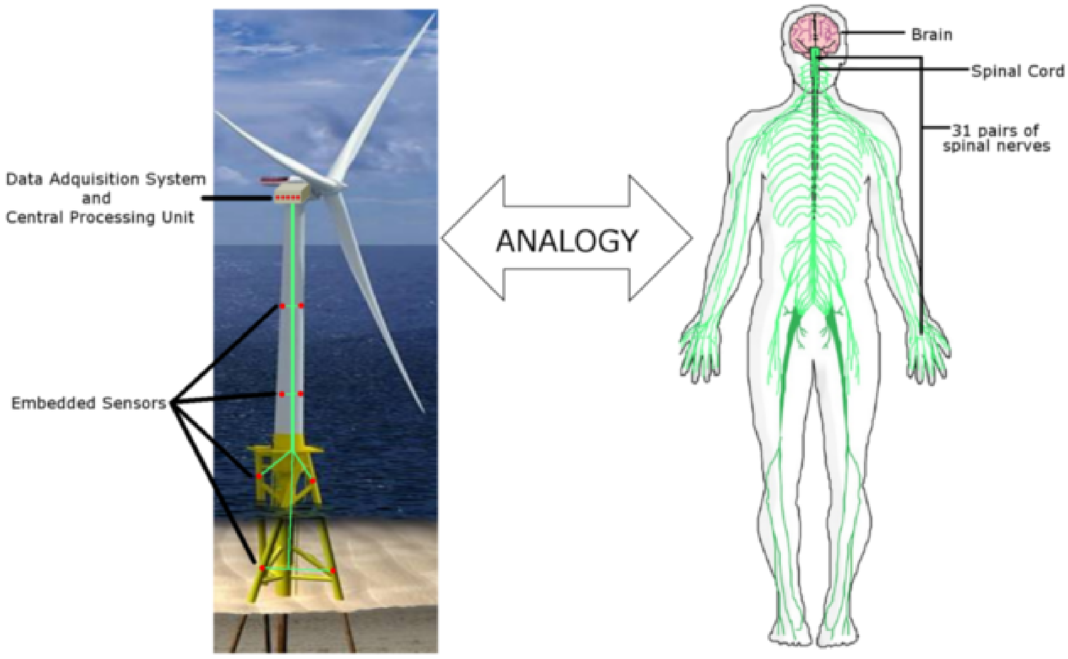



**Figure 1.3.** *SHM vs Human system [147]*

As it can be seen in Figure 1.4, there are other types of structures. If the structure is able to repair itself, using an actuator, that will be a Smart structure, and other combinations are also present in the Figure 1.4.

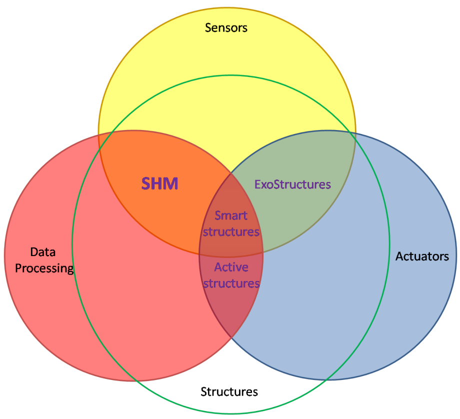



**Figure 1.4.** *Combination of different properties in different types of structures. The SHM would be framed within structures capable of sensing and data processing.[43]*

### 1.2.1 SHM level 1: Damage detection

Damage detection is the first level of an SHM system. Damage detection is very important to avoid either human or economical disasters. If a damage is detected in the moment it has been created, safer structures will be built, and some action could be done before the disaster happens. For example, some action could be done before a bridge collapses, or before a wind turbine collapses (see Figure 1.5). In many cases, it is enough with ringing the alarm when something is going wrong. In fact, nowadays the industry asks mainly for level 1 solutions.

**(a)** *Broken bridge* **(b)** *Broken turbine [34]*

**Figure 1.5.** *Structural Disasters*

The schema presented in Figure 1.6, represents the damage detection approach, and the steps that are needed to perform in order to be able to detect damage. First of all, it is needed to have a database where the structural response is stored. From that database, the newest data are taken, and the classifying of the behavior of the structure depending on the Environmental and Operational Conditions (EOC) starts. The comparison between the undamaged pattern and the actual pattern gives a damage indicator. Once the damage indicator is calculated, it is checked whether this indicator is into the range of healthy structure or not. If everything is OK, the next measurement is checked. If the indicator is out of range, the integrity of sensors is analyzed. It has to be taken into account that the life of a sensor will probably be shorter than the life of the structure. If one of those does not work correctly, the wrong data is eliminated, and the indicator is estimated again. Otherwise, if the sensors work fine, the alarm is activated. In most of the cases, it is enough to detect damage and there is no need of locating it, or quantifying it. If it is needed, the next SHM levels can be explored in order to give more information about that. In order to jump higher in the SHM levels, it is necessary to have conquered the level below. The higher levels are introduced in the next section.

Among the advantages achieved after applying a damage detection method to a structure, it can be found:

- Reduction in time and money costs of inspection and maintenance.
- Reduced probability of accidents.
- Increasing the profitability of the installation, because the structure works for more time.
- Knowledge of the actual status of the installation.

Because of these advantages, the interest in investigation of good and reliable damage detection methods is

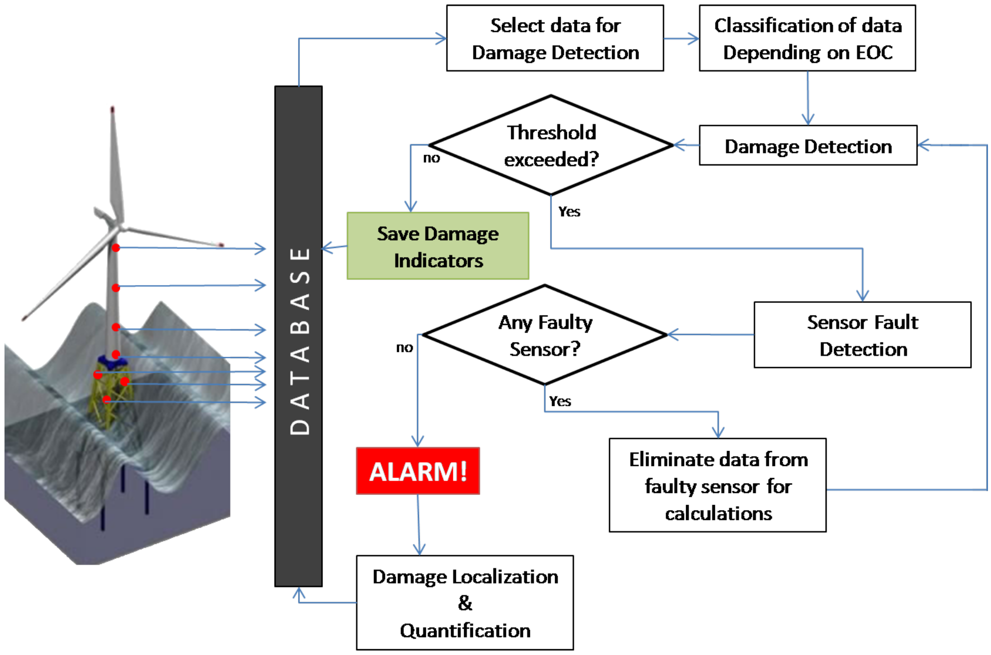



**Figure 1.6.** *SHM level 1: damage detection schema [88]*

nowadays very strong, so that the structures can have a more competitive and longer live. In section 2.1 a review of damage detection methods is presented.

### 1.2.2 SHM levels 2, 3 and 4: localization, quantification and prognosis

In these levels, the damage is located, quantified and the remaining life of the structure is calculated. It is really useful to know the location and severity of the damage, in that way, the maintenance workers can act immediately in the right place if the damage is really big, or the structure can be stopped for security reasons (stopping the wind turbine or closing a bridge for example). Knowing how long the structure can work before the catastrophe is also interesting but the works published about this field are not as long as in the other SHM levels. The need of really good models makes it hard to work on these SHM levels.

The objective of this thesis is the Detection of the damage, lets say the level 1 of the SHM levels. The importance of the other levels in this work is not as important as the first level. That is why a background in these levels is not shown in the present work.

### 1.2.3 SHM vs Non-Destructive Testing (NDT)

Because of the similarities of both methods, a distinction between NDT techniques and SHM is required. In both cases, the goal is to detect defects in the structure, but between the two technologies there are important differences [74], such as:

- Sensor network location: In the SHM sensor network is integrated in the structure and that makes it part of the structure, whereas in NDT, it is independent and can be detached from the structure.

- Distance between the damage and the sensor. NDT measure data, only a very limited area and they can be relocated if required to inspect another part of the structure. In SHM, being integrated sensor network, the inspection area of each sensor must be generally higher, due to problems that have a dense sensor network: weight, integration, etc.
- SHM is not necessarily limited to inspections, but also it can be done in real time or performing successive measurements.

On the whole, the main difference is that one of them is a Monitoring solution, while the other is a Testing solution. Testing only works when a test is running, while the Monitoring works continuosly.

## 1.3 Main contribution

This thesis defends the importance of the right selection of the data and the proper transformation of these can stand out the results obtained from a damage detection solution. A complete methodology for damage detection was built, and it was applied to different types of structures in order to validate the work.

These basis were built and tested, for later applying a data preprocessing to test if better results can be obtained. In general, the data collected from the structures is gathered by accelerometers, and the input excitation is unknown and unpredictable, so, it can be said that only output data is used.

Signals are preprocessed using Principal Component Analysis (PCA) or/and some feature selection algorithm (Unsupervised minimum Redundancy Maximum Relevance (UmRMR)). Later, the damage detection solution is applied. For this damage detection method, some damage indicators were developed and compared.

Making use of accelerometer information, data driven approaches for the damage detection strategy were studied. The paradigm of damage detection is divided into different tasks, starting with the Environmental and Operational Changes compensation of the data, for later applying a damage detection method. Besides in order to know if the damage detection algorithm works properly, the integrity of the sensors is tested. This three steps are taken into account in this thesis as basis for damage detection in Wind Energy Structures (WES).

The developed methodologies were subjected to extensive experimental validations by means of three simulated models: simple mass and spring system, offshore tower finite element model and a offshore UPWIND Bladed model; and one real scaled structure: offshore laboratory tower model. All the results are included and discussed to demonstrate the reliability of the approaches.

## 1.4 Objectives

The main objective of the current Thesis proposed here is to develop a methodology for the detection of damages in Wind Energy Structures (WES) using the paradigm that any damage in the structure produces changes in the vibrational responses. In this Thesis, the damage detection methods, the compensation of the EOC, and the sensor fault detection are discussed. This thesis defends that the results of a damage detection method can be improved if a good preparation of the data is done. This preparation should be in a way that the containing information is the best for damage detection methods.

### 1.4.1 Specific objectives

1. To study the problem of monitoring and damage detection in structures.
2. To study, analyze, propose, implement and evaluate different damage detection methods in Wind Energy Structures.
3. To study, analyze, propose and implement different types of data preprocessing methods to prepare the data in such way that the containing information is the best for damage detection methods for a good data representation and damage detection improvement.
4. To validate and adjust the methodology developed using theoretical structures.
5. To validate the methodology using laboratory scale wind-turbine tower.

## 1.5 General results

According to each specific objective, some comments about the results are summarized below. Most extensive descriptions are included in the document.

1. **To study the problem of monitoring and damage detection in structures.**

   The Structural Health Monitoring problem, its applications and current developments were studied and discussed in various scenarios. The author attended an European course: " Advanced course: Structural Health Monitoring" performed in 2011 in IK4-Ikerlan-Mondragon, where some of the most relevant topics and its applications were presented by some of the relevant researchers in the area. A wide review was done with the information acquired while this PhD was going on; this review is shown in chapter 2.

2. **To study, analyze, propose, implement and evaluate different damage detection methods in Wind Energy Structures.**

   Using the information acquired during the previous state, different damage detection methods were studied and analyzed. After a deep analysis, one of them was implemented and evaluated in different structures, starting from simulated ones to continue with the real scale model. The proposed method is based on Stochastic Subspace Identification, and good results are obtained with it.

   As a contribution in this area: some new damage indicators that make the algorithm faster were developed.

   In order to compensate the Environmental and Operational Conditions (EOC) which provides the structure a proper operation under different scenarios, a review was done, and a solution was implemented, using a Fuzzy clusterization method (fuzzy C-means). The results of the compensation showed that the compensation method is valid for different kind of structural behaviors.

A damage detection methodology should be able to check whether the received information is appropriate or not. So as to deal with this problem, a short review of sensor integrity methods was also performed, and based in Mutual Information (MI) a sensor fault detection algorithm was designed. The results show that this solution, that is in a preliminary state, is able to detect sensor faults.

- Publications:

  a) Zugasti E, Gonzalez A.G, Anduaga J, Arregui MA, and Martínez F, "Structural Damage detection in laboratory tower using Null Space Algorithm", *Proc. Smart'11 Saarbrucken* (2011), 79–86.

  b) Gonzalez A.G, Zugasti E, Anduaga J, Arregui MA, and Martínez F, "Structural fault detection in a laboratory tower using an AR algorithm", Proc. Smart'11 Saarbrucken (2011), 69–78.

  c) Zugasti E, Gonzalez A.G, Anduaga J, Arregui MA, and Martínez F, "NullSpace and AutoRegressive damage detection: a comparative study", *Smart Materials and Structures* (2012), 085010.

  d) Zugasti E, Gonzalez A.G, Anduaga J, Arregui MA, and Martínez F, "A Comparative Assessment of Two SHM Damage Detection Methods in a Laboratory Tower", *Advances in Science and Technology* (2012), 232–239.

  e) Zugasti E, Arrillaga P, Anduaga J, Arregui MA, and Martínez F, "Sensor Fault Identification on Laboratory Tower", *Proceedings of the 6th European Workshop of SHM* (2012), 1093–1100.

3. **To study, analyze, propose and implement different types of data preprocessing methods to prepare the data in such way that the containing information is best for damage detection methods.**

   A short review on data preprocessing solutions was perfomed, and how we could apply them to the damage detection problem. Some different preprocessing methods were implemented: PCA, UmRMR and a combination of both. These preprocessing methods results were compared to the ones without any preprocessing, and the results show that the preprocessing of the data is able to enhance the damage detection results.

   - Publications

     a) Zugasti E, Mujica LE, Anduaga J, Arregui MA, and Martínez F, "Feature Selection - Extraction Methods based on PCA and Mutual Information to improve damage detection problem in Offshore Wind Turbines", *Key Engineering Materials* (2013), 620–627.

     b) Zugasti E, Mujica LE, Anduaga J, C-P. Fritzen, "Data Preprocessing based on PCA and MI to improve Damage Detection in Structural Health Monitoring", *Structural Control and Health Monitoring,* Waiting to be accepted.

4. **To validate and adjust the developed methodology using simulated data from real Wind-Turbine models.**

Three case studies were selected. First, a basic spring and mass model was used to validate the proposed solutions. Later a simulated laboratory tower model was used to verify whether the methodology was still applicable for more complex structures. Finally, a BLADED model of a real wind turbine was used (UPWIND project) for the final validation of the methodology, with different EOC and damages in the offshore jacket.

- Publications

  a) Zugasti E, Anduaga J, Arregui MA, and Martínez F, "NullSpace Damage Detection Method with Different Environmental and Operational Conditions", *Proceedings of the 6th European Workshop of SHM* (2012), 1368–1375.

5. **To validate the methodology using laboratory scale Wind-turbine tower.**

   The real world case study was done by means of a laboratory scale tower, which was manufactured keepeing many similarities to a offshore wind turbines. Real damage is created in the jacket substructure, and different EOC are simulated using different kinds of vibrations. The results show that it is possible to detect damage in every case.

   - Publications

     a) Gonzalez A.G, Zugasti E, Anduaga J, "Damage Identification in a Laboratory Offshore Wind Turbine Demonstrator", *Key Engineering Materials* (2013), 555–562.

     b) Zugasti E, Mujica L.E, Anduaga J, Arregui MA, and Martínez F, "Damage Detection for different environmental conditions using fuzzy clustering", *Mechanical Systems and Signal Processing,* Waiting to be accepted.

## 1.6 Research framework

This thesis was supported in general through the projects: the research line L3 of IK4-IKERLAN, and DPI2011- 28033 funded by the Spanish Government. The first one is a research line in the research center IK4-IKERLAN where the thesis was developed.

The second project is: “Smart Structures: Development and Validation of Monitoring and Damage Identification Systems with Application in Aeronautics and Offshore Wind Energy Plants (AEROLICA)” which is a coordinated project with the Laboratory of Composite Materials and Smart Structures (LCMSS) from “Universidad Politécnica de Madrid” which is leaded by Professor Alfredo Guemes, the CoDAlab group from “Universitat Politécnica de Catalunya”, which is leaded by Professor Jose Rodellar and Sensors department of IK4-IKERLAN. Its main objective is the development of new monitoring systems and data processing methodologies for damage identification in smart structures, with emphasis in two key industrial sectors: aeronautics and offshore wind energy plants. The project integrates basic research on sensors and model-free, data-driven identification approaches with development of practical algorithms and numerical and experimental validations.

## 1.7 Organization of the work

This work is organized in 9 chapters. The first one is the current, that talks about SHM, the objectives, the general results, and the organization of the work. In the second chapter, a review of damage detection methods is found, where different damage detection methods are discussed and filtered by the nature of the used sensor. In the third chapter, the theoretical background is discussed, depicting the tools applied in this thesis. Fourth chapter describes the different structures used to validate the proposed methodology, being three numerical models and one real scale laboratory tower.

Chapter five is concerned to the damage detection and how the damage detection strategy is developed. Chapter six explains the data preprocessing solution used in this thesis for a better and faster damage detection. Besides review of feature selection and extraction solutions is presented. In chapter seven the clustering solution for the different Environmental and Operational Changes compensation is explained, and a short review of the different EOC compensation methods is depicted. The sensor fault detection method is detailed in chapter 8. Finally, conclusions and future research chapter closes this work, where comments about the developed methodologies and the obtained results are discussed.

# Chapter 2

# Review on damage detection solutions

SHM and damage detection has been widely studied in the last two decades. The more complex the structures are, the more complex damage detection systems are needed. In this work, WES structures are being taken as target application of the damage detection solution. In order to know where to start this work, the work done in the past must be studied so that the possible solutions to the problem can be found, or at least a starting point can be found. In this chapter, different types of works in damage detection are reviewed so as to find a starting point for the problem studied in this work.

## 2.1 SHM damage detection classification

In this section, different types of SHM damage detection methods are presented. They are classified by the nature of the sensor used or the principal physical parameter studied. The classification is made in the next way: methods using *Fiber-optic sensors*, methods using *piezoelectric sensors*, methods using *Electrical Impedance* to detect damage, methods using *Low Frequency Electromagnetic techniques* to detect damage, methods using *Capacitive methods* and finally, a subsection of *others* has been created in order to comment the ones that are not included in the main classification subsections.

### 2.1.1 By fiber-optic sensors

Fiber-optic technology started in the seventies, for long-distance telecommunications, and it has experienced an exponential growth during the last three decades. Sensing applications are a small spin-off from this technology, taking advantage of developments in optoelectronic components and concepts.

The optical fiber (OF) itself is a pipe for light, transmitting information, but it may also be sensitive to changes in the external environment surrounding the fiber, such as temperature, strain or chemical composition. Then, it becomes a sensor if these changes can be determined unequivocally. For example, when a very narrow pulse of light is launched along an OF, the reflection of waves, called back-scattered radiation, dispersed inside the optic fiber is proportional to its temperature. It is possible to measure the back-scattered light along the fiber length; and from the intensity of the collected signal, the temperature distribution can be derived.

The common advantages of all kinds of optical fiber sensors arise from their small size, and their non electrical nature, making them immune to electromagnetic interferences and electrical noise. For smart structures, local intrinsic sensors are in the host material.

For smart sensing structures and damage detection, Fiber Bragg Gratings (FBG) are widely used [35, 112, 62]. The basic idea is to change, at the core of the optical fiber and for a short length, a periodic modulation of its refractive index. This will behave as a series of weak partially reflecting mirrors, which, by an accumulative phenomenon of repeated interferences called diffraction, will reflect back the optical wavelength that is exactly proportional to their spacing. An Optical Spectrum Analyzer will be able to detect these changes, and transform it into readable information.

The multiple advantages of FBGs over conventional electrical gauges as strain sensors allow a progressive introduction of “sense by light” technologies into damage detection for structures.

FBGs are passive, point-strain sensors, and this is a limitation on their use in damage sensing applications. In order to use them, an array of FBGs could be used, and using it the strain distribution could be monitored in a known load situation. A small crack would make changes in the limited surrounding area, and this system would not be effective. This means that a large amount of structural damage is needed to detect the damage this way [6].

FBGs have an advantage over conventional sensors that is due to the higher sensitivity to vibration or heat than the strain gauges and consequently are far more reliable, which allows them to be embedded into the structure. It must be taken into account that the applicability of this technique is determined by the structure. A previous knowledge of strain and stress distributions and critical points is necessary, in order to find the optimal sensor distribution.

In order to detect damage in the structure, the spectral perturbations associated with internal stress are measured. Internal residual stresses cause peak splitting [111]. Peak splitting occurs due to the effect of birefringence of the FBGs when subjected to lateral loading, i.e. unequal loading along the two perpendicular axes of the fibre. This phenomenon holds an important amount of information that can be exploited: structural damage can release part of the residual stresses, and the effect can be seen as a distortion in the spectrum of the sensor, opening up a new line of research in the use of fiber-optic sensors as embedded damage sensors.

This is still an open research field, and important efforts are being made to analyze the behavior of FBGs when submitted to these phenomena, and to obtain the actual strain field applied to the grating by demodulating its spectral information. In [99], a simple test was presented to show this effects; four 10 mm long FBGs were embedded in a 25 mm long portion of a photosensitive optical fiber. Then, the fiber-optics were embedded into an epoxy multilaminated panel, without coating. This experience helped to establish the basis for damage detection using FBGs. The results were good, after 7 impacts changes in the light spectra could be seen, and after drilling different holes, the spectra changed significantly.

In [6] some conclusions of using this type of techniques for damage detection are listed. Between the advantages comparing them to the conventional strain sensing, these are named:

- Low size and weight, embeddable capability, single-ended cabling
- Long-term stability; it can be used for load monitoring throughout the structural life
- Inherent multiplexability, typically 10 sensors/fiber without decreasing reading speed
- Immunity to electromagnetic noise and the ability to work in harsh or explosive environments

The development of large sensor arrays address lots of current efforts. This arrays afford a detailed map of the strain field in a complex structure. This will require new optoelectronics and signal processing systems, able to handle at high speed the information coming from several hundred sensing points and it should reduce this information to the significant events.

FBGs are not only effective in strain responses, these type of sensors can provide very valuable information on chemical processes, such as corrosion in metals or degradation. This is a very active research area and efforts are being made to apply them in the intelligent materials processing.[200, 58]

In Wind turbines, this method is mostly used in blades, but different types of implementations can be found. For example, Bang *et al* [7] introduces a FBG-based sensing system for use in multi-MegaWatt scale wind turbine health monitoring, and describes the results of preliminary field tests of dynamic strain monitoring of the tower structure of an onshore wind turbine. So as to monitor the dynamic strain behavior of the tower and substructure of onshore and offshore wind turbines, he installed 41 FBGs on the supporting structures of the wind turbines.

On blades, several works have been done. Recently, 2 works have been published [171, 135]. In the first one, Turner presents test field results on the mechanical measurements from an experimental composite blade for S-Blade experimental wind turbine program, instrumented with FBG temperature and strain sensors. In the second one, a real-time monitoring system with FBG sensors was designed and applied to monitor blades, of a 2 MW prototype of a wind turbine, in operation.

Finally, Guemes *et al* [62], introduced a way to make measurements with distributed optical fibers. In this paper, they talk about how the sensing should be done in order to have good results. Five plain mono-mode optical fibers were bonded at the surface of a wind turbine blade (45m.). This solution was compared to classical extensometry. They obtained similar accuracy on both, but with their method, the set-up of the tests was simpler and the information on strain distribution along the blade better.

### 2.1.2 By piezoelectric sensors

When talking about the piezoelectric sensors, methods based on different principles can be found. The first one is based in *Acoustic Emission* while the other is based on *Acousto-Ultrasonics.*

#### *2.1.2.1 Principle1: Acoustic Emission (AE)*

*"Acoustic Emission is primarily used to study the physical parameters and the damage mechanisms of a material, but it is also used as an on-line Non-Destructive Testing technique. The phenomenon is based on the release of energy in the form of transitory elastic waves within a material having dynamic deformation processes. The waves, with different types and frequencies, propagate in the material and detect possible modifications before reaching the surface of the studied sample. The surface vibration is collected by a piezoelectric sensor. Later it is amplified and provides the acoustic emission signal."* [6]

The typical source of an AE wave within a material is the appearance of a crack from a defect when the material is put under constraint, or when a pre-existing crack grows, which causes a transitory mechanical wave to emerge from the latter. This techinique is able to detect evolutionary defects, but is not able to detect passive defects.

One of the structural field where AE is used is the aviation industry. The real challenge of the application of AE in this field is the in-flight monitoring of aircraft structure. The main challenge comes from the background noise, such as vibration-induce noise, airflow noise, electromagnetic interference and transient noise. It appears that the AE could be used on an aircraft in flight, since a difference of at least 30 dB is found between the impact signal and flight background noise [72, 44].

This technology is used to monitor and feed back information to the on-board vehicle computers about the condition of a spaceship, keeping in mind that the main threat in space travel is micrometeorite impacts. This becomes specially relevant for structures, such as fuel tanks and fuel systems for which composites are becoming mainstream. Once the system has detected and located the occurrence of a damage, the system performs an Acousto-Ultrasonic test across the impact in order to rate the damage severity. This is achieved by actively pulsing the sensors and capturing the received digitalized waveform for comparison with waveforms captured during calibration on the ground. The results of this test are then fed into an algorithm that gives a go/no-go command to the tripulation in the spaceship.

On the whole, AE techniques are significant in SHM for many kinds of structure, and particularly in air safety. Traditional AE parameter analysis allows a simple, rapid and cost-effective inspection or damage detection.

In the field of Wind Energy, recently Yun [198], investigated the adoption of acoustic emission detection to reduce power dissipation of SHM systems employing the impedance and the Lamb wave methods. An acoustic emission sensor, according to [198], continuously monitors acoustic events, while the SHM system is in sleep mode. When an acoustic event is detected by the sensor, the SHM operations are performed. The proposed system avoids unnecessary operation of SHM solutions, this saves power.

Lin [104], describes AE techniques based on Hilbert-Huang transform (HHT) that were recently exercised to characterize the AE signals released from the wind turbine bearing. The HHT is a way to obtain instantaneous frequency data. It is designed to work well for data that are non stationary and nonlinear. In contrast to other common transforms like the Fourier transform, the HHT is more like an algorithm (an empirical approach) that can be applied to a data set, rather than a theoretical tool. They analyzed the AE signals from the wind turbine bearing test using Hilbert-Huang transform. The results showed that the AE in the wind turbine bearing can be described in terms of features like frequency and energy.

#### *2.1.2.2 Principle2: Acousto-Ultrasonics (AU)*

The AE described in the previous section makes use of piezoelectric sensors bonded on or embedded in a structure in a passive way. The same kind of attached sensors can also be used in an active way to produce and detect high-frequency vibrations. A transmitter is used to send diagnostic stress wave along the structure and a receiver is used to measure the signal, which has been modified because of the presence of damage in the structure. This wave propagation approach is very effective in detecting damage in the form of geometrical discontinuities.

Nowadays, it is generally used for 2D type structures (plate structures for example), although some works have been made for 3-D parts [167], there, bulk waves are used. In 2D parts, lamb waves are used.

Lamb waves are basically two-dimensional propagating waves in plate-like structures. This waves are dispersive, that means that their speed depends on the frequency and the thickness of the plate. Usually, a plate or wave is characterized by the dispersion curves, which represent the phase velocities of all existing modes plotted versus the product of the frequency and the thickness. Lamb waves, have the advantage of propagating over long distances without appreciable attenuation. [153]

The most attractive parameters to measure are natural frequencies and damping, according to [6]. This can be done through a limited number of point-to-point measurements on the structure. With several measurements, mode shape can be recovered and used to detect damage, and locate it.

The global guide to build a damage detection implementation using lamb waves can be summarized this way:

1. Material characterization: measuring the stiffness and the density of the material.
2. Damage introduction and characterization: after placing sensors on the material, damage is introduced (impacts or holes) and the damage threshold is determined (corresponding to the level of the plate that seems to be damaged).
3. Lamb wave interrogation: after the damage is done, the damage is located using lamb waves.

So as to conclude, this type of damage detection is made mainly for plate structures, and it is very sensible, only if the modes are changed during the damage. The localization of the damage is efficient for a simple damage. Also the damage identification is possible as recently has been published in [151].

When wind energy is refered, Frankstein *et al* [46] reports about a monitoring system which should monitor the condition of rotor blades and detect and locate structural changes before total failure. It is based on a combination of measuring techniques with guided waves in the ultrasonic frequency range and low frequency modal analysis. The method is tested on a real rotor blade (40 m). He combines a sensor network with the Operational Modal Analysis (OMA) method, mode shape with locally sensitive monitoring methods, based on guided elastic waves (Acoustic Emission and Acousto Ultrasonics). Both, AE and AU give good results in the damage detection.

### 2.1.3 By electrical impedance

The aim of the impedance-based damage detection is to measure the global electrical resistance. This seems to be a valuable technique for monitoring fiber fractures in unidirectional materials, and the delamination process connected with a modification of the resistive tracks in the laminates.

The Impedance-Based damage detection (IBDD) method makes use of the electromechanical coupling of PZT patches. When a PZT transducer is bonded to a structure it forms a collocated sensor and actuator, often referred to as a self-sensing actuator. When a voltage is applied across the PZT, the structure is displaced and conversely, when the structure is displaced a voltage is developed in the PZT transducer. Therefore, the PZT transducer can both actuate the surrounding area of the structure as well as sense the resulting structural response. If the PZT is driven with a sinusoidal voltage, this will cause the local area of the structure to vibrate and the structural response will cause an electrical response in the PZT. [141]

In papers [98, 178, 2] is shown that macroscopic detection of damage is possible using electrical resistance measurements by placing electrodes at the edges of the specimen and by monitoring the variations of the longitudinal electrical resistance.

In [132], in order to evaluate the sensitivity of the IBDD impedance signals issued from fatigue tests were used to create a meta-model designed to predict the fatigue life of the structure from the changes in the impedance signals. Fatigue testing is an experimental procedure that produces a permanent, progressive and localized structural change. This process occurs while the material is subjected to conditions that produce dynamic tensions in one or more points that can produce cracks or, in some cases, the complete failure after a sufficient number of load cycles [183]. The fracture caused by fatigue is due to the nucleation and propagation of cracks appearing in the test sample subjected to mechanical stress. Fracture occurs suddenly without issuing any prior signal since the crack is not visible during the test. When damage occurs, the structure suffers from fiber fractures. This will cause apparent decrease on the voltage, so it will increase Resistivity.

Talking about Wind Energy, Pitchford, in [141] applied the electrical resistance method to 2 different wind turbine blade types, the CX-100 and TX-100. He uses two types of damages, a simulated one (indirect damage), using a C-clamp, and the actual damage, was produced in 3 different locations. From the results, the impedance method was able to detect damage on the blade section. The sensing range was around 10-30 cm depending on the sensor and type of damage. Considering the size of Wind Turbine blade, this may seem to be a rather small range. Still, he declares that IBDD is a promising method to use on blades either in critical locations or in conjunction with other SHM methods which both utilized the same PZT patches.

### 2.1.4 By low frequency electromagnetic techniques

A family of electromagnetic techniques, which makes it possible to obtain good information about the health of structures made of composites, was developed using electromagnetic methods. These techniques consist of determining the state of health of a structure by measurement of its main electrical parameters, the electrical conductivity and/or the dielectric permittivity, since damage induces locally significant variations in these two or three parameters.

In the case of electromagnetic methods [6], the sensor integration is made by embedding an active layer which is about 100-200 $\mu m$ of thickness, in the structure (see Figure 2.1). This layer can be bonded onto the inner face of the structure or inserted between two layers of a multi-layer structure.

There are three possible techniques: the magnetic technique, the electric technique and the hybrid technique. Which of these methods is most suitable depends on the type of material. The magnetic method is based on the variation of electrical conductivity. So, it would be best used with conductive materials and particularly carbon epoxy structures. The electric method, which is based on the variation of dielectric permittivity, is suited for use with dielectric structures such as glass epoxy structures and sandwich structures. For the hybrid method, it is a little more complicated. Since this method is based both on the conductivity variation and on the dielectric permittivity variation, it is theoretically possible to use this method with any kind of material. However, as the electric method is better adapted for dielectric structures, it will be preferred in

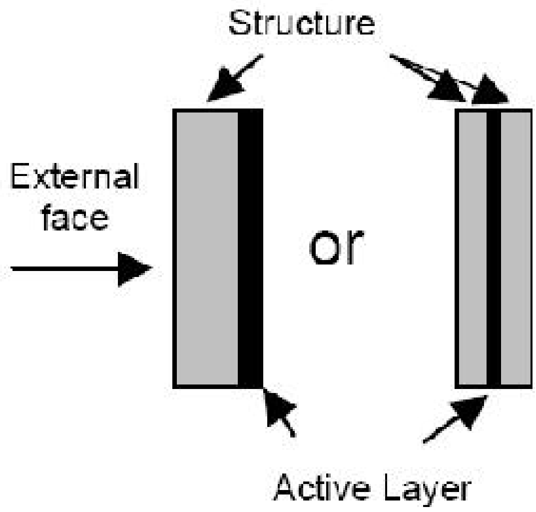



**Figure 2.1.** *Sensor integration (electromagnetic technique)*

this case. The hybrid method gives the best results when it is used with composite structures consisting partly of a conductive medium and partly of a dielectric medium.

In this type of damage detection methods, a data reduction process is often necessary, and this is particularly appropriate in the case of electromagnetic techniques, where the noise level is relatively important. This means that signal processing is very important; recent developments in signal processing make it possible to decrease the noise level considerably and to extract relevant information.[97]a

### 2.1.5 By capacitive methods

The capacitive method principle [32] consists of placing two (or more) electrodes on the outer surface of the samples and applying a voltage between them. This system forms a capacitor and changes in capacitance are indicative of the internal constituents (such as the nature of the materials or their moisture content).

In order to apply the configuration of conventional parallel plate capacitors, contact with the material under study from two opposite sides is required.

The simplest type of capacitive probe is based on the so-called parallel plate capacitor. Two electrodes of area $S$, separated by the distance $e$, enclose a material of dielectric constant $\varepsilon_r$ as can be seen from Figure 2.2. A uniform electric field redirected perpendicularly to the plates is created, and the capacitance of the system is proportional to the permitivity of the media.

The capacitance value is found by means of a resonant circuit delivering an alternating voltage (note that a different kind of electronics, for instance an electronic bridge, can be used). The resonant frequency shift is then obtained simply by using a frequency analyzer.

This type of monitoring has been used mainly for monitoring historical buildings; The basic idea is to have two metallic electrodes embedded in the material, and to apply an alternating electric current ($I$) between them. This system forms a capacitor, and changes in capacitance are indicative of the internal constituents (including the nature of the materials).

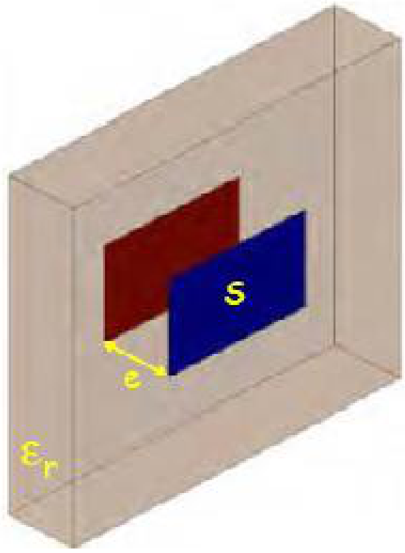



**Figure 2.2.** *Capacitance*

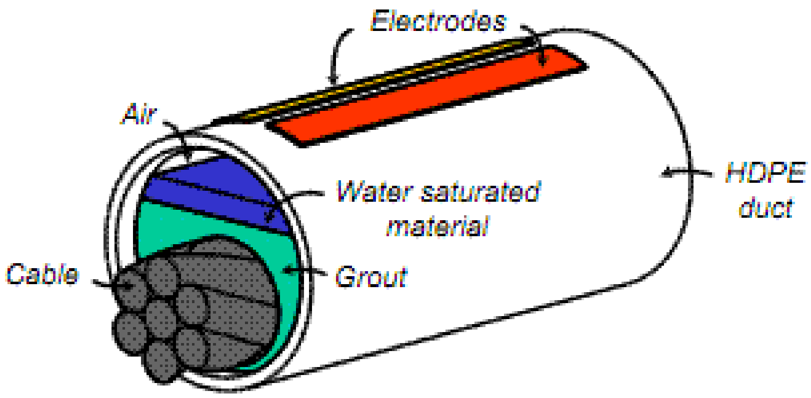



**Figure 2.3.** *Tension cables with HDPE duct filled with cement grout [164]*

A capacitive sensing system indicates the presence of water, known to be at the origin of most common pathologies of concrete structures. Although it could be used for SHM of concrete structures, the interpretation of the signals are difficult. This difficulty is now being filled with the help of a modeling approach.

Some applications of this method have been applied for damage detection. For example, in [164] this technique is used in order to monitor "external" post-tension cables. These cables are generally placed in ( HDPE) ducts shown in Figure 2.3, where the residual space is filled under high pressure with a cement grout intended to prevent corrosion. Sometimes this cement grout is not perfect, and can contain high amount of water or grout voids. The detection of such defects inside an opaque duct is unachievable visually from the outside, so the capacitance method is used in order to detect damage inside the duct.

The same year, Klysz et al. [85] applied the same capacitive method, among others, in a Bridge (Empalot Bridge, France) constructed in 1915. They tried to evaluate the cover concrete of the bridge by some Non-Destructive Testing methods. They used 3 different types of capacitive sensors, being able to reach different depths. The results showed that the big electrodes were more sensitive to large volume damaged areas in depth of 2 or 3 centimeters. Medium sensors were more sensitive to moisture near the surface. Finally, the small ones were too dependent to the quality of the surface, so they were not very useful.

Another application in cover concrete was done by Derobert *et al*[31]. He applied the capacitive method to measures the moisure content, and also used a Ground Penetrating Radar (GPR) in order to compare the results. Both results were successfully compared during an experimental campaign conducted in the laboratory against several control test slabs.

In the near future developments will focus on the implementation of array sensors and on data processing suited to each application. There are lots of types of structures out there, and each of them has a different frequency responses. the new implementations should characterize these structures in a wide frequency range. Several research is going on this field currently. [6]

Ice accretion on wind turbines is a major problem in cold climates that reduces power generation and fatigues turbine components. The detection of ice in wind turbine blades, is not a damage detection, but ice can lead to damage, so it is considered really important to be able to detect ice in wind turbine blades, because it can mean that damage can appear easier. In [130], Owusu *et al* detects ice in several types of structures, but mainly he focuses his thesis in wind turbine ice detection, specially on capacitive methods. On the other side, Homola[69] tried over 30 types of ice detection techniques for wind turbines, and in his conclusions states that one of the best ice detector is the capacitance method.

### 2.1.6 Others

There are also other types of SHM damage detection methods that were not commented before, and they will be resumed in the next lines:

The laser-doppler vibrometer (LDV) is a non-contact velocity transducer, which is based on analysis of the Doppler effect. The laser outgoing beam of the LDV, acts directly on the surface of interest. The frequency and amplitude of the vibration are extracted from the Doppler frequency shift of the beam; this frequency shift is due to the surface movement [108]. The laser Doppler vibration meter is a promising method to analyze large areas due to its high resolution. Furthermore, it is a non contact method, which simplifies implementation. However, the price is still high for incorporation into a structure. A Wind Energy Structure application on this field can be found in [131]; Ozbek and Rixon use the LDV for a remote monitoring of the Wind Turbine ( Figure 2.4 shows the measuring points).

The thermal image uses temperature as principle. This method detects anomalies or defects in the layer located below the surface of the material. It is based on the temperature difference observed in the studied area, monitored by sensors and infrared cameras [5]. The temperature difference of a damaged structure when it is compared with an undamaged area is related to the difference of thermal diffusion and indicates irregularity or material damage. The advantage of this method is that it is capable of producing an image of the measure, which facilitates a quick evaluation, even for a non-professional user. Thermal imaging methods can be divided according to the thermal excitation method used during the testing. Thus, they differ in active and passive methods. Passive methods are used to study materials that are in a higher temperature than air temperature. Therefore they are limited to specific materials and applications. By contrast, active methods employ a heat source that can be light bulbs, heat guns, etc..

**Figure 2.4.** *The Markers Ozbek [131] used to measure the wind turbine*

Shape memory alloys can also be used. The shape memory alloys have a memory that can be initiated from a change in effort or temperature. This type of alloy allows the creation of passive detection systems, where power supply is only needed during the interrogation of the sensor, while the sensor reading is stored in the form of the sensor itself [174, 175]. This method is still new and needs a strong research effort to develop a monitoring strategy with it.

Eddy currents are widely used for inspection of conductive materials by inducing electrical currents in the test material and capturing any variation of the induced currents. This method would detect changes in specific places of the structure where the sensor should be placed [60], making it suitable for the development of local methods of monitoring.

There are also the vibration-based methods, the ones that use vibration measuring sensors (piezoelectics, accelerometers,...) in order to detect the vibrations in the structure. This area is large, and it will be deepened in the next chapter, because these methods are the ones that have been used to complete this thesis.

Finally, this chapter explained the most known techniques, but this is a field that continues growing each day, and new techniques arise every year, so it is important to be up to date with damage detection.

## 2.2 Vibration based techniques for SHM

### 2.2.1 The principle

According to [50] the principle which uses vibrations as characteristics of solid bodies to test their quality or consistency and distinguish good or bad conditions is widely used in daily life. For example, when buying drinking glasses, it is commonly accepted that the bright sound indicates a flawless glass, and a dull tone refers to a imperfect glass. Traditionally, experienced traders tested the quality of large cheeses by knocking on them and listening to the sound. The degree of ripeness of melons can also be tested by a similar procedure. Many other examples can be found.

The same basic principle can also be applied to civil structures, but using sensors for detecting the vibrations. The effects of material defects, like cracks or delaminations, on the dynamic behavior of a structure have been studied in [19, 129], by using just vibration techniques. The classical way to gain information on the measurement of an existing structure (with respect to its dynamic behavior) is to retrofit this structure with a set of sensors and excite it with an actuator or using the natural environmental forces.

In order to see if something has changed, the measurement data have to be evaluated and some characteristic features, such as means, variances, maximum/minimum values, spectral information, etc., have to be extracted by signal analysis. The actual values are compared with the reference values which derive from the undamaged state of the monitored system.

In a vibration test, the excitation and response are always measured and recorded in the form of time history. There are three different domains in which it is posible to examine data for damage detection. The first one is in the Time Domain; this means that data knows how a signal changes over time. On the other hand, in Frequency Domain, data is transformed in order to show how much of the signal lies over a range of frequencies. Finally, in the Modal Analysis, data shows what are the characteristics of each vibration mode according to the point in the structure. Usually this modal information is extracted from frequency domain, although new works have shown how to extract the information directly form time-domain[59, 15]. Also, combined time-frequency analysis, based on wavelet analysis, has become an important tool in data analysis [160].

Vibration methods can also be classified as model-based or data-driven based methods. The model-based method assumes that a detailed numerical model of the structure is available for damage detection (for example a Finite Element Model); while the response-based (or data-driven) method depends only on experimental response data from structures.

A classification depending on the mathematical base of the damage detection method will be made in the next section.

### 2.2.2 Method classification

#### *2.2.2.1 Natural frequency based methods*

These methods use the natural frequency change as the basic feature for damage identification. The natural frequency change can be measured using a low number of sensors in some points of the structure; this fact makes it attractive.

There are 2 different types of approaches inside these methods.

- The forward problem

  The aim of this method is to determine the natural frequency changes of a given structure based on damage location and severity, and it serves as a theoretical foundation for natural frequency-based methods. The forward problem [168] investigates frequency shifts for known types of damage. The damage can be modeled mathematically for later comparing it to the measured frequencies of the damaged system. The forward problem has been widely used since the mid-1970s until mid-1990s.

Some of the damages studied with this solution were: Gudmundson [61] used an energy-based perturbation approach and derived an explicit expression for the resonance frequencies of a wide range of damaged structure. This method can account for a loss of mass in addition to a loss of stiffness. Hu and Choy[71] addressed the issue of determining frequency sensitivity for simply supported beam with one crack and developed analytical relationships between the first-order changes in the eigenfrequencies and the location and severity of the damage. This method requires symbolic computation of the characteristic equation. Morassi [119] also showed that the frequency sensitivity of a cracked beam-type structure can be explicitly evaluated by using a general perturbation approach. Frequency sensitivity turns to be proportional to the potential energy stored at the cracked cross section of the undamaged beam. Moreover, the ratio of the frequency changes of two different modes turns to be a function of damage location only.

The methods described above, are only valid for small defects. Kasper *et al* [82], derived the explicit expressions of wave-number shift and frequency shift for a cracked symmetric uniform beam. These expressions apply to beams with both shallow and deeper cracks. This explicit expressions are based on high frequency approximations, so, they are generally inaccurate for the fundamental mode and for a crack located in a boundary-near field.

- The inverse problem:

  This method determines damage characteristics of a given structure based on natural frequency measurement. The inverse problem calculates damage parameters, such as crack length and/or location, from frequency shifts. The inverse problem typically attempts to achieve Level 2 or Level 3 damage identification while the forward problem typically achieves only Level 1 damage identification. This method, is almost as old as the Forward one, but it is still in use. About the inverse problem, some works have been made in this field; for example, Liang *et al* [101] developed a method based on three bending natural frequencies for the detection of crack location and quantification of damage magnitude in a uniform beam under simply supported of cantilever boundary conditions. The method involves representing crack as a rotational spring and obtaining plots of its stiffness with crack location for any three natural modes through the characteristic equation. The point of intersection of the three curves gives the crack location and stiffness. The crack size is then computed using the standard relation between stiffness and crack size based on fracture mechanics. An other example is the one from Zhong *et al* [201] who proposed a new approach based on auxiliary mass spatial probing using the spectral center correction method, to provide a simple solution for damage detection by just using the output-only data.

In conclusion, the focus on the use of frequency shifts for damage identification has been prolific, but the investigation is still ongoing. Successful identification algorithms have generally been limited to identification of a single or a few damage locations. Equally, the most successful applications have been applied to small laboratory structures.

#### 2.2.2.2 *Mode shape-based methods*

Measurement of the mode shapes of a structure [18] requires either a single excitation point and many sensors or a roving exciter with one or more fixed sensors. Many modal analysis techniques are available for the extraction of mode shapes from the data measured in the time domain [39, 106]. Damage detection methods have been developed for the identification of damage based directly on measured mode shapes or mode shape curvatures.

- Direct comparison of mode shapes

  Two commonly used methods to compare two sets of mode shapes are the Modal Assurance Criterion, MAC [4] and the Coordinate Modal Assurance Criterion, COMAC [102]. The MAC value can be considered as a measure of the similarity of two mode shapes. A MAC value of 1 is a perfect match and a value of 0 means they are completely dissimilar. Thus, the reduction of a MAC value may be an indication of damage. The COMAC is a point wise measure of the difference between two sets of mode shapes and takes a value between 1 and 0. A low COMAC value would indicate discordance at a point and thus is also a possible damage location indicator. Some applications of these applications can be found in [18].

  A drawback of many mode shape based methods is the necessity of having measurements from a large number of locations. Apart from this drawback, there is the fact that when having big structures, the mode shapes change little by little, so sometimes for the moment you have realized about the small change in the mode shape it is too late. The calculation of mode shapes needs big amount of sensors, and the calculation in operational conditions (Operational Modal Analysis, OMA) for the type of structures we are talking about, is not an easy task to do. In two papers, Ren and De Roeck [145, 144] used the idea of employing the orthogonality condition sensitivities. Their algorithm was demonstrated on a laboratory scale concrete beam. They concluded that, though mode shape based methods are well verified with simulated data, there are significant difficulties with full-scale structures - the predominant ones being noise and measurement errors, mode shape expansion of incomplete measurements and accurate well correlated modeling of test structures.

- Mode shape curvatures

  Gunes [63] says that the use of mode shapes curvatures in damage identification is based on the assumption that the changes in the curvatures of mode shapes are highly localized to the region of damage and that they are more pronounced than changes in the displacements of the mode shapes.

  Modal curvatures have also been used in conjunction with other measured data to identify damage. Oh and Jung [128] used both dynamic and static data from tests on a bowstring truss. Best results were achieved when mode shape curvatures and static displacements were used in combination. The number of modal curvatures useable in damage identification routines is, naturally, limited to the number of displacement mode shapes available.

In conclusion, mode shapes and their derivatives have been widely used to identify damage. Some evidence [152] suggests that methods based on mode shapes are more robust than those based on natural frequency shifts. There are, nevertheless, some discussions over the usefulness of mode shapes alone in damage detection even from the same authors.

According to [18], such uncertainty has led to the investigation of other methods such as the use of operational deflection shapes, which have many similarities to mode shapes. More complex formulations involving the use of mode shapes have also been investigated, such as modal strain energy methods, which use modal curvatures and the dynamically measured flexibility and the residual force vector, which combine the use of natural frequencies and mode shapes.

#### 2.2.2.3 *Modal strain energy*

When a particular vibration mode stores a large amount of strain energy in a particular structural load path, the frequency and shape of that mode are highly sensitive to changes in that load path [18]. So checking this strain energy it is possible to determine damage location. The literature has generally concentrated on beam like elements (see [18]).

Kim et al. [83] applied both a frequency based and a modal strain energy based method to identify damage (assumed to be single) location and size in a simulated beam. Two modes were used in each method. The frequency based method was based on the ratio of change in the eigenfrequencies. Curvature, for use in the modal strain energy method, was calculated by spline interpolating 289 modal displacements at the nodes of the beam modal. It was found that the modal strain energy method gave a more accurate prediction of location than the frequency based method.

Recently, Yan *et al.* [195], proposed a damage detection method based on an efficient algebraic algorithm of element modal strain energy sensitivity for detecting damage, also the location and severity. The method adopts a closed form of element modal strain energy sensitivity.

Several works about Modal Strain energy has been published, and when a prework has been done about the structure, and when it is known what kind of damages are the easiest to appear, this method is a good method when it is wanted to locate damage.

#### 2.2.2.4 *Residual force vector method*

With access to measured mode shapes, natural frequencies and an initial baseline model it is possible to formulate what is known as a Residual Force Vector, RFV. Each mode (i) of the damaged structure (Natural frequencies and mode shapes) satisfy an eigenvalue equation. [197]

$$(K_d - \lambda_{d_i} M_d) \tag{2.1}$$

$$\phi_{d_i} = 0 \tag{2.2}$$

With $\lambda_d$ being the square of the natural frequency, and $\phi_d$, the mode shape of the damaged structure is measured and therefore fully known for several modes. Assuming that the stiffness, $K_d$, and mass, $M_d$, matrices associated with the damaged structure, are defined as,

$$K_d = K_a + \Delta K \tag{2.3}$$

$$M_d = M_a + \Delta M \tag{2.4}$$

Then, the Residual can be defined as:

$$R_i = (K_{Rd} - \lambda_{d_i} M_d)\phi_{d_i} \tag{2.5}$$

Each mode provides a single Residual Force Vector. This vector may be physically interpreted as the harmonic force excitation that would have to be applied to the undamaged structure, represented by $K_a$ and $M_a$, at the frequency $\lambda_{d_i}$, so that the structure would respond with mode shape $\phi_{d_i}$.

There will be one residual for each mode. If the mode shapes are sparsely measured, either reduction of the system matrices or expansion of the mode shapes is necessary. Reduction of the system matrices destroys the structure of the matrices and therefore the direct use of the RFV for location is not useful. However, with sufficient measurements, the RFV seems to be a robust method for the location of damage and its use in sizing damage is certainly promising.

Yang *et al.* [197], developed a damage detection methodology using this method. In order to have a damage indicator for the method, he uses an indicator proposed by Doebling [33] named minimum-rank elemental update (MREU). He applied the method to a plane truss structure, and generated three damage cases. Results of the application example showed that the node residual force vector could preliminarily locate the probable damages in measured locations or unmeasured locations, but he noted that the absolutely accurate damage localization was impossible for noisy measured mode shapes. He also reported that the MREU technique could identify structural damages only when the number of mode shapes used in the calculation equals the rank of the perturbed matrix. Since, in practice, the expected rank of the perturbed matrix is unknown, he concludes saying that the MREU technique is limited to be used in actual engineering practice.

#### *2.2.2.5 Model updating based methods*

The literature concerned with model updating has provided a rich source of algorithms adaptable to damage identification. Furthermore, many damage identification algorithms rely on a well correlated numerical model of the structure in its initial state. Several issues arise when creating a correlated numerical model; the measured data chosen to be matched by the model, the accuracy of the initial model, the size and complexity of the model, the number of updating parameters and the non-uniqueness of resultant model in matching the measured data.

The accuracy of the initial model of a structure used to identify damage with an updating algorithm is important. Fritzen and Jennewein [48] used sensitivity based algorithms to locate and detect damage. It was found that even the use of Bernoulli-Euler beams instead of Timoshenko theory shifted the higher eigenfrequencies, so that no reasonable results were obtainable.

The size of the model to be updated is important, though with available computing power increasing constantly, it is now possible to tackle larger and more complex models than ever before. However, as model-updating problems are usually solved by iterative methods that require the solution of the analytical problem at least once in each iteration, its application to large models can be very hard to process. Moller and Friberg [117] proposed a method that reduced the problem by projection onto a subspace spanned by a reduced number of modes. This resulted in substantial computational time savings.

Papadopoulos and Garcia [133] presented a method of model updating and damage identification, which accounted for structural variability. The statistical properties of the healthy mass and stiffness parameters and the mean healthy natural frequencies and mode shapes of the system were first determined. The mean damaged natural frequencies and mode shapes of the system were then simulated. The number of modes available was assumed to be equal to the number of damage parameters and these parameters were determined. The statistical properties of the damaged stiffness were then determined and probabilistically compared to the healthy stiffness to yield an estimate of the probability of damage.

Model updating using FRF (Frequency Response Function) measurements directly has also been utilized for damage identification [202, 20]. The initial, and obvious, advantage in using FRF data over modal data is that it negates the need to identify the modal parameters from measurements and to perform mode-pairing exercises. A further advantage in using FRF data over modal data in model updating is that FRF data can provide much more information in a desired frequency range than modal data which is limited to just a few FRF data points around resonance. Grafe [57] also points out that, by using the many more data points available, systems of updating equations can be easily turned into over-determined sets of equations. Care should be taken to avoid ill-conditioned matrices, however, as adjacent points in the FRF are unlikely to contain significantly different information about the system.

In summary, model-updating methods have been used extensively in damage identification algorithms. In model updating, the engineer is forced to use his/her judgment to choose likely parameters and locations in the model that are in error. In damage identification the lack of knowledge of location leads to difficulties in applying the same methods due to an increased number of parameters. Many authors have overcome this problem by making assumptions about the location and form of damage. Those that have not made these assumptions have found that they require large measured data sets to avoid ill-conditioning in the updating equation sets.

#### *2.2.2.6 Frequency Response Function (FRF) based methods*

Frecuency Response Function (FRF) is also used to detect damage, instead of extracting modal data from the datasets. Lee and Shin [96], said that modal data can be contaminated by modal extraction errors in addition to measurement errors, because they are derived from data sets. They also said that a complete set of modal data cannot be measured in all but the simplest structures. That is why they say that FRF data can provide much more information on damage in a desired frequency range compared to modal data.

A real time condition monitoring approach was proposed by Lim et al. [103]. Changes in the continuously monitored FRF amplitude, damping and frequencies were interpreted as indications of damage. The advantage of continuous real time monitoring is that it gives an operator early warning, so that appropriate action may be taken before a catastrophic failure occurs.

Rizos et al.[146] treat the problem of damage detection in stiffened aircraft panels via a non-parametric FRF based method. The FRF estimates are demonstrated to exceed their normal variability bounds under skin damage, while the method accounts for uncertainties and statistical variabilities. Finally, Hwang and Kim [73] present an FRF based method, whose effectiveness is numerically demonstrated via simulation examples based on Finite Element (FE) models of a simple cantilever and a helicopter rotor blade. Although no statistical framework is incorporated, the method is reported to achieve a satisfactory level of precision with respect to damage diagnosis.

#### 2.2.2.7 *Wavelet transform methods*

The idea of breaking down a signal into different series of local basis functions are the wavelet transforms (WT). Wavelets have different characteristics, those are the scale and translation. Any particular local feature of a signal can be analyzed by looking at those characteristics. The transform may be applied and mapped to the space or time domain of the structure. This is in contrast to the Fourier transform, which is generally used to map from the time domain to the frequency domain.

The singularities in a signal are detected by the wavelet transforms. Knowing this, they can be used to find changes in mode shapes, or to locate a change in a sensor signal. When applied to the space domain, it is very important the number of DOFs measured. The finer the resolution of measurements in the space domain, the more information the wavelet analysis can provide.

Kumara *et al.* [163] and Sohn et al. [156] suggested using Continuous Wavelet Transform to detect delamination of composite structures. The system is designed to analyze the responses of an active SHM system using piezoelectric sensors. Damage detection is performed by observing the signal energy in a wavelet scalogram (The magnitude of the Continuous Wavelet Transform).

By Mujica *et al.* [124], A hybrid reasoning methodology is applied to a complex aerospace structure, and its effectiveness is assessed in identifying and locating the position of impacts. The methodology combines the use of: (i) Case-Based Reasoning; in a ‘learning mode’ (ii) The Wavelet Transform is used to extract principal features of a signal providing information about the impact locations. (iii) Self-Organizing Maps are trained as a classification tool in order to organize the old cases in memory with the purpose of speeding up the reasoning process.

Recently, an experimental study [177] was published for the location detection of a delamination in a beam structure under a static displacement with a spatial wavelet transform. In this research, two delaminated cantilever beams with different dimensions and materials subjected to a static displacement at their free ends are investigated experimentally. Through both the finite element model (FEM) and experimental studies, the detection of the delamination location using spatial wavelet analysis is achieved effectively.

Giurgiutiu et al. [55] reviewed some different damage identification in helicopter components and identified the WT as one of the most efficient methods for mechanical components health monitoring specially for early identification of incipient damage.

#### *2.2.2.8 Neural network methods*

Neural networks arose from the study of biological neurons and refer to a computational structure that has multiple inputs and a single output. Neural networks have been applied successfully in many diverse applications including vibration based damage identification [179, 203]. These types of solutions are applicable to problems with lots of information on database, but difficult to find an algorithm to work with those data.

The basic strategy for developing a neural network-based approach to be used in connection with vibration-based monitoring of engineering structures is to train a neural network to recognize different damage scenarios from the measured response of the structure, strains, modal parameters, etc. For instance, a neural network might be trained with natural frequencies and mode shape components as input and the corresponding damage state as output.

The training of a neural network needs appropriate data, that contains the information aboutt the cause and effect. This can be seen as a drawback, because this means that in order to train the neural network, the sets used should be damaged and undamaged structure readings. The damaged data can be obtained by measurements, or model tests, through numerical simulation or as a combination of all three types of data.

Ramu and Johnson [143] applied back propagation neural networks to identify damage. The network was found to be effective. The topology of the network was found to be critically important for performance. An interesting aspect of the work of Marwala and Hunt [109] was the proposal of a committee of neural networks. Marwala [110] demonstrated the use of the committee approach on a damaged experimental cylinder. Three networks were trained and their outputs combined to give better predictions than by the three networks separately. Each network was trained with different data, namely FRFs, Modal data and Wavelet Transform Data. The improved performance of the committee was reasoned to be due to different structural alterations having different relative apparent effects in the frequency, modal and time domains.

In [121], Mujica *et al.* used an Artificial Neural network in order to be able to solve a Case-based reasoning (CBR) cycle. A hybrid reasoning system is developed for damage assessment of structures. The system combines the use of a model of the structure with a knowledge-based reasoning scheme to evaluate if damage is present, its severity (severity and dimension) and its location. Using a given model (or several models), the structural dynamic responses to given excitations are simulated in the presence of different forms of damage. In a 'learning mode' an initial casebase is created with the principal features of these damage responses. When the system is working in its operating mode, data acquired by sensors are used to perform a diagnosis by analogy with the cases stored in the casebase, reusing and adapting old situations. Whenever a new situation is detected, it is retained in the casebase to update the available information.

Recently [105], presented an experimental verification of a structural damage recognition technique based on a fiber Bragg grating array and a back propagation neural network. This method was applied in a flat plate. The plate structure was loaded using a lever and a weight, and damage was introduced by putting a hole in the plate. The neural network was able to identify damage to the plate.

An other recent work by Dumlupinar [36], explains how the mechanical parts (gearbox and rack-pinion) of a mobile bridge have been monitored. The prediction of the gearbox and rack-pinion fault detection is carried out with artificial neural networks (ANN) using the time domain vibration signals. Several statistical parameters are selected as characteristic features of the time-domain vibration signals. The results indicate that the vibration monitoring data, with selected statistical parameters and particular network architecture, give good results to detect damage on the structure.

#### *2.2.2.9 Genetic Algorithm methods*

Genetic Algorithms (GA) are methods for optimization of functions based on the random variation and selection of a population of solutions. They are part of what may be described as evolutionary algorithms, which have been developed since the 1950s [115]. They can handle multi-modal solutions, so that makes them capable of identifying damages using more information.

Genetic Algorithms have been used for the minimization of the cost function defined from the diferences between experimental and numerical eigenvalues and eigenvectors [24], natural frequencies [107], mode shapes [24], or their combinations [68].

For example Chiang and Lai [23] describe a two-stage process where the damage is initially located and then in a second stage a GA is used to quantify the damage in the identified elements successfully. The method was demonstrated on a simulated truss structure of 13 elements with up to 3 elements damaged.

Yan [194] proposes a GA-based approach for impact load identification, which can identify the impact location and reconstruct the impact force history simultaneously. In his study, impact load is represented by a set of parameters, thus the impact load identification problem in both space (impact location) and time (impact force history) domains is transformed to a parameter identification problem.

#### *2.2.2.10 Statistical methods*

Farrar and Doebling [41] suggested that the vibration based damage detection problem is fundamentally one of statistical pattern recognition. They thought that a non-model based pattern recognition methods were are good way of detecting damages, and more effective in real life inplementations. The concept was guided to the novelty detection. Novelty detection is concerned with the identification of any deviations in measured data relative to data measured under normal operating conditions. This makes a need of a learning phase and a detectin phase. When the structure is in a undamaged state, the learning phase is made, and the features derived from the structure are extracted, while in the detection phase, these features are compared to the ones that are being calculated in order to determine if the structure is still in the same condition.

Lots of works have been made using auto-regressive modeling. Worden et al. [190], considered statistical process control approaches to damage detection. while in case of Fanning and Carden [40], it was demonstrated clearly that this statistical pattern recognition approach was clearly more effective than other single/few sensor algorithms. Fassois and Kopsaftopoulos [42] have made a review on these statistical methods, dividing them into parametrical and non parametrical. In this case, all the methods classified in the review are put into test using a Laboratory Truss Structure.

Non-model-based statistical pattern recognition techniques are also suitable for data sets obtained through ambient excitation only, for example traffic or wind loading on a bridge structure. A disadvantage of these methods is that they are probably limited to Level 1 or possibly Level 2 identification. [18]

INRIA in France [9] proposed a statistical model based damage detection and localization method utilizing a subspace based residual and a statistical analysis of aggregated sensitivities of the residual to damage. Damage is flagged when the value of the residual passes a statistically based decision rule. The method is applicable to cases where only output data is available and was developed from subspace based stochastic identification methods [10].

Nichols [126] applied a Mutual Information (MI) approach to detect damage induced nonlinearities in a structure. Damage in structures is frequently modeled as the introduction of a nonlinearity into a structure of structural component that is otherwise (in a healthy state) accurately described by a linear model. Nichols presented in [126] a method for detecting damage induced nonlinarities in a structure, based on its vibrational response. This approach measures the absolut nonlinearity and therefore does not require an explicit measurement of the healthy structures dynamics. The proposed approach targets the presence of nonlinearity and is therefore not affected by global changes in stiffnes (environmental effects for example).

In structural health monitoring (SHM), Principal Component Analysis (PCA) [78] has been extensively applied to measured vibration signals for dimensionality studies,[189, 199, 123] to remove the influence of the environmental effects from the vibration characteristics,[134] for extracting structural damage features,[159, 166] to discriminate features from damaged and undamaged structures [155, 29, 56, 125, 170] and for clustering a classifi- cation of acoustic emission transient,[77] among others.

Aplying the PCA principle [120], by Mujica *et al.* They explore the use of PCA and T2 and Q-statistic measures to detect and distinguish damages in structures. A PCA model is built using data from the undamaged structure as a reference base line. The defects in a turbine blade are simulated by attaching a mass on the surface at different positions. Data from sets of experiments for undamaged and damaged scenarios are projected into the PCA model. The first two projections, and the Q-statistic and T2-statistic indices are analyzed. Q-statistic indicates how well each sample conforms to the PCA model. It is a measure of the difference or residual between a sample and its projection into the principal components retained in the model, while the T2-statistic index is a measure of the variation of each sample within the PCA model.

#### *2.2.2.11 Other vibrational methods*

In the literature, there are also some techniques that do not fall easily into any of the categories described above. Gatulli and Romeo [54] proposed an adaptive, on-line control algorithm for both vibration suppression and damage detection. The method was demonstrated on a simulated three DOF system with one actuator. Large control efforts are required when an abrupt change in system properties occur, as the controller attempts to compensate and return the monitored responses to their initial values. These efforts may therefore be used as indicators of damage.

Tan et al. [165] used strain gauges to monitor the dynamic response of reinforced concrete slabs. Plots of measured dynamic strain showed unique deflection signatures that varied with the internal state of the slab, thereby suggesting that these could potentially be used for condition monitoring and residual strength identification.

### 2.2.3 WES vibrational applications

Vibrational solutions are highly used in wind turbine SHM solutions. Some global solutions have been used in order to be able to have an integrated approach of SHM in wind turbines. For example, in [148], Rolfes *et al* proposed an integrated approach to SHM in a wind turbine, by using wireless sensors, eight biaxial accelerometers and two strain gauges, in order to be able to detect all the possible vibrations. The damage detection method only needs two fixed accelerometers at the top of the turbine tower and two strain gauges installed at the tower bottom. For the undamaged state: dynamic stress, measured by strain gauges, is proportional to dynamic velocity, which can be derived from measured acceleration signals. This relation is valid when sensor locations are in line with the eigenform occurring. The sensor locations have to be chosen according to the maximum eigenform amplitudes and the maximum stress locations. If damage occurs, the relation between the dynamic velocity of these sensors will not be the same, and a alert about the existence of a damage will be created.

In [3], Adams *et al* explain how using modal properties and a statistical model damage can be detected using vibrational data. The process starts with the best location for sensors (accelerometers) continuing with the feature extraction form those signals and finally calculing the frequency shift and the Modal Assurance Criterion discordance of the signal to be analysed.

In [51], Kraemer and Fritzen use almost the same sensor distribution as Rolfes in [148], but the damage detection method is different. He uses some statistical methods, Null Space damage detection and Auto Regresive (AR). Apart from damage detection, in this paper, Fritzen also talks about the importance of the sensor fault identification, so as to know if the readings obtained from the sensors are well or not. He also tries to locate damage using a finite element model.

Online damage detection is an important area where neural networks have been used. Oberholster and Heyns [127] proposed a methodology for monitoring the online condition of axial flow fan blades with the use of neural networks. Results from a stationary experimental modal analysis of the structure were used for identifying global blade mode shapes and their corresponding frequencies. It was demonstrated that it was possible to classify damage for several fan blades by using neural networks with online vibration measurements from sensors not necessarily installed on the damaged blades themselves.

In [47], Friedmann *et al* introduce different types of damage detection methods for wind turbine, some of them are vibration based and other are not. Concerning about the section dealing with vibrational analysis, it is interesting how he uses the random decrement method to eliminate the random input variable from the data, and how this is done in the smart sensor. That way, the smart sensor sends less information to the central processing unit. This article also includes a literature review of methods used for extracting health parameters from modal properties as well as the topic Operational Modal Analysis (OMA). The measurement system developed makes use of one of those OMA methods and combines it with the Random Decrement method to design a data acquisition system that can be implemented on a smart sensor network. As examples, the application of this system to the model of a wind turbine as well as to a full scale pedestrian bridge is described.

In [154] Smarsly *et al* present a SHM system for wind-turbines. This paper describes the design and prototype implementation of a multi-agent software [185] paradigm for a self-managing SHM system. An integrated monitoring concept is proposed for continuous assessment of structural performance and safety as well as self-diagnostics and management of the SHM system. It gives a very good overview and detailed execution of how a damage detection SHM system should be autonomous, and which steps should take into account. He describes 3 subsystems:

- **S1: The hardware:** the turbine and the sensors
- **S2: The real time data adquisition:** perform in real-time the data saving and data processing tasks such as condensing, converting and storing of the acquired data sets.
- **S3: On demand monitoring system:** operating according to an on- demand basis by a user, a software agent [186] or an application tool to perform the detection itself.

The proposed concept was validated with the continuous real-time monitoring of a wind turbine for almost a one-year period. This long term validation experiment was able to demonstrated that the system he introduced was capable of reliably detecting anomalies and system malfunctions such as sensor breakdowns or temporarily unavailable resources.

Kraemer [90] recently, wrote about the work done in Wind Turbines and Structural Health Monitoring; He talks about vibrational methods for SHM, and how they can be used to achieve a almost complete schema of Structural Health Monitoring as shown in Figure 1.4. He uses data from a offshore wind turbine in order to detect damage (proven with more than one method), to be able to detect if a sensor is faulty or not, to be able to localize the damage using a model-updating method, and finally the load characterization, to be able to say how severe the damage is.

Another complete thesis is the work of Barthorpe [8]. He talks about SHM for aerospace structures, and SHM in general, but mostly on vibration data. He concentrates his work on Model-based SHM methods, and Data-based ones. He presents two works of Model-based SHM methods, and 3 more of Data-based ones. Apart from detecting damage, he is able to localize it using model-updating techniques.

## 2.3 Conclusions

A review of the state of the art revealed numerous and diverse damage detection methods. It is an active field, many types of sensors are available, and several approaches are being developed based on different principles. In general, the literature demonstrates that there is no universal optimum method for damage detection.

Additionally, no algorithm has been proposed yet, which can be applied universally to identify any type of damage in any type of structure. There is no unique solution to the damage detection problem. The idea is to find the solution by many ways, also by combining different algorithms. For each problem, there will be a specific solution for it.

In this case, the author of this thesis is especially interested in algorithms that work using output only data. This is the case of big structures, such as, bridges, wind turbines, or buildings. These structures are very difficult to excite, so, usually, environmental sources are taken as excitation sources (wind, cars, or other vibrations) and only the response of the structure is stored.

As seen in the pages above, during last years a wide range of vibrational methods have been developed. These methods have mainly accelerometer responses as input. A subgroup of them, are the statistical vibration methods that are not based on the knowledge of the physical model. This fact, makes them specially promising, because they learn how the structure works, and creates a simple statistical/mathematical model that is able to detect damage. The drawback of these type of methods is that each structure is unique; that means that the simple statistical/mathematical model needs to be calculated for every structure. A generic model should not be taken for a bunch of structures that theoretically are the "same"; because every implementation could vary, depending on the foundation for example. This drawback could be an advantage depending on how it is seen. It is true that the user should train every structure, but when the damage occurs, the user is sure that something really happened to the structure, because it is not like before any more.

Considering all these conclusions, and the type of structures this thesis is interested in, Wind Energy Structures (WES), the method that has been chosen to work with is a method based on Stochastic Subspace Identification. It is a output only method, that creates a simple mathematical model for each structure after a training period for each one. The method is based on the Null-Space analysis of the Hankel matrix (see next chapter), and it is able to detect changes in the structure. This method is based on the work done by Basseville *et al* and Fritzen *et al* [10, 49]. It is a vibrational time-domain method, so no data conversion is needed.

Taking into account the needs of a WES, this method is one most suitable. It is an output only method; this is needed because the input data in a WES will be the environmental data, which is difficult to measure. It creates a simple mathematical model; this can be a drawback, but also an advantage, as explained before, because every structure is trained individually to know how it behaves in a healthy state. It is based on a well known mathematical base, the Stochastic Subspace Identification (SSI); SSI is largely used in structural design and control in order to extract the modal parameters from a structure [15]. It is a time-domain method; no data conversion is needed, so any loss of information generated by transformations is prevented. Last, but not least, the method is not new, and several works have been presented, all of them with good and interesting results [192, 22, 114, 88, 51, 84, 92]. Taking into account these reasons, it has been decided that the Null-Space method is a good starting point for this thesis on damage detection.

In this direction, what the author of this thesis defends is that a good preparation of the data in such way that the containing information is the best for damage detection methods for a good data representation and damage detection improvement. For this purpose, the NullSpace damage detection algorithm will be used as a tool to compare different results of different data preprocessing solutions.

# Chapter 3

# Theoretical Background

## 3.1 Introduction

In this section the theoretical background to the present thesis is briefly reviewed. An overview of the vibration analysis of structures will first be provided. This overview explains how vibration is able to characterize different behaviors in the structures. For damage detection, vibrational solutions were used. Specifically, Stochastic Subspace Identification (SSI) methods, so a short review on SSI is described. Information Theory is a basic methodology for Feature Selection methods and sensor fault detection. Feature Selection and Extraction are later discussed, and also methods for clustering are detailed. Finally, sensor placement algorithms are described.

## 3.2 Vibration analysis of structures

**Vibration:** *"Vibration is a mechanical phenomenon whereby oscillations occur about an equilibrium point. The oscillations may be periodic such as the motion of a pendulum or random such as the movement of a tire on a gravel road."* [188]

**Structure:** *"A structure is a combination of parts fastened together to create a supporting framework, which may be part of a building, ship, machine, space vehicle, engine or some other system."* [12]

*"Before the industrial revolution started, structures usually had a very large mass because heavy timbers, castings and stonework were used in their fabrication; also the vibration excitation sources were small in magnitude so, the dynamic response of structures was extremely low"* [12]. Over the last 200 years, with the advent of relatively strong lightweight materials such as cast iron, steel and aluminum, and increased knowledge of the material properties and structural loading, the mass of structures built to fulfill a particular function has decreased. The efficiency of engines has improved and, with higher rotational speeds, the magnitude of the vibration exciting forces has increased. This process of increasing excitation with reducing structural mass and damping has continued at an increasing pace to the present day when few, if any, structures can be designed without carrying out the necessary vibration analysis, for their dynamic performance to be acceptable.

According to [12], there are two factors that control the amplitude and frequency of vibration in a structure: the applied excitation and the dynamic response of the structure to that particular excitation. Changing either the excitation or the dynamic characteristics of the structure, the vibration characteristics will change .

The excitation can appear from external sources such as foundation vibration, cross winds, waves, currents, earthquakes; or from internal sources such as moving loads or internal engines. These excitation forces and motions can be periodic. The response of the structure to these sources of excitations can be different depending on the dynamic characteristics of the structure. The structure can also be excited with a known signal, but it is not interesting for this work, because the real wind turbines are huge, and it would be difficult to excite them with a known signal.

It is necessary to analyze the vibration of the structures to extract the natural frequencies and predict the response to the expected excitation. Analyzing the natural (or resonance) frequencies of a structure it is found that if the structure is excited in those frequencies, high vibration amplitudes, dynamic stresses and noise levels will increase. The resonance should be avoided in the design phase. In this phase the vibration analysis can be carried out most conveniently by adopting the following three-stage approach:

- Stage I. Devise a mathematical or physical model of the structure to be analyzed.
- Stage II. From the model, write the equations of motion.
- Stage III. Evaluate the structure response to a relevant specific excitation.

Dynamic characteristics of a damaged and undamaged body are, as a rule, different between them. This difference is caused by a change in the structure and can be used for the detection of damage. Many mechanical structures in real service conditions are subjected to effects of different dynamic loads, temperature and corrosive medium, with a consequent growth of fatigue cracks, corrosive cracking and other types of damage. The immediate visual detection of damage is difficult or impossible in many cases. In this connection, the use of vibration methods of damage diagnostics is promising.

## 3.3 Stochastic Subspace Identification

**Stochastic Subspace Identification techniques:** *"Stochastic Subspace Identification techniques are parametric time domain estimators"*[15]

Since the pioneering work of Overschee *et al.* [173] was presented almost two decades ago, there is no doubt that the Stochastic Subspace Identification (SSI) techniques are one of the most well-known and used parametric time domain estimators. However, sometimes the exact physical modeling is not needed engineering applications. In this section the basis of the SSI are explained.

### 3.3.1 Models of systems and system identification

A dynamic model [173], described in Figure 3.1, covers almost all physical, economical, biological, industrial, technical, etc. phenomena. One could distinguish between mental, intuitive or verbal models, or graphically oriented approaches such as graphs and tables, but in this context the major interest lies in mathematical models. The mathematical models can be described as differential (continuous time) or difference (discrete time) equations. The dynamic behavior of a system in the function of time can be described if these models are used. Mathematical models exist in all scientific disciplines. The applications of these models are really wide. Models are used when experimenting with the real system is too expensive, dangerous or impossible.

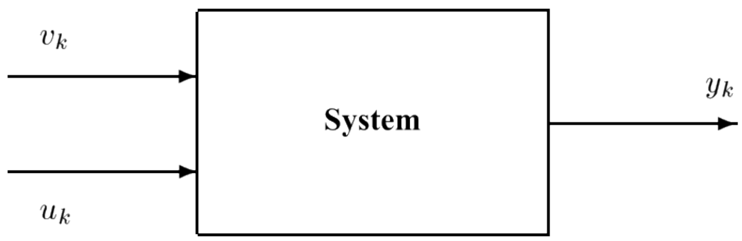



**Figure 3.1.** *Description of dynamic system [173]*

A dynamic system is composed with deterministic inputs $u_k$, outputs $y_k$ and disturbances $v_k$ (see Figure 3.1). All arrows represent vector signals and $k$ is the discrete time index. The user can control $u_k$ but not $v_k$. In some applications, either $u_k$ or $v_k$ can be missing. The measured (input and output) signals provide useful information about the unknown system.

According to [173], basically, there are two main roads to construct a mathematical model of a dynamic system. Physicists are interested in models (physical laws) that fully explain the essential mechanisms of observed phenomena and that are not falsified by the available experiments. These models need nonlinear partial equations. This is called the analytic approach. It rigorously develops the model from first principles.

For engineers however, developing this type of models takes a lot of time, and is often much too involved to be really useful. The reason is that the goal of engineers is not the model, its potential engineering applications. In words of [173], *"The quality of a model is dictated by the ultimate goal it serves. Model uncertainty is allowed as long as the robustness of the overall system is ensured. Engineers, in contrast with mathematical physicists, are prepared to trade-off model complexity versus accuracy."*

The message in [173], is that system identification provides a meaningful engineering alternative to physical modeling. Compared to models obtained from physics, system identification models can not fully explain the system in the whole working range, but it does in a limited case. Sometimes they also lack of direct physical meaning. On the other hand, they are simpler to obtain and use and, these models are simple in their limited working range. Of course, there are still problems such as the choice of an appropriate model structure, the fact that many systems are time-varying and the often largely underestimated measurement problems (appropriate sensors, sampling times, filters, outlier detection, etc.).

In this thesis, the interest is focused on a system identification methodology as a tool which provides an acceptable model able to detect damages on structures

### 3.3.2 Discrete time formulation

The response from a system as a function of time is considered as:

$$y(t) = \left\{ \begin{array}{c} y_1(t) \\ y_2(t) \\ y_3(t) \\ \vdots \\ y_M(t) \end{array} \right\}. \tag{3.1}$$

The structural system can be considered in classical formulation as a multi-degree of freedom structural system as the described by the following equation

$$M\ddot{y}(t) + D\dot{y}(t) + Ky(t) = u(t), \tag{3.2}$$

where M,$D$,K, is the mass, damping and stiffness matrix, and where $u(t)$ is the input. In order to take this classical continuous time formulation to the discrete time domain the easiest way is to introduce the State Space formulation as follows

$$x(t) = \left\{ \begin{array}{c} y(t) \\ \dot{y}(t) \end{array} \right\}. \tag{3.3}$$

Introducing the State Space formulation, the original $2^{nd}$ order system equation given by Equation 3.2 simplifies to a first order equation as follows

$$\dot{x}(t) = A_c x(t) + Bu(t) + w(t), \tag{3.4}$$

$$y(t) = Cx(t) + v(t), \tag{3.5}$$

where $C$ is the observation matrix and the system matrix $A_c$ (in continuous time) and the load matrix $B$ are given by:

$$A_c = \left[ \begin{array}{cc} 0 & I \\ -M^{-1}K & -M^{-1}D \end{array} \right], \tag{3.6}$$

$$B = \left[ \begin{array}{c} 0 \\ M^{-1} \end{array} \right]. \tag{3.7}$$

Besides, vectors $w(t)$ and $v(t)$ denote, respectively, the state noise and measurement noise processes, which are assumed to be Gaussian white-noise sequences with zero mean.

The principal advantage of this formulation is that the general solution can be found by means of [80]:

$$x(t) = exp(A_c t)x(0) + \int_0^t exp(A_c(t-\tau))Bu(\tau)d\tau, \tag{3.8}$$

where the first term is the solution to the homogenous equation and the last term is the particular solution. To take this solution to discrete time, we sample all variables like $y_k = y(k\triangle t)$ and thus the solution to the homogenous equation becomes:

$$x_k = exp(A_c k\triangle t)x_0 = A_d^k x_0, \tag{3.9}$$

$$y_k = Cx_k = CA_d^k x_0. \tag{3.10}$$

So in a more general way, the SSI system is:

$$x_{k+1} = A_d^k x_k + w_k, \tag{3.11}$$

$$y_k = Cx_k + v_k, \tag{3.12}$$

The idea of Stochastic System Identification is to estimate the system state sequence $x_k$ from the measured response sequence $y_k$ and then estimate the system matrices. The estimation of the matrices is conducted by the Hankel matrix.

### 3.3.3 Understanding the Hankel matrix

A way of estimating a SSI model is based on the Hankel matrix. This section is focused on details about this estimation and the application of the estimation matrix to the damage detection paradigm. The Figure 3.1, shows an input-output system. From now on it will be assumed that there is no $u_k$, or at least, it will not be taken into account. Based on the work done in [173] the stochastic response from a system as a function of time will be considered as:

$$Y = [y_1\, y_2 \cdots\cdots y_M] \tag{3.13}$$

The concept of subspace identification for linear systems, which was applied to modal analysis of structures in [59, 15], is based on the definition of the Hankel matrix. This matrix may be calculated in two ways corresponding to either the covariance-driven or data-driven subspace identification algorithms.

- The covariance-driven Hankel matrix is given by:

$$H_{p,q} = \begin{bmatrix} \Lambda_1 & \Lambda_2 & \cdots & \Lambda_q \\ \Lambda_2 & \Lambda_3 & \cdots & \Lambda_{q+1} \\ \vdots & \vdots & \ddots & \vdots \\ \Lambda_{p+1} & \Lambda_{p+2} & \cdots & \Lambda_{p+q} \end{bmatrix}; \qquad q \geq p, \tag{3.14}$$

where $p$, $q$ are user-defined parameters and $\Lambda_i$ represents an unbiased estimate of the correlation matrix at time lag . This comes directly from the definition of the correlation estimate [13]. The Block Hankel matrix defined in SSI is simply a gathering of a family of matrices that are created by shifting the original data matrix. Different $\Lambda_i$ may be estimated from a set of $N$ output data samples $y_k$ (as taken from Equation 3.12) as:

$$\Lambda_i \simeq \left(\frac{1}{N-i-1}\right)\sum_{k=1}^{N-i} y_{k+i}y_k^t. \tag{3.15}$$

This Hankel matrix may be factorized into two subspaces if Singular Value Decomposition is used. From these subspaces, specially from the left kernel subspace, the modal information may be extracted.

- The data-driven Hankel matrix is given by:

$$H_{j,2i} = \left[\begin{array}{cccc} y_1 & y_2 & \cdots & y_j \\ \cdots & \cdots & \cdots & \cdots \\ y_i & y_{i+1} & \cdots & y_{i+j-1} \\ \hline y_{i+1} & y_{i+2} & \cdots & y_{i+j} \\ \cdots & \cdots & \cdots & \cdots \\ y_{2i} & y_{2i+1} & \cdots & y_{2i+j-1} \end{array}\right] \equiv \frac{Y_P}{Y_f} \equiv \frac{Past}{Future}, \tag{3.16}$$

where $2i$ is the user-defined number of row blocks, and $j$ the number of columns. The Hankel matrix is split into a "past" and a "future" part of $i$ block rows. The principal idea in modal analysis is to retain all the information in the past for predicting the future through an orthogonal projection of the row space of "future" outputs into the row space of "past" outputs.

From these matrices, it is possible to obtain the modal parameters and system matrices. This is explained in detail in [15] and [59]. However, for damage detection case the modal parameters are not interesting, and system matrices are not needed. The main goal is to detect whether the structure has changed or not. For that purpose, the Hankel matrix is the basic tool containing all the dynamic properties of the structure that we will use for that purpose. In chapter 5 how this changes are detected is explained.

## 3.4 Information theory

**Information Theory:** *"Information theory is a branch of applied mathematics, electrical engineering, bioinformatics, and computer science involving the quantification of information."[27]*

Information Theory is one of the few scientific fields fortunate enough to have an identifiable beginning - Claude Shannon's 1948 paper [150]. The story of the evolution of how it progressed from a single theoretical paper to a broad field that has redefined our world is a fascinating one. It provides the opportunity to study the social, political, and technological interactions that have helped guide its development and define its trajectory, and gives us insight into how a new field evolves.

### 3.4.1 Information sources

An information source is a mathematical model for a physical entity that produces a succession of symbols called "outputs" in a random manner. The produced symbols may be real numbers such as voltage measurements from a transducer, binary numbers as in computer data, two dimensional intensity fields as in a sequence of images, continuous or discontinuous waveforms, and so on. The space containing all of the possible output symbols is called the alphabet of the source and a source is essentially an assignment of a probability measure to events consisting of sets of sequences of symbols from the alphabet. It is useful, however, to explicitly treat the notion of time as a transformation of sequences produced by the source. Thus in addition to the common random process model we shall also consider modeling sources by dynamical systems as considered in ergodic theory.

### 3.4.2 Entropy

In information theory [150], Entropy is a measure of "uncertainty" or "information" content of a information source. In this context, the term usually refers to the Shannon entropy, which quantifies the expected value of the information contained in a message, and it is defined as follows:

$$H(X) = -\sum_{x \varepsilon \chi} p(x) log(p(x)), \tag{3.17}$$

where $X$ be a discrete random variable, that takes values in some set $\chi$.

The $log$ is a base 2 logarithm, and this makes the unit to be $bits$. If probability of $x$ is 0 at a point, there is a problem of definition, so, it is said that $0log0 = 0$.

The probability is always between 0 and 1, and the logarithm of that probability will always be negative (or 0). This means that the Entropy of a variable will always be non negative $H(X) \geq 0$. Usually entropy can be also defined as a expected value (E) of the variable $X$:

$$H(X) = E(-log(p(X))) \tag{3.18}$$

It is important to remark that the definition of Entropy only depends on the probability distribution or $p(X)$. This means, that the values inside of $X$ are not important, but their probability is the only thing evaluated for the calculation of Entropy.

Now that the entropy is defined, lets see an example of how Entropy is able to tell us about the information of a variable.

#### *3.4.2.1 Shell game example*

*"The shell game (Three shells and a pea) is portrayed as a gambling game. The game requires three shells, and a small, soft round ball, about the size of a pea, and often referred to as such. It can be played on almost any flat surface, but on the streets it is often seen played on a mat lying on the ground, or on a cardboard box. The person perpetrating the swindle begins the game by placing the pea under one of the shells, then quickly shuffles the shells around. Once done shuffling, the operator takes bets from the audience on the location of the pea."*[187]

Lets call $X$ random variable to the first shell, $Y$ to the second one and $Z$ to the third one. Lets say each variable takes the value 1 when the pea is inside the shell and 0 if it is not ($X,Y,Z \in \{1,0\}$) and lets suppose that we know somehow that the probabilities are $p(X) = 1/2$, $p(Y) = 1/2$, $p(Z) = 0$. Knowing this, there is some uncertainty about the problem; and if we could ask a question about where the pea is located, what should we ask? There is 0 uncertainty about the variable $Z$, the probability is null, so it would be stupid to ask if the pea is under shell 3. So we can say, that asking about shell 3 gives us zero "information" gain. Lets see this using Entropy of Equation 3.17:

$$\begin{aligned} H(X) &= 1, \\ H(Y) &= 1, \\ H(Z) &= 0. \end{aligned}$$

This easy example shows that the Entropy is able to demonstrate that the more uncertainty the variable has, the more information provides.

### 3.4.3 Mutual Information

In probability theory and information theory, the Mutual Information (MI) of two random variables is a quantity that measures the mutual dependence between them. [184]

Mutual information measures the amount of information contained in a variable or a group of variables, in order to predict the dependent one. It has the advantage to be model independent and nonlinear at the same time. Model independent means that no assumption is made about the model that will be used on the spectral variables selected by mutual information; nonlinear means that the mutual information measures the nonlinear relationships between variables, contrarily to the correlation that only measures the linear relations.

#### *3.4.3.1 Mathematical definition*

Let $X$ and $Y$ be two variables (they can have scalar or vector values). Lets also denote $\mu_{x,y}$ the joint probability density function (pdf) of $X$ and $Y$. The marginal density functions are given by:

$$\mu_x = \int \mu_{x,y}(X,Y)dy, \tag{3.19}$$

$$\mu_y = \int \mu_{x,y}(X,Y)dx. \tag{3.20}$$

At this point, the Entropy ($H$), as seen in subsection 3.4.2, is defined as a measure of disorder, or more precisely unpredictability therefore the uncertainty on $X$ or $Y$ is given by:

$$H(X) = -\int \mu_X(x) log(\mu_X(x))dx, \tag{3.21}$$

$$H(Y) = -\int \mu_Y(y)log(\mu_Y(y))dy. \tag{3.22}$$

The joint uncertainty of the (X,Y) pair is given by the joint entropy, defined as follows:

$$H(X,Y) = -\int \mu_{X,Y}(x,y)log(\mu_{X,Y}(x,y))dxdy. \tag{3.23}$$

On the other hand, from Figure 3.2 it can be seen, how mutual information is calculated from entropy. So this way, Mutual Information is:

$$I(X,Y) = H(X) + H(Y) - H(X,Y). \tag{3.24}$$

Finally, combining the previous equations, the mutual information between the variables $X$ and $Y$ is defined by:

$$I(X,Y) = \iint \mu(x,y)log\frac{\mu_{X,Y}(x,y)}{\mu_X(x)\mu_Y(y)}. \tag{3.25}$$

Therefore, the only thing needed for the mutual information calculation is the $\mu_{X,Y}$ or the joint probability density.

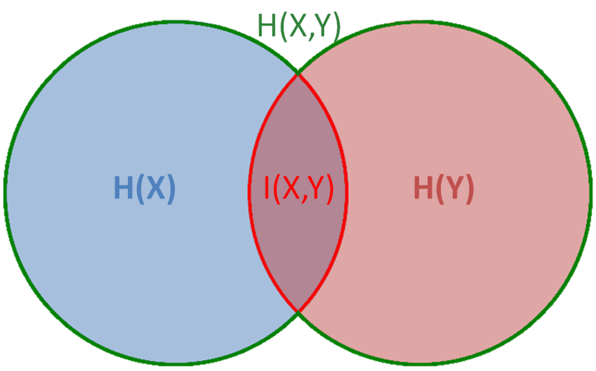



**Figure 3.2.** *Mutual Information visualization*

### *3.4.3.2 General properties*

According to [162] the most important property of MI is that it is always non-negative. It is equal to zero, if and only if, $X$ and $Y$ are totally independent:

$$I(X,Y) \geq 0. \tag{3.26}$$

Another important feature of MI is its invariance under homeomorphisms of $X$ and $Y$. If $X\prime = F(X)$ and $Y\prime = G(Y)$ are smooth and uniquely invertible maps, then:

$$I(X',Y') = I(X,Y). \tag{3.27}$$

The $M$-dimensional MI shares with $I(X,Y)$ the invariance under homeomorphisms for each $X_m$, and the fact that it is limited by the value obtained for a Gaussian with the same covariance matrix. The next important property is the grouping property, as follows:

$$I(X,Y,Z) = I((X,Y),Z) + I(X,Y). \tag{3.28}$$

Here, $I((X,Y),Z)$ is the MI between the two variables $Z$ and $(X,Y)$, considering the fact that a random variable does not need be a scalar. Indeed, anything said so far holds also if $X,Y,\ldots$ are multi-component random variables.

It is known that MI is symmetric theoretically talking. But, in practice, sometimes slight differences are found depending of the MI Estimation method, there can be slight differences. But on the whole, we can say that:

$$I(X,Y) = I(Y,X). \tag{3.29}$$

An other fact about MI is that the estimate of the value $I(X,X)$ this should be equal to $H(X)$. This can be seen in the Figure 3.2. So we can see that:

$$I(X,X) = H(X). \tag{3.30}$$

The MI between two variables, can never be higher than the Entropy of both variables. So it can be said that the highest possible value for MI is the smallest entropy value of one of the variables:

$$I(X,Y) \leq H(X)\ ;\ I(X,Y) \leq H(Y). \tag{3.31}$$

*3.4.3.3 Mutual Information estimation*

As was explained in the first section, the Mutual Information estimation of two variables, needs the joint probability of those variables. Very crude approximations to MI based on cumulative expansions are popular because of their ease of use. But they are valid only for distributions close to Gaussian and can mainly be used for ranking different distributions by interdependence, and much less for estimating the actual dependencies. Expressions obtained by entropy maximization using averages of some functions of the sample data as constraints [76] are more robust, but are still very crude approximations. Finally, estimates based on explicit parametrization of the densities might be useful but are not very efficient. Methods based on kernel density estimators are more promising [118, 161].

The most straightforward and widespread approach for estimating MI more precisely consists in partitioning the supports of $X$ and $Y$ into bins of finite size, and approximating it by the following finite sum:

$$I(X,Y) = I_{binned}(X,Y) = \sum_{i,j} p(i,j) log \frac{p(i,j)}{p_x(i)p_y(j)}. \tag{3.32}$$

The problem with the estimators described above is that, their use is usually restricted to one- or two-dimensional probability density functions. However, there is a mutual information estimator for high dimensional variables (or equivalently for groups of real valued variables); in this case, other estimators suffer dramatically from the curse of dimensionality; in other words, the number of samples that are necessary to estimate the probability density function grows exponentially with the number of variables.

The multivariate algorithms proposed in [93] are based on entropy estimates from k-nearest neighbor distances. This implies that they are data efficient (with $k = 1$ we resolve structures down to the smallest possible scales), adaptive (the resolution is higher where data are more numerous), and have minimal bias. Numerically, they seem to become exact for independent distributions, i.e. the estimators are completely unbiased (and therefore vanish except for statistical fluctuations) if $\mu(x,y) = \mu(x)\mu(y)$. This was found for all tested distributions and for all dimensions of $x$ and $y$. It is of course particularly useful for an application where the test for independence. In [93] it can be found how this is calculated, but as a result, it comes that mutual information is:

$$I(X_1, X_2, \ldots, X_m) = \psi(k) + (m-1)\psi(N) - \frac{1}{N}\sum[\psi(n^i_{X_1}+1) + \psi(n^i_{X_2}+1) + \ldots + \psi(n^i_{X_m}+1)]. \quad (3.33)$$

In the previous equation, $\psi$ is the Digamma function [182]; N is the number of points in the variable, k is the number of the nearest neighbor we are assuming, $n_x$ is the new number of neighbors in the marginal space.

## 3.5 Feature selection and extraction

**Feature Extraction:** *"In pattern recognition and in image processing, feature extraction is a special form of dimensionality reduction."[169]*

**Feature Selection:** *"In machine learning and statistics, feature selection, also known as variable selection, is the process of selecting a subset of relevant features for use in model construction."[169]*

Sometimes too much information can reduce the effectiveness of classification algorithms. Some of the columns of data attributes assembled for building and testing a model may not contribute meaningful information to the model. Some of these data may actually detract from the quality and accuracy of the model.

For example, you might collect a great deal of data about a given population because you want to predict the likelihood of a certain illness within this group. Some of this information, perhaps much of it, will have little or no effect on susceptibility to the illness. Attributes such as the number of cars per household may have no effect whatsoever.

Irrelevant attributes add noise to the data and affect model accuracy. Noise increases the size of the model, the time and system resources needed for model building.

Moreover, datasets with many attributes may contain groups of attributes that are correlated. These attributes may actually be measuring the same underlying feature. Their presence together in the build data can skew the logic of the algorithm and affect the accuracy of the model.

Wide data (many attributes) generally presents processing challenges. Model attributes are the dimensions of the processing space used by the algorithm. The higher the dimensionality of the processing space, the higher the computation cost involved in algorithmic processing.

To minimize the effects of noise, correlation, and high dimensionality, some form of dimension reduction is sometimes a desirable preprocessing step. Feature selection and extraction are two approaches to dimension reduction.

- Feature extraction: Combining attributes into a new reduced set of features
- Feature selection: Selecting the most relevant attributes

### 3.5.1 Principal Component Analysis as Feature extraction

When the input data to an algorithm is too large to be processed or it is suspected to be notoriously redundant, then the input data will be transformed into a representation set of features. Transforming the input data into the set of features is called feature extraction. If the extracted features are carefully chosen, it is expected that the features set will extract the relevant information from the input data in order to perform the desired task using this representation instead of the original [65].

There are several Feature Extraction methods such as, Independent Component Analysis (ICA) [75], Non-linear Dimensionality Reduction (NLDR) [95] or Partial least squares regression (PLS regression)[1], but the most known one is Principal Component Analysis (PCA).

Principal Component Analysis (PCA) is a technique of multivariable analysis [78] which may provide arguments for how to reduce a complex data set to a lower dimension and reveal some hidden and simplified structure/patterns that often underlie it. It was developed by Karl Pearson in 1901 and integrated to the mathematical statistics in 1933 by Harold Hotelling. The goal of PCA is to discern which dynamics are more important in the system, which are redundant and which are just noise. This goal is essentially achieved by determining a new space (coordinates) to re-express the original data, filtering that noise and redundancies based on the variance-covariance structure of the original data. PCA can be also considered as a simple, non-parametric method for data compression and information extraction, which finds combinations of variables or factors that describe major trends in a confusing data set. Among their objectives it can be mentioned: to generate new variables that could express the information contained in the original set of data, to reduce the dimensionality of the problem that is studied and to eliminate some original variables if its information is not relevant. In order to develop a PCA model it is necessary to arrange the collected data in a matrix $X$. This $n \times m$ matrix contains information from $m$ sensors and $n$ experimental trials [120]. Since physical variables and sensors have different magnitudes and scales, each data-point is scaled using the mean of all measurements of the sensor at the same time and the standard deviation of all measurements of the sensor. Once the variables are normalized, the covariance matrix $C_x$ is calculated as follows:

$$C_x = \frac{1}{n-1} X^T X. \tag{3.34}$$

It is a square symmetric $m \times m$ matrix that measures the degree of linear relationship within the data set between all possible pairs of variables (sensors). The subspaces in PCA are defined by the eigen-vectors and eigenvalues of the covariance matrix as follows:

$$C_x\widetilde{P} = \widetilde{P}\Lambda, \tag{3.35}$$

where the eigen-vectors of $C_x$ are the columns of $\widetilde{P}$ and the eigenvalues are the diagonal terms of $\Lambda$ (the off-diagonal terms are zero). Columns of matrix $\widetilde{P}$ are sorted according to the eigenvalues by descending order and they are called as (by some authors) Principal Components of the data set or loading vectors. The eigen-vectors with the highest eigenvalue represents the most important pattern in the data with the largest quantity of information. Choosing only a reduced number $r < n$ of principal components, those corresponding to the first eigenvalues, the reduced transformation matrix could be imagined as a model for the structure. In this way, the new matrix $P$ ($\widetilde{P}$ sorted and reduced) can be called as PCA model. Geometrically, the transformed data matrix $T$ (score matrix) represents the projection of the original data over the direction of the principal components $P$:

$$T = XP. \tag{3.36}$$

In the full dimension case (using $\widetilde{P}$), this projection is invertible (since $\widetilde{P}\widetilde{P}^T = I$ ) and the original data can be recovered as $X = T\widetilde{P}^T$. In the reduced case (using $P$), with the given $T$, it is not possible to fully recover $X$, but $T$ can be projected back onto the original $m$-dimensional space and obtain another data matrix as follows:

$$\hat{X} = TP^T = (XP)P^T. \tag{3.37}$$

Therefore, the residual data matrix (the error for not using all the principal components) can be defined as the difference between the original data and the projected back.

$$\varepsilon = X - \hat{X} \tag{3.38}$$

$$\varepsilon = X - XPP^T \tag{3.39}$$

$$\varepsilon = X(I - PP^T) \tag{3.40}$$

To perform PCA is simple in practice through the basic steps [120]:

1. Organize the data set as an $n \times m$ matrix, where $m$ is the number of measured variables and $n$ is the number of trials.
2. Normalize the data to have zero mean and unity variance.
3. Calculate the eigen-vectors - eigenvalues of the covariance matrix.
4. Select the first eigen-vectors as the principal components.
5. Transform the original data by means of the principal components (projection).

### 3.5.2 Feature selection methods

The central assumption to use a feature selection technique is due to redundant or irrelevant features contained by the original data. Redundant features are those which provide no more information than the currently selected features, and irrelevant features provide no useful information in any context. Feature selection techniques are a subset of the more general field of feature extraction. Feature extraction creates new features from functions of the original features, whereas feature selection returns a subset of the features [28, 64]. Feature selection techniques provide three main benefits when constructing predictive models:

- Improved model interpretability,
- Shorter training times,
- Enhanced generalization by reducing Overfitting [26].

Feature selection is also useful as part of the data analysis process, as shows which features are important for prediction, and how these features are related.

There are several methods for Feature Selection Methods. For example these can be found in the literature.:

- Random Sampling (RS)[45]: The most trivial form of feature selection consist of a uniform random sub-sampling without repetition. Such an approach leads to features as independent as the original but does not pick the informative ones. This leads to poor results when only a small fraction of the features actually provide information about the class to predict.
- Mutual Information Maximization (MIM) [45] maximizing individually the mutual information with the relevant variable. Selection based on such a ranking does not ensure weak dependency among features, and can lead to redundant and poorly informative families of features.
- Mutual Information Feature Selection (MIFS) [11] is a greedy selection algorithm that uses the mutual information $I(X_i, Y)$ between the feature $X_i$ and the relevant variable $Y$, and all relations of the mutual information between variable $X_i$ and the rest of selected features so far $X$.

There are much more, and a complete list of the Feature Selection methods can be found in [16]; Among these methods, in this thesis some of them have been used, and are explained in the next subsections.

#### *3.5.2.1 Minimum Redundancy - Maximum Relevance (mRMR)*

This Feature Selection method was used by [140], it presents a solution able to select features that have maximum relevance to a class object and minimum redundancy between them. For that purpose, Mutual Information is used.

Features can be selected in many different ways. One scheme is to select features that correlate strongest to the class label. This has been called maximum-relevance selection. On the other hand features can be selected to be mutually far away from each other while still having "high" correlation to the class labels. These labels have information about what are the most interesting things in the Dataset; for example, an email filter is based on a set of rules applied to each incoming message, tagging it as spam or “ham” (not spam). This filter could be an example of a Class Label. Information in the header and text of each message is converted into a set of numerical variables such as the size of the email, the domain of the sender, or the presence of the word “free”.

This scheme, termed as Minimum Redundancy Maximum Relevance (mRMR) selection has been found to be more powerful than the Mutual Information Maximization (MIM).

Mutual information is used to measure the level of similarity between features and the level of correlation between feature and class. Therefore, the MI of features should be minimized to decrease the redundancy among them. The MI of feature and class should be maximized to retain the high correlation between feature and class. According to [140] the criterion of minimum redundancy is defines as follows:

$$Red(f_i) = \min_{F \subset S} \frac{1}{|F|^2} \sum_{i,j \in F} I(f_i, f_j), \tag{3.41}$$

where$|F|$ is the number of features in the seeking feature subset $F$ and $I(f_i, f_j)$ is the MI of two features $f_i$ and $f_j$. It is used to measure the level of similarity between $f_i$ and $f_j$. The feature space $S$ contains all of the candidate features. In the same way, the criterion of maximal relevance is defined as follows:

$$Rel(f_i) = \max_{F \subset S} \frac{1}{|F|} \sum_{i \in F} I(c, f_i), \tag{3.42}$$

where $I(c, f_i)$ quantifies the relevance between feature $f_i$ and the targeted class $c = \{c_1, c_2, ..., c_k\}$. The mRMR feature subset can be obtained by optimizing the conditions described in (Equation 3.41) and (Equation 3.42) through either the difference form or quotient form

$$\max_{F \subset S} \left\{ \sum_{i \in F} I(c, f_i) - \frac{1}{|F|} \sum_{i \in F} I(f_i, f_j) \right\}, \tag{3.43}$$

$$\max_{F \subset S} \left\{ \sum_{i \in F} I(c, f_i) / \frac{1}{|F|} \sum_{i \in F} I(f_i, f_j) \right\}. \tag{3.44}$$

#### 3.5.2.2 Unsupervised minimum Redundancy - Maximum Relevance (UmRMR)

Based on the previous section,the unsupervised way to use the same idea for Feature Selection when no class labels are available was introduced in [191]. There, it is confirmed the effectiveness of the unsupervised feature selection criterion by the theoretical and practical proof.

The goal of UmRMR is to find those variables which have minimal redundancy and maximal relevance, by using Mutual Information to measure the level of similarity between features and Entropy to gauge the level of Information of each feature, but with a latent class label. The relevance of a feature is redefined as the average Mutual Information to the whole feature set as follows:

$$Rel(f_i) = \frac{1}{n} \sum_{j=1}^{n} I(f_i, f_j) = \frac{1}{n} \left( H(f_i) + \sum_{1 \le j \le n, j \ne i} I(f_i, f_j) \right) \tag{3.45}$$

where $H(f_i)$ (Entropy of $f_i$) indicates the information content included in feature $f_i$, which should be large, and the other term is the amount of information content included in all the other features due to the knowledge of $f_i$ (Mutual Information between $f_i$ and the rest of variables), which should be also large. If only relevance is taken into account then it can lead to the loss of information to the least extent because it may be redundant to a feature selected in the previous run. That is why the calculation of redundancy is needed.

In order to define the redundancy, first the conditional relevance (Equation 3.46) is defined, to know what is the information gain of selecting $f_k$ if we have already selected $f_i$. So, the redundancy (Equation 3.47) is defined as the difference between the relevance of $f_k$ and the conditional relevance of $f_k$, if $f_i$ is previously selected.

$$Rel(f_k|f_i) = \frac{H(f_k|f_i)}{H(f_k)} Rel(f_k), \tag{3.46}$$

$$Red(f_i, f_k) = Rel(f_k) - Rel(f_k|f_i). \tag{3.47}$$

To define which is the variable with minimal redundancy and maximal relevance, a sequential forward search is performed to rank the features according to the following equation:

$$l_m = \max_{F \subset S} \left\{ Rel(f_i) - \frac{1}{|F|} \sum_{f_k \in F} Red(f_i, f_k) \right\} \tag{3.48}$$

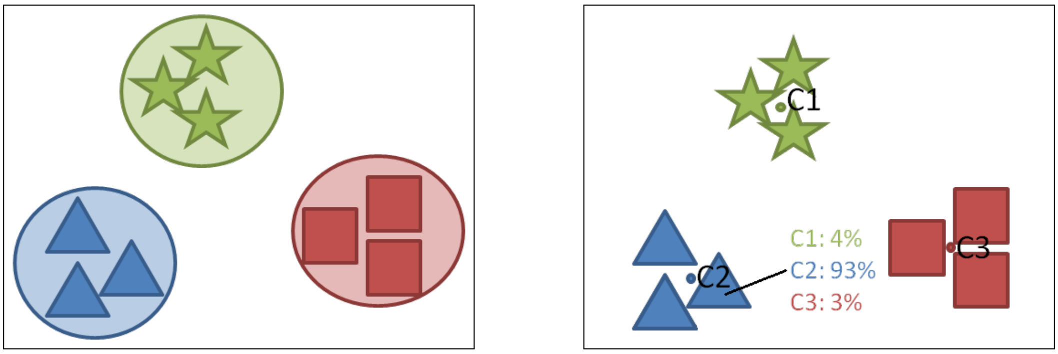
## 3.6 Cluster analysis

**Clustering:** *"Cluster analysis or clustering is the task of grouping a set of objects in such a way that objects in the same group (called cluster) are more similar (in some sense or another) to each other than to those in other groups (clusters)."[100]*

Clustering involves the task of dividing data points into homogeneous classes or clusters so that items in the same class are as similar as possible and, items in different classes are as dissimilar as possible. Clustering can also be thought as a form of data compression, where a large number of samples are converted into a small number of representative prototypes or clusters. Depending on the data and the application, different types of similarity measures may be used to identify classes, where the similarity measure controls how the clusters are formed. Some examples of values that can be used as similarity measures include distance, connectivity, and intensity.

There are mainly two types of clustering methods, the "hard clustering" and "soft or fuzzy clustering" methods. In hard clustering, data is divided into distinct clusters, where each data element belongs to exactly one cluster. In fuzzy clustering, data elements can belong to more than one cluster, and associated with each element is a set of membership levels. These indicate the strength of the association between that data element and a particular cluster. Fuzzy clustering is a process of assigning these membership levels, and then using them to assign data elements to one or more clusters.

In our work, this is interesting in order to make different clusters for different Environmental and Operational Conditions. With this solution different undamaged models can be stored depending on the working condition of the structure.




**(a)** *Hard clustering* **(b)** *Soft Clustering*

**Figure 3.3.** *Clustering representations*

### 3.6.1 Hard clustering: Self Organizing Maps

**Hard-Clustering:** *"Hard clustering, data element pattern belongs exclusively to a single cluster"* [38]

A Self-Organizing Map (SOM) is a special kind of Artificial Neural Network (ANN) converting the relationships between high-dimensional data into simple geometric relationships of their image points on a low dimensional display [86]. This type of network has the special property of generating one organized map in the output layer based on the inputs allowing the grouping of the input data with similar characteristics into clusters. To do that, the SOM internally organizes the data based on features and their abstractions from input data. In order to aid the user in understanding the cluster structure, additional visualization techniques such as the U-Matrix [172], cluster connections [113], or local factors [81] have been developed. In particular, these maps have been used in practical speech recognitions, robotics, process control, and telecommunications, among others [91].

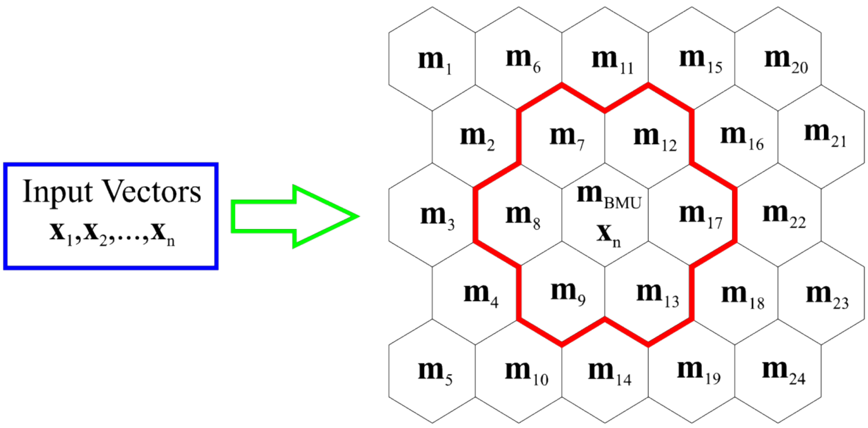



**Figure 3.4.** *Elements in a Self Organizing Map [86]*

In general, the SOM works by assigning weights to each relation between the input data and the each cluster in the map. The SOM algorithm starts working with a random initialization of these weights. The training is done by comparing the input data set with the weight vectors calculating their Euclidean distance in order to find the best matching unit (BMU). The updating process takes into consideration a neighborhood set $N_c$ around the cell $\mathbf{m}_{BMU}$, and by each learning step just the cells within $N_c$ are updated (Figure 3.4). This updating process is defined by Equation 3.49.

$$\begin{cases} \mathbf{m}_i(t+1) = \mathbf{m}_i(t) + \alpha(t)(\mathbf{x}(t) - \mathbf{m}_i(t)) & if \quad i \in N_c(t) \\ \mathbf{m}_i(t) & if \quad i \not\in N_c(t) \end{cases}, \tag{3.49}$$

where $t$ denotes current iteration, $\mathbf{m}_i$ is the current weight vector, $x$ is the target input vector, and $\alpha(t)$ is a scalar called adaptation gain which is between 0 and 1, and it is reduced each time. Finally, each incoming dataset could be presented to the map followed by the updating process or all datasets are compared to the map before executing any updating. These methods are known as the sequential and batch algorithms, respectively. After the training phase, different groups will normally form in the map which can be distinguished according to their location on the map. The U-Matrix, which shows the average distance of a cell to its neighboring cells, can be used to depict the difference between the groups. The U-Matrix will normally contain visible boundaries separating the different groups providing an idea of the extent of their difference. The training algorithm used here is implemented in a Matlab-Toolbox created by [176].

### 3.6.2 Fuzzy clustering: Fuzzy C-means

**Fuzzy(soft)-Clustering:** *"Fuzzy clustering (also referred to as soft clustering), data elements can belong to more than one cluster, and associated with each element is a set of membership levels."[100]*

This technique was originally introduced by Jim Bezdek [139] as an improvement on earlier clustering methods. It provides a method that shows how to group data points that populate some multidimensional space into a specific number of different clusters. The Fuzzy C-means clustering algorithm is based on the minimization of an objective function called C-means functional. It is defined by Dunn [37] as:

$$J(X;U) = \sum_{i=1}^{C} \sum_{j=1}^{N} (\mu_{ij})^m ||x_i - c_j||^2, \tag{3.50}$$

where $m$ is any real number greater than 1, $\mu_{ij}$ is the degree of membership of $x_i$ in the cluster $j$, $x_i$ is the $i_{th}$ of d-dimensional measured data, $c_j$ is the d-dimension center of the cluster, and $||*||$ is any norm expressing the similarity between any measured data and the center. $C$ is the number of clusters, $N$ is the number of datasets, and $U$ the matrix that contains all the membership of each dataset.

Fuzzy partitioning is carried out through an iterative optimization of the objective function shown above, with the update of membership $\mu_{ij}$ and the cluster centers $c_j$ by:

$$\mu_{ij} = \frac{1}{\sum_{k=1}^{C} \left( \frac{||x_i - c_j||}{||x_i - c_k||} \right)^{\frac{2}{m-1}}}, \tag{3.51}$$

$$c_j = \frac{\sum_{j=1}^{N} \mu_{ij}^m x_i}{\sum_{j=1}^{N} \mu_{ij}^m}, \tag{3.52}$$

This iteration will stop when $max_{ij} \left\{ ||u_{ij}^{(k+1)} - u_{ij}^{k}|| \right\} < \varepsilon$, where $\varepsilon$ is a termination criterion between 0 and 1, whereas $k$ are the iteration steps. This procedure converges to a local minimum or a saddle point of $J_m$. The step by step explanation can be seen in the algorithm shown in Figure 3.5:

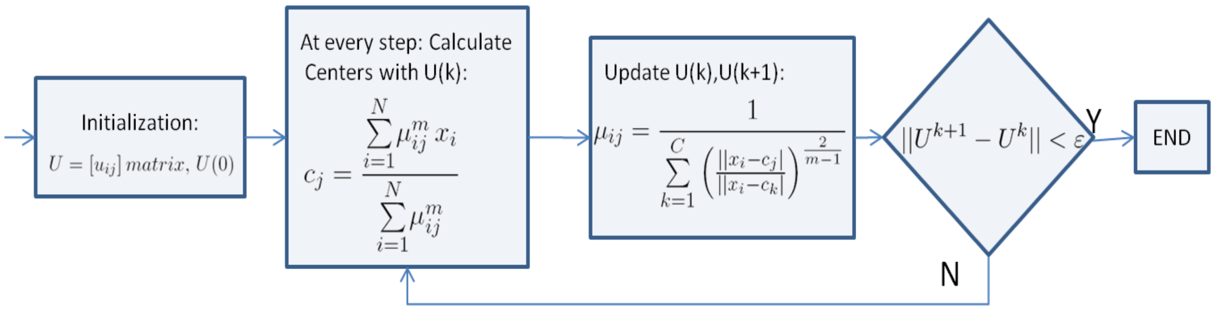



**Figure 3.5.** *Fuzzy C-Means step by step [100]*

## 3.7 Sensor placement

The optimal sensor location is found using the Sensor Elimination by Modal Assurance Criterion (SEAMAC) method implemented in FemTools. The Modal Assurance Criterion (MAC) [136] is commonly used to compare mode shapes. Each term in the MAC-matrix measures the squared cosine of the angle between two mode shapes i.e. $MAC_{i,j} = \cos^2 \Theta_{i,j}$ and is calculated as

$$MAC_{i,j} = \frac{|\ \{\Psi_i\}^t \{\Psi_j\}\ |^2}{(\{\Psi_i\}^t \{\Psi_i\}) \left( \{\Psi_j\}^t \{\Psi_j\} \right)} \tag{3.53}$$

where $\Psi$ is the modal shape. The MAC is able to tell how similar are the mode shapes.

When $MAC_{i,j} = 0\%$, the $i$-th and $j$-th mode shapes are orthogonal to each other. Hence, the mode shapes are most linearly independent when all off-diagonal terms of MAC are zero. The other way around, a $MAC_{i,j} = 100\%$ , the modes are totally the same.

The SEAMAC algorithm is a sensor elimination algorithm. This method tries to find a measurement point configuration that minimizes MAC values in off-diagonal terms. The method SEAMAC is based on eliminating iteratively one by one those degrees of freedom that show lower impact on the MAC values. This iterative process stops when you get a default MAC matrix, high values in the diagonal terms and low values in off-diagonal terms.

## 3.8 Remarks and conclusions

This chapter has shown a brief description of the theory that will be applied in the general methodology for damage detection. It has been described what vibration analysis is and how it is applied to structures. There has also been shown what Stochastic Subspace Identification is, and how it is defined. Information theory basics have been presented, and how these can be applied for Feature Selection. The Clustering strategies have been described and will be applied in Environmental and Operational Conditions compensation. Finally the Sensor Location method has been commented. As will be shown in the next chapters, each of these methods have been previously used separately and there is no references that show their use together as is developed in this thesis for damage detection.

# Chapter 4

# Case studies

The methodologies developed and presented in this thesis were subjected to different experimental tests using simplified structures and structures in real scale. In particular, four structures were tested: three numerical and a real one. The numerical structures are:

- A simple mass and spring system,
- A tower finite element model,
- A working wind-turbine system,

whereas the real one is:

- A laboratory offshore tower model.

More descriptions about the physical features, excitations signal and applied damages are included in the following sections.

## 4.1 Simple mass and spring system

The first model where the test was carried out is a numerical model simulated in MATLAB. This model consists of 15 masses connected with springs. In Figure 4.1, a representation of this numerical model is shown. Each mass is connected with the next one using a spring, and each spring has its spring constant. In order to excite the structure, a force is introduced where the first mass is located.

The damages are simulated by changing the spring constant of the third spring ($K_3$), in different percentages. The weakest damage is a change in the spring constant of 1%, the second one 10% and the last one 50%. The names for these damages are D1,D2,D3 consecutively. A summary is shown in Table 4.1.

The sampling rate is 1000Hz, and the simulation time is 30 seconds for each dataset.

**Table 4.1.** *Simulation parameters of the numerical model*

| Dataset | % of change in $K_3$ |
|---|---|
| Healthy | 0 |
| D1 | 1 |
| D2 | 10 |
| D3 | 50 |

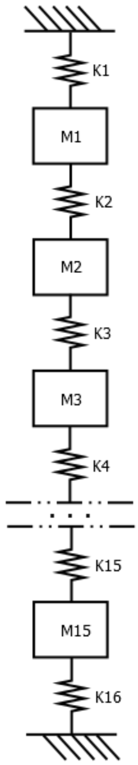



**Figure 4.1.** *Simple mass and spring system representation*

This model, thanks to its simplicity, is a good starting point to test the different solutions presented in this work. Analyzing the results from this structure it is easier to understand the effects of the damage detection system.

**Sensor placement:** The virtual sensors are placed in each of the masses. This structure is a simple one, so no sensor placement algorithm was used to locate the optimum sensor locations. The model gives us the displacement of each of the masses, and these displacements are transformed into accelerations.

## 4.2 Tower Finite Element model

The second model is still a numerical model based on Finite Elements. This model was used to build the real structure used in this thesis, which is described in section 4.4. Apart from using it as a base to build the real structure, this model was made functional, it is able to give time responses, and it is possible to create damage in it.

As can be seen in Figure 4.2, it is made to be similar to the ones used in jacket based offshore support structures. The tower is composed by 3 cilindrical tubes, while the jacket is modeled as a multi-member structure. The top part, simulates the nacelle of a wind turbine.

The vibration modes of the structure are important in order to know the behavior of the structure. In this tower, a Finite Element Analysis (FEA) was performed in order to have the knowledge of the modes. In this case, the first 18 modes are analyzed, which are located under 100 Hz. The first ten mode shapes shown in

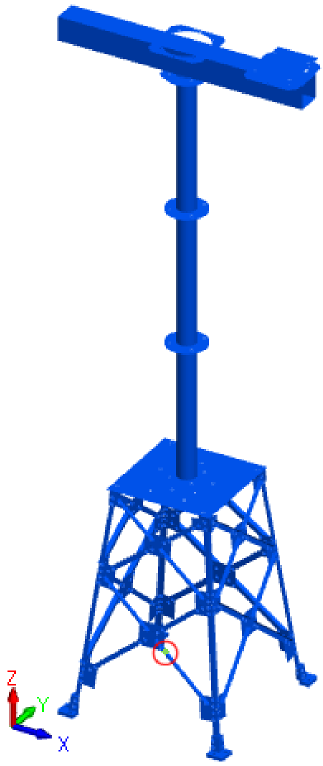



**Figure 4.2.** *FEM tower model*

Table 4.2, are the typical modes that are found in tower shaped structuresIn tower shaped structures, some of the modes have a name.

**Table 4.2.** *Finite Element Tower Modes*

| Mode | Freq. (Hz) | Mode Shape |
|---|---|---|
| 1 | 2.13 | 1st bending mode in Y |
| 2 | 2.16 | 1st bending mode in X |
| 3 | 17.25 | 1st Tower torsion mode |
| 4 | 17.53 | 1st bending mode in jacket |
| 5 | 39.88 | 2nd bending mode in Y |
| 6 | 40.35 | 2nd bending mode in X |
| 7 | 41.77 | Local Jacket mode |
| 8 | 49.94 | Local Jacket mode |
| 9 | 50.12 | Local Jacket mode |
| 10 | 61.41 | Local Jacket mode |

**Damage severity:** Three crack damages of different lenghts were simulated (see Table 4.3). These cracks were located in a member of the substructure. This damage location can be found inFigure 4.2, in green color, inside a red circle.

**Table 4.3.** *Simulated damages in FEM model*

| Dataset | Crack length |
|---|---|
| D1 | 2mm |
| D2 | 3mm |
| D3 | 5mm |

In order to quantify the damage induced in the model, a study of modal parameters was carried out. First of all, a modal comparison of the different models was done. A Modal Assurance Creterion (MAC) was used to compare the mode shapes of the healthy structure against the biggest damage (D3). The MAC, compares the mode shapes of a structure. As shown in Figure 4.3 and resumed in Table 4.4, X and Y axes represent the number of the mode calculated by the solver of the software, while Z axis represent the percentage of similarity between two mode shapes. It can be seen that almost no changes in frequency and shape are perceived. Therefore, it means that according to modal analysis, the 5mm crack located in the substructure is a very small damage and it can not be detected using this modal method.

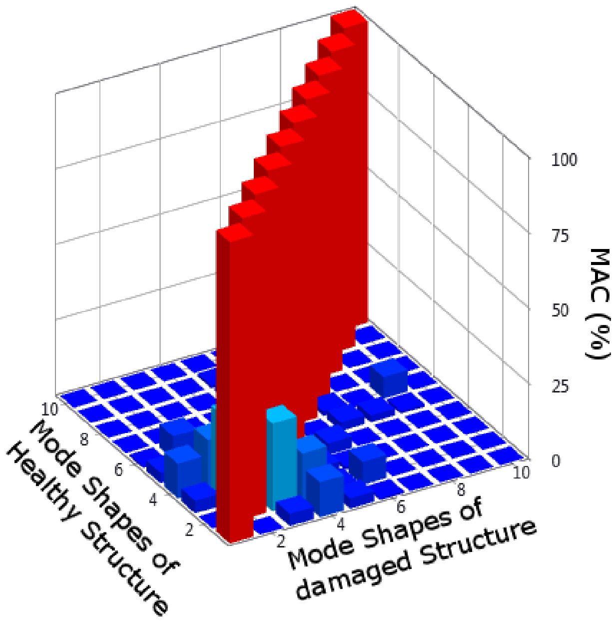


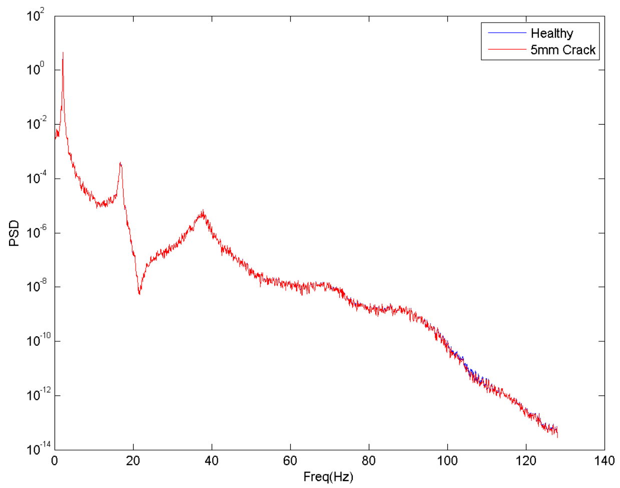

**Figure 4.3.** *MAC Healthy vs D3*

On the other hand the Power Spectral Densitie (PSD) is a wide used technique for signal processing, statistics, and physics which represents the power per hertz (Hz), or energy per hertz. It also can be used for checking the damage severity. In Fig.4.4a it can be seen that both signals have almost the same PSD. This means that the damage is small.

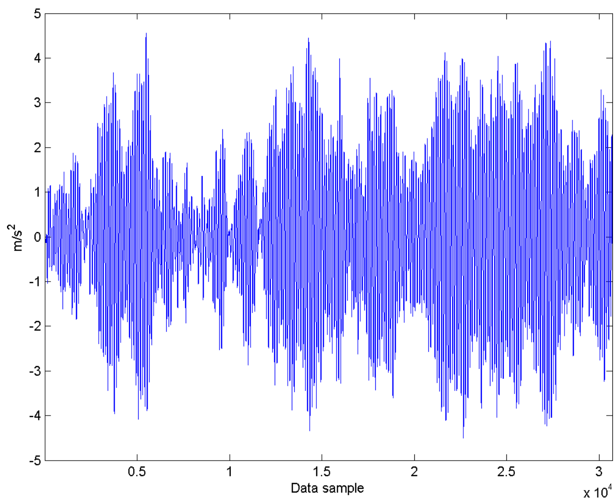
In order to quantify the comparison of both PSDs, a correlation coefficient of each PSD is calculated, and both of them really close to 1, that means that both PSDs are almost the same. Therefore, it means that according to the PSD method, the 5mm crack located in the substructure is a very small damage and it can

**Table 4.4.** *Modal Comparison Resume*

| Mode | Resonance Freq. (Hz) | | Diff. Hz (%) | MAC (%) |
|---|---|---|---|---|
| | Healthy | Damaged | | |
| 1 | 2.1362 | 2.1363 | 0.01 | 100 |
| 2 | 2.1665 | 2.1666 | 0 | 100 |
| 3 | 17.253 | 17.253 | 0 | 100 |
| 4 | 17.542 | 17.541 | -0.01 | 100 |
| 5 | 39.896 | 39.898 | 0.01 | 100 |
| 6 | 40.389 | 40.393 | 0.01 | 100 |
| 7 | 41.783 | 41.784 | 0 | 100 |
| 8 | 49.878 | 49.882 | 0.01 | 100 |
| 9 | 50.077 | 50.083 | 0.01 | 100 |
| 10 | 61.424 | 61.424 | 0 | 100 |




**(a)** *PSD Healthy vs D3, Sensor 3 data*




**(b)** *Sensor 3 - time domain data - Healthy*

**Figure 4.4.** *Sensor Data Comparison*

not be detected using it.

**Sensor placement:** In order to be able to monitor the behavior of the tower against the damage, it is necessary to place sensors on it. For that purpose, the Sensor Elimination Method using Modal Assurance Criterion (SEAMAC) sensor location algorithm was used. As explained in section 3.7, SEAMAC takes as a possible sensor location any of the nodes of the FEM model. Knowing this, the best possible result that can be obtained is to locate a sensor in each of the nodes and calculate its MAC. The result of this is shown in Figure 4.5. The final MAC result after reducing the accelerometer number should be worse than the one shown in Figure 4.5, because the sensors are going to be less than the number of nodes. In Figure 4.5 the X and Y axes represent the number of the mode calculated by the solver of the software, while Z axis represent the percentage of similarity between two mode shapes. These mode shapes are calculated using a FEA solver. In the X and Y axis of the MAC figures “FEA” acronyms are found. This explains that those modes are calculated using a FEA solver.

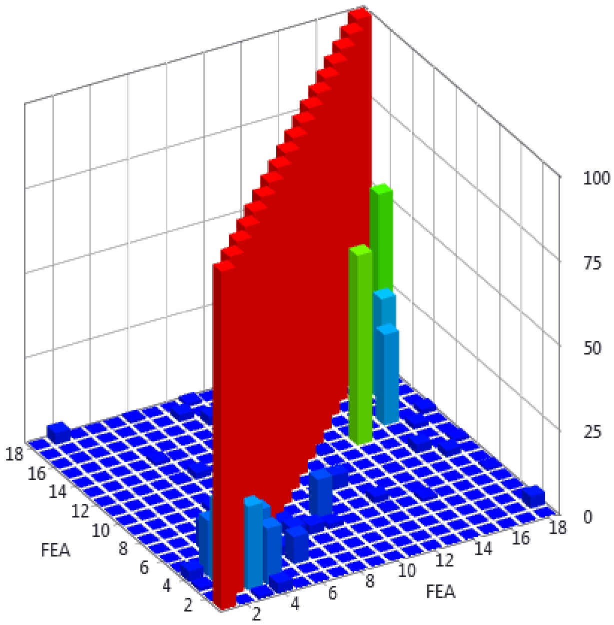
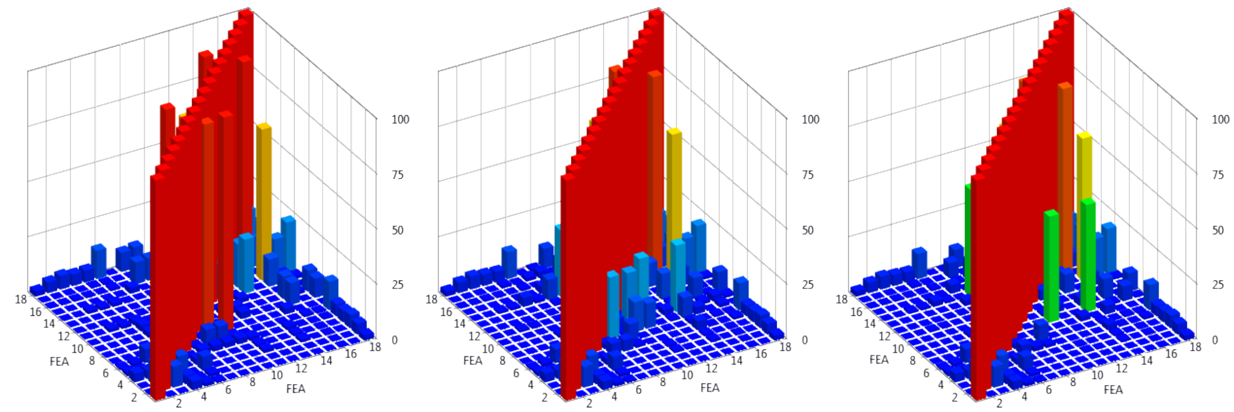



**Figure 4.5.** *AutoMAC FEM model*

After knowing the best MAC that the algorithm is able to give locating sensors in all the nodes, the iterative reduction of the accelerometers starts. The maximum number of accelerometers to be placed in the structure is taken as 10. In this case, afterwards the real structure will be built, and the maximum amount of accelerometers accepted by the data acquisition system is 10 triaxial accelerometers. No minimum value for the number of accelerometers was chosen. After applying the method for 10, 9, 8, 7, 6, 5 and 4 accelerometers, the values concerning to the summation of the Off-diagonal terms are shown in Table 4.5, while the visual results of some of the results are the ones shown in Figure 4.6. Again the X and Y axes represent the number of the mode captured using the sensors number and placement, while the Z axes represent the similarity between different mode shapes, using the sensor configuration.

In order to build a criterion to select the sensors that are going to be used, a criteria was used. At most, the summation of the Off-Diagonal terms should not be higher than the double of the best possible solution. This criteria already tells us that at least 8 sensors are needed. After knowing the minimum necessary sensors, a visual inspection of the MAC results are done. The most interesting option corresponds again to 8 accelerometers. Reduction to 7 sensors give us a substantially worse MAC (3 big value terms) and increasing to 9 accelerometers does not improve the MAC significantly (not even 100 reduction in Off-Diagonal terms). So this configuration is used for the Sensor network in this structure. The result of the 8 accelerometers correspond to the configuration shown in the Figure 4.7.




**(a)** *7 sensors* **(b)** *8 sensors* **(c)** *9 sensors*

**Figure 4.6.** *SEAMAC Results for different accelerometer number in FEM model*

**Table 4.5.** *Sum of the Off-Diagonal terms*

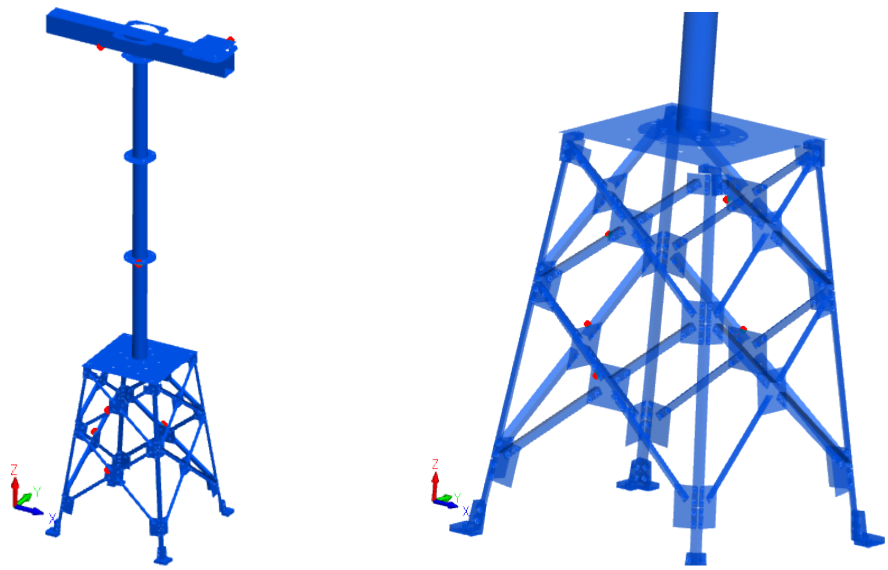
| Sensor amount | $\sum Off - Diagonal(\%)$ |
|---|---|
| 107867 (All possible Nodes - AutoMAC) | 303 |
| 10 | 456 |
| 9 | 515 |
| 8 | 607 |
| 7 | 713 |
| 6 | 883 |
| 5 | 1260 |
| 4 | 1580 |

## 4.3 UPWIND Bladed model

The third numerical structure is a wind turbine model based on the UPWIND project constructed by [79], and it is implemented in the software Bladed by [53]. In this section the properties of the support structure are presented.

The properties of the tower for the UPWIND NREL offshore 5-MW baseline wind turbine will depend on the type of the support-structure used to carry the rotor-nacelle assembly. The type of support structure will, in turn, depend on the installation site, whose properties vary significantly through differences in water depth, soil type, wind and wave severity. Offshore support-structure (OSS) types include fixed-bottom monopiles, gravity bases, space-frames—such as tripods, quadpods, and lattice frames (e.g., "jackets")—and floating structures. This model is built with a jacket support-structure, as can be seen in Figure 4.8. This support-structure is composed with jacket.

In order to have different types of data, several operating conditions of the turbine were simulated. For this purpose, different turbulent winds and nacelle orientations were used. Turbulent winds are centered in $8\,m/s$, $16\,m/s$, $25\,m/s$ speeds, while the Nacelle orientation changes between $0°, 20°, 50°\,and\,75°$ from north.



**(a)** *Angle view* **(b)** *Jacket detail*

**Figure 4.7.** *8 Sensor configuration in FEM model*

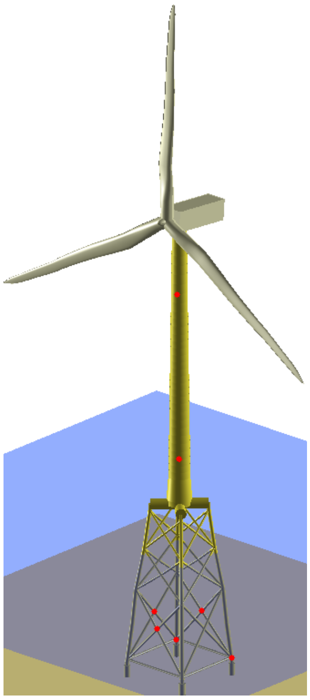
**Damage seventies:** To simulate different damage levels, the wall thickness of the member situated in the second level of the jacket (the blue member shown in Fig.4.8b) is reduced in 0.01%, 0.05%, 0.1%, 0.5%, 1%, 5%, 10%, 15%, 20% and 25%.

The simulation time is $50s$ for each data set with a sampling frequency of $500Hz$. The resulting amount of data is large. There are 12 datasets for each Structural state and each EOC, resulting in 720 datasets.

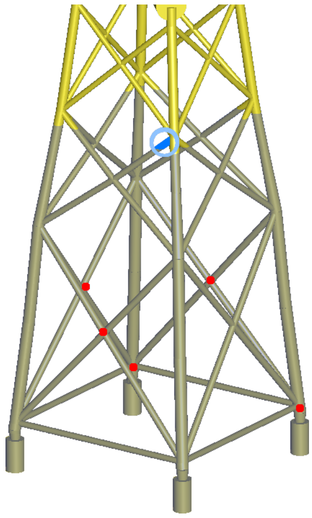
In order to quantify the damage induced in the model the PSD method has been used. The modal method is not available in these simulations, and that is why the PSD method is the only one used. In Figure 4.9 it is shown that both PSDs are almost the same, and the correlation coefficient of both signals are really close to 1. This means that the damage induced in the model is small, and that there is no way of detecting it using the PSD method.

**Sensor placement:** Having a complex structure, it is important to know where the sensors should be located. Using the method explained in section 3.7, the sensors were located in the structure. The methodology used is similar to the one used for sensor location in the previous case study, but in this case, some modes are selected.

First of all, a modes selection was done. The FEM model of the turbine allows to calculate the modes of the whole structure, including blades. In this case the damage detection is centered in the Support Structure of the Wind Turbine. This Support Structure is composed with the jacket and the tower. The selection will contain all the tower and jacket modes. To determine which modes are tower and jacket modes and which are blades modes the strain energy distribution for each mode is calculated. After that, the modes that have a high proportion of strain energy in tower or jacket are selected. After a visual inspection of the mode shapes, all the local modes were discarded, as well as the high frequency modes. Taking into account the size of the structure, everything above 2Hz was considered as high frequency mode. Having this selection of modes,



(a) *Sensor Locations on OSS (red dots)*



(b) *Jacket Detail with damage Location (Blue)*

**Figure 4.8.** *UPWind Model*

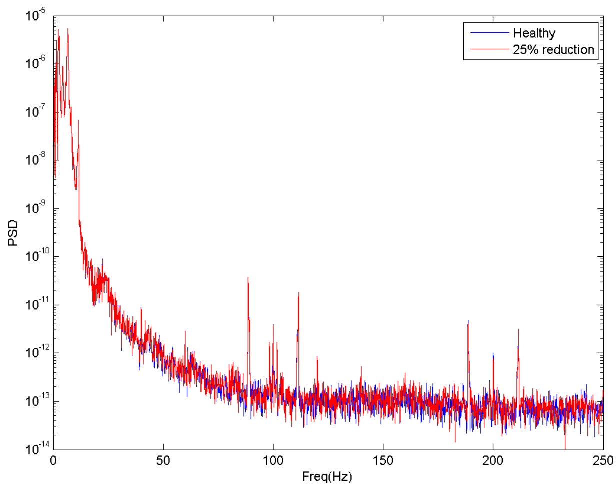



**Figure 4.9.** *PSD Healthy vs 25% reduction, Sensor 4 data*

global and low frequency ones, the Sensor placement algorithm is applied using them, just as applied to the tower model in previous section.

As explained in section 3.7, SEAMAC is a sensor elimination method, and it takes as a possible sensor location any of the nodes of the FEM model. Knowing this, the best possible result that can be obtained is to locate a sensor in each of the nodes and calculate its MAC (Figure 4.10). The result should be worse than the one shown in Figure 4.10, because the sensors are going to be less than the number of nodes.

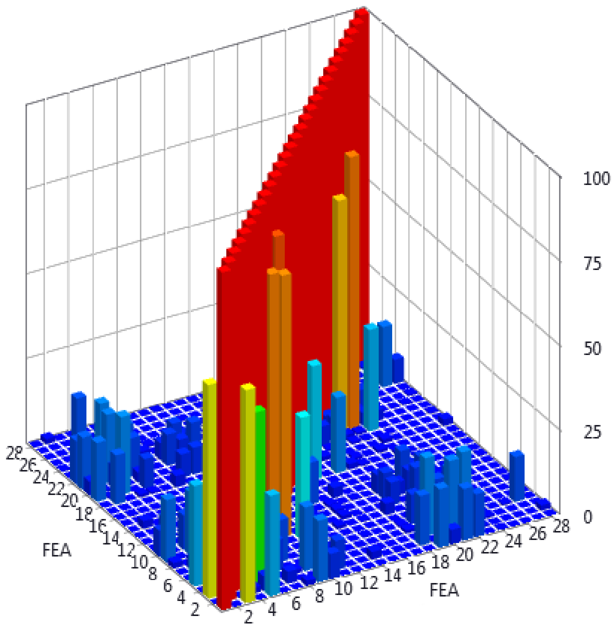
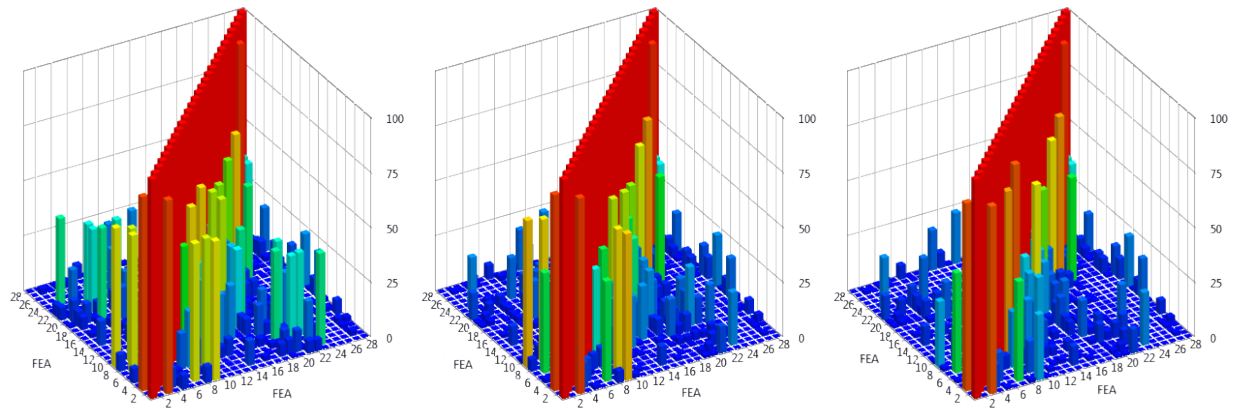



**Figure 4.10.** *AutoMAC for UPWIND*

After having the best result that the algorithm is able to give, the iterative reduction of the accelerometers starteds. The maximum number of accelerometers to be placed in a turbine is taken as 10 triaxial, remember that we are building an SHM system, and this system is part of the structure, this means that the costs of the structure get higher with more accelerometers. No minimum value for the number of accelerometers was chosen. After applying the method for 10, 9, 8, 7, 6, 5 and 4 accelerometers, the values concerning to the summation of the Off-diagonal terms are shown in Table 4.6, while the visual results of some of the results are the ones shown in Figure 4.11.

In order to build a criterion to select the sensors that are going to be used, the same principle was used as in the previous section. At most, the summation of the Off-Diagonal terms should no be higher than the double of the best possible solution. This already tells us that at least 7 sensors are needed. The most interesting option corresponds to 7 accelerometers. The increase to 8 accelerometers does not improve the MAC significantly (not even a 250 reduction in Off-Diagonal terms). So this configuration is used as sensor network in this structure. The result of the 7 accelerometers correspond to the configuration shown in the Figure 4.12.

It is important to remark that no accelerometer was placed in the Splash Zone (see Fig. 1.1a) of the Wind turbine. This zone is one of the most dangerous area in the jacket for an accelerometer, because sea is always hitting that area.




**(a)** *6 sensors* **(b)** *7 sensors* **(c)** *8 sensors*

**Figure 4.11.** *SEAMAC Results for different accelerometer number for UPWIND*

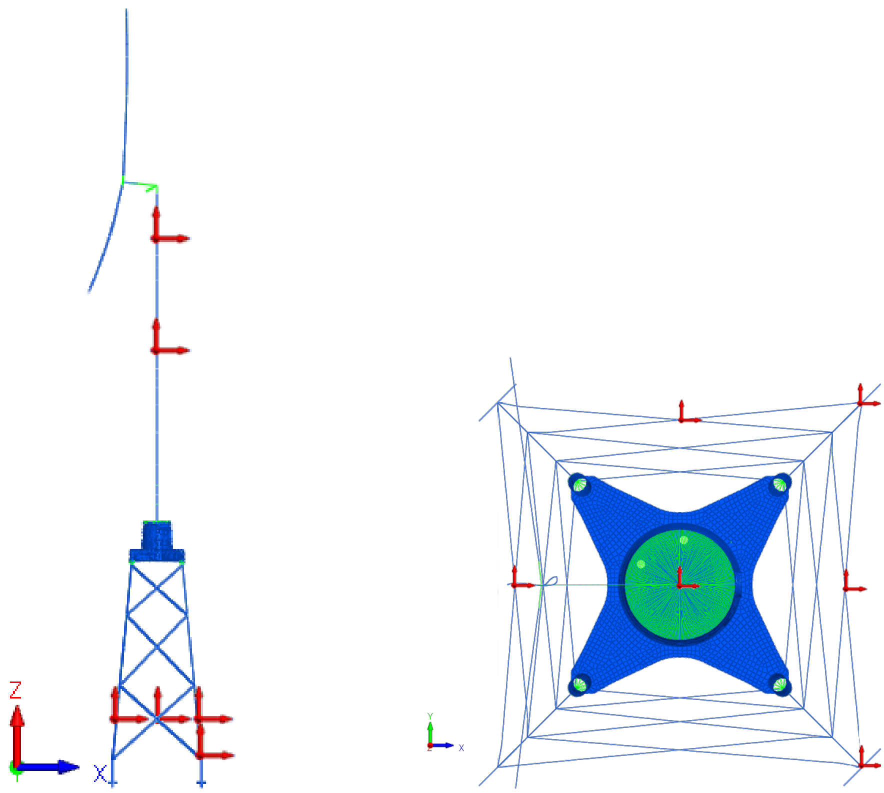
**Table 4.6.** *Sum of the Off-Diagonal terms*

| Sensor amount | $\sum Off - Diagonal(\%)$ |
|---|---|
| 267 (All possible Nodes - AutoMAC) | 1320 |
| 10 | 1720 |
| 9 | 1890 |
| 8 | 2150 |
| 7 | 2390 |
| 6 | 2750 |
| 5 | 3260 |
| 4 | 3920 |

## 4.4 Laboratory tower model

Finally, the real structure used in this thesis is a tower model, similar to those of a wind turbine, see Figure 4.13. The structure is 2.7 m high; the top piece is 1 m long and 0.6 m width. The tower is composed of three sections joined with bolts, while the jacket is composed with several sections, all of them joined with bolts. The damage is introduced as a crack in one of these sections, see Fig. 4.13b. As it can be seen in the Fig. 4.13a, on the top of the structure a modal shaker is located. This shaker simulates the nacelle mass and the environmental effects of the wind over the whole structure. Applying an electrical signal to the shaker, (white noise) the vibration needed to excite the structure is created. The simulation of different wind speeds is also simulated with this shaker, by changing the amplitude of the input electrical signal. In order to simulate the nacelle orientation changes, the top part of the structure spins $0º, 30º\, and\, 90º$; 0º is the basic position shown in Fig. 4.13a.

The vibration modes of the structure are important in order to know the behavior of the structure, and how data should be acquired. In this tower, an Operational Modal Analysis was performed in order to have a good quality Finite Element Model. In this case, we analyze the first 10 modes, which are located under




**(a)** *Side view* **(b)** *Top view*

**Figure 4.12.** *7 Sensor configuration in UPWIND*

100 Hz. In Table 4.7 the frequency results of the OMA are shown. In this OMA some of the modes are not present. The structure, is mainly excited in X direction. The fact that the excitation is mainly in X direction means that the Y modes have no so much power, and the OMA method is not able to see them.

**Table 4.7.** *OMA frequency results*

| Mode | Freq. (Hz) | Mode shape |
|---|---|---|
| 1 | (not found) | 1st bending mode in Y |
| 2 | 2.22 | 1st bending mode in X |
| 3 | 17.51 | 1st Tower torsion mode |
| 4 | 17.73 | 1st bending mode in jacket |
| 5 | (not found) | 2nd bending mode in Y |
| 6 | 41.8 | 2nd bending mode in X |
| 7 | 42.8 | Local Jacket mode |
| 8 | 50.01 | Local Jacket mode |
| 9 | 50.08 | Local Jacket mode |
| 10 | 60.07 | Local Jacket mode |

**(a)** *Photo*

**(b)** *Damage Location*

**Figure 4.13.** *Laboratory tower*

In order to simulate different wind speeds, the amplitude of the input wave that goes to the shaker was changed, increasing its amplitude. The shaker has an amplifier, that way the input signal can be amplified before it arrives to the shaker itself. This amplifier has as input the white noise signal, and as output the input signal amplified depending on the gain the user has adopted. For this test, 3 different amplitudes were used: *one*, *two* and *three*. Where *one* is the signal itself , and *three* the input signal amplified by means of three.

**Damage severity:** The damages introduced are shown in Fig.4.13b; The damage is introduced in one of the bars, and it is a 5mm crack. The time for each data set is $60s$ with a sampling frequency of $256Hz$.

In order to calculate the severity of the seeded damage, some Power Spectral Density (PSD) was calculated, as no Modal information of the damaged Structure was calculated. Taking into account the explanations in previous sections, it is a good approach to see the PSDs of the time signals to calculate the severity of the damage in terms of frequency changes. If the changes in PSD are small, the damage is said to be small. For example in Figure 4.14 almost no change in the PSD is visually found.

Once again, the correlation coefficient of the PSDs is calculated in order to know how correlated the Fre-

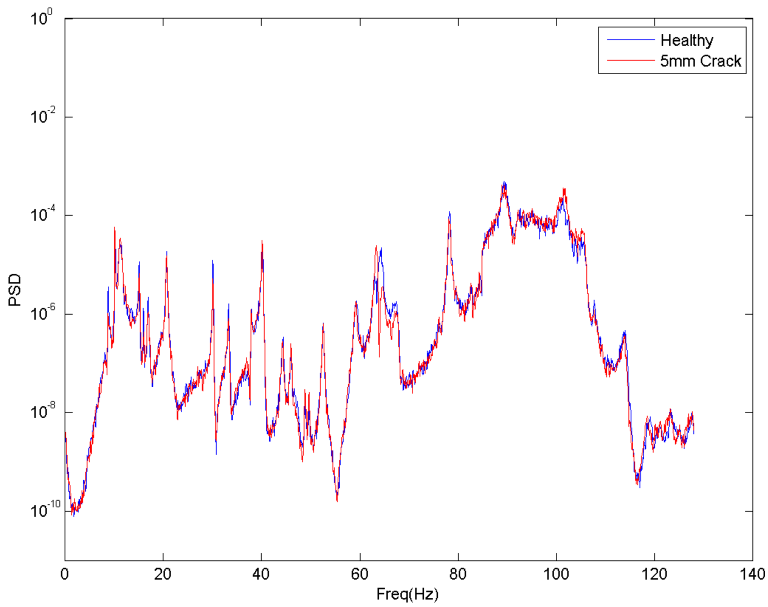



**Figure 4.14.** *PSD of Sensor 3*

cuency signals are. In Table 4.8 the values are shown. All of them are higher than 0.95 or 95%. this means that the PSDs are really similar. Taking all this into account, it can be said that the 5mm crack damage is small for this structure.

**Table 4.8.** *Correlation Coefs for different Sensor PSDs*

| Sensor Number | Correlation |
|---|---|
| 1 | 0,970 |
| 2 | 0,977 |
| 3 | 0,987 |
| 4 | 0,969 |
| 5 | 0,959 |
| 6 | 0,990 |
| 7 | 0,992 |
| 8 | 0,953 |
| 9 | 0,998 |
| 10 | 0,997 |
| 11 | 0,973 |
| 12 | 0,992 |
| 13 | 0,994 |
| 14 | 0,972 |
| 15 | 0,995 |

**Sensor placement:** To detect the structural response, some accelerometers are placed in the tower. The method used to find the optimum location and amount of these sensors has been explained in section 4.2. The result of the method resulted in 8 triaxial accelerometers that are shown in Figure 4.7.

## 4.5 Remarks and conclusions

The use of different case studies helps to validate the methodology in different areas. The first case study is a simple one, just to know that everything works well, and that theoretically it can be done. The second one is also simple, but bigger, and if the methodology is well detected in this one, it means that it could be detected in the real laboratory tower. The UPWIND model is a challenging case study, because a real wind turbine is being simulated in real conditions and in power production mode. Finally, the Laboratory tower helps to translate the methodology to the reality.

The induced damages are small to see a remarkable frequency change in the structures, and the sensor placement is a important step in order to have rich information.

# Chapter 5

# Damage detection

Damage detection is the first level of an SHM system. Damage detection is very important to avoid either human or economical disasters. If a damage is detected in the moment it has been created, safer structures will be built, and some action could be done before the disaster happens. As was described in chapter 2, among the vibrational statistical damage detection methods, Stochastic Subspace Identification (SSI) methods are widely used to build models that are able to extract the modal information from the structure. For damage detection, in this thesis, there is no need of extracting the modal information because the damage detection algorithm works directly on detecting changes in the structure, using time domain data.

In this chapter, the bases of the NullSpace damage detection algorithm are explained, and the results for each case study are shown.

## 5.1 Damage detection algorithm

In this section the algorithm itself and the different steps of the process are explained. The algorithm has two phases, the *learning* one and the *detection* one.

In the first phase, the data used is data from a healthy structure and the healthy model is constructed. The bases for constructing the model are explained in the next sections. In this part the algorithm learns how the structure behaves in a healthy state.

In the second one, the input data has to be evaluated. The model constructed in the learning phase is applied to the incoming data so as to determine if the structure is still in a healthy state or not.

### 5.1.1 Learning process

The Learning process has $n$ inputs (datasets) and 2 outputs. The inputs are the healthy signals coming from the accelerometers, and the outputs are the NullSpace ($U_{h0}$ ) and the variability factor ($\Sigma$), which changes depending on the Damage Indicator used. Both outputs are explained in the next sections. The number of healthy datasets needed ($n$) for the learning process is not a fixed number; the more datasets used for learning, the more robust it is, and less false positives appear.

Figure 5.1 shows the scheme of the learning process. Before going step by step to describe the learning phase, the different variables of this process are explained.

- $Y_k$ is the $k^{th}$ input or dataset; where $k \in [1,n]$. This input consists of a matrix containing all the measurements of each sensor. The dimension of $Y$ is shown in Equation 5.1, where $i$ is the number of sensors and $j$ the number of samples.

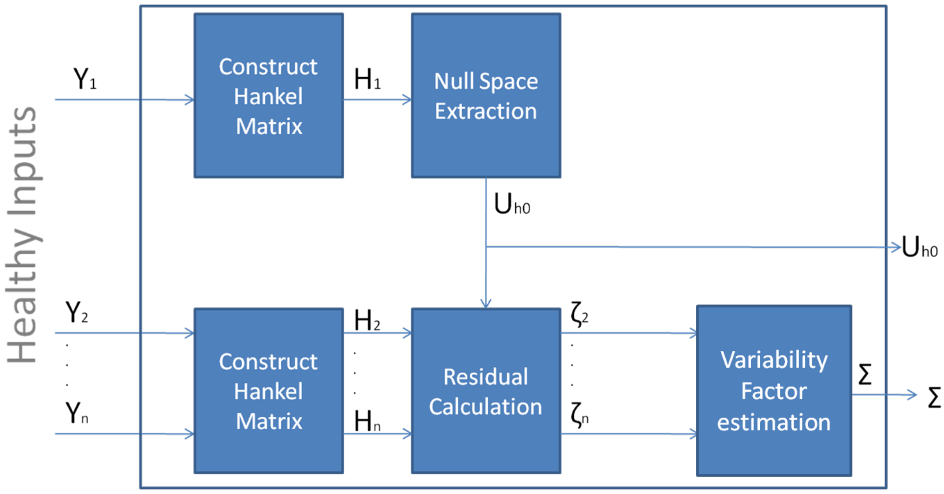



**Figure 5.1.** *NullSpace damage detection: Learning phase [49]*

$$Y = \begin{bmatrix} y_{1,1} & y_{1,2} & \cdots & y_{1.j-1} & y_{1,j} \\ y_{2,1} & y_{2,2} & \cdots & y_{2.j-1} & y_{2,j} \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ y_{i,1} & y_{i,2} & \cdots & y_{i.j-1} & y_{i,j} \end{bmatrix} \tag{5.1}$$

- $H_k$ is the Hankel matrix corresponding to the $Y_k$ input; it corresponds to the $k^{th}$ input. This matrix is constructed as shown in subsection 3.3.3, and is the base of SSI.
- $U_{h0}$ is the NullSpace of the $H_1$ Hankel Matrix. It is calculated as shown in section 5.2, in the next section.
- $\zeta_k$ is the $k^{th}$ residual; it corresponds to the $k^{th}$ input. It is calculated as shown in section 5.3, in the next section.
- $\Sigma$ is the variability factor. As shown in subsection 5.3.2, it can be estimated three different ways. They are defined in the next section.

**Learning step by step:** There are $n$ healthy inputs and there are differences between the first input and the rest datasets. The first one is used to find the NullSpace, and the rest are used to find the variability factor.

On one hand, using the first dataset, its Hankel matrix is determined, and later the NullSpace matrix for that first input is determined using the Singular Value Decomposition.

On the other hand, the other inputs are used to determine the variance of the healthy structure. After finding the Hankel matrix for each of the inputs, using Equation 5.4 and Equation 5.5, defined in the next section, the residuals for each input are calculated. Finally, depending on the chosen Damage Indicator the variability factor will be found in one way or another. From this Learning process, the NullSpace matrix ($U_{h0}$), and the Variability Factor ($\Sigma$) are stored for the detection process. This two variables are the ones that construct the model.

### 5.1.2 Detection process

In the detection phase, $m-(n+1)$ are the inputs to be evaluated. This value amount, if we are talking about a online monitoring system, is really proportional to time the structure is operating, so this value can be very large.The other 2 inputs are coming from the learning process, and are the variables that construct the model $(U_{h0}, \Sigma)$. As output we have $m-(n+1)$ Damage Indicator values. Each DI corresponds to its input. The value of the Damage Indicator tells us whether the structure is damaged or not. The variables that take part in this process are the same as the ones used in the learning phase (subsection 5.1.1).

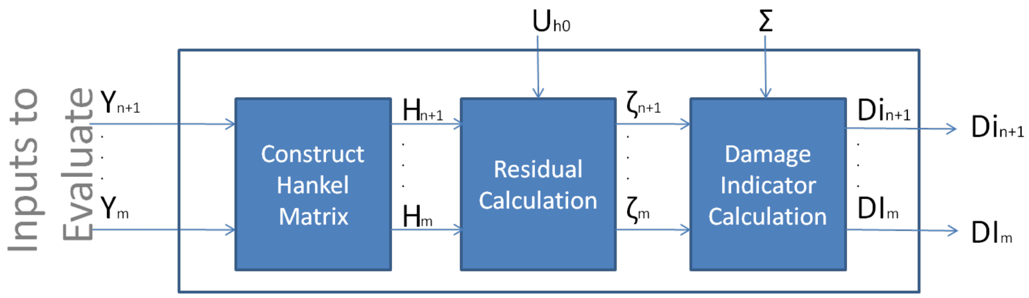



**Figure 5.2.** *NullSpace damage detection: Detection phase [49]*

**Detection step by step:** The detection is done almost the same way as the second part of the learning process. Instead of calculating the variability factor, it is applied in order to determine if the dataset is still inside the limits that the variability explains. First of all, the Hankel matrices are constructed, one for each incoming data. These Hankel matrices are multiplied with the NullSpace matrix $U_{h0}$ coming from the learning process in order to determine the residual $\zeta$ using Equation 5.4 and Equation 5.5, defined in the next sections. Once again, there is one residual for each input dataset. Finally each residual is evaluated depending on the variability factor chosen (Equation 5.7, Equation 5.9 or Equation 5.11), and the Damage Indicator of the structure is determined. These DIs are later plotted in order to have a visual diagnostic tool.

## 5.2 NullSpace analysis of the Hankel Matrix

The base mathematical foundations about modal identification on structures was presented in section 3.3. This thesis, is not focused on identifying the modal parameters of the structure. Instead, only relative changes of characteristic features are necessary for structural damage assessment. For this purpose, a method based on the null subspace (NullSpace) concept of the Hankel matrices can be used. subsection 3.3.3 shows how the Hankel matrix is defined. The condition based parameter in order to be able to detect damage was introduced by [49] and is derived from the Covariance driven Hankel matrix defined in Equation 3.14. To find the NullSpace, a singular-value decomposition (SVD) on the Hankel matrix is performed. In linear algebra, the SVD is a factorization of a matrix, with many useful applications in signal processing and statistics, and it is defined as

$$H_{p,q} = U_H S_H V_H^t, \tag{5.2}$$

where $U_H$ is a unitary matrix, $S_H$ is a rectangular diagonal matrix with nonnegative real numbers on the diagonal, and $V_H^t$ (the conjugate transpose of V) is unitary matrix. The diagonal entries $S_{i,i}$ of $S$ are known as the singular values of $H_{p,q}$. The columns of $U_H$ and the columns of $V_H$ are called the left-singular vectors and right-singular vectors of $H_{p,q}$, respectively.

In this moment the NullSpace of the Hankel matrix ($U_{h0}$) has to be found. The NullSpace is a matrix that makes the next property to be true:

$$U_{h0}^t H_{p,q} = 0. \tag{5.3}$$

This null hypothesis is the base of the damage detection method. Basically, the healthy structure data will have similar null hypothesis. So, using a $U_{h0}$ from a learning state of the structure and applying it to a healthy response, the value will be small, while applying it to a damaged response, the value will be higher.

$U_{h0}$ contains the maximum number of independent column vectors that span the column null space of $H$. In order to find it, we have to find which singular values ($S_H$) are equal to zero, and take the left-hand singular vectors ($U_H$) corresponding to those null singular values.

The basic model is found using this NullSpace, but in order to give variability to the model, more data are needed. So, a learning phase is needed use several healthy data and give variability to the basic model. Next sections talk about how the damage algorithm uses this null hypothesis to create a damage detection algorithm.

## 5.3 Damage detection - Bases

### 5.3.1 Residuals

Taking as a base the work done by Fritzen in [88], a variant of that damage detection method was implemented.

Using the idea that has been shown in section 5.2; if the structure is undamaged, the product between NullSpace ($U_{h0}$) and a Hankel matrix calculated using data coming from a healthy structure (shown in Equation 5.3) should be equal or really close to zero because both should have the same (or at least similar) NullSpace. If damage occurs, this product should be different from zero. The result of that multiplication is called residue matrix,

$$R_{i,j} = U_{h0}^t H_{i,j}, \tag{5.4}$$

where $R_{i,j}$ is the residual matrix, the $U_{h0}$ is the NullSpace of the first Healthy dataset (see subsection 5.1.1) and $H_{i,j}$ is the Hankel matrix of a different input.

This residual matrix already has information about the state of the structure, but it is very large and a simpler way of representing the damage is needed. Apart from that, no variability was used in this model. In order to insert this variability into the model and so as to have a easier way of representing the damage we should make some transformation to this residue matrix.

First, a vectorization operator is applied. This operator rearranges the columns of the $R$ matrix into one vector, by

$$\zeta = vec(R_{i,j}), \tag{5.5}$$

where $\zeta$ is the residual, and $vec$ is a vectorization operation.

Having the data in form of residual ($\zeta$), the next step is to insert variability to the system. For that purpose, different types of Damage Indicators (DI) were used and developed.

### 5.3.2 Damage Indicators (DI)

As the name explains, Damage Indicator, indicates the existence of damage; if the value is low, there is no damage, and on the contrary, if the value is high, damage is present in the structure. DI calculation has two steps. First, in the learning phase the variance of the structure is calculated. In the second step, that variance is used to know if the structure is still inside the limits of being healthy. The transformation from the residual to DIs gives the result as scalar values, that way it is easier to determine if there is damage or not, just by looking to a number. Three different Damage Indicator values were used and compared.

#### *5.3.2.1 Mean Residual (MR)*

This DI was developed for this work, and it is a contribution of this thesis. The mean value of all the residuals used in the learning phase is calculated by

$$\widehat{\Sigma_m} = \left(\frac{1}{n-1}\right) \sum_n \zeta_n, \tag{5.6}$$

where $n$ is the number of inputs in the learning phase.

Using this mean value vector ($\widehat{\Sigma_m}$) the damage indicator is calculated dividing every value of the residual vector ($\zeta$), with the values of the mean value vector ($\widehat{\Sigma_m}$ ), for later, in the detection phase, to calculate the mean value of this result as damage indicator value by

$$DI_m = \left(\frac{1}{n-1}\right) \sum_k \frac{\zeta_{n+t}}{\widehat{\Sigma_m}}, \tag{5.7}$$

where $\zeta_{n+t}$ is the residual of the dataset that is being evaluated, and $k$ is the number of values in $\zeta_{n+t}$.

#### *5.3.2.2 Covariance Matrix Estimate (CME)*

This indicator is used by Fritzen [49]. In the first step, using the different residuals ($\zeta$) of the undamaged structure, the covariance estimate is constructed. This covariance estimate is a big matrix, and it is calculated by

$$\widehat{\Sigma_c} = \left(\frac{1}{n-1}\right) \sum_n \zeta_n \zeta_n^t, \tag{5.8}$$

where $n$ is again the number of inputs in the learning phase.

For the second step, a residual vector that is going to be evaluated is needed. For each evaluation residual vector, the Equation 5.9 will be applied to have a scalar value that is able to tell whether damage exists. The Damage Indicator is given by

$$DI_c = \zeta_{n+1}^t \widehat{\Sigma_c}^{-1} \zeta_{n+t}, \tag{5.9}$$

where $\zeta_{n+t}$ is the residual of the dataset that is being evaluated.

#### 5.3.2.3 Scalar Covariance (SC)

Yan [192] proposes to calculate a scalar value for each dataset, instead of building the Covariance Matrix Estimate. It is similar to Fritzens' idea, but instead of having a huge matrix, it only needs a scalar value for the variance application. It is calculated by

$$\widehat{\Sigma_s} = \left(\frac{1}{n-1}\right) \sum_n \zeta_n^t \zeta_n, \tag{5.10}$$

where $n$ once again the number of inputs in the learning phase.

In the second step, the same idea as before can be found, but with a scalar value. The damage is detected, by

$$DI_s = \frac{\zeta_{n+t}^t \zeta_{n+t}}{\widehat{\Sigma_s}}, \tag{5.11}$$

where $\zeta_{n+t}$ is the residual of the dataset that is being evaluated.

## 5.4 Threshold

During the learning phase, a threshold is calculated. If the DI of a dataset is above that threshold value, the structure will be considered as damaged, and the other way around, if the DI is below that value, it will be considered as healthy.

This threshold value is calculated using the same datasets that are used in the learning process. For that purpose, a detection process is performed with the datasets used for learning. The output of this process are once again the Damage Indicators concerning the learning process datasets.

Using these DIs their mean value is calculated and 3 times the standard deviation of these DIs (Equation 5.13) is added to that mean value (Equation 5.12). Supposing that these DIs continue a normal distribution, this means that the 99% of the values should be below that threshold.

$$\mu = \left(\frac{1}{n}\sum_{k=1}^{n} DI_k\right) \tag{5.12}$$

$$\sigma = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (DI_i - \mu)^2} \tag{5.13}$$

So, in short, the threshold ($\alpha$) value of the solution is calculated as:

$$\alpha = \mu + 3\sigma \tag{5.14}$$

## 5.5 Results

In this section the results for the damage detection method will be shown, applied to the different case studies. For each case study the different ways of calculating the Damage Indicators are used, and a comparison between each of them is done. Finally a conclusion is written and the best of the ways to calculate the DIs will be chosen to continue using it in the next sections.

### 5.5.1 Simple mass and spring system

This model, as explained in section 4.1, is a structure simulated in MATLAB. The damages introduced in the model are simulated as changes in the spring constant ($K_3$). The damage detection method results are shown in Figure 5.3, for the different Damage Indicators.

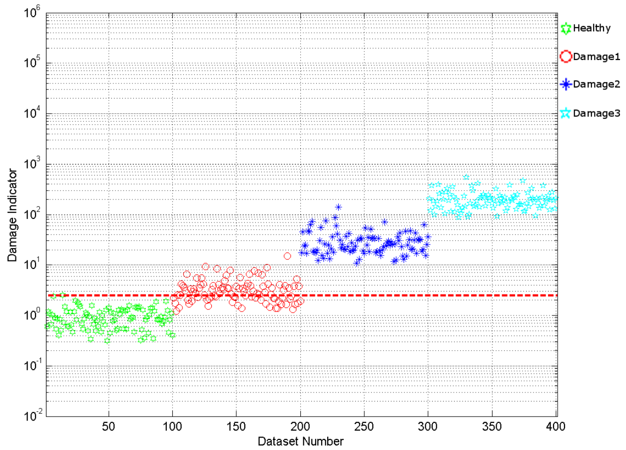
The dimensions used for the creation of the Hankel matrix in this case are $p = q = 5$ (see Equation 3.14). It is said in [142], there appears to be no steadfast rule for choosing these dimensions and as a result it is necessary to perform a convergence study on the data to gain any sort of confidence in the results. In this case, the convergence resulted in the value specified before.

All of three DIs are able to detect damage correctly for the biggest damages. For the Damage 1, the smallest one, some datasets are not well detected, and in some cases some healthy datasets are classified as damaged datasets. On one hand, the fact of being able of correctly detect damage tells which is the best DI. A resume can be found in Table 5.1, where it can be seen that CME Damage Indicator is the one giving no false positives and the one that few false negatives is able to give. On the opposite site, the MR Damage Indicator is the worst, giving some false positives, and high false negatives.

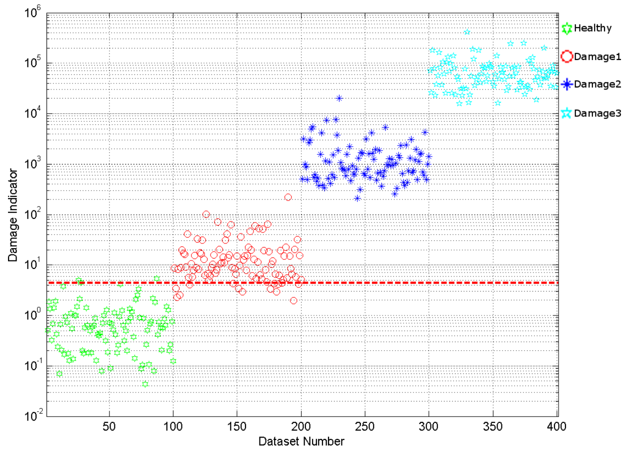
**Table 5.1.** *DI comparison results for Model*

| Damage | False Positives (%) | False Negatives for the smallest damage (%) |
|---|---|---|
| Mean Residual | 2 | 36 |
| Scalar Covariance | 2 | 14 |
| Covariance Matrix Estimate | 1 | 14 |

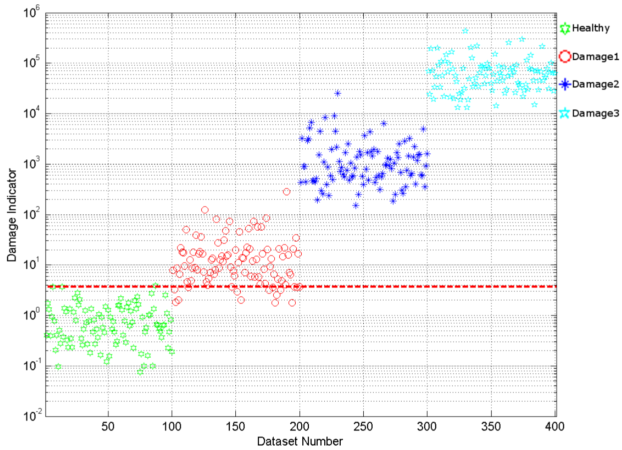
On the other hand, there is the sensitivity factor of the Damage Indicator. For that purpose, all the DIs were normalized to fit between 0 and 1. This normalization allows to see the sensitivity of the solution. If the jump between different damages is bigger, this will mean that the solution is more sensitive.




**(a)** *Mean Residual Damage Indicator*




**(b)** *Scalar Covariance Damage Indicator*




**(c)** *Covariance Matrix Estimate Damage Indicator*

**Figure 5.3.** *Simple Mass and spring System Results*

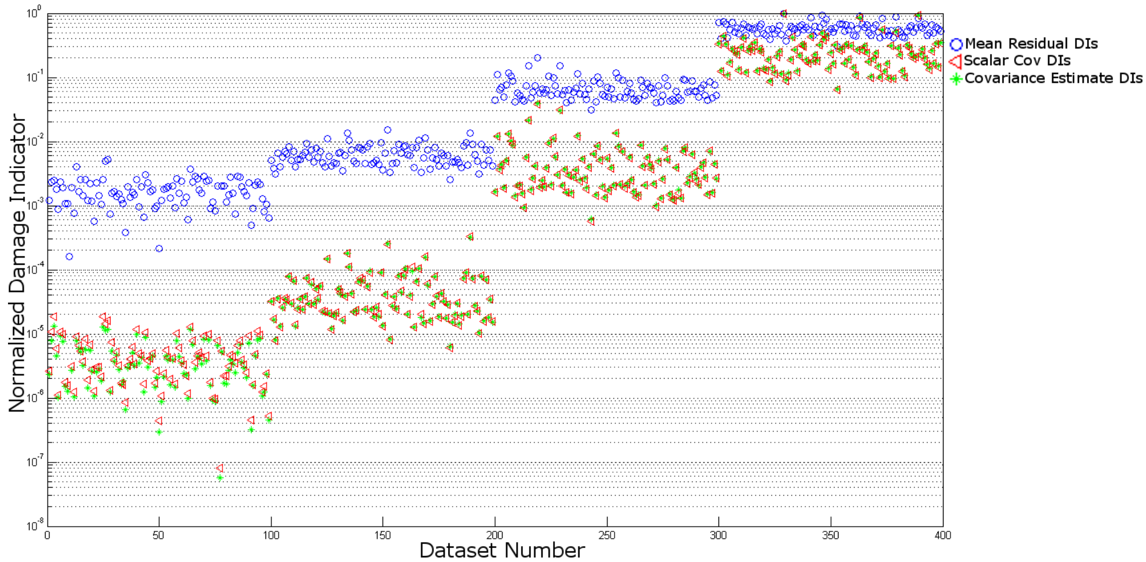



**Figure 5.4.** *Model - Normalized Damage Indicators Comparison*

The MR Damage Indicator is by far the less sensitive one, because the values for Healthy and Damaged are already quite high comparing to the other two. The CME and SC give similar results, although the CME is a little more sensitive. These Sensitivity factor along with the False Positive and False negative rates and the DI values (positive and big), make the CME DI the best solution.

### 5.5.2 Tower Finite Element model

The numerical model identified in section 4.2, is a FEM model. The simulations are done using ANSYS transient analysis, where the input is modeled as a random white noise on top of the structure, and the response from the sensors are extracted. The simulated damages are cracks of different lengths, in one of the members of the tower. The dimensions used for the creation of the Hankel matrix are $p = q = 5$.

The damages are well detected by all of the DIs, but some strange things appear in Figure 5.6 (it is on the back of this chapter). It seems that the 3 mm crack is classified as lower damage level than the 1mm crack for example. This problem is further studied in chapter 6. Apart from that problem, some false positives appear in the results, in two of the cases, the CME case and the SC case, while in the MR case, as it is not as sensitive as the other Damage Indicators, there is no such problem. The results are resumed in Table 5.2.

**Table 5.2.** *DI comparison result for FEM*

| Damage | False Positives (%) | False Negatives (%) |
|---|---|---|
| Mean Residual | 0 | 0 |
| Scalar Covariance | 0 | 0 |
| Covariance Matrix Estimate | 0 | 0 |

The comparison of all three in terms of sensitivity are shown in Figure 5.5. Again, the most sensitive is the CME Damage Indicator, while the SC is quite close to it. The MR Damage Indicator is the less sensitive. In this case, as some false positives appear in the most sensitive DIs, the MR DI is the best in classifying the state of the structure.

### 5.5.3 UPWIND Bladed model

The model analyzed in this subsection is the one presented in section 4.3. The damages introduced are stiffness changes in the joint painted in blue in Figure 4.8. The damage detection method results are shown in Figure 5.7, for the different Damage Indicators. The dimensions used for the creation of the Hankel matrix are $p = q = 60$. This structure is bigger and is a working wind turbine; this means that more precision is needed, that is why bigger $p$ and $q$ are needed.

Again, all of three are able to detect damage correctly for the biggest damages. For the tiny damages it can be seen that not all of them are detected. The sensitivity factor is very important in this case, because these changes are done in a working simulated wind turbine. The changes are proportional to the sensitivity that the algorithm is able to give in a real system. It can be seen that the CME Damage Indicator solution is

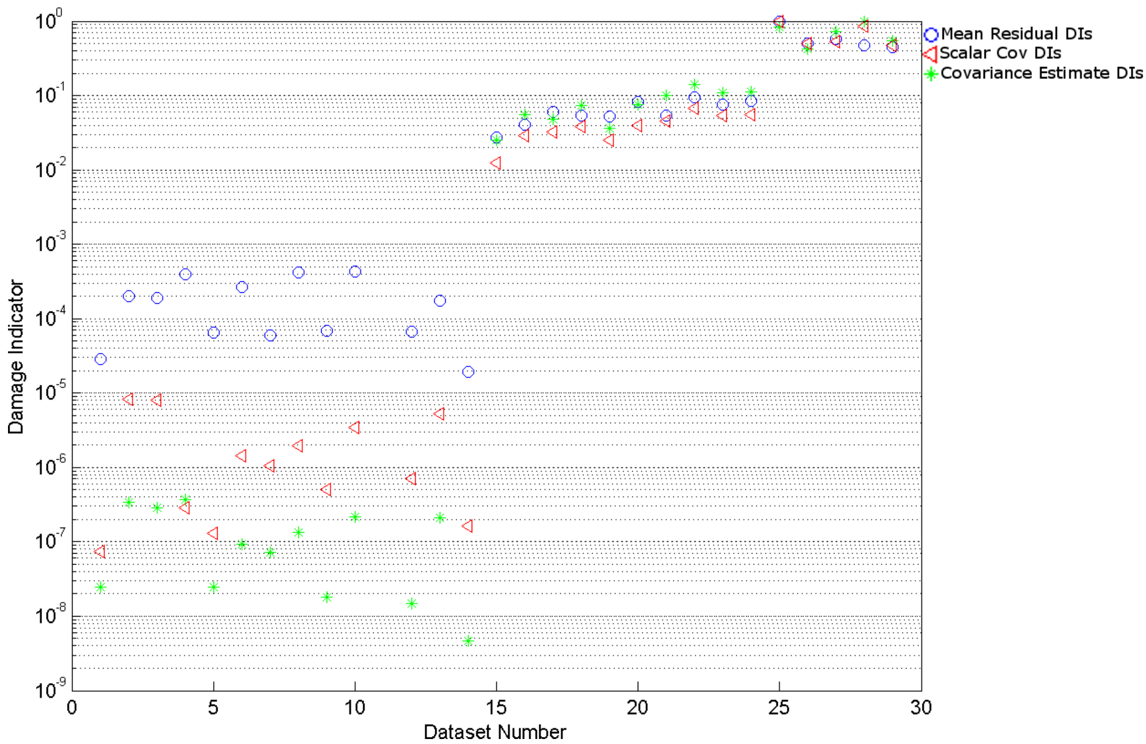



**Figure 5.5.** *FEM - Normalized Damage Indicators Comparison*

the most sensitive, because it is able to detect the 0.5% of reduction in the stiffness of the joint. If the false positives are taken into account, the MR Damage Indicator is the winner this time. The resume can be found in Table 5.3.

**Table 5.3.** *DI comparison result for UPWIND*

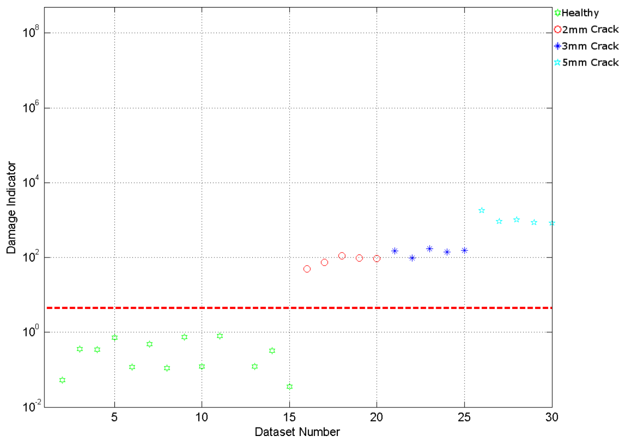
| Damage | False Positives (%) | False Negatives (%) |
|---|---|---|
| Mean Residual | 8.3 | 75 |
| Scalar Covariance | 8.3 | 91.6 |
| Covariance Matrix Estimate | 8.3 | 8.3 |

In Figure 5.9, the different sensitivities are again compared using the Normalized Damage Indicator value. The results show that MR is the less sensitive, while the other two are very close to each other, but the CME is still a little bit better.

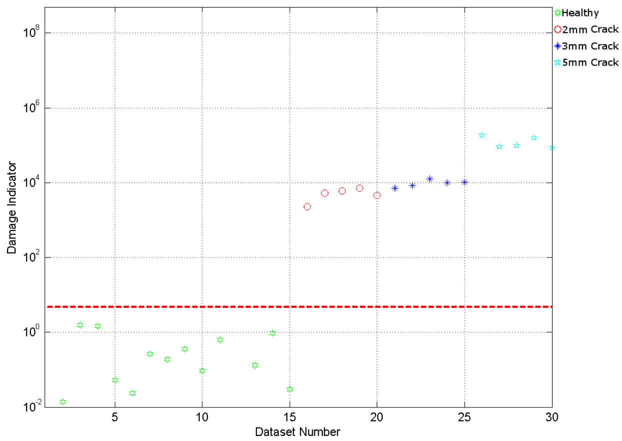
Again on the whole, CME Damage Indicator is the best in this case.

### 5.5.4 Laboratory tower model

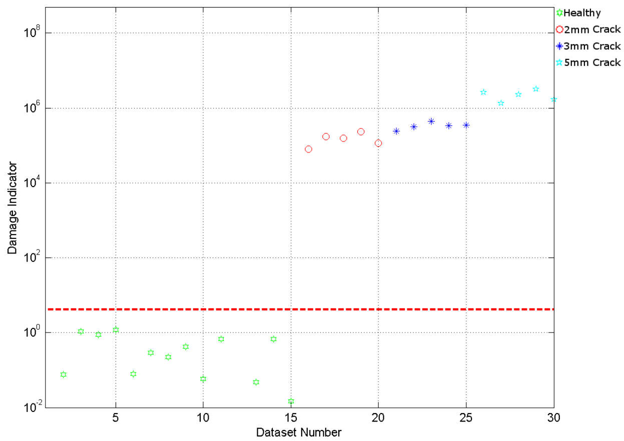
The real structure analyzed is the one presented in section 4.4. The damages introduced are real 5mm cracks in a jacket section that was placed in the jacket at different locations. The broken section can be seen in Fig.4.13b. The dimensions used for the creation of the Hankel matrix are $p = q = 60$.




**(a)** *Mean Residual Damage Indicator*




**(b)** *Scalar Covariance Damage Indicator*




**(c)** *Covariance Matrix Estimate Damage Indicator*

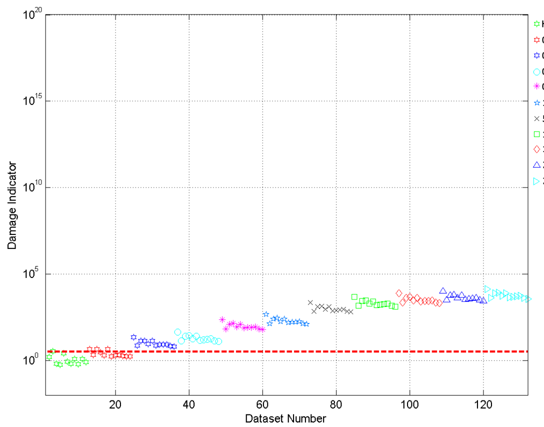
**Figure 5.6.** *FEM tower model Results*

There are different yellow bars in the substructure. The original bars are yellow bars, while the damaged ones are steel colored bars. In the learning phase a non original healthy bar was used as well as original yellow bars. This means that two undamaged versions of a healthy bar were used in the learning phase, one of them the original and a replica, so that the bar change wasn't detected in the process of damage detection, that way we were focused on the damage, and not to the bar change.

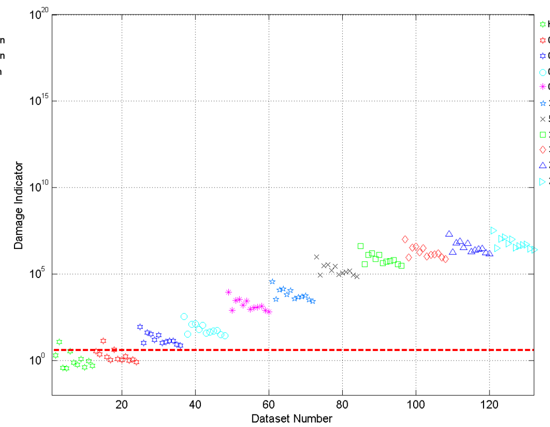
**Table 5.4.** *DI comparison result for Tower*

| Damage | False Positives (%) | False Negatives (%) |
|---|---|---|
| Mean Residual | 0 | 17.14 |
| Scalar Covariance | 0 | 62.85 |
| Covariance Matrix Estimate | 0 | 0 |

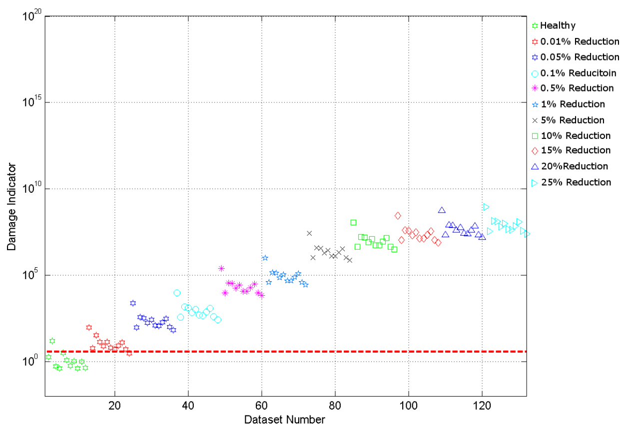
This time, the damages are really small as shown in the previous chapter. In total 7 different damages were placed in the structure. The severity of the damage was always the same, 5 mm crack, the only difference is the location. Each damage was named "Dx.y" where "D" means "damage" the "x" is the height of the




**(a)** *Mean Residual Damage Indicator*




**(b)** *Scalar Covariance Damage Indicator*



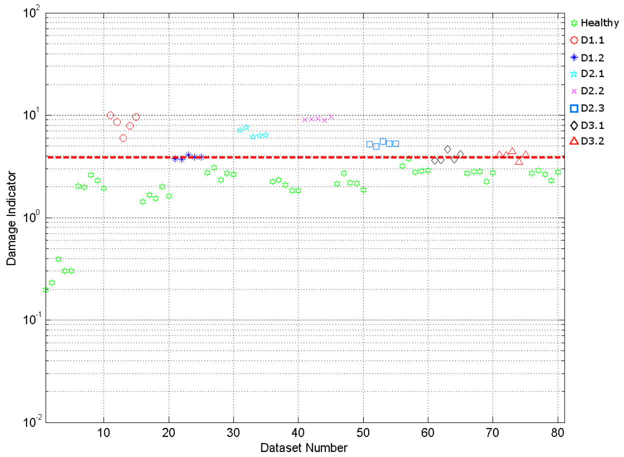

**(c)** *Covariance Matrix Estimate Damage Indicator*

**Figure 5.7.** *UPWIND Results*

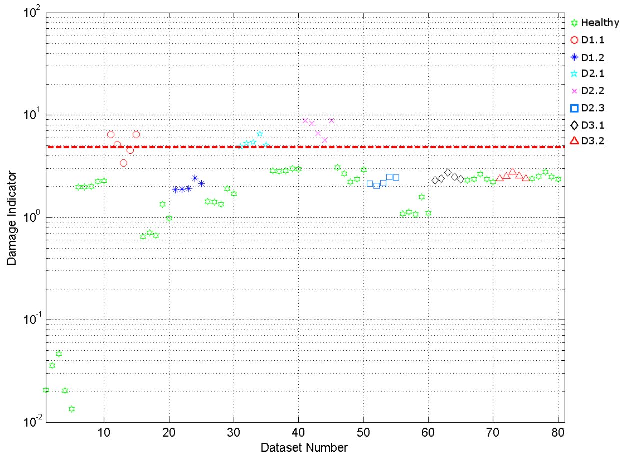
damage and the "y" the position in that height. In this case 3 different heights where used, and 2 or 3 different positions, depending the height.

The results in Figure 5.8 show that in this case, the CME method is the only one correctly detecting the damage. All Green values mean that the structure is in healthy condition, and the other colors mean that the structure is damaged in different parts of the substructure. The severity of the damage is always the same, 5mm crack. The experiment is performed the next way: first data is acquired while the structure is in healthy mode with the yellow member. The yellow member is removed and the healthy replica is located in its place, and data is again acquired. After that, the healthy replica member is removed in order to change it with a damaged member, and the data acquisition is performed. Later, the damaged member is removed so as to replace it with the yellow member, and again, data is acquired. This way the repeatability of the structure is measured. After this sequence is done, we move to another member.

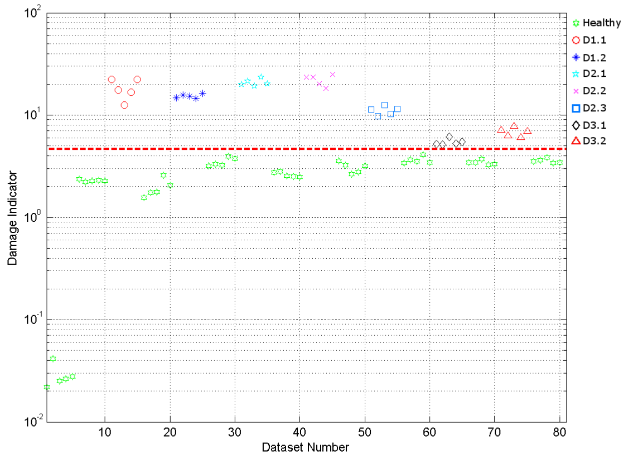
A resuming table can be found in Table 5.4. It must be said that the damage introduced to the structure is very small. In this structure it can be seen that the CME Damage Indicator is the most suitable for the experiment. In this case there is no need of a comparison between the different DIs, because the only one with good results is the CME damage indicator. In the MR case the sensitivity is not enough to classify different damages, while the SC method is not able to correctly differentiate the damages. Finally the CME discriminates properly the damages.




**(a)** *Mean Residual Damage Indicator*




**(b)** *Scalar Covariance Damage Indicator*




**(c)** *Covariance Matrix Estimate Damage Indicator*

**Figure 5.8.** *Tower Results*

## 5.6 Discussion

In this chapter the development, implementation and explanation of a damage detection method has been explained, which is applicable to different types of structures. This method will be used in the next chapters of this thesis. The method has been combined with different Damage Indicators. These DIs are able to detect very small damages in different types of structures.

The performance of the methodologies presented for damage detection using NullSpace as pattern recognition tool has been also tested in this chapter. A baseline model has been built, in which different Damage Indicators were used in order to find the most sensitive one. These Damage Indicators were applied in different case studies, 1 generic model, 2 Turbine mockup models (simulated and Real) and a simulated working wind turbine. The results revealed that the approaches have potential for real applications and can be used to evaluate the state of a structure.

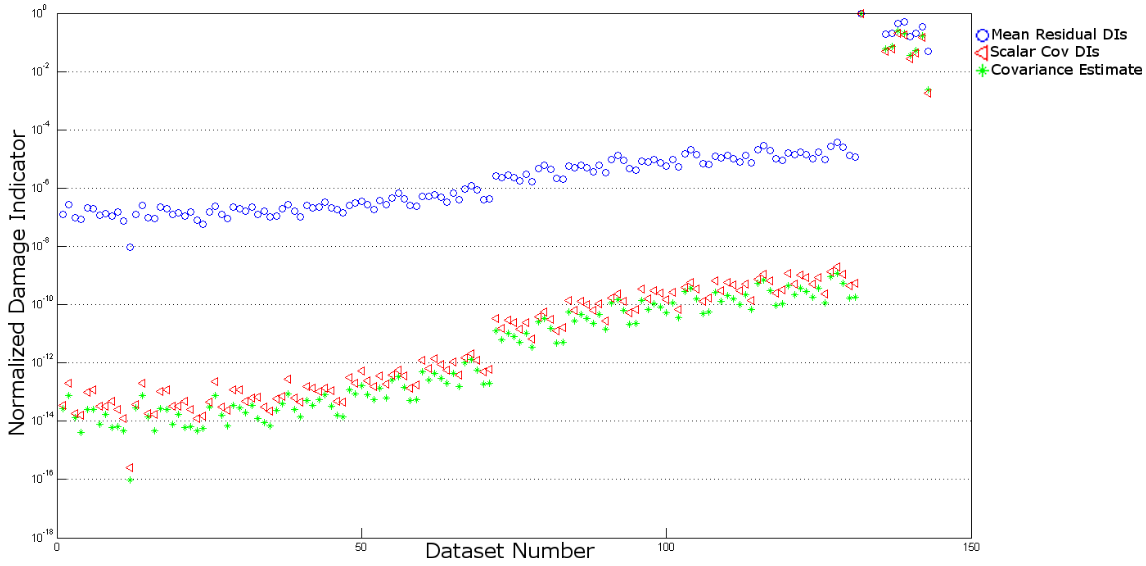



**Figure 5.9.** *UPWIND - Normalized Damage Indicators Comparison*

Some important elements can be highlighted from the results in this chapter:

- The results showed that there are differences between the data from the undamaged structure and the different damages, and these differences can be used to define the presence of damages in the structures. Similarly, the presented plots allowed in most cases to separate and distinguish damages between them.
- The results from different Damage Indicators show that three of them are able to indicate how damaged the structure really is. In most cases the CME Damage Indicator is the most sensitive while the MR is the less sensitive.

In general it is possible to conclude that, in all the cases, the evaluation of all the phases allow to define the presence of a damage in the structure. The CME Damage Indicator is the most sensitive, and in from this moment on, this Damage Indicator will be used in order to continue the work.

In the next chapter, the data preselection will be explained.

# Chapter 6

# Data Preprocessing for damage detection

## 6.1 Introduction

Data Preprocessing (DP) is a step needed in order to prepare the data to be inserted in the damage detection phase. Apart from that function, the raw data can be transformed or selected, to obtain the most suitable information, or simply, the data can be normalized in order to eliminate the effects of certain gross influences. In this chapter, the transformation of the data is tackled, and how this can help to obtain better damage detection results.

In [67], Halfpenny talks about the importance of preprocessing the signals gathered by SHM sensors and controllers, and which kind of errors can appear if a poor preprocessing is done. On the other hand, according to [160], the preprocessing is divided into 3 parts: cleansing, normalization and data selection.

The importance of Data Preprocessing is also discussed in [47], where it is said that in a distributed sensor network, it is important to preprocess the data in the sensor itself in order to have free bandwidth and not congesting the network.

This chapter is concerned to the transformation of the original data an its influence over the final results in damage detection.

## 6.2 Data normalization

Data Normalization is an important step for data preprocessing. In applications where data are collected and arranged the normalization is used. For instance, in [120] Mujica arranged data from a 3D way (DataSets x Samples x Sensors) into a 2D unfolded matrix for later apply different scaling methods to the matrix in order to normalize the data. For this kind of data sets (unfolded matrix), several studies of scaling have been presented in the literature: continuous scaling (CS), group scaling (GS) and auto-scaling (AS). According to these studies, GS is selected for this work because it considers changes between sensors and does not process them independently.

In Figure 6.1, the schematic view of the Group Scaling is shown. In this schema, $k$ are the number of sensors while $n$ are the sample numbers. There are $k$ number of mean values, $\mu_k$, one per sensor, and one Standard Deviation (STD) value, $\sigma$. The STD value is calculated using all data samples by Equation 6.2 using the $\mu_G$ shown in Equation 6.1, while the mean values are calculated per sensor using Equation 6.3. Finally, for each sensor data, the Equation 6.4 is applied for the normalization.

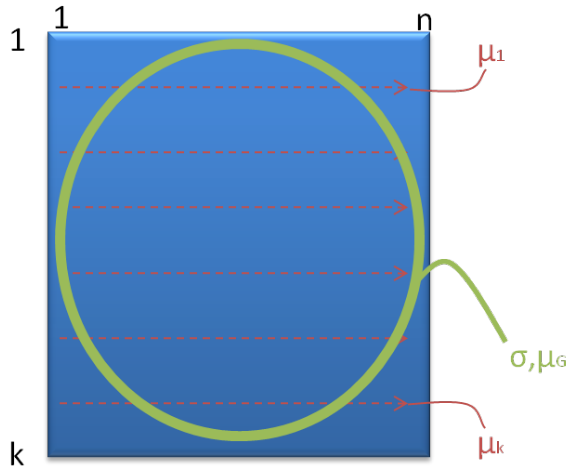



**Figure 6.1.** *GS Normalization schema*

$$\mu_G = \frac{\sum_{n=1}^{N}\sum_{k=1}^{K} x_{kn}}{NK} \tag{6.1}$$

$$\sigma = \sqrt{\frac{\sum_{n=1}^{N}\sum_{k=1}^{K} (x_{kn} - \mu_G)}{NK}} \tag{6.2}$$

$$\mu_k = \frac{\sum_{n=1}^{N} x_{kn}}{N} \tag{6.3}$$

$$\bar{x}_{kn} = \frac{x_{kn} - \mu_k}{\sigma} \tag{6.4}$$

## 6.3 Feature extraction

As was previously explained, this method is based on PCA. The schematic view of the complete methodology for damage detection is depicted in Figure 6.2. The damage detection algorithm (NullSpace) is used as a tool to compare different preprocessing methods. The Damage Indicator used for this tests is the Covariance Matrix Estimate.

In order to extract the features, a dataset that belongs to the healthy structure is used to calculate the PCA model (the matrix $\widetilde{P}$ sorted and reduced in Equation 3.35) . Afterwards, the dataset gathered from the current structure (learning and detection datasets) are projected into the choose PCs, $T$ in Equation 3.36. The projected data are used as the input to the NullSpace damage detection method. So it can be said that the data entering to the damage detection phase is data from "virtual" sensors, because the data has changed, and it doesn't belong to the readings of the sensors any more, but it does to the structure. Using the data from these virtual sensors, the NullSpace algorithm is able to detect changes in the structure.

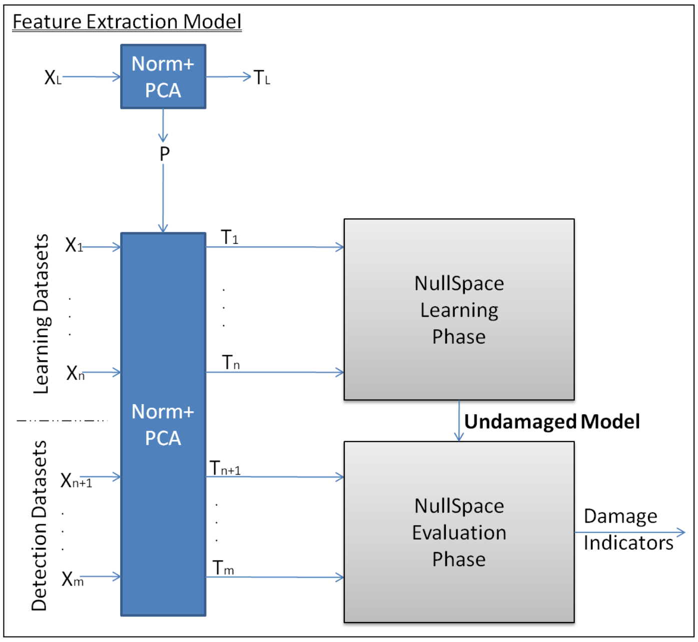



**Figure 6.2.** *Feature Extraction*

## 6.4 Feature selection

The Feature Selection algorithm uses UmRMR (see subsubsection 3.5.2.2). In Figure 6.3 the schematic view of the preprocessing is shown. UmRMR method is able to select the features, accelerations in our case, that in terms of information theory, are most relevant but least redundant. As explained in subsection 3.4.2 and in subsection 3.4.3, using tools as Entropy and Mutual Information, the amount of information in one sensor can be measured, therefore the most relevant and least redundant information can be selected.

In the first step, all the healthy datasets are used in order to find which sensors contain the best information. The result of applying the UmRMR gives the order of the sensors, from the most informative to the least informative. In this way, the number of sensors to select depends on the score of each sensor. The criterion to select the amount of sensors is given by the PCA. In this case, the number of PCs corresponding to the 99% of the variance is the number of sensors that are going to be selected. Finally, the dataset ($Y_i$) that is used for damage detection method is the original dataset ($X_i$) eliminating the information from the sensors that were not selected. In this way, the preprocessing does not make any changes to the incoming data. It just selects the best suited sensors for that structure. The information is not transformed into something else.

## 6.5 Mixed preprocessing

This preprocessing method uses first the UmRMR feature selection method and, subsequently the PCA feature extraction. Figure 6.4 shows the schematic view of the method.

In first step, the most informative sensors are found applying all the healthy datasets to the UmRMR method as detailed in section 6.4. Afterwards, the healthy dataset ($X_L$) with the assigned sensors is used to calculate

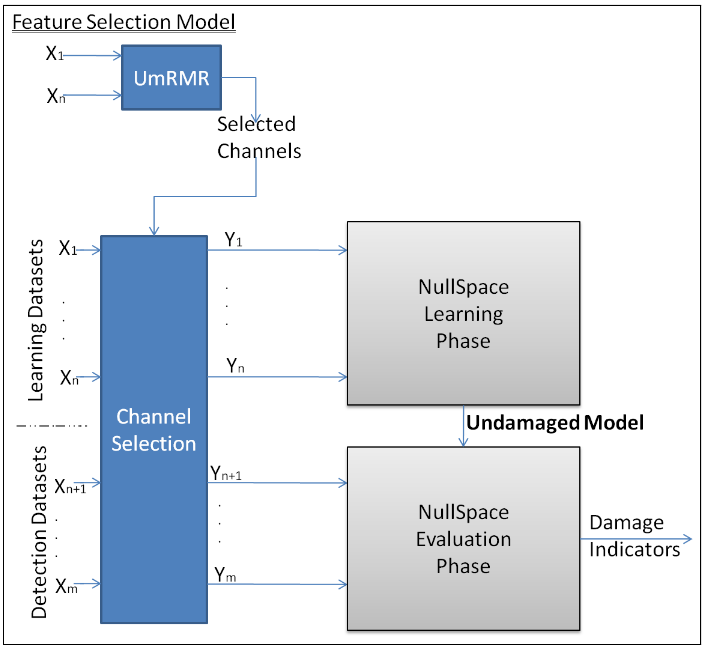



**Figure 6.3.** *Feature Selection*

the PCA model. In this way, the channels (or sensors) are selected and the features are extracted.

Finally, the dataset ($T_i$) used for the damage detection method is obtained after selecting the appropriate sensors (given by UmRMR outputs ($Y_i$)) and projecting them into the PCA model.

It should be highlighted that using a preprocessing that extracts features using PCA firstly and later selects features using UmRMR has no sense, since PCA extracts and selects the most relevant components.

Once again, the NullSpace method is used for a comparison between different preprocessing methods. The preprocessing needs two steps as well, the first to find the data to select and extract and the second one to apply the result of the first step to the incoming datasets.

In the first step, the first part is the same as the one in, the most informative sensors are found using UmRMR. After that, a healthy dataset is loaded into the system, and after the channel selection is done, the PCA is used so as to find the PCs and the transformation matrix. That way, we obtain some channels to select, and then, the PCA information for the later transformation.

In the second step, using the information gathered in the first step, first the channel selection is done (using the info of the UmRMR output). Once the channel selection is done, using the information about the PCA gathered in the previous step, the data is transformed into virtual sensors. Finally, the transformed data is inserted into the damage detection method.

This DP method, is a mixture of the previous two. First, data is selected, and then, the selected data is transformed. Again, using PCA we are able to make a even further dimensionality reduction. In the section 6.6 this part is discussed.

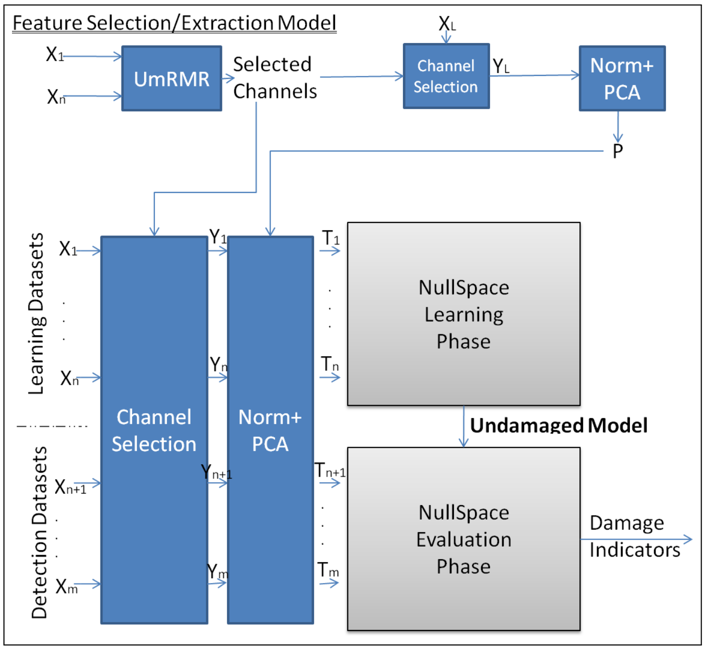



**Figure 6.4.** *Feature Selection-Extraction*

## 6.6 Preprocessing results

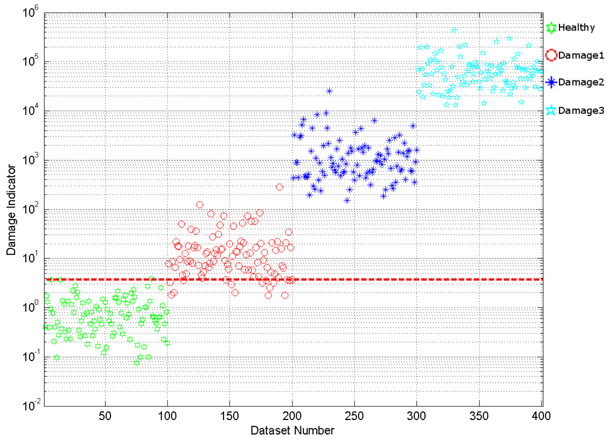
All the preprocessing methods proposed in the previous sections are analyzed, compared and discussed. To aim this goal, the damage detection method based on NullSpace (detailed in chapter 5) using the CME damage indicator is applied to all the structures described in chapter 4.

### 6.6.1 Simple mass and spring system

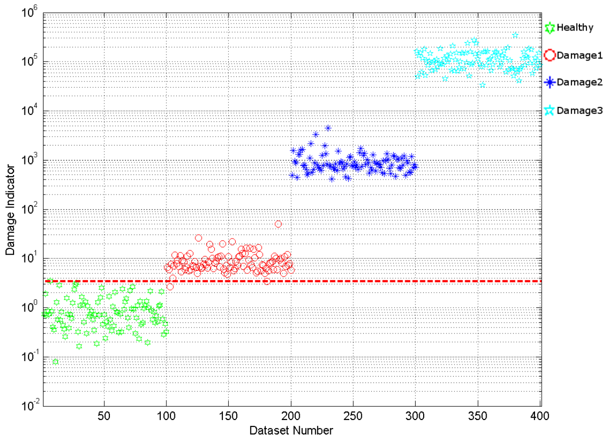
The damages introduced in this numerical model equipped with 15 biaxial accelerometers (30 channels), are damages simulated as changes in the spring constant ($K_3$) . The damage detection is based on NullSpace. Its results for each preprocessing method are shown in Figure 6.5. In all plots x-axis represents the number of experiments (or datasets) and, y-axis the CME damage indicator by each experiment. Each shape denotes the state of the structure and besides, the threshold (red dashed line) is depicted.

In Fig. 6.5a are shown the results without using any type of preprocessing. Subsequently, Fig. 6.5b-Fig. 6.5e show results using different preprocessing methods, as follows: Feature extraction retaining the 100% of the variance in the PCA model (no dimensionality reduction); Feature extraction retaining 99% of the variance in the PCA model (10PCs); Feature selection of 10 most relevant and less redundant information using UmRMR, in order to compare the results with the previous method, 10 sensors were selected; and finally, selecting 10 sensors as the previous case and extracting 100% of the variance of these selected sensors into the PCA model (no dimensionality reduction after the selection, therefore 10Pcs)

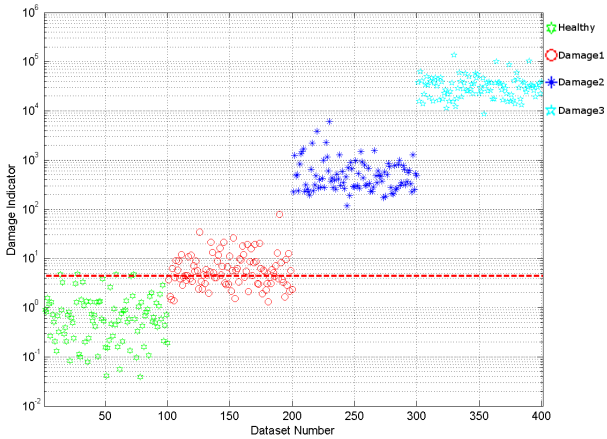
It must be said that the results of the damage detection method without any preprocessing, are already quite good for this case, but applying the PCA without any dimensionality reduction the results obtained are better. If Dimensionality reduction is applied and 99% of the variance is taken, the results get worse,



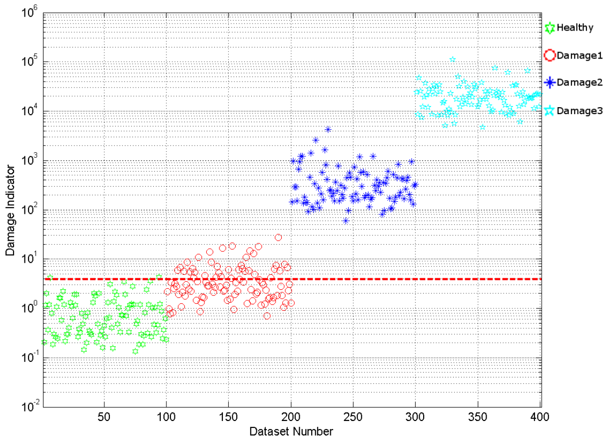

**(a)** *Without Preprocessing*



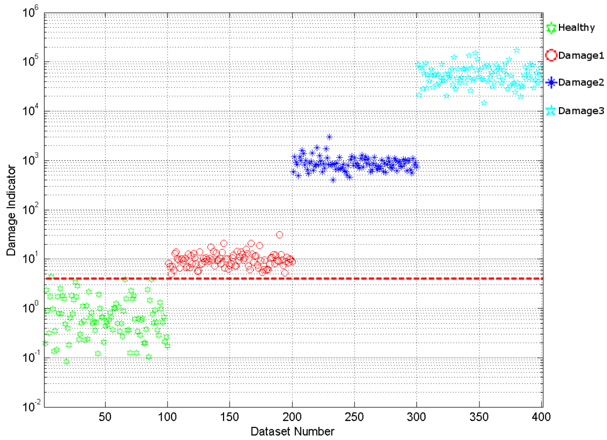

**(b)** *Extracting features with 100% variance*




**(c)** *Extracting features with 99% of the variance*




**(d)** *Selecting 10 sensors*




**(e)** *Selecting 10 sensors and extracting with 100% of the variance*

**Figure 6.5.** *Damage detection on the simple mass and spring model; Comparison between preprocessing methods*

as it is logical, because some information is lost. The same happens when from the 15 biaxial available sensors (30 total sensors) the 10 most important uniaxials are taken, the results get worse. However, when the 10 most relevant sensors are taken and PCA is applied to them, the results obtained with just 10 virtual sensors are better than the base results, and even when just PCA is applied and all components are chosen.

A comparative between them can be found in Table 6.1, there, the amount of false positives, the amount of false negatives and the time for processing each dataset are displayed.

Concerning to the computational cost for processing the Damage Indicator for each dataset, some of the presented preprocessing methods are able to reduce the time spent.

**Table 6.1.** *Damage detection on the simple mass and spring model; general comparison*

| Preprocessing | False Positives(%) | False Negatives(%) | Time Per Dataset |
|---|---|---|---|
| No Preprocess | 1 | 14 | 0.55 seg |
| PCA100 | 0 | 2 | 0.55 seg |
| PCA99 | 4 | 42 | 0.4 seg |
| UmRMR 10 | 2 | 63 | 0.4 seg |
| Mixed 10 | 1 | 0 | 0.4 seg |

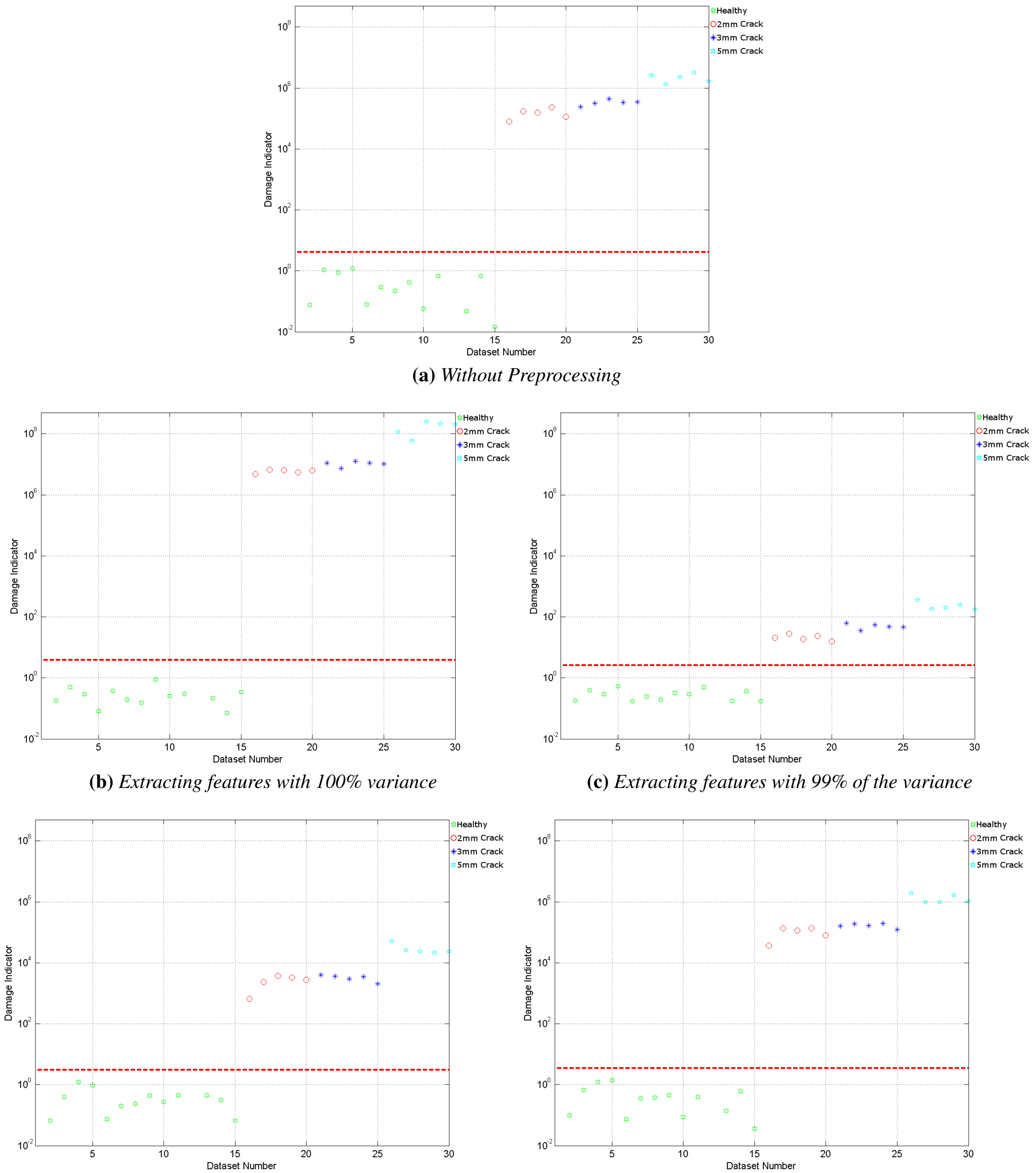
### 6.6.2 Tower Finite Element Model

This model is a structure simulated in ANSYS (see section 4.2). The damages introduced are different cracks in the substructure (2mm, 3mm and 5mm long). The results for each of the preprocessing methods are shown in Figure 6.6. As described in the section of this case study (section 4.2), eight triaxial sensors are configured, this means that 24 channels are used for damage detection based on NullSpace.

As the previous section, all plots represent the CME damage indicator by experiment denoting the state of the structure. In Fig. 6.6a the results without using any type of preprocessing are shown . Subsequently, Fig. 6.6b-Fig. 6.6e show results using different preprocessing methods, as follows: Feature extraction retaining the 100% of the variance in the PCA model (no dimensionality reduction); Feature extraction retaining 99% of the variance in the PCA model (12PCs); Feature selection of 12 most relevant and less redundant information using UmRMR, in order to compare the results with the previous method (the 99%PCA), 12 sensors were selected; and finally, selecting 12 sensors as the previous case and extracting 100% of the variance of these selected sensors into the PCA model (no dimensionality reduction after the selection, therefore 12Pcs). In order to be able to compare the different cases the scaling used in the different sub-figures is the same.

Once again, the damage detection method itself is able to give a good result with 8 triaxial sensors. The gap between damaged and healthy datasets is huge. Anyway with the preprocessing, the results can become better, or at least equal, with less amount of sensors. For the Feature Extraction case sensitivity is gained if no dimensionality reduction is used, and the sensitivity is lost with the 99% of the variance, but the damage is well detected in both cases.

In the Feature Selection case, it is shown how the use of 12 selected sensors (the half of the original ones) still is able to detect damage. This solution gives better results than the one using PCA with the 99% of the variability retained. The last figure shows how the results change when the mixed preprocessing is




**(a)** *Without Preprocessing*

**(b)** *Extracting features with 100% variance*

**(c)** *Extracting features with 99% of the variance*

**(d)** *Selecting 12 sensors*

**(e)** *Selecting 12 sensors and extracting with 100% of the variance*

**Figure 6.6.** *Damage detection on the tower FEM model; Comparison between preprocessing methods*

used. Using the half of the sensors used in the base measurements, and preprocessing the data, in terms of sensitivity, almost the same result is obtained.

Concerning to the computational cost for processing the Damage Indicator for each dataset, some of the presented preprocessing methods are able to reduce the spent time. In this case, it is reduced to the half, but only when dimensionality reduction is made.

**Table 6.2.** *Damage detection on the FEM tower model; general comparison*

| Preprocessing | False Positives(%) | False Negatives(%) | Time Per Dataset |
|---|---|---|---|
| No Preprocess | 0 | 0 | 1.4 seg |
| PCA100 | 0 | 0 | 1.4 seg |
| PCA99 | 0 | 0 | 0.7 seg |
| UmRMR 12 | 0 | 0 | 0.7 seg |
| Mixed 12 | 0 | 0 | 0.7 seg |

### 6.6.3 UPWIND Bladed Model

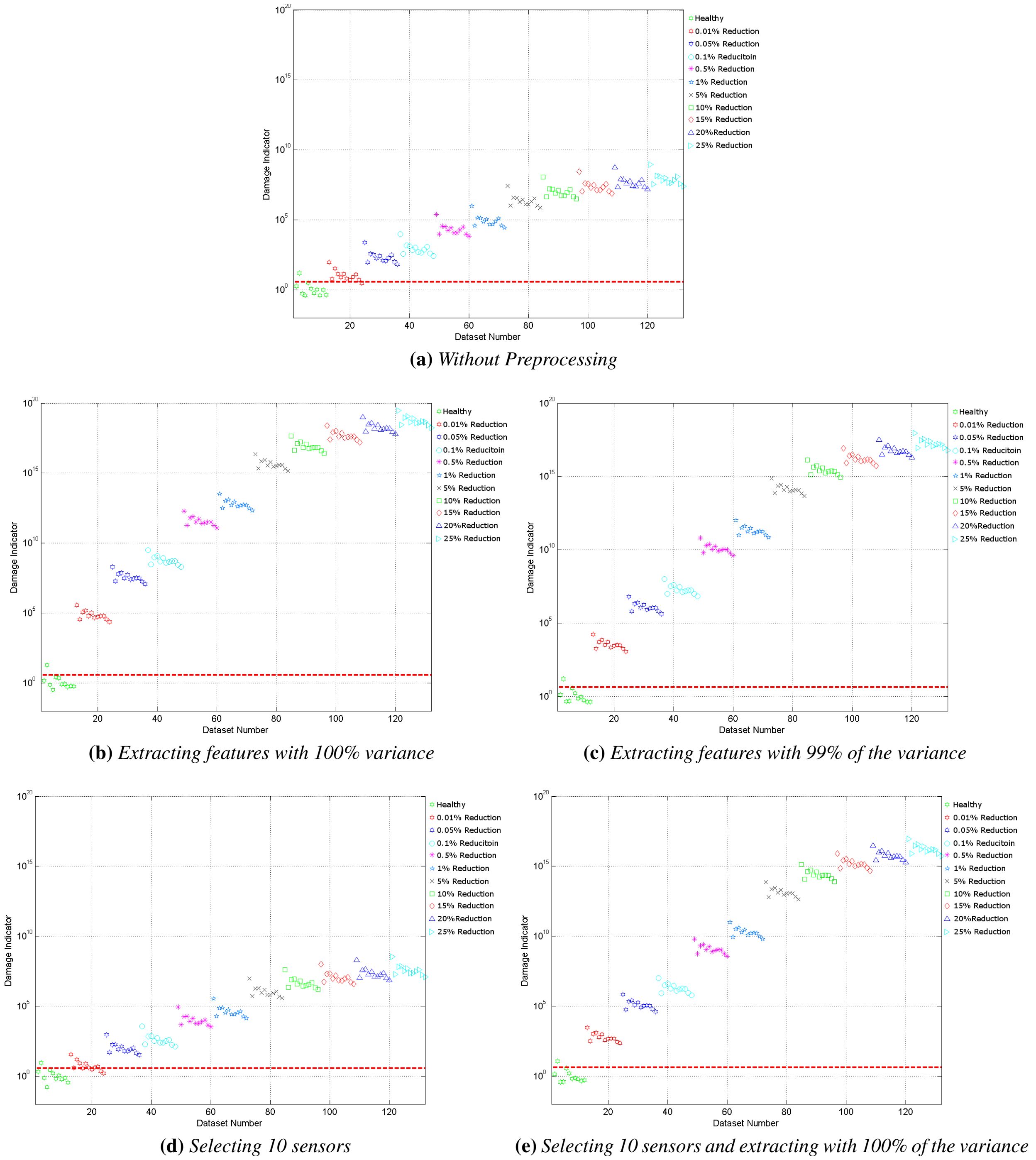
The BLADED simulated model (see section 4.3) datasets are also put into comparison. The damages introduced to the structure are reductions of wall thicknesses of the member shown in Figure 4.8. The reductions are 0.01%, 0.05%, 0.1%0.5%, 1 %, 5%, 10%, 15%, 20%, 25% on the wall thickness of that specific member. Seven Triaxial accelerometer (21 sensors) measurements are used for damage detection based on NullSpace.

As the previous section, all plots represent the CME damage indicator by experiment denoting the state of the structure. In Fig. 6.7a are shown the results without using any type of preprocessing. Subsequently, Fig. 6.7b-Fig. 6.7e show results using different preprocessing methods, as follows: Feature extraction retaining the 100% of the variance in the PCA model (no dimensionality reduction); Feature extraction retaining 99% of the variance in the PCA model (10PCs); Feature selection of 10 most relevant and less redundant information using UmRMR, in order to compare the results with the previous method (the 99%PCA), 10 sensors were selected; and finally, selecting 10 sensors as the previous case and extracting 100% of the variance of these selected sensors into the PCA model (no dimensionality reduction after the selection, therefore 10Pcs). In order to be able to compare the different cases the scaling used in the different sub-figures is the same.

The result of the first image (Fig. 6.7a) is the result using CME Damage Indicator with no preprocessing. The other figures are the results after using different types of DP. Organized as in the previous sections, the second image (Fig. 6.7b) corresponds to the Feature Extraction method with no dimensionality reduction. The results get better thanks to the preprocessing without any dimensionality reduction, but if 99% of the variability is taken into account (10 Principal Components) the damage detection looses sensitivity.

If the 10 most informative sensors are selected (Fig. 6.7d) the results show a similar performance that it had in the RAW results with 21 sensors. If the mixed solution is used, we achieve the Fig. 6.7e.

Using just the half of the sensors in mixed preprocessing, much better results are achieved, and similar results as extracting features with both 100% and 99% variance retained in the PCA model. The results of the damage detection method with no preprocessing are good, but in this structure it has been shown that the correct preprocessing can change the results, and better ones can be achieved. In Table 6.3 a comparative is made. It shows that most of the results are good. As a dimensionality reduction is made, the computational time is smaller in the some results. Again, at least the same results can be achieved with less sensors and less processing times.




**(a)** *Without Preprocessing*

**(b)** *Extracting features with 100% variance*

**(c)** *Extracting features with 99% of the variance*

**(d)** *Selecting 10 sensors*

**(e)** *Selecting 10 sensors and extracting with 100% of the variance*

**Figure 6.7.** *Damage detection on the UPWIND turbine; Comparison between preprocessing methods*

### 6.6.4 Laboratory Tower Model

The data taken from the laboratory tower model shown in section 4.4 was also used to test the different preprocessing methods. The damages seeded to structure were 5mm cracks in some of the members of the jacket. These members are situated at different heights of the jacket. In total seven different damages where placed in the structure. Each damage was named as follows: “Dx.y” where “D” means “damage” the “x” is

**Table 6.3.** *Damage detection on the Upwind model; general comparison*

| Preprocessing | False Positives | False Negatives | Time Per Dataset |
|---|---|---|---|
| No Preprocess | 1 | 1 | 6.9 seg |
| PCA100 | 1 | 0 | 6.9 seg |
| PCA99 | 1 | 0 | 4.3 seg |
| UmRMR 10 | 1 | 4 | 4.3 seg |
| Mixed 10 | 1 | 0 | 4.3 seg |

the height of the damage and the “y” the position in that height. Three different heights where used, and 2 or 3 different positions, depending the height. 8 Triaxial accelerometers were used (total of 24 channels). In this case, all green values mean that the structure is in healthy condition, and the other colors mean that the structure is damaged in different parts of the substructure.

In order to test also the repetitiveness of the methodology, the experiments were performed as follows:

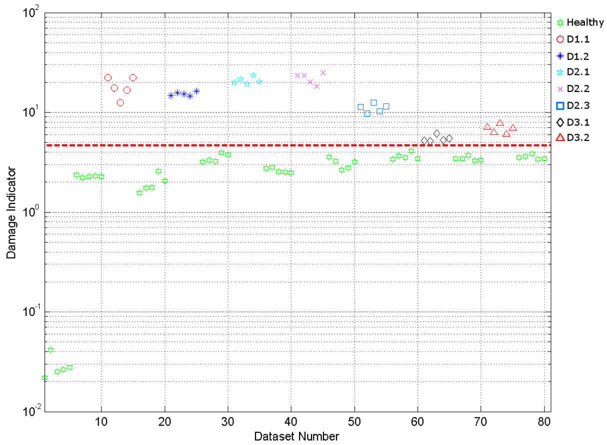
To build the healthy model, all elements or members of the jacket are undamaged, however, there is another member also undamaged (a replica) that was replaced for some original ones. The structure with these changes is still considered healthy. This is made to not detect the bar change when the damaged bar is placed in the structure. The fact that changing the bars with a replica gives the variability of the bar change to the healthy model. Therefore, many experiments (15 original +10 with replica) were performed to build the healthy model.

The testing datasets, five experiments are performed using the healthy structure. subsequently one healthy member is replaced by the replica member (still undamaged) and another five experiments were performed. After that, a healthy member (for instance, the member 1,1) is replaced for one damaged member, and five experiments were performed (D1.1 in Figure 6.8). Afterwards, this damaged member is replaced with the original healthy member, and data is acquired again. This procedure is repeated for several members.

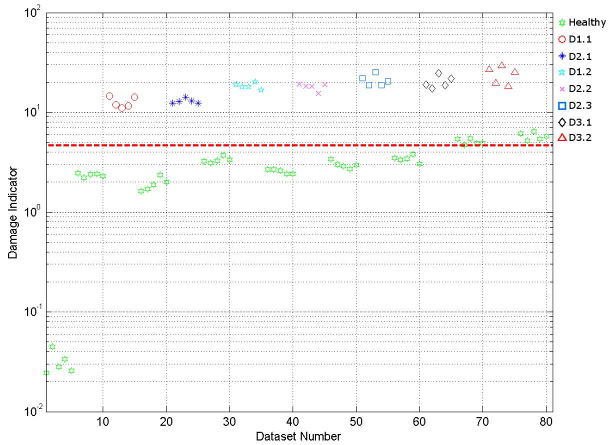
Following the same outline as used in the previous sections, the first image Fig. 6.8a shows the result of the damage detection with no preprocessing, and the others show the results after applying the preprocessing. This first image shows that the damage detection itself works correctly detecting damage. The Feature Extraction method with no dimensionality reduction shown in Fig. 6.8b shows good results, and the sensitivity of the solution gets better because the gap between the damaged and undamaged is bigger, although some of the healthy datasets, after some changes, were detected as damaged. The same happens in Fig. 6.8c, the results with 10PCs are good, but false positives appear.

If the 10 most informative sensors are used in Fig. 6.8d, where the results get better and no false positives are present. In fact with less than the half of the sensors, similar performance is shown. Finally, if the mixed solution is used Fig. 6.8e, it can be seen that the results get a little better.

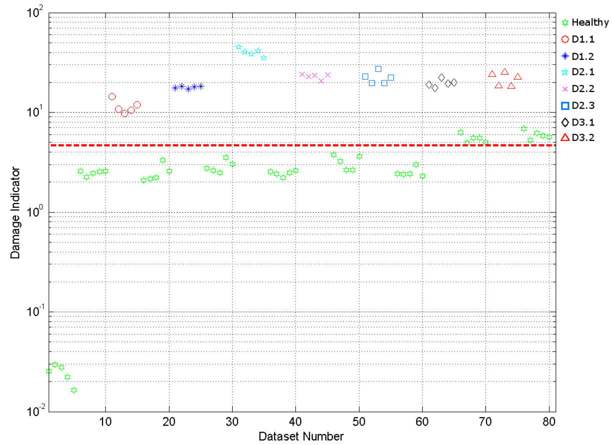
Once again, it is clear that not all of the sensors are needed for a good damage detection. If the most informative ones are picked out, the damage is well detected. Apart from that, if the features are extracted, the detection becomes easier. In the result with no preprocessing, the damaged datasets from the upper



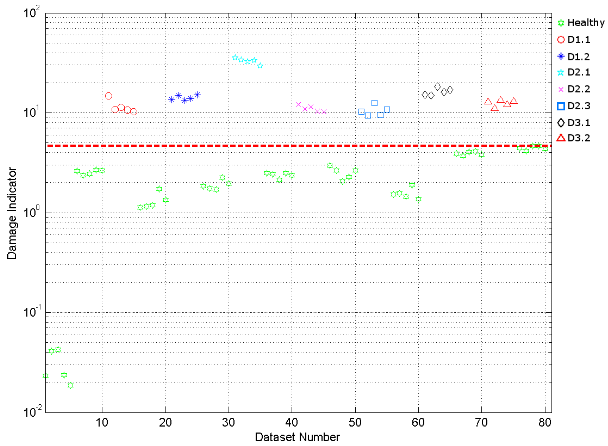

**(a)** *Without Preprocessing*



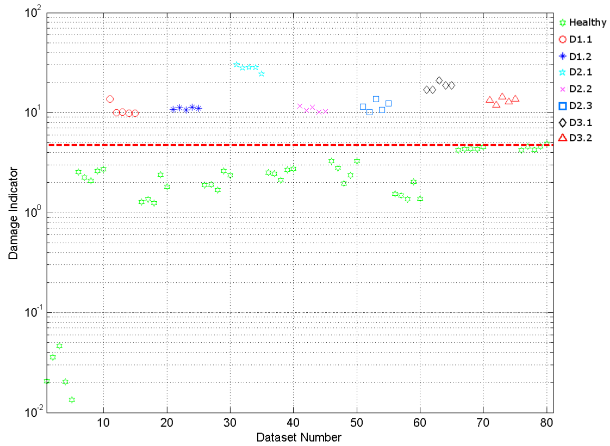

**(b)** *Extracting features with 100% variance*




**(c)** *Extracting features with 99% of the variance*




**(d)** *Selecting 10 sensors*




**(e)** *Selecting 10 sensors and extracting with 100% of the variance*

**Figure 6.8.** *Damage detection on the laboratory tower; Comparison between preprocessing methods*

height (D3.1 and D3.2) where classified as damaged but their value was almost the same as the threshold. On the contrary, if the preprocessing is used, the gap between the damaged and undamaged is bigger and it is easier to detect the damage.

Considering the computation time to process each dataset, if no preprocessing is used, the time needed is around 9 seconds per dataset, whereas if it is reduced to 10 features, this goes down to 6 seconds.

**Table 6.4.** *Damage detection on the Laboratory tower; general comparison*

| Preprocessing | False Positives | False Negatives | Time Per Dataset |
|---|---|---|---|
| No Preprocess | 0 | 0 | 9 sec |
| PCA100 | 10 | 0 | 9 sec |
| PCA99 | 10 | 0 | 6 sec |
| UmRMR 10 | 0 | 0 (+ gap) | 6 sec |
| Mixed 10 | 1 | 0 (+ gap) | 6 sec |

## 6.7 Discussion

In this chapter the preprocessing of the data was tackled. The preprocessing is applied to the data from the structure in order to have more efficient data to detect damage. Three preprocessing methods were developed for this work. A Feature Extraction method, based on the Principal Component Analysis. A Feature Selection method, based on the Unsupervised minimum Redundancy Maximum Relevance; and a combination of both: first selecting the features, and afterwards, extracting them. Using these preprocessing methods, another step in the methodology was developed.

It is shown that the correct preprocessing of the data can contribute to a better damage detection process, with less sensors. In fact, among the preprocessing methods proposed in this work, the mixed method (feature select + extract) is the best one.

The conclusion here, is that more sensors does not mean that we will get better damage detection results, in fact, the correct number of sensors with a good preprocessing method gives us better results than a huge amount of sensors. It can also be seen that the work done to select the amount of sensors in chapter 4, is good for modal identification, but it is not the best for damage detection.

This chapter shows that the preprocessing is very interesting for damage detection because it helps to improve the detection and at the same time, it helps to reduce the amount of sensors that must be placed in the structure. In this way, the cost associated with the material necessary for SHM (sensors, cable, ...), the work of placing them in the structure, and the amount of data acquisition inputs are considerably reduced.

# Chapter 7

# Environmental and Operational Changes (EOC) compensation for damage detection

## 7.1 Introduction

Environmental and Operational Conditions (EOC) play an important role when dealing with long term monitoring, because they complicate the damage detection procedure and sometimes it is impossible to detect damage if these are not taken into account. In fact, the variations in the input signals due to the EOC are bigger than the variations due to a damage. Therefore, its influence should be compensated. Depending on the chosen strategy, the EOC compensation methods can be classified in those using the measurements of the EOC itself or the ones that do not use these EOC data; (see [157] and [90]).

Several methods for damage detection under changing operational conditions can be found in the literature. For instance, Sohn proposed a compensation combining AR-ARX (AR models with exogenous inputs) models with Non Linear Principal Component Analysis (NLPCA) in [158]. ARX models are used by Peeters to compensate the temperature effects on bridge eigenfrequencies [138]. In this way, Kullaa applied missing data analysis or factor analysis in [94] to eliminate the environmental effects from damage sensitive features. Besides, Deraemaeker diminished the EOC-effects on damage indicators provided by modal filters by means of factor analysis [30]. A local PCA was proposed by Yan in [193]. some classification techniques were used in [116] by Moll for structural damage diagnosis under changing environmental conditions. Mujica [122] uses an extended PCA to detect damages at different temperatures. Self Organizing Maps (SOMs) are used to compensate the EOC effects on damage features like modal data and coefficients of auto-regressive models in [91] by Kraemer. A systematic review of the methods for compensation of environmental conditions (until 2007) can be found in [157].

### 7.1.1 EOC on Wind Energy Structures

The large spectrum of EOC effects on the structural dynamics can be well exemplified by means of Wind Energy Plants (WEP). Here, the changing EOCs (wind velocity, wind direction, temperature, orientation of the nacelle, rotational speed of the blades and atmospheric conditions) strongly influence the dynamic behavior of the plant. Sometimes, also the boundary conditions are changing (e.g. by ground erosion). For example, at low wind speed only a small number of lower modes is excited. It is also known from bridges that a high wind velocity can cause changes in the eigenfrequencies and a varying temperature affects the dynamic behavior of structures[157]. These effects appear also in case of WEPs [90]. Since the structure of the WEP is not perfectly symmetric along the tower axis (caused by transformers, pumps, etc. which are placed along the tower), the distribution of moment of inertia changes due to the orientation of the nacelle therefore, the dynamic properties of the system. On the other hand, according to [14], the eigenfrequencies of the blades are non-linearly dependent of the rotational speed of the rotor, and besides, they can change with the blade's pitch angle.

Regarding excitation mechanisms, WEPs are mainly excited stochastically by wind and waves. But also the angular speed of the rotor plays a major role in the structural excitation. In that case the structure is periodically excited by the stall-effect appearing in the instant when a blade passes the tower. The mentioned periodic excitation can be amplified by additional flap moments generated by mass differences between the blades. The structural excitation induced by the mentioned stall-effect is stronger than the one induced by a high wind speed level [66].

## 7.2 Fuzzy C-means and NullSpace, the compensation

There are several possibilities to compensate the Environmental and Operational Conditions to detect damage, as seen in section 7.1. The solution implemented in this work is based on the generation of a healthy baseline for different EOCs. In order to find these different baselines, fuzzy c-means algorithm was used as clusterization method (section 3.6). This Fuzzy clusterization method is able to find cluster centers by optimization of a objective function (Equation 3.50). For a given EOC, each dataset belongs to every cluster in a certain degree. These degrees are used in order to create a healthy baseline for that EOC. So, for each dataset there is a healthy baseline, which is calculated using the Hankel matrices in the center of the clusters and the distance between the center EOC and the current EOC.

The application of the clustering method to the damage detection method is done in the way that the fuzzy nature of the clustering method is maintained. This means that for each different EOC a compensated value of the different baselines is used in order to find a estimated value of the baseline for that exact EOC value.

In this case, the learning process modelizes how the structure behaves for different environmental conditions. In order to be able to learn correctly, the environmental information is needed for the algorithm to know in which conditions the structure is in the moment to determine the existence of damage. So the inputs to the algorithm will be the information from the structure, and the environmental conditions, while the output will be a Damage Indicator; see Figure 7.1 for a representation of the different parts of the method.

As in the unclustered NullSpace, the algorithm will have to learn how the structure behaves (**learning phase**) and a decision is made in a query phase (**detection phase).** The clustering is done in the learning phase, and the information from the clustering is used in the detection phase.

It is important to remember that this method of EOC compensation is able to estimate the behavior of the healthy structure even if in the learning phase it was not able to modelize that exact EOC. This is done thanks to the fuzzy nature of the clustering method.

### 7.2.1 Learning phase

In this phase, data corresponding to the healthy structure will be used. The first step is to perform the primitive NullSpace as shown in chapter 5. Using the damage indicators from the primitive NullSpace

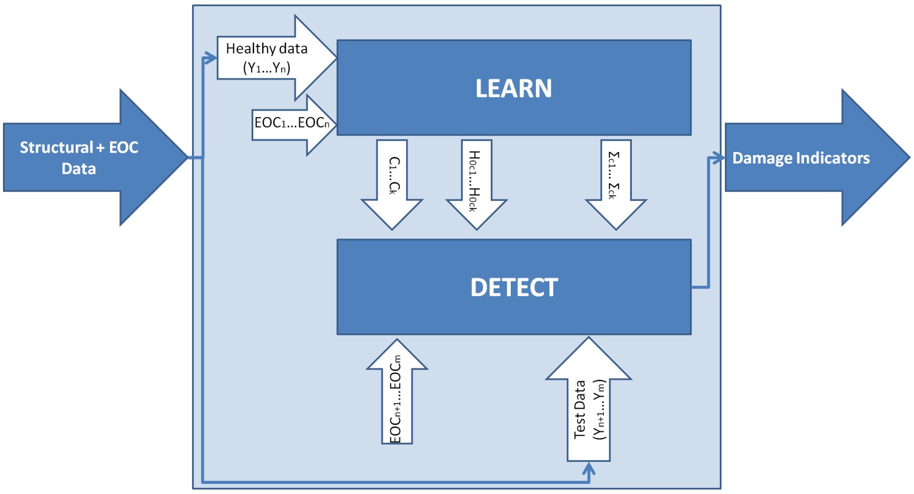



**Figure 7.1.** *Environmental and Operational Conditions - the algorithm*

results and the Environmental and Operational data for each dataset, the fuzzy classification is performed, and the centers are calculated. This is shown in Figure 7.2.

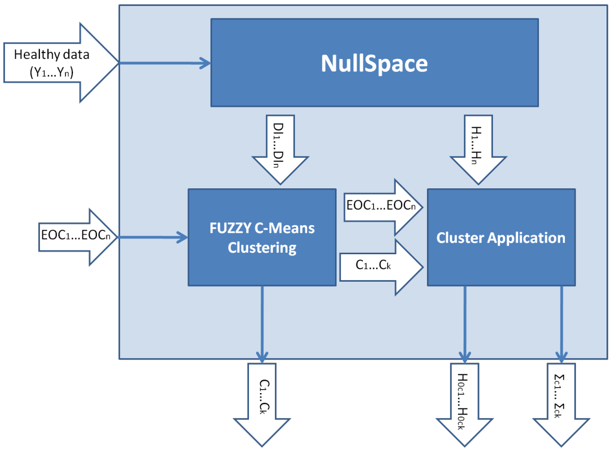



**Figure 7.2.** *Environmental and Operational Conditions - Learning phase*

In the *Cluster Application* block the centers ($C_K$) calculated in the previous block (*fuzzy c-means clustering*) are used. Along the centers, the Hankel matrices used in the first phase ($H_X$) and the environmental conditions ($EOC_X$) are used as inputs to the next block (*Cluster Application*). Its goal is to estimate a covariance matrix $\widehat{\sum}$ for each cluster.

For each environmental condition, its healthy condition is estimated just by applying the distance to the centers (see Equation 7.1). A Hankel matrix is estimated by weighting it with the distance to the different centers. That way, a baseline Hankel matrix for each different environmental condition is calculated. The reference Hankel matrix is estimated the next way:

$$H_{sX} = \sum_{k=1}^{K} \mu_{ij} H_{0Ck} \tag{7.1}$$

being $\mu_{ij}$the distance between the center $k$ and the EOC $x$ of the current data; $K$ the number of centers of

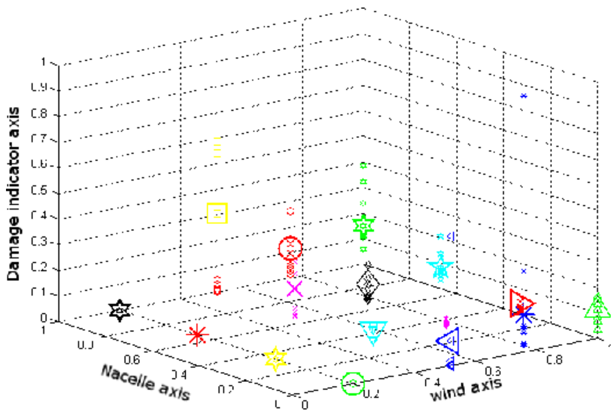



**Figure 7.3.** *Fuzzy Classification Output*

the cluster; and $H_{0Ck}$the Hankel matrix of the center $k$. This means, that the healthy condition is estimated using the distances to the center of the clusters, and not just applying the nearest information of the closest center. This way the fuzzy nature of the classification is preserved and used in order to have a more precise solution.

Once the reference Hankel matrix is estimated, its NullSpace ($U_{h0}$) is calculated, remember that the NullSpace is the matrix that has the property that is shown in Equation 5.3. As it was told before, there will be a NullSpace for each data set. Once the NullSpace is calculated, the residual for the data set is extracted. This is done using the Hankel matrices coming from the data set corresponding to the EOC.

$$R_X = U_{h0X}^t H_X \tag{7.2}$$

The vectorization is applied to the Residual Matrix $R_X$ (Equation 5.5) . All the residuals will construct the Covariance matrices $\widehat{\sum}$. There is a covariance matrix per cluster center. Each residual will construct the covariance matrix of the closest center using the Equation 5.8, being $n$ the number of data sets that correspond to each center. In this case, there is no covariance estimate for each EOC. So the closest Covariance matrix will be applied to the result of the estimated NullSpace and the Data Hankel Matrix.

The outputs from the learning phase, will be the cluster centers($C_K$), the Hankel matrices($H_{0Ck}$) for the centers and the Covariance estimates ($\widehat{\sum}_{ck}$). All these variables are going to be needed in the detection phase (see Figure 7.1).

### 7.2.2 Detection phase

Using the data extracted in the learning phase, in the detection phase data from the learning phase should be applied to the new datasets to be classified. In this phase, it is decided if a data set corresponds to the healthy structure or not. This phase is similar to the one that was done in the second phase of learning. The estimation of the reference healthy Hankel matrix is done in the first detection part, to know how the healthy structure should work for those exact Environmental and Operational Conditions. For this purpose the same equation used in the second learning phase is applied, Equation 7.1. Using this Hankel matrix, the NullSpace ($U_{h0}$) is found, just as in the learning phase.

Once the baseline for those EOC is built, using the structural data that has to be classified the Hankel matrix is constructed. Using these Hankel matrices, and the estimated NullSpace, the residual matrix is found, given by Equation 7.2 and the residual using the vectorization shown in Equation 5.5.

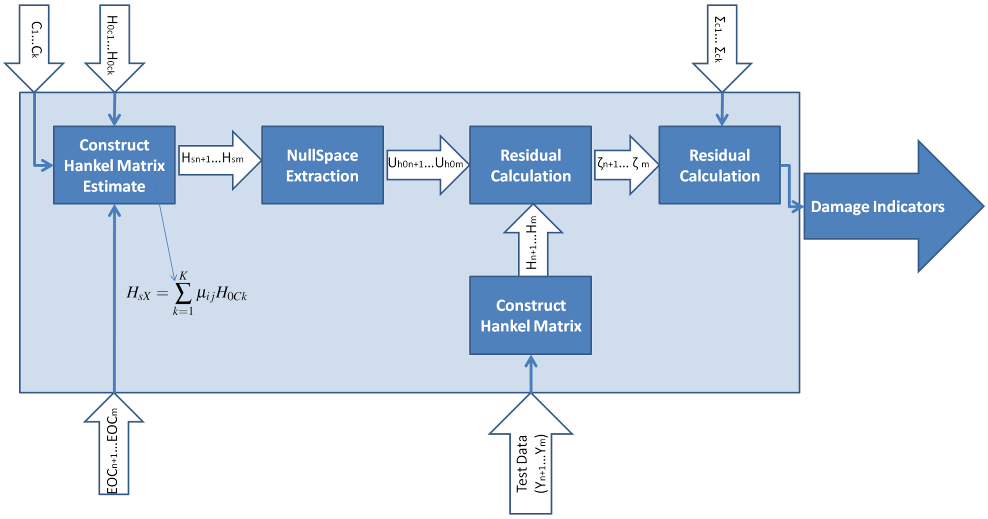



**Figure 7.4.** *Environmental and Operational Conditions - Detection phase*

Finally, for the Damage Indicator, the covariance $\widehat{\Sigma}_k$ is used. There are more than one covariance matrices, one for each center. The one that belongs to the closest center is applied. The Damage Indicator is found the next way:

$$DI = \zeta_{n+1}^{t} \widehat{\Sigma}_{CX}^{-1} \zeta_{n+1} \tag{7.3}$$

The detection process is shown in Figure 7.4. In a brief, for each incoming data, the EOC are used to estimate the reference Hankel matrix, and for each reference Hankel matrix $H_{sX}$, a NullSpace is extracted $U_{h0X}$. The structural data is rearranged in a Hankel matrix $H_X$, and the corresponding NullSpace is multiplied with this incoming Hankel matrix, using Equation 7.2. This way the residuals are found. Finally, for finding the Damage Indicators, the different $\widehat{\Sigma}_{ck}$ matrices are used applying the Equation 7.3.

## 7.3 Results

In this section, the results obtained compensating the EOCs using the methodology proposed in this thesis for damage detection based on NullSpace and Fuzzy C-means clustering are depicted, analyzed and compared with the primitive NullSpace without compensation. To aim this goal, the UPWIND model and the Laboratory tower structures are employed.

### 7.3.1 UPWIND Bladed model

As was described in section 4.3 the following damages were simulated, 0.1%, 0.5%, 1%, 5% wall-thickness reduction in one of the members of the structure. Not all the damages used for basic detection are used for the compensation, because the simulation time for each dataset costs a lot, computationally speaking. Taking into account that with the same level of damage different simulations must be made, with different EOCs, it was decided to do it with 4 damages.

In order to simulate different EOCs, nacelle orientations and wind speeds were changed during the simulation environment. The winds used were turbulent winds with different means. In this case, the winds are centered in $8\,m/s$, $16\,m/s$, $25\,m/s$ speeds, while the Nacelle orientation changes between $0^{o}, 20^{o}, 50^{o}\,and\,75^{o}$ from north.

Figure 7.5 shows the CME Damage Indicator by each dataset using the NullSpace methodology without any type of compensation. Different colors and shapes represent different cases. The green star datasets are the ones used for the learning phase, the blue rhombus are the healthy ones not used for learning. The next four colors are the ones corresponding to each damage (brown triangle 0.1% reduction of wall thickness in that member, fuchsia circle 0.5% blue star 1% and cyan plus 5%). The dashed gray line corresponds to the threshold value. Finally the dotted red color lines represent mean value of the DIs for each damage.

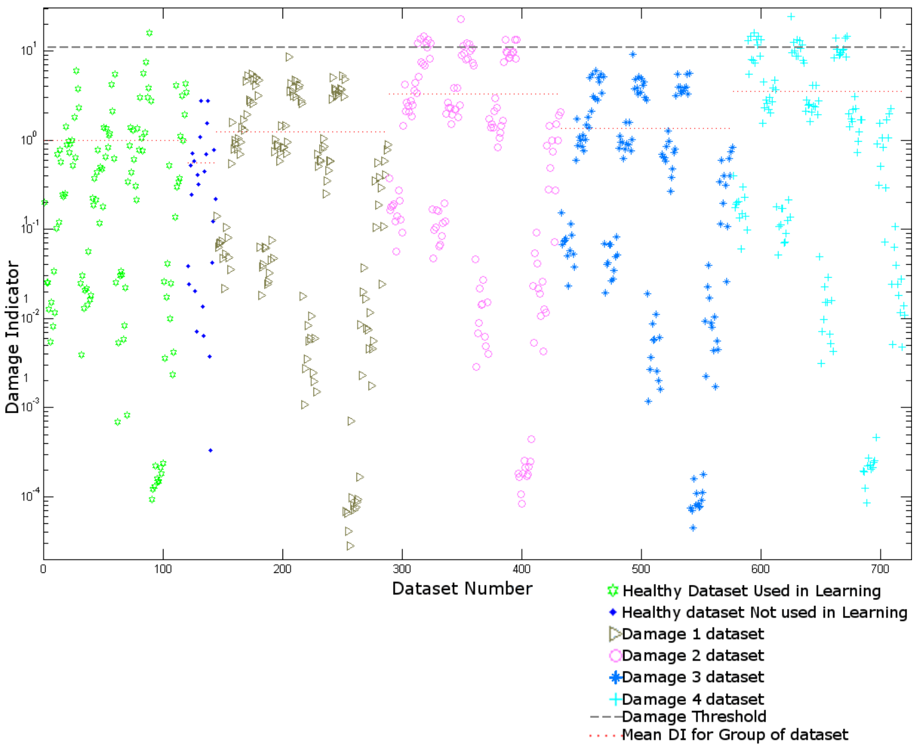



**Figure 7.5.** *UPWIND - Primitive NullSpace Results*

From Figure 7.5 it can be seen that the primitive NullSpace is not able to differentiate between the variations due to the EOC and the ones due to the damages. The method is also again more sensitive to the EOC than to the damage itself, and damaged and undamaged data are almost in the same level. So the variability given to the healthy model by adding the different environmental conditions in the same model, makes the the primitive method not able to detect the damage for different EOC.

On the other hand, Figure 7.6 shows the CME damage Indicator by each dataset using the NullSpace methodology with a 12 cluster compensation (one per EOC - 3 wind speeds and 4 nacelle orientations).

The color and shapes represent the same case as the shown in the previous case. It is clear that the damages are well detected. The difference between the damage indicators of the damaged experiments and the threshold is at least one order of magnitude. Almost all the healthy experiments not used for learning are well defined as undamaged, just one of the DIs is greater than the threshold.

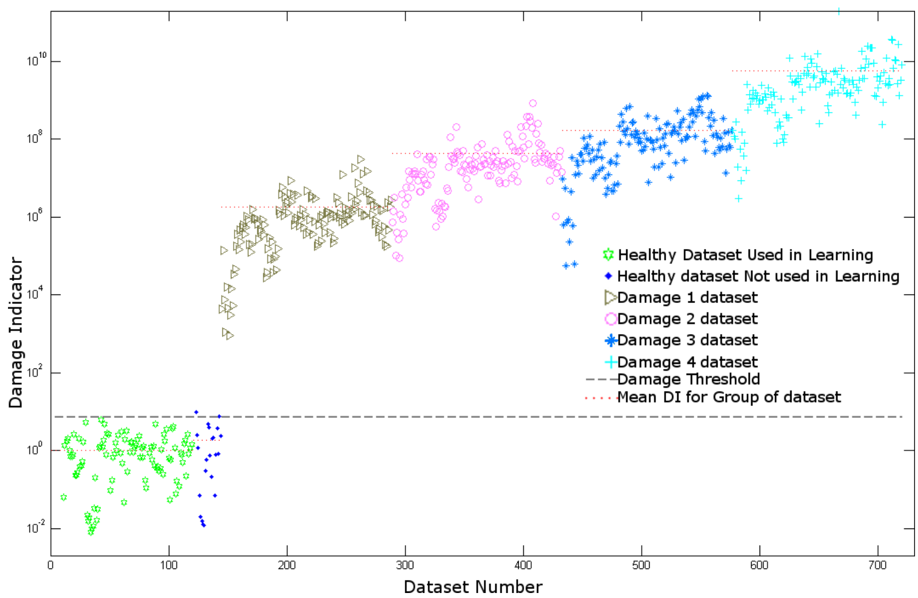



**Figure 7.6.** *UPWIND - Clustered NullSpace Results*

### 7.3.2 Laboratory tower model

In this case, only one of the damage locations has been used for the test. This has been the D2.1. Again, the amount of experiments needed for the test, grow with the different EOCs.

In order to simulate the different EOCs, the wind and nacelle orientations were changed. The wind was simulated by changing the amplitude of the shaker signal. For this test, 3 different amplitudes were used: *one*, *two* and *three*. Where *one* is the signal itself coming from the white noise excitation system, while *two* means that the input signal is amplified by means of two and *three* the input signal amplified by means of three. The nacelle orientations tried in this case were the next ones: $0^{\circ}, 30^{\circ} and 90^{\circ}$. For the nacelle orientations, the top part of the structure was moved to those exact grades. For the clusterization, 9 clusters were used. One for each different condition, three winds and three orientations.

Figure 7.7 shows the Damage Indicator bye each dataset using the NullSpace methodology without any type of compensation. Like in the case above, the green and dark blue points correspond to the healthy structure. The green squares were used in the learning phase, while the dark blue stars not. The red circles correspond to the damaged structure. The gray dash line represents the Damage Threshold, and the dotted color lines correspond to the mean value of the indicators in each case.

As in UPWIND model case, the primitive NullSpace is not able to differentiate between the variations due to the EOC and the ones due to the damages. The method is also again more sensitive to the EOC than to the damage itself, and damaged and undamaged data are almost in the same level. So the variability given to the

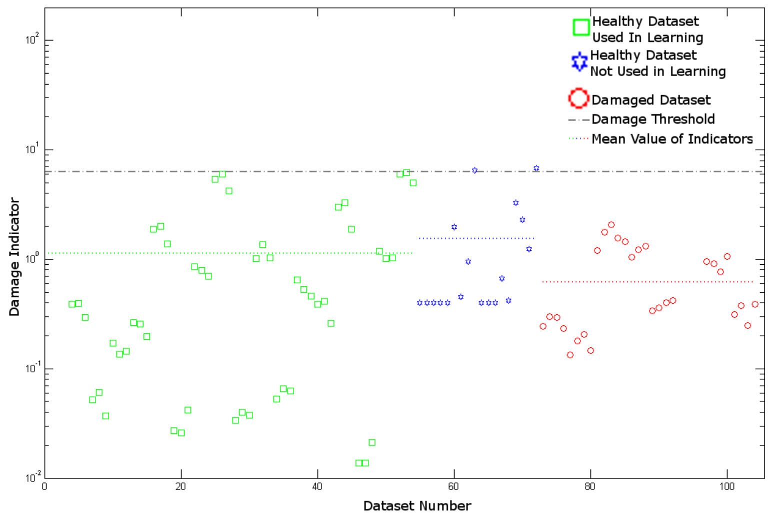



**Figure 7.7.** *Laboratory Tower - Primitive NullSpace Results*

healthy model by adding the different environmental conditions in the same model, makes the the primitive method not able to detect the damage for different EOC.

On the other hand, Figure 7.8 shows the damage indicators using the compensation method. The color and shape scheme is the same as in the previous figure, and the results are much better than the unclustered method. Every damage is well detected and there are no false positives.

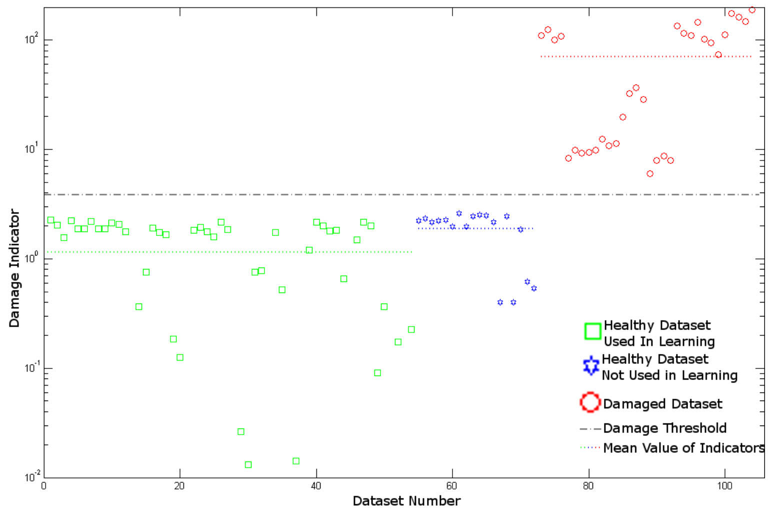



**Figure 7.8.** *Laboratory Tower - Clustered NullSpace Results*

## 7.4 Discussion

First of all, it is important to highlight that the primitive NullSpace method was not able to detect damage when different EOCs change the state of the structure. Thanks to the fuzzy classification, the clustered NullSpace damage detection method was able to correctly detect damage in the test structures in different environmental conditions.

The results also have some logical explanations. The mean value of the Damage Indicators (red dotted lines), in both cases, indicates higher values in the cases where the damage is more severe, as can be expected to obtain, since a greater level of damage is related to a higher value of the metric. Although the Damage Indicators are proportional to the damages, this proportionality is not enough to distinguish the different defects among them.

It is important to remark that the use of this solution is not fixed to the conditions used exactly in the learning phase, since this method is able to estimate the healthy conditions in a point near a cluster center.

# Chapter 8

# Sensor Fault Detection (SFD)

## 8.1 Introduction

The integrity checking of the sensors is a important functionality part on an SHM solution. The alarm for the damage detection can only be activated when the integrity of the sensors has been validated. Otherwise, false alarms can be generated.

In that way, it can be said that sensor fault detection is an important part of damage detection itself. There is not a proper damage detection without being certain that the information gathered is reliable. In order to have a secure Structural Health Monitoring (SHM) system, the state of the sensors should be known. When the sensors are placed in a structure, they work correctly, but usually the lifespan of a structure is larger than the sensors' lifetime. In this chapter, a Sensor Fault Detection (SFD) method based on Mutual Information is explained. This work is based on [87], but the way of processing the information in order to create a baseline was adapted; and besides the final sensor fault identificator is calculated in a different way.

Methods of SFD can be classified into two different categories. On one hand, the ones that implement the SFD in two steps, residual generation and fault detection by applying different algorithms for each task, and on the other hand, methods that employ a single algorithm for both tasks.

### 8.1.1 Two steps algorithms

Among the methods for detecting errors in the sensors, the residual generation plays a very important role. Therefore, there are some methods where different algorithms are used for the generation of residuals and for sensor fault detection. Wei works on the detection and fault isolation in wind turbines and chooses to divide the process into three distinct phases: residual generation, fault detection and fault isolation [181]. For residual generation he uses Kalman filters; later, the fault detection is performed with algorithms CUSUM and GLRT LS. These algorithms are methods that are based on Subspace Identification. And finally, he uses the double Kalman filters for the isolation of these faults. This method was applied to detect sensor faults in wind turbines as additive fault, multiplication fault and drift fault.

In [180] a comparison was made between MKF (Mixture Kalman filter) and SMA (M Stochastic algorithm). It was demonstrated that both methods provide accurate tracking of the states of the sensors but MKF method provides better results in terms of efficiency and precision.

In [52] the process of detection and isolation of faults in sensors was divided in two phases. In the first block, a generation GOS algorithm (Generalized observer scheme) was performed and, in the second block, using a decision system, residuals were analyzed with the algorithm CUSUM to detect and isolate faults in the sensors. Galvez applied this method of SFD for Structural Monitoring to industrial applications such as induction machines and wind turbines, with satisfactory results.

Yang [196], also gave special importance to the generation of residuals, so he opted to split the process into different phases. First, residue signals were generated with the method "steady-state-based" for "lock-in-place" sensors. This method is implemented by an algorithm based on Linear Matrices (LMI) that gives an integrated design of a filter. Once the residual signal is obtained, the fault detection is performed comparing the result with a threshold.

### 8.1.2 One step algorithms

Other researchers in this area, have preferred to work with a single algorithm or method. Lopez carried out an implementation of ANN (artificial neural networks) for the detection of failure in microprocessor-based smart sensors [137]. This method is based on the propagation of data through the network map, thus enabling self-diagnosis and monitoring of real-time data. The paper does not indicate that any application on fault detection sensors for Structural Monitoring field but, it could be used for data analysis and feature extraction or pattern recognition.

Another method investigated was KPCA (Kernel Principal Component Analysis) [70]. This method arose from PCA (Principal Component Analysis). KPCA is an extension of PCA for non-linear distributions. Hong Xing achieved satisfactory results in two typical sensor errors [70]: "step bias fault" and "zero drift fault", effectively discriminating sensor fails at a relatively high speed. Although the method can be applied in industrial processes, chemical and biological agents, it is not specified whether was been applied.

Chen conducted an extensive effort to detect errors in wireless sensor networks [21]. Making use of DLFS (Distributed Fault Detection of Wireless Sensor Networks), based on the Mutual Testing, proved that this algorithm has a high error detection rate and low false alarm ratio for calibration errors, complete failure and noise error variable.

Kraemer presented a parallel study on methods AR (AutorRegressive Models) and MI (Mutual Information) for failure detection sensors [87]. He made two different experiments, one in the laboratory and another in a real wind turbine. In the first experiment all failures were well detected. In the real wind turbine case, several data was tested and all existing faults were detected. Both methods were validated using data from accelerometers.

Buethe proposes to use the coupled electro-mechanical admittance to detect damage of the sensors and in its bonding layer [17]. The help of a temperature dependent theoretical model provides influences of changing environmental and operational conditions. The model is then compared with FEM-results.

## 8.2 Sensor Fault Detection based on Mutual Information

The algorithm used for this work, is an algorithm that uses Mutual Information as a base. This work was done using the implementation of Mutual Information that was used for Feature Selection. This is located in the second group of SFD classification, the one step algorithms.

The basic idea is that the MI of any sensor comparing to an other one, should remain the same if the sensors are working properly. Mutual Information, as seen in subsection 3.4.3, measures the mutual dependence of the two variables. So basically, in a learning phase, the algorithm learns how the MI of each sensor versus all the rest is; for later to check if the Mutual Information of the sensors has changed.

The MI for all possible combinations of sensor outputs $y_m$ and $y_l$ (except $m = l$) is computed, which leads to an MI-matrix for all combinations $m, l$. The basic idea is that the mutual information changes when a sensor fault $f_m$ is present; let us say in the $m$-th channel:

$$\widetilde{y}_m = y_m + f_m \tag{8.1}$$

This fault appears only in the $m$-th channel. Thus all combinations with index $m$ should show a change of the MI. This allows to localize the faulty sensor. More than one faulty sensor can be simultaneously detected in the same way.

### 8.2.1 MI matrix

Let us define the Mutual Information Matrix ($MI_{mat}$) as a matrix that has as elements, all the MI values between all the sensors in the structure. These values are able to give information about how dependent is each sensor of the others. For the k-th experiment (or dataset) this matrix is defined

$$MImat^k = \begin{bmatrix} MI_{1,1} & MI_{1,2} & \cdots & \cdots & MI_{1,N} \\ MI_{2,1} & MI_{2,2} & \cdots & \cdots & MI_{2,N} \\ \vdots & \vdots & \ddots & \cdots & \vdots \\ \vdots & \vdots & \cdots & \ddots & \vdots \\ MI_{N,1} & MI_{N,2} & \cdots & \cdots & MI_{N,N} \end{bmatrix}, \tag{8.2}$$

where $MI_{i,j}$ denotes the MI between the $i-th$ sensor and the $j-th$ sensor. It is noted that this matrix is simetric because the MI value of the sensor $i$ with the sensor $j$, is the same as the value of the sensor $j$ with the sensor $i$ as shown in subsubsection 3.4.3.2. Besides the MI value for one sensor with itself, is equal to the Entropy of that sensor. The size of this matrix is determined by the number of sensors in the structure ($N$)

### 8.2.2 Sensor Fault Indicator

One possibility to visualize the faulty sensor is to use the relative change in the MI as a sensor fault indicator (SFI):

$$SFI_k = \frac{|MImat^k - MImat^{Ref}|}{MImat^{Ref}} \tag{8.3}$$

where $k$ is the MI matrix of the actual data set and the upper index $Ref$ represents the baseline MI matrix. If any sensor is damaged, the resulting matrix should show a change in the SFI referring to the faulty sensor.

## 8.3 Methodology

In order to have a robust algorithm, several types of variations were implemented, the one shown below, is the one that was chosen. The base idea comes from [87] but the algorithm itself has changes from the original work. This way a more sensitive algorithm was obtained.

Among the changes, the signal preprocessing block is found. As Mutual Information calculates differences between data, statistically, it is not sensitive to gain errors without this step. The reference SFI also is a contribution that was not used in the base idea. This reference allows us to know how SFIs should look like, when no damage is present, and it is used in order to make the algorithm more sensitive. The way of arranging the final SFI is also changed. Instead of a matrix view, a vector SFI has been built, which allows to find the error easier.

The algorithm is divided into two phases. In the first part of the algorithm the sensors are known to be working well, and a baseline is built. In the second phase it is needed to identify whether the sensors work well. The algorithm provides a metric that indicates the existence of the fail in the sensors.

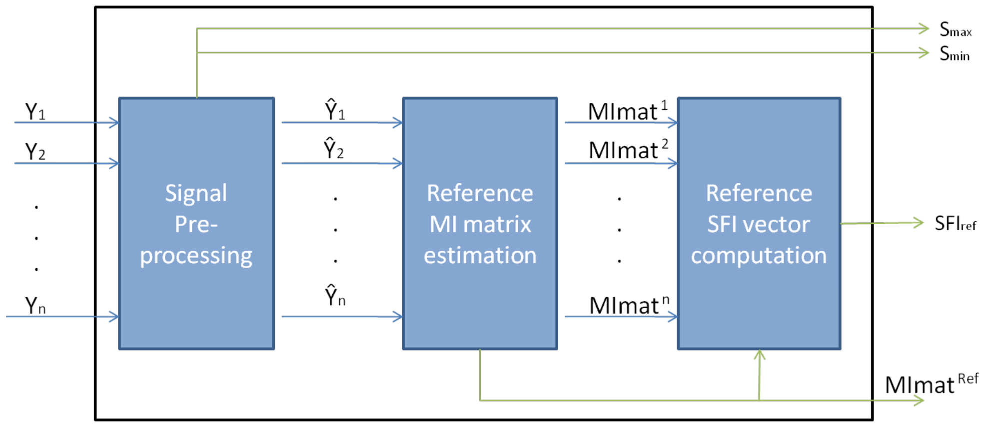



**Figure 8.1.** *Sensor Fault Detection: Learning Phase*

### 8.3.1 Learning phase

In the learning phase of the sensor fault detection methodology, all the MI matrices obtained from the healthy structure are used to build the baseline.

In the Figure 8.1, the learning phase of the algorithm in a block diagram is shown. The objective of this part is to know how the MI between sensors change when no damage is present in the sensors. The different blocks are divided as: the first block, some signal characteristics will be extracted, the maximum and minimum values of each sensor, and these maximum and minimum values will be stored for the detection phase. These values are used in order to be sensitive to the gain error.

Once the signal is preprocessed, the reference MI matrix is estimated $(MImat^{Ref})$. The Mutual Information value for each sensor pair is estimated, and saved in different matrices, one per experiment. Once all the MI values for each pair of sensor in each different state are known, the reference Mutual Information matrix will be calculated using the mean value of all the learning datasets, as follows:

$$MImat^{Ref} = \frac{\sum_{k=1}^{n} MImat^{k}}{n}. \tag{8.4}$$

On the other hand, the matrix of sensor fault indicator of each dataset is calculated as follows [89]

$$SFI_k = \frac{|MImat^{k} - MImat^{Ref}|}{MImat^{Ref}}, \tag{8.5}$$

where $MImat^{k}$ is the MI matrix of the current data set and the upper index $Ref$ represents the baseline MI matrix. If any sensor is damaged, the resulting matrix should show a change in the SFI referring to the faulty sensor.

The reference SFI ($SFI_{ref}$) is finally vectorized containing the mean value of each SFI matrices, as follows:

$$SFI_{ref} = \sum_{j=1}^{nsens} \left( \frac{\sum_{k=1}^{n} SFI_k}{n}. \right), \tag{8.6}$$

where $nsens$ is the number of sensors in the structure. This means that the $SFI_{ref}$ will contain a value for each sensor of the structure, and it is a vector.

### 8.3.2 Detection phase

The block diagram of the Detection Phase is shown in Figure 8.2. In the detecting phase all the matrices calculated from the current dataset are compared to the baseline ones to see differences between them and infer about the state of the sensors. From the learning phase $S_{min}$, $S_{max}$, $MImat^{Ref}$ and $SFI_{ref}$ are kept

The incoming dataset is limited using the limiters from the learned signal ($S_{min}$, $S_{max}$). Once the signal is preprocessed, the MI matrix is calculated as Equation 8.2 and subsequently its $SFI$ (by using the $MImat^{Ref}$ from the learning phase) as Equation 8.3. Finally the SFI matrix is transformed into a vector and compared with the $SFI_{ref}$ to calculate the fault indicator. This fault indicator is a vector, that contains a fault indicator value for each sensor. If the value of the Fault indicator is much bigger than the other values, means that the sensor is faulty.

## 8.4 Results

In order to simulate the sensor fault, three types of failures were assumed. The first fault is made by changing the signal of the accelerometer directly, by adding a white noise (1dB addition to the measured power of

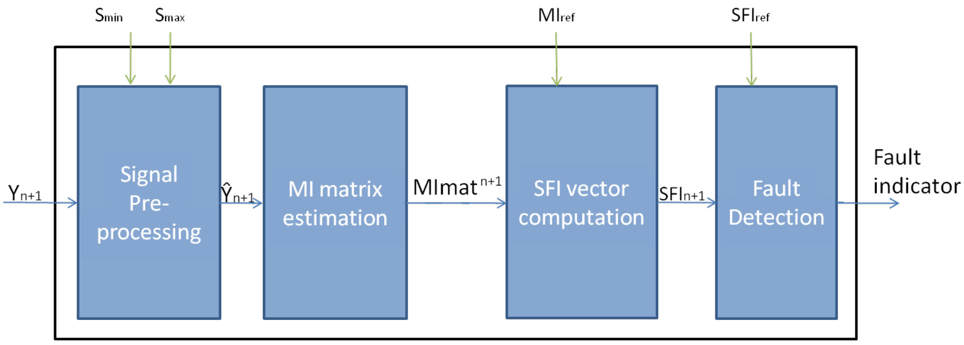



**Figure 8.2.** *Sensor Fault Detection: Detecting Phase*

the signal) to the properly captured signal. The second fault was seeded as a gain error in the sensor. For that purpose the signal in the sensor was multiplied by means of 2. The third approach was done by acting directly on the sensor; The sensor itself was totally detached from the structure, simulating a sensor fall. For the last one, a reusable putty-like pressure-sensitive adhesive was attached between the sensor and the structure, that way the damping of the sensor increases, and simulates a faulty sensor.

The laboratory tower (section 4.4) was used to test this methodology. This structure was equipped with 16 sensors channels. 5 triaxial sensors and one uniaxial sensor which was placed in the 4th channel. All the damages where seeded in this sensor, as was the only one using only one single channel of the data acquisition system.

### 8.4.1 No fault

Figure 8.3 shows the result of the Sensor Fault Detection algorithm when all the sensors work correctly. As the SFI value is normalized, when no fault is present all the values are close to one. In other words, the difference between the SFIs of the sensors is really small.

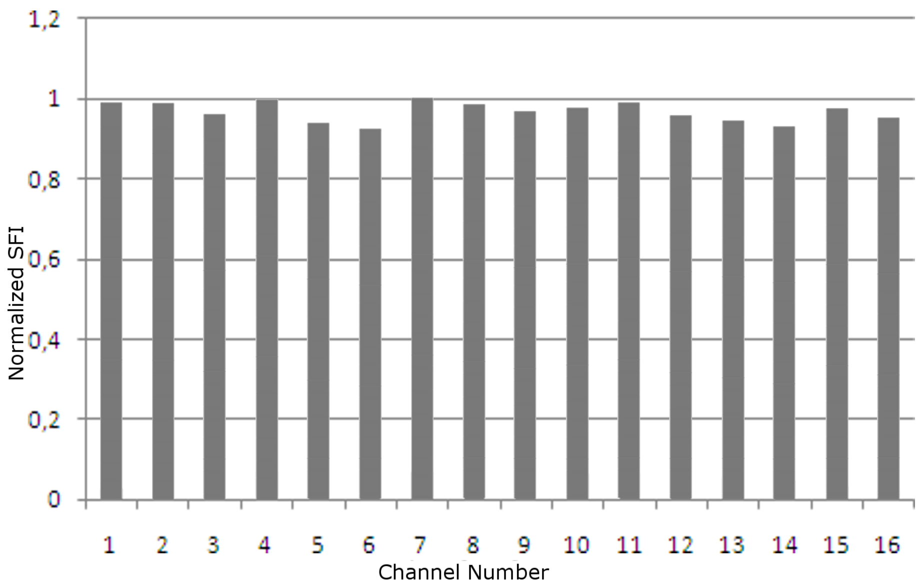



**Figure 8.3.** *Sensor Fault Indicators for Healthy sensors*

### 8.4.2 Noise addition fault

All the sensors were correctly placed. The signal of the uniaxial sensor (4th channel) was changed, and the noise was added to the original signal. The Figure 8.4 shows the normalized SFI by each channel. It can be seen that the methodology proposed in this thesis is able to detect the fault. The fault indicator in the 4th channel is much greater than the others. That means that the value of Mutual Information for that channel changed a lot comparing it with the rest of the channels.

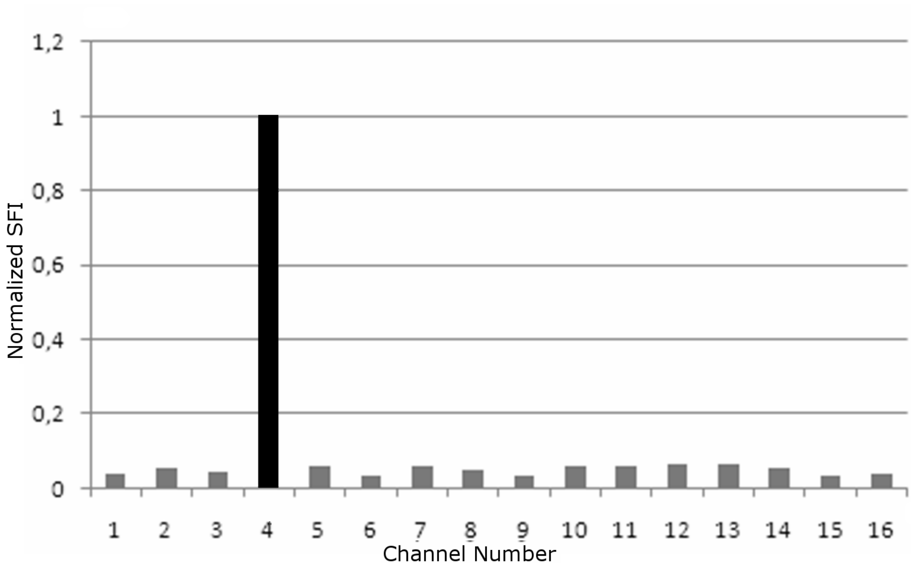



**Figure 8.4.** *Fault indicators by sensor channel with Noise addition fault*

### 8.4.3 Gain error fault

All the sensors were, again, correctly placed. The signal of the uniaxial sensor was changed, and it was multiplied by means of two. This simulates a sensor gain error. In Figure 8.5 it can be seen that the fault indicator in the 4th channel is much greater than the others, and that the methodology proposed is able to detect this type of faults.

### 8.4.4 Sensor fall fault

In this case the uniaxial (4th channel) sensor was detached completely from the structure. The Figure 8.6 shows also that something happened to the 4th sensor, and it was well detected by the algorithm. Again, the change of MI in the 4th channel is the biggest.

### 8.4.5 Adhesive change fault

In this case, also the uniaxial sensor (4th channel) was attached with a special adhesive. As the Figure 8.7 shows, the results were satisfactory. When 5mm thick adhesive is placed under the sensor the fault indicator

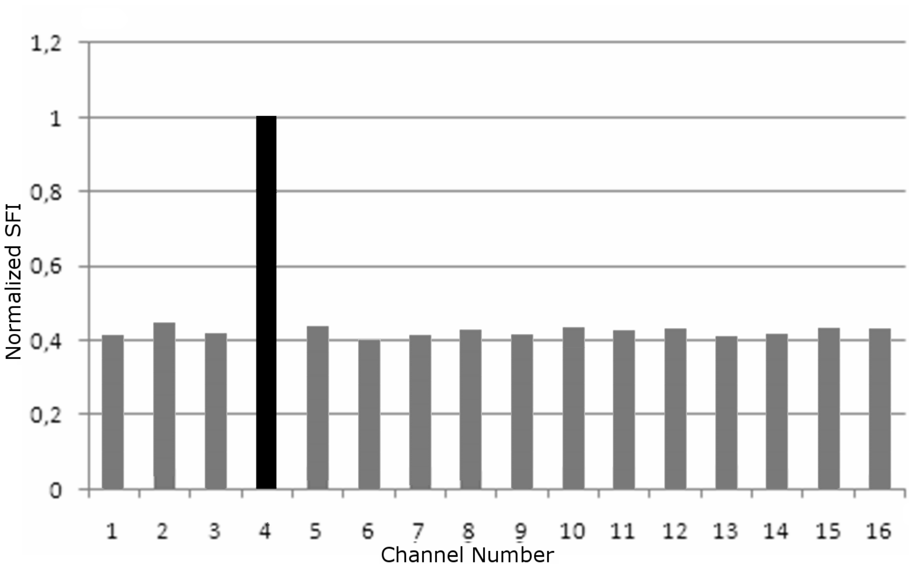



**Figure 8.5.** *Fault indicators by sensor channel with gain error fault*

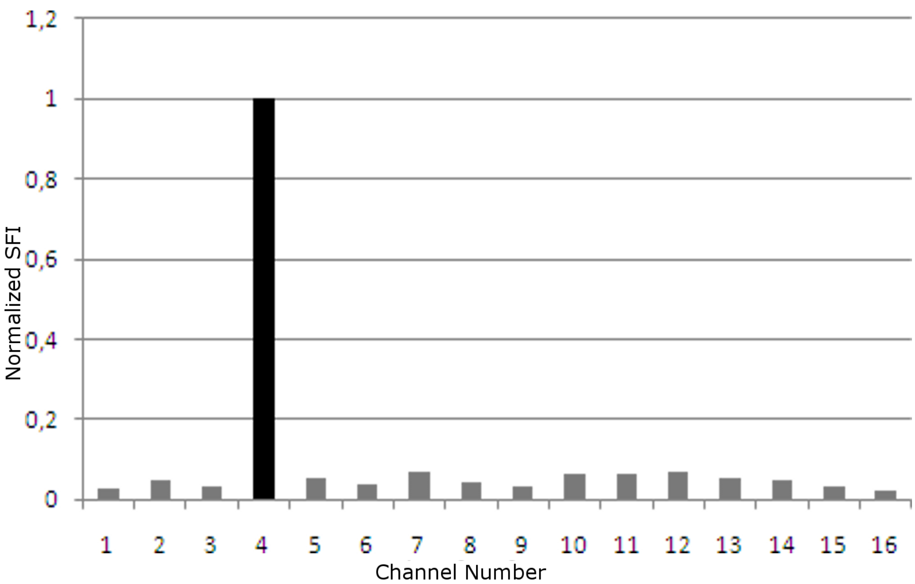


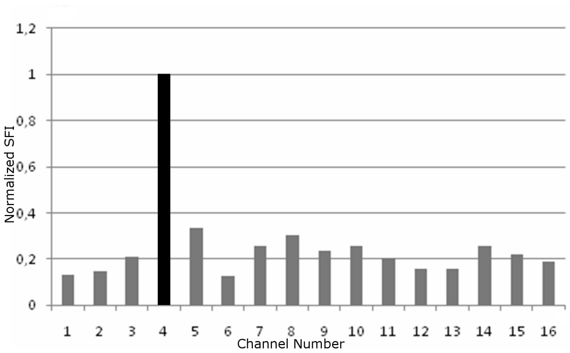

**Figure 8.6.** *Fault indicators by sensor channel with sensor fall fault*

on the faulty sensor is 4 times bigger than the others. When 2mm thick adhesive is placed under, the results are not as sensitive, although in both cases the fault is correctly detected. More tests where also made attaching thicker adhesives, and the error gets bigger.

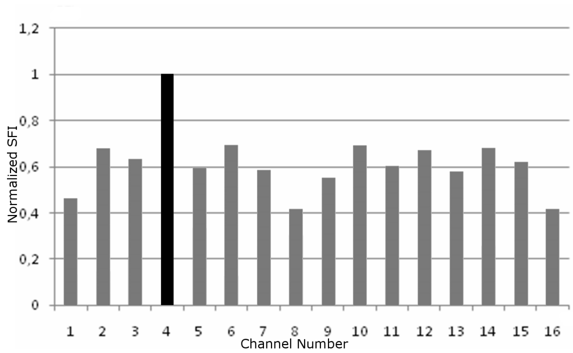
## 8.5 Discussion

Sensor Fault Detection is needed if damages in real structures are going to be detected. It is important to know if variations in the vibrational responses are being detected because of a real damage is present in the structure, or it is being detected because a sensor is broken.

In this chapter a method for sensor fault detection was proposed adapting the development in [89]. The




**(a)** *5mm adhesive addition in 4th channel*




**(b)** *2mm adhesive addition in 4th channel*

**Figure 8.7.** *Fault indicators by sensor channel with different adhesive change faults*

methodology was integrated into a global SHM solution. This method is based on the information theory, and more precisely, on Mutual Information. Mutual Information analyzes the dependence between sensors information. If that information dependence changes between 2 different states, it can be said that the sensor is faulty. In order to know how that dependance really is, a learning phase is needed where the baseline dependence is calculated. In the evaluation phase, the baseline dependances are compared to the ones calculated using the new ones.

As contribution of this thesis, the baseline is calculated in a different way. The fact that the SFI is calculated both in the learning phase and in the evaluation phase, and this being a vector, and not a matrix, helps to have a more sensitive algorithm.

The method has been validated using the laboratory tower, and it is able to detect the faulty sensors by simulating change in the signal, and also by acting on the hardware (the accelerometer in this case).

# Chapter 9

# Conclusions and future research

The main contribution of this thesis is the development of a general methodology for damage detection in WEP structures. This methodology included: preprocessing, damage detection, compensation of Environmental and Operational Conditions and sensor fault detection. On the other hand, this methodology was validated and tested in several structures.

Firstly, a background on damage detection is presented and several kinds of damage detection strategies were studied before selecting the implemented in this thesis. The background of the sensors department in IK4-Ikerlan helped to research in the wide technological solutions for sensorial solutions. This state-of-the-art work in SHM sensors is basic to achieve real and commercial solution.

As contribution, this damage detection method is complemented by adding different Damage Indicators. A comparison and discussion about the results after the implementation of these Damage Indicators in different case studies is presented.

Once, a sensitive strategy for damage detection was defined, with some preprocessing data methods. These methods were analyzed and implemented, and demonstrated that damage detection accuracy was improved if the original data is preprocessed with the techniques described here.

The problem of Environmental and Operational Conditions is always present in structures. These changes can mask the damage effects over vibrational response of the structure. In order to compensate them, a fuzzy clusterization method was developed and included in the damage detection methodology. The results are encouraging and promising.

Finally, a sensor fault detection methodology was developed, since the knowledge of the state of the sensors is very important if an online damage detection system is desired in real applications.

## 9.1 General conclusions

The main objective of this work was to develop a complete damage detection methodology for wind turbines. This objective was achieved and the damage detection methodology has been put into test, with good results.

This statement is supported by the fact that they can work properly with any type of structure regardless of whether it is a simple structure or a more complex one, as a wind turbine.

The different subtasks include damage detection, data preprocessing, Environmental and Operational Conditions compensation and sensor fault detection. All subtasks were correctly addressed, and good results were obtained for all of them. Although the inspection was performed under controlled laboratory conditions or mathematical models, the results showed a potential use in real applications. The applicability of the methodology is enhanced by the following elements:

- The methodology itself. The methodology is thought to be applied on an operating wind turbine following the steps needed for the damage assessment.
- The preprocessing step. This step allows to normalize, organize, extract and select the important information of the signals, in order to perform an adequate analysis of the data.
- The Environmental and Operational Conditions compensation step. The use of Fuzzy clustering methods to classify different statistical models allows to obtain and estimate a baseline model for different operating scenarios.
- The use of damage indicators. These indicators allow to identify drifts in the structural behavior to define the presence of damages by comparing the data from different structural states with the undamaged state.
- The sensor checking. This step checks if the sensors that are used for damage detection are working properly or not. This implementation provides a high level of reliability to the methodology.

## 9.2 Observations and concluding remarks

This thesis has contributed with the development of a Structural Health Monitoring (SHM) system for Wind Energy Structures, based on pattern recognition techniques. It is important to say, that although the Wind Energy Structures have been tackled, this methodology, focused on damage detection, is applicable to different types of structures. From the application of this system, several advantages were obtained as shown and demonstrated by the results presented int this manuscript. One of them is the data preprocessing solution, that helped to have a more precise damage detection method, and helps to improve the computational time needed for processing each dataset.

In general, several conclusions can be drawn from this thesis. They are organized in six subsections: case studies, instrumentation and data acquisition, preprocessing, environmental and operational changes, damage detection and finally, sensor fault detection.

### 9.2.1 Case studies

The case studies proposed in this work include both, simple structures and complex ones. The Simple mass and spring system is a simple model that helped us to validate the methodologies in an early state of the development, it is easy to understand it and induce damages. The model, built in MATLAB®, was a good start to prove different solutions. In fact, this case study is always the first one that is used to validate the methodologies.

The second case study, the Finite Element Model of the Tower, was used to determine if the methodology still worked in more complex structures. Thanks to this mathematical model, it was verified that little cracks could be detected.

The third model, the UPWIND offshore tower model plays an important part on the work. Bladed® is a software that is able to validate and certificate wind turbines. The models on Bladed are real wind turbines, working and making energy, in a simulated world. The fact that the damage detection solutions works well using the data coming from this model, guarantees the proper operating of the system proposed here. It can be said that it is a way to validate the methodologies in the real world.

Finally, the laboratory tower was the real structure used in this work. The tower helped to validate the method in the real world, and different EOCs were induced in the structure in order to try to do it more realistic.

As a conclusion, the case studies selected for the work included both, simple and complex cases, and that way the validity of the work has been proven.

### 9.2.2 Instrumentation and data acquisition

Starting from the instrumentation level, it is possible to conclude that the use of the accelerometers is a viable solution for structural inspection.

They provide the following advantages:

- Good for output only solutions
- They can work in a wide range of frequencies
- They can be easily attached to any structure and they are available in different sizes and presentations.
- The fact of having biaxial or triaxial accelerometers, helps to know the vibrations in different directions on a single point

The selection of vibration based solution was made after a wide range and wide field of research in the field of sensors in the state-of-the-art.

As has been shown in this thesis, the location of these accelerometers is well studied before attaching them to the test structures. It is important to know the best locations for these sensors in order to obtain the maximum information possible. For that purpose, some Finite Element Models were used. The method of selecting the best sensor locations takes into account the Modal Assurance Criterion (MAC), eliminating the sensors positions that have the least effect in that MAC.

The data acquisition system has changed during the development of this thesis. Everything about the data acquisition system is explained in the Appendix A. Two different system were used, OROS and Compact RIO. All of them have their advantages and disadvantages. In short, the last one, the Compact RIO makes possible to acquire data and automatically launch the damage detection solution.

To conclude, the instrumentation, the location of the sensors, and the data acquisition has been carefully selected so as to have a good compromise between, costs and efficiency.

### 9.2.3 Preprocessing methodology

The preprocessing of the gattered data has shown that the efficiency of the method can vary. If a good preprocessing is made, better results will be obtained, while on the contrary, if a bad preprocessing is made, the results can lead to bad results. It is very important to know how to preprocess the data for the damage detection to be more sensitive.

This work contributed in introducing three different data preprocessing methods and applying them before using a specific damage detection algorithm (NullSpace). Results of each method are analyzed and finally, they are compared. By applying these data preprocessing methods, a more sensitive and a more effective damage detection algorithm is obtained. The damage detection methodology showed that it is capable of detecting really small damages in the tested structure. Besides, if this method is supported by preprocessing methods, the results get better, and less information is used to build the model. Thanks to this reduction, the execution time gets smaller, and this helps to have a more effective damage detection method. Being able to detect damage using less sensors shows that the fact that having more sensors does not mean that the information they give is really used to detect damage.

In short, the proprocessing of the data is a critical tool to extract the best information form the sensors.

### 9.2.4 Environmental and Operational Changes

In the real conditions, statistical pattern recognition methods suffer from a disadvantage: they are not sensitive to the different conditions that can lead to a different structural behaviour. In this work, that disadvantage has been worked out thanks to a Fuzzy Classification method, that creates different patterns for different conditions. Thanks to the Fuzzy nature of the classification method, these patterns are applied in certain degree depending on the condition the structure is working in that certain moment.

Thanks to that solution, the methodology is able to operate in different conditions.

### 9.2.5 Damage detection

The statistical pattern recognition method, NullSpace, is able to detect damages in a structure using global information of the structure, taking the information from transducers. The information from the transducers is rearranged in different ways in order to have a mathematical model that contains all the dynamic information of the structure. This information is used firstly, to build the baseline model, and secondly to classify the datasets, comparing them to the baseline model.

One of the contributions of this thesis is to propose, develop and compare some variations of the NullSpace and decide which one is the most sensitive one. It was found that the CME Damage Indicator was the most sensitive one in almost every case. Also, the performance of the indicators presented for damage detection was also tested presenting good results.

This damage detection method was tested in all four case studies, with satisfactory results. In particular it is very interesting the fact that in the laboratory tower the only solution able to detect damages correctly is the CME NullSpace solution. And other interesting result is that using the UPWIND model case study, the method was able to distinguish the damages clearly, and this guarantees that the method is valid for the real world application.

In general, the results showed that the different damage indicators do not change the results very much, but if the damages are small, the good choice of the Damage Indicator can lead to a good detection.

### 9.2.6 Sensor Fault Detection

The Sensor Fault Detection for a SHM system is a functionality needed, because the information from the transducers is the only information that the SHM system has in order to classify the structure state.

In this thesis a Sensor Fault Detection method is based on Mutual Information. The Mutual Information quantifies the similarity on the sensors information, and it is a good way to know if a sensor is working correctly. The Mutual Information between the sensors is calculated in a baseline phase, later it is used to verify if the MI has been changed.

The methodology showed good results, demonstrating that it is able to detect the usual damages in the sensors.

## 9.3 Future work

This thesis has contributed to SHM and specially to the data preprocessing area, but many open issues still remain. The following subjects are outlined as future works specifically related to the system developed in this thesis.

### 9.3.1 Tests with real wind turbines in real conditions

Although the UPWIND model is a real simulated model, it is not still a real wind turbine. Next step should consist of gathering data from a real operating wind turbine and use it to validate the methodology and confirm whether the results are as good as the ones presented in this thesis. The most difficult part in this area, apart from the natural challenge of going from laboratory conditions to the real world, is obtaining real data in damaged conditions.

### 9.3.2 EOC: finding the optimum number of clusters

This is a very important phase for a real implementation of solution. It could be possible to make as much as clusters possible, and the results are going to be good, but it wouldn't be the most efficient computationally speaking. The computation in the outer field is not going to be the best, so this could be taken into account, and a way to find the optimum number of clusters should be worked out.

### 9.3.3 Evaluation of different statistical methods

The damage detection method used in this work was the NullSpace damage detection method. In order to have a more secure damage detection system, it could be possible to implement different damage detection methods and integrate them in the methodology, in that way, the solution could have different Damage Indicators coming from different ways of calculating them.

### 9.3.4 Evaluation of preprocessing step with different damage detection methods

The preprocessing step presented on chapter 6, is a good way to find the optimum data that enters the damage detection block. This helps to have a solution that is more efficient computationally speaking. In this work, the results are obtained only by using the NullSpace damage detection method. It would be interesting to test the preprocessing solution with other damage detection algorithms and see if the results are still better than the RAW implementation of the algorithm.

### 9.3.5 Going up in different SHM levels

In this thesis, damage detection was the main topic. In Structural Health Monitoring, damage detection is the first level of tasks. Although in some applications (such as Wind Turbines) the industrial companies usually seek for a level 1 SHM system, going up in these SHM levels is a task that should be made in order to have a complete SHM system. A complete SHM system reduces costs and creates more secure structures than a level 1 SHM system.

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# Appendix A

# Appendix

## A.1 Publications

1. Zugasti E, Gonzalez A.G, Anduaga J, Arregui MA, and Martínez F, "Structural Damage detection in laboratory tower using Null Space Algorithm", *Proc. Smart'11 Saarbrucken* (2011), 79–86.
2. Gonzalez A.G, Zugasti E, Anduaga J, Arregui MA, and Martínez F, "Structural fault detection in a laboratory tower using an AR algorithm", Proc. Smart'11 Saarbrucken (2011), 69–78.
3. Zugasti E, Gonzalez A.G, Anduaga J, Arregui MA, and Martínez F, "NullSpace and AutoRegressive damage detection: a comparative study", *Smart Materials and Structures* (2012), 085010.
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## A.2 SHM Instrumentation and Software

The Laboratory where the tests were made is located in IK4-Ikerlan, in Mondragon, Basque Country. In this section the instrumentation and software that has been used and created in this thesis is presented.

### A.2.1 Transducers

**Triaxial accelerometers** are the most used type of accelerometers in this thesis. In this case general purpose accelerometers were used. PCB Piezoelectric 356A17 type accelerometers have the frequency range we are interested in (0.4 - 4000 Hz) and a sensitivity of $500\,{}^{\mathrm{mV}}/_{\mathrm{g}}$.

**Figure A.1.** *PCB356A17 Accelerometer*

**Uniaxial accelerometer** was used when a sensor fault had to be simulated. As the other accelerometers where triaxial, it was difficult to simulate one damaged sensor. The accelerometer used was a BK4507 accelerometer from Brüel&Kjaer. The frequency range is 0.3- 6000 Hz and a sensitivity of $100\,{}^{\mathrm{mV}}/_{\mathrm{g}}$.

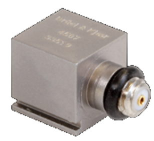
**Figure A.2.** *BK4507 Accelerometer*

**Electromagnetic shakers** convert electric signals into mechanical displacements. This was used as input excitation of the tower model. It is a permanent magnet shaker. LDS V406 is the model of the shaker, and it is able to give 89$N$ force when a random signal is applied. The working frequency range is 3-9,000 Hz.

**Figure A.3.** *LDS V406 shaker*

### A.2.2 Acquisition systems

**Oros-OR36** is a data acquisition system. it is a synthesis of components usually used separately for measurements: analyzer, recorder, conditioners in a single portable instrument. It has 16 inputs and 2 outputs. Thanks to its hard drive, the measurements can be stored in it without the need of a computer. The software it comes with, NVGate, is a great tool to do a first data analysis, thanks to the online FFT analysis tool.


**Figure A.4.** *Oros OR36 system*

**NI-Compact RIO** is a real-time embedded system for industrial control, manufactured by the American company National Instruments. For this work it has been used as a data acquisition system. Thanks to the features the system is able to offer, a remote data acquisition system has been built. It is able to store data in an internal FTP server and send them to a remote computer when it is asked to do it.


**Figure A.5.** *CRio system*

### A.2.3 Software

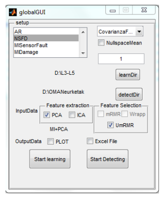

**Figure A.6.** *Matlab GUI*

**Matlab** has been used to implement all the methodology. Starting with Data Preprocessing, following with the Environmental and Operational Conditions compensation, damage detection method and sensor fault detection. A visual tool to use the methodology has been created, with all different possibilities.

**Labview** was used to create an online damage assessment solution. Thanks to the possibilities that the Compact RIO is able to offer, an online and remote damage detection platform was created. This platform is able to calculate the Damage Indicators while the system is taking data from the structure. It is based on two nodes; the first one is the Compact RIO, which takes the data, stores it and sends it to a remote PC. This remote PC is running a software that apart from configuring the Compact RIO remotely, is able to launch the damage detection method. It uses the program made in Matlab for this purpose.

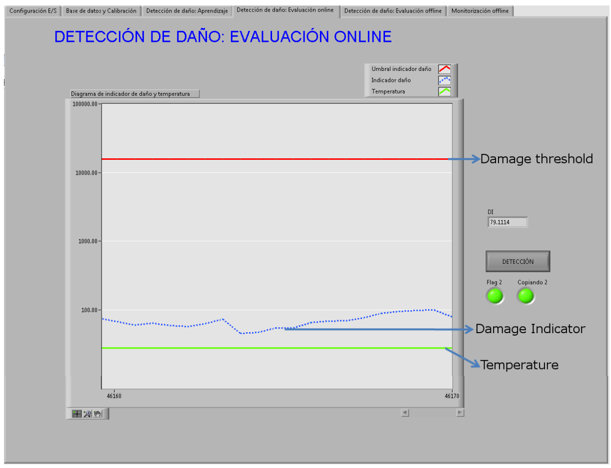


**Figure A.7.** *LabView User Interface*

**Bladed** is a industry standard integrated software package for the design and certification of onshore and offshore turbines. It provides users with a design tool that has been validated against measured data from a wide range of turbines and enables them to conduct the full range of performance and loading calculations. It is able to conduct multibody structural dynamics, and modeling a wind turbine in different scenarios.

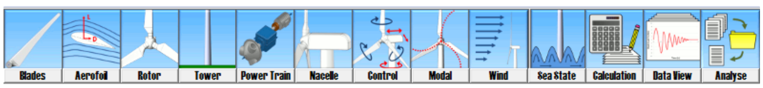


**Figure A.8.** *Bladed Definition and simulation header*

**FemTools** is a solver and platform independent Computer-Aided Engineering (CAE) software program providing advanced analysis and scripting solutions in the areas of: Structural static and dynamics simulation, Experimental modal analysis, Verification, validation and updating of FE models for structural analysis, Design optimization, Robust design.

### A.2.4 Remote Damage Detection system

Among the methodology, a online remote damage detection system was developed using the Compact RIO and LabView environment. This system is able to collect data independently in a remote area, and send them to a work station located somewhere else. Thanks to the 3G connection connected to the CRio, the device can be located anywhere with a 3G network coverage.

The device stores the structural data from the accelerometers in an internal hard drive, and it runs a File Transport Protocol (FTP) server among with a Virtual Private Network (VPN) server.

On the other side, the client PC is running a program that is able to connect to the CRio using the VPN network. Using the VPN network, the remote PC is connected to the FTP server and asks for the measurements. When the measurements are sent to the remote PC from the CRio, the damage detection method enters in the game. Depending on a flag, the dataset will be used for a learning phase, threshold detection phase, or damage evaluation phase. In Figure A.9 the schematic view of this system can be found.

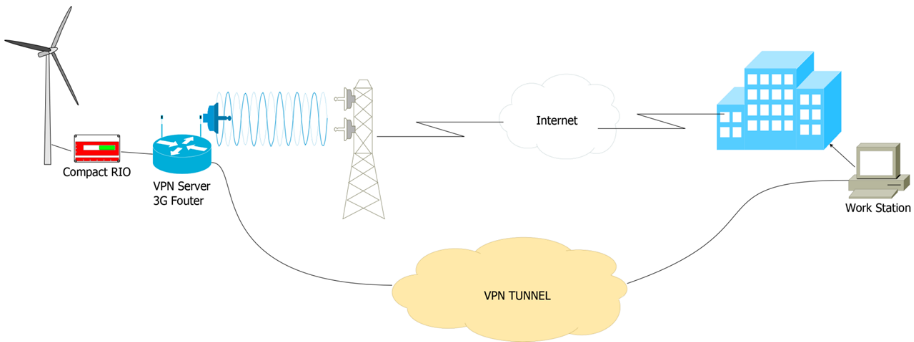


**Figure A.9.** *Remote SHM system*