NEW APPROACHES ON FAULT DETECTION AND DIAGNOSIS FOR STRUCTURES MANINTENANCE MANAGEMENT

by

CARLOS QUITERIO GÓMEZ MUÑOZ

Under the Direction of

Dr. Fausto Pedro García Márquez

A thesis submitted in partial fulfilment of the requirements for the Degree of

Doctor of Philosophy (International Doctor)

at the

University of Castilla-La Mancha
Ciudad Real
Spain

July, 2016
Outcomes

Researcher Profiles

- ![Google Scholar](https://scholar.google.es/citations?user=nslTQ7IAAAAJ&hl=es)
- ![ResearcherID](https://researcherid.com/): Carlos_Quiterio_Gomez_Munoz
- ![ORCID](https://orcid.org): 0000-0002-3506-5993
- ![ResearcherID](https://researcherid.com/): C-1339-2016

As part of this research, the following works and papers in journals and international conferences have been published:

Summary

- International Journals: 12 (3 JCR published)
- Patents: 3
- Books: 2 (100% internationals)
- Conference Papers: 9 (100% int.)
- Awards: 1
- Co-Dirección of Master Dissertation: 1
- Degree Projects' Co-Dirección: 6
- Publications: 26 (100% int.)
- Publications as 1st author: 16 (76%)
Outcomes

Journals

*Nomenclature: Authors Names. (Year). Title. Journal Details. [IF (impact factor), X/Y (Journal Position/Total number of journals into the Subject Category), Subject Category].*


2. **Gomez Muñoz, C. Q.**, De la Hermosa Gonzalez-Carrato, R., Trapero Arenas, J. R., & Garcia Márquez, F. P. (2014). A novel approach to fault detection and diagnosis on wind turbines. *Global Nest Journal, 16*(6), 1029-1037. [IF: 0.698, 177/210, Environmental Sciences]. (The contribution of the author to this paper has been: Design of experiments; Performance of experimental procedure and discussion of results.)


Manuscripts under review


Outcomes

Maintenance Management in Concentrate Solar Plants. Lecture Notes in Electrical Engineering (Springer). pp. 999-1008. [SCImago 0.12; Source Normalized Impact per Paper 0.122]

8. Segovia Ramirez, I.; Gómez Muñoz, C.Q.; García Márquez, F.P. A condition monitoring system for blades of wind turbine maintenance management. Lecture Notes in Electrical Engineering (Springer). In press. [SCImago 0.12; Source Normalized Impact per Paper 0.122]

9. Arcos Jimenez, A.; Gómez Muñoz, C.Q.; García Márquez, F.P.; Long, Z. Artificial intelligence for concentrated solar plant maintenance management. Lecture Notes in Electrical Engineering (Springer). In press. [SCImago 0.12; Source Normalized Impact per Paper 0.122]

Patents:


Outcomes

Books (International Chapters)


International conferences (full papers in proceedings)


Outcomes


**Award**


**Master dissertation**


**Co-direction of Master Dissertation**

Parrilla López-Brea, A., “*Estudio de un nuevo sistema de monitorización de palas de aerogeneradores mediante ensayos no destructivos*”. Director: Fausto Pedro García Márquez. Co-Director: **Carlos Quiterio Gómez Muñoz.** Nº: 15-4-325021. ETSII Ciudad Real. UCLM, October 2015.
Degree Projects’ co-direction


# Table of Contents

Acknowledgements .................................................................................................................. 3  
Outcomes .................................................................................................................................. 1  
Table of Contents ........................................................................................................................ IX  
Index of Figures ........................................................................................................................... 13  
Index of Tables ............................................................................................................................ 19  
List of Acronyms .......................................................................................................................... 21  
Summary ...................................................................................................................................... XXV  

1 Background ............................................................................................................................... 1  
   1.1 Wind turbines ..................................................................................................................... 1  
       1.1.1 Wind turbine blades ................................................................................................. 5  
       1.1.2 Icing blades problem ............................................................................................... 6  
       1.1.3 The mud and mosquito problem ............................................................................. 10  
   1.2 Concentrated solar Plants ................................................................................................. 11  

2 Non-Destructive Testing ............................................................................................................ 13  
   2.1 State of the Art ............................................................................................................... 13  
   2.2 Classification .................................................................................................................. 14  
   2.3 Guided Waves .................................................................................................................. 18  
       2.3.1 Structures with two surfaces like plates ................................................................. 18  
       2.3.2 Pipe type structure ............................................................................................... 19  
   2.4 Theoretical principles of the infrared thermography ....................................................... 21  

3 Condition Monitoring System ............................................................................................... 25  
   3.1 Introduction ..................................................................................................................... 25  
   3.2 Condition monitoring for Wind turbines ......................................................................... 25  
       3.2.1 Condition monitoring for icing blades detection employing guided waves ............. 26  
       3.2.2 Condition monitoring for icing blades detection employing an infrared radiometer .......................................................................................................................... 29
# Table of Contents

3.3 Condition monitoring for Concentrated Solar Power ..........33
3.3.1 Structural degradation mechanisms ..................................33
3.3.2 State-of-the-art of Non-Destructive Evaluation techniques for CSP plants ..............................................................36
3.3.3 Test RIG. ........................................................................41
3.3.4 Ultrasonic system ..............................................................45
3.3.5 A New Electromagnetic Acoustic Transducer for Condition Monitoring.............................................................46
4 Signal Processing and Pattern Recognition Approaches ..............49
4.1 Wavelet Transform ...............................................................49
4.2 ARX .................................................................................52
4.2.1 Models ............................................................................52
4.2.2 Methodology .....................................................................53
4.3 Auto-correlations ..................................................................55
4.3.1 Envelope and smooth .......................................................55
4.3.2 Correction method ...........................................................56
4.4 Defect Location ....................................................................57
4.4.1 Triangulation method .......................................................57
4.4.2 Paths convergence ...........................................................63
4.5 Damage sizing .......................................................................70
4.5.1 Size damage determination ...............................................71
4.5.2 Obtaining the attenuation curve ........................................73
4.6 Obtaining the attenuation curve of the reflected pulse ..............76
4.7 Determine the severity of the damage ......................................79
4.8 Neural Networks ..................................................................81
4.8.1 Feature extraction from ultrasonic signal ...............................81
4.8.2 Pattern Recognition by Neuronal Network (Multilayer Perceptron) ........................................................................82
5 Case Studies and Results ...........................................................87
5.1 Infrared Radiometer ................................................................87
5.1.1 Results and discussion ......................................................88
5.1.2 Conclusions .......................................................................92
5.2 Wavelet ..............................................................................93
5.2.1 Wavelet Transform in Wind Turbines for Ice Detection ......93
5.2.2 Wavelet Transform in Concentrated Solar Plants ...............102
5.3 ARX for SHM in Concentrated solar plants .........................109
5.3.1 Experimental results .......................................................109
5.3.2 Conclusions ................................................................. 113

5.4 Auto-correlations: Wind turbines: Fault detection employing guided waves.............................................................................. 113
   5.4.1 Properties of the employed wind turbine blade.................. 113
   5.4.2 Data analysis and signal processing.................................. 118
   5.4.3 Defect detection and location........................................... 120
   5.4.4 Results............................................................................ 122
   5.4.5 Conclusions................................................................. 125

5.5 Defect Location .................................................................. 126
   5.5.1 Wind turbines: Acoustic emission in wind turbine blades. 126
   5.5.2 Concentrated solar plants: Defect Location....................... 140

5.6 Edges location..................................................................... 141

5.7 Crack location..................................................................... 144

5.8 Damage sizing................................................................... 147
   5.8.1 CSP: Autocorrelations and Ratio curve for Damage Sizing. 147
   5.8.2 CSP: Damage sizing by analysing the attenuation curve.... 148

5.9 Neural Networks.................................................................. 150
   5.9.1 Wind turbines: Detection of mud in WT blades............... 150
   5.9.2 CSP: Pattern recognition for temperatures...................... 154

6 Big Data for Condition Monitoring............................................. 159
   6.1 Big Data for Wind turbines maintenance............................ 159
      6.1.1 State of art................................................................. 159
      6.1.2 Big Data in Structural Health Monitoring........................ 160
      6.1.3 Proposed methodology............................................... 163
      6.1.4 Big data and cloud computing...................................... 169
      6.1.5 Proposed Infrastructure............................................... 172
      6.1.6 Conclusions................................................................. 176

   6.2 Big Data for Concentrated Solar Plants............................... 176
      6.2.1 Cloud Computing for Concentrated Solar Power.......... 177
      6.2.2 Neural Networks Techniques and Fuzzy Logic Controllers. 183
      6.2.3 Case study: Results...................................................... 187
      6.2.4 Conclusions................................................................. 188

7 Conclusions......................................................................... 191

References .............................................................................. 193
Index of Figures

Figure 1.1 Annual installed wind power capacity in the world [17]. .................. 2
Figure 1.2 Offshore Service of Vestas-MHI [17]. .................................................. 3
Figure 1.3 Failure rates and downtime from two large surveys of European WTs over 13 years. ......................................................................................... 4
Figure 1.4. Illustration of icing blades. ................................................................. 7
Figure 1.5. Power losses due to different alarms in Icing Blades .................... 10
Figure 1.6 Accumulation of mud and mosquitos on a WT blade .................... 10
Figure 1.7. Growth in installed solar thermal power generation capacity of Spain (projects in operation). An astounding total of 14,231 MW in potential solar thermal projects is currently under consideration in Spain [45]. ....... 11
Figure 2.1. Propagation modes of Lamb waves (Symmetric and Antisymmetric) ............................................................................................. 19
Figure 2.2. Propagation of a Shear Horizontal wave in a plate ......................... 19
Figure 2.3. Lamb cylindrical waves. Flexural mode ........................................... 21
Figure 3.1 Icing detection system ...................................................................... 28
Figure 3.2. Thermal infrared radiometer, comprises a thermopile and a thermistor ................................................................. 29
Figure 3.3 Positioning the temperature sensor on the wind turbine blade ....... 31
Figure 3.4. Scheme of the experimental set up for ice detection by thermal infrared radiation .......................................................... 31
Figure 3.5 Data acquisition system ................................................................. 32
Figure 3.6 Schematic showing the design of the test rig ................................. 42
Figure 3.7 Test rig for CSP simulations ............................................................. 43
Figure 3.8 Detail of the junction of the collector tubes in the experimental platform (a) and in an actual concentrator solar installation (PSA) in Almeria, Spain ................................................................. 44
Figure 3.9 Laboratory for ultrasonic NDT in pipes........................................... 46
# Index of Figures

<table>
<thead>
<tr>
<th>Figure</th>
<th>Description</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>3.10</td>
<td>Picture of 1st generation EMAT transducers</td>
<td>47</td>
</tr>
<tr>
<td>3.11</td>
<td>EMAT transducers for CSP scheme</td>
<td>47</td>
</tr>
<tr>
<td>3.12</td>
<td>Principle of EMAT transmitter and receiver for longitudinal inspection</td>
<td>48</td>
</tr>
<tr>
<td>4.1</td>
<td>Wavelet decomposition structure</td>
<td>50</td>
</tr>
<tr>
<td>4.2</td>
<td>Wavelet Decompositions Levels</td>
<td>51</td>
</tr>
<tr>
<td>4.3</td>
<td>Decomposition detail five (D5), De-noised D5 and extracted residual noise</td>
<td>52</td>
</tr>
<tr>
<td>4.4</td>
<td>Location of Vertices A, B and C and the defect D</td>
<td>57</td>
</tr>
<tr>
<td>4.5</td>
<td>Wave front of the acoustic emission collected by the nearest Sensor C</td>
<td>58</td>
</tr>
<tr>
<td>4.6</td>
<td>Location of Point E, set by the delay between the excitation time in Sensors C and B</td>
<td>59</td>
</tr>
<tr>
<td>4.7</td>
<td>Scheme of the acoustic emission delays for locating the source</td>
<td>60</td>
</tr>
<tr>
<td>4.8</td>
<td>Initial conditions to locate the source of the acoustic emission</td>
<td>61</td>
</tr>
<tr>
<td>4.9</td>
<td>Identification of edges echoes algorithm</td>
<td>63</td>
</tr>
<tr>
<td>4.10</td>
<td>Smooth of the envelope using Wavelet low pass filter</td>
<td>64</td>
</tr>
<tr>
<td>4.11</td>
<td>Theoretical and experimental comparison for edges identification</td>
<td>64</td>
</tr>
<tr>
<td>4.12</td>
<td>Boundaries location using an algorithm which compares theoretical (cross) and experimental (triangle) values of ToF</td>
<td>66</td>
</tr>
<tr>
<td>4.13</td>
<td>Potential crack locations establishing relations between the two possible ways</td>
<td>67</td>
</tr>
<tr>
<td>4.14</td>
<td>Location of the crack by two methods: Comparison with &quot;as commissioned&quot; and location by convergence of different paths</td>
<td>67</td>
</tr>
<tr>
<td>4.15</td>
<td>Two shortest paths from Tx and Rx detecting the defect. The distance is given in centimeters</td>
<td>68</td>
</tr>
<tr>
<td>4.16</td>
<td>Reflections from the edges registered by sensor (Rx)</td>
<td>71</td>
</tr>
<tr>
<td>4.17</td>
<td>Algorithm scheme of identification of echoes from edges</td>
<td>72</td>
</tr>
<tr>
<td>4.18</td>
<td>Edges reflections of echoes</td>
<td>73</td>
</tr>
<tr>
<td>4.19</td>
<td>Attenuation curve of the forward path using two points</td>
<td>75</td>
</tr>
<tr>
<td>4.20</td>
<td>Attenuation curve of the forward path using Levenberg-Marquardt method</td>
<td>76</td>
</tr>
<tr>
<td>4.21</td>
<td>Time when the pulse is reflected from the crack and time when the echo is collected for the transducer</td>
<td>77</td>
</tr>
<tr>
<td>4.22</td>
<td>Displacement of the attenuation curve to adapt the behaviour of the ultrasonic pulse</td>
<td>78</td>
</tr>
<tr>
<td>4.23</td>
<td>Attenuation curve of an ultrasonic pulse that is reflected from a defect</td>
<td>79</td>
</tr>
<tr>
<td>4.24</td>
<td>Energy of an ultrasonic pulse before and after being reflected by a defect</td>
<td>80</td>
</tr>
</tbody>
</table>
## Index of Figures

<table>
<thead>
<tr>
<th>Figure</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Figure 4.25</td>
<td>Multilayer perceptron scheme, where the inputs are the AR parameters, and the outputs are the temperature.</td>
</tr>
<tr>
<td>Figure 4.26</td>
<td>Sigmoid activation function.</td>
</tr>
<tr>
<td>Figure 5.1</td>
<td>Wind turbine blade with aluminum foil set up.</td>
</tr>
<tr>
<td>Figure 5.2</td>
<td>Frozen wind turbine blade without icing (left) and with icing (right).</td>
</tr>
<tr>
<td>Figure 5.3</td>
<td>Radiometric temperatures measured by the IRT in both surfaces (white paint and aluminum foil).</td>
</tr>
<tr>
<td>Figure 5.4</td>
<td>Normalized sum of both temperatures (measured on white paint and aluminum foil on the blade).</td>
</tr>
<tr>
<td>Figure 5.5</td>
<td>Blade dimensions and sensors locations.</td>
</tr>
<tr>
<td>Figure 5.6</td>
<td>(a) Wind turbine blade at room temperature and; (b) frozen blade with ice on the surface.</td>
</tr>
<tr>
<td>Figure 5.7</td>
<td>Signal in sensor 1 at 30 kHz in the three different scenarios.</td>
</tr>
<tr>
<td>Figure 5.8</td>
<td>Signal in sensor 2 at 30 kHz in the three different scenarios.</td>
</tr>
<tr>
<td>Figure 5.9</td>
<td>Energy of each state and frequency received in sensor 1.</td>
</tr>
<tr>
<td>Figure 5.10</td>
<td>Energy of each state and frequency received in sensor 2.</td>
</tr>
<tr>
<td>Figure 5.11</td>
<td>Wavelet decompositions (Approximations and details), received by sensor 1.</td>
</tr>
<tr>
<td>Figure 5.12</td>
<td>Wavelet decompositions (Approximations and details), received by sensor 2.</td>
</tr>
<tr>
<td>Figure 5.13</td>
<td>Placement of the EMAT on austenitic steel plate.</td>
</tr>
<tr>
<td>Figure 5.14</td>
<td>Heater pad on the plate.</td>
</tr>
<tr>
<td>Figure 5.15</td>
<td>Signals obtained by the EMAT with the plate at 40 °C and 180 °C.</td>
</tr>
<tr>
<td>Figure 5.16</td>
<td>Percentage of signal information in each decomposition.</td>
</tr>
<tr>
<td>Figure 5.17</td>
<td>Energy of ultrasonic signals for each temperature.</td>
</tr>
<tr>
<td>Figure 5.18</td>
<td>Periodogram of the sensor 1 signal measurements.</td>
</tr>
<tr>
<td>Figure 5.19</td>
<td>Actuator pulse input (upper panel). Sensor 1 measurements (middle panel). Sensor 2 measurements (lower panel).</td>
</tr>
<tr>
<td>Figure 5.20</td>
<td>Cross-correlation graph between sensor 1 and sensor 2.</td>
</tr>
<tr>
<td>Figure 5.21</td>
<td>Actual values and predicted output with 100 steps ahead.</td>
</tr>
<tr>
<td>Figure 5.22</td>
<td>Wind turbine blades (damaged and undamaged).</td>
</tr>
<tr>
<td>Figure 5.23</td>
<td>Structural scheme of the wind turbine blade.</td>
</tr>
<tr>
<td>Figure 5.24</td>
<td>Layers configuration of the composite material. E-glass twill fiber (yellow) and E-glass biaxial fiber (grey).</td>
</tr>
<tr>
<td>Figure 5.25</td>
<td>Composite and honeycomb sandwich (left) and aluminum honeycomb structure (right).</td>
</tr>
<tr>
<td>Figure 5.26</td>
<td>Wind turbine blade scheme (mm). A, B and C areas are the disbonds between the honeycomb and the skin.</td>
</tr>
<tr>
<td>Figure 5.27</td>
<td>Scheme of the damages introduced in the manufacture process (mm).</td>
</tr>
</tbody>
</table>
Index of Figures

Figure 5.28 ultrasonic signals at different distances (50 kHz)............................................. 119
Figure 5.29 Received signals at 200 cm (green signal) and 210 (blue signal) cm from the tip of the blade.................................................................................................................. 120
Figure 5.30 Envelopes of the signals employing Hilbert Transform and........................................ 121
Figure 5.31 Autocorrelation of the signals at 200 cm (green signal) and 210 (blue signal) cm from the tip of the blade.................................................................................................................. 121
Figure 5.32 Ratio curve of the pair of signals at 200 cm and 210 cm............................................ 122
Figure 5.33 Maximum of the ratio curve for each pair of signals................................................ 125
Figure 5.34 Wind turbine section with sensors for acoustic emission location................................ 128
Figure 5.35 Wave front propagation from the acoustic emission source........................................ 129
Figure 5.36 Measuring the experimental propagation velocity in the composite material.......................... 130
Figure 5.37. Peak detection of the acoustical emission collected by Sensor 1 (blue) and Sensor 2 (green) to obtain the experimental propagation velocity in the composite material.................................................. 131
Figure 5.38. Pre-processing of the signal. Wave front collected by Sensors C (blue), B (green) and A (red)................................................................................................................................. 132
Figure 5.39. First experiment. Case Study 1...................................................................................... 133
Figure 5.40. Scheme for Case Study 2............................................................................................. 136
Figure 5.41. Scheme for Case Study 3............................................................................................. 137
Figure 5.42. Scheme for Case Study 4............................................................................................. 138
Figure 5.43. Scheme of the location of the acoustic emission for the first case study.......................... 139
Figure 5.44 Location of the crack in the pipe and location of the MFCs........................................... 141
Figure 5.45 Identification of edges echoes algorithm.......................................................................... 141
Figure 5.46 Edges reflections of L(0,2) mode by comparing the theoretical and experimental values of ToF......................................................................................................................... 143
Figure 5.47 Edges reflections of L(0,1) mode by comparing the theoretical and experimental values of ToF......................................................................................................................... 143
Figure 5.48 Two shortest paths from actuator to sensor detecting the crack...................................... 145
Figure 5.49 Echo coming from the crack via path a.......................................................................... 145
Figure 5.50 Crack location relative to the left edge in meters............................................................ 146
Figure 5.51 Ratio curve between the autocorrelations of each signal with the benchmark signal................................................................................................................................. 147
Figure 5.52 Actuator and sensor placement....................................................................................... 149
Figure 5.53 Process flow for determining the level of mud and dirt on the blade.................................. 151
Figure 5.54 Mud on the wind turbine blade section........................................................................... 152
Figure 5.55. Set of signals for level 1 of mud. Signals collected by the sensor for different frequencies................................................................................................................................. 152
Index of Figures

**Figure 5.56.** Neural network results for ultrasonic signals at 25 kHz (left) and signals at 18, 20, 25, 30, 40 and 50 kHz (right). ................................................................. 153

**Figure 5.57.** Error Histogram of the neural network 15-15-5 .................. 154

**Figure 5.58** Use of ultrasonic pulses for detecting the temperature of the test rig pipes. ............................................................................................................. 156

**Figure 5.59** Success rate of the AR employed ........................................ 157

**Figure 5.60** Success rate of the neural network to determine the temperature range............................................................................................................. 158

**Figure 6.1** Wind turbine condition monitoring for blade and tower ............. 163

**Figure 6.2:** Functional Schema of Signal Analysis ....................................... 164

**Figure 6.3:** Sensor location in a wind turbine blade .................................... 166

**Figure 6.4:** Crack delay signal simulations. The source is located by triangulation algorithms ................................................................. 167

**Figure 6.5:** Crack source location by triangulation algorithms .................. 168

**Figure 6.6:** Hierarchy of Service Models in Cloud Computing Industry ........ 170

**Figure 6.7:** Storage of the CSP power plants in Spain. The Spanish Association of Solar Thermal Power Industry (PROTERMOSOLAR) ................ 178

**Figure 6.8:** Flux data Scheme of the proposed processing data system based on Cloud Computing ................................................................. 181

**Figure 6.9** Proposed Cloud Computing platform to jointly analyse and control a group of CSP plants. The example shows the Spanish Association of Solar Thermal Power Industry (PROTERMOSOLAR) ................ 182

**Figure 6.10** Location of the crack in the pipe and location of the transducers ............................................................................................................. 187

**Figure 6.11** Clustering results ........................................................................ 188
# Index of Tables

<table>
<thead>
<tr>
<th>Table</th>
<th>Description</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Austenitic Stainless Steel Properties</td>
<td>45</td>
</tr>
<tr>
<td>2</td>
<td>Lists a series of emissivity values for common materials and natural surfaces in the spectral range 8-14 μm (ASTER spectral library)</td>
<td>88</td>
</tr>
<tr>
<td>3</td>
<td>Measured values of voltages registered by the sensor on a wind turbine surface and aluminium foil</td>
<td>90</td>
</tr>
<tr>
<td>4</td>
<td>Wavelet Decomposition of the received signal in the sensor 1</td>
<td>97</td>
</tr>
<tr>
<td>5</td>
<td>Physical properties of 316Ti steel and the influence of temperature</td>
<td>103</td>
</tr>
<tr>
<td>6</td>
<td>Wavelet Decompositions and Energy of the signals at different temperature</td>
<td>106</td>
</tr>
<tr>
<td>7</td>
<td>Laminated physical properties used in the wind turbine blades</td>
<td>115</td>
</tr>
<tr>
<td>8</td>
<td>Disbonds dimensions</td>
<td>117</td>
</tr>
<tr>
<td>9</td>
<td>Maximum discrepancy between signals</td>
<td>123</td>
</tr>
<tr>
<td>10</td>
<td>First case study: detection time; delay with C; delay; theoretical distance; experimental distance</td>
<td>133</td>
</tr>
<tr>
<td>11</td>
<td>Initial data of the first case study</td>
<td>133</td>
</tr>
<tr>
<td>12</td>
<td>Second case study: detection time; delay with C; delay; theoretical distance; experimental distance</td>
<td>134</td>
</tr>
<tr>
<td>13</td>
<td>Initial data of the second case study</td>
<td>134</td>
</tr>
<tr>
<td>14</td>
<td>Third case study: detection time; delay with C; delay; theoretical distance; experimental distance</td>
<td>134</td>
</tr>
<tr>
<td>15</td>
<td>Initial data of the third case study</td>
<td>134</td>
</tr>
<tr>
<td>16</td>
<td>Fourth case study: detection time; delay with C; delay; theoretical distance; experimental distance</td>
<td>135</td>
</tr>
<tr>
<td>17</td>
<td>Initial data of the fourth case study</td>
<td>135</td>
</tr>
<tr>
<td>18</td>
<td>Predicted damage by comparison of ratio curve with benchmark</td>
<td>148</td>
</tr>
<tr>
<td>19</td>
<td>Depths and relevance degree of each cut</td>
<td>149</td>
</tr>
</tbody>
</table>
Index of Tables

Table 20 Endogenous Data of the CSP plant...............................................................179
Table 21 Exogenous Data of the CSP plant...............................................................180
### List of Acronyms

<table>
<thead>
<tr>
<th>Acronym</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>Approximations</td>
</tr>
<tr>
<td>A0</td>
<td>Antisymmetric mode zero (Lamb wave)</td>
</tr>
<tr>
<td>ACFM</td>
<td>Alternating Current Field Measurement</td>
</tr>
<tr>
<td>AE</td>
<td>Acoustic Emission.</td>
</tr>
<tr>
<td>AIC</td>
<td>Akaike Information Criterion</td>
</tr>
<tr>
<td>AISI</td>
<td>American Iron and Steel Institute</td>
</tr>
<tr>
<td>ANN</td>
<td>Artificial Neural Network</td>
</tr>
<tr>
<td>ARX</td>
<td>Autoregressive exogenous.</td>
</tr>
<tr>
<td>ASTER</td>
<td>Advanced Spaceborne Thermal Emission and Reflection Radiometer</td>
</tr>
<tr>
<td>AV</td>
<td>Automated Vision</td>
</tr>
<tr>
<td>BMU</td>
<td>Best Matching Unit</td>
</tr>
<tr>
<td>CBM</td>
<td>Condition Based Maintenance.</td>
</tr>
<tr>
<td>CM</td>
<td>Condition Monitoring.</td>
</tr>
<tr>
<td>CMS</td>
<td>Condition Monitoring System.</td>
</tr>
<tr>
<td>CSP</td>
<td>Concentrated Solar Power</td>
</tr>
<tr>
<td>CWT</td>
<td>Continuous Wavelet Transform.</td>
</tr>
<tr>
<td>D</td>
<td>Details.</td>
</tr>
<tr>
<td>DIN</td>
<td>Deutsches Institut für Normung</td>
</tr>
</tbody>
</table>
## List of Acronyms

<table>
<thead>
<tr>
<th>Acronym</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>DSG</td>
<td>Direct Steam Generation</td>
</tr>
<tr>
<td>DWT</td>
<td>Discrete Wavelet Transform.</td>
</tr>
<tr>
<td>EC</td>
<td>Eddy Current</td>
</tr>
<tr>
<td>EMAT</td>
<td>Electromagnetic Acoustic Transducer</td>
</tr>
<tr>
<td>FDD</td>
<td>Fault Detection and Diagnosis.</td>
</tr>
<tr>
<td>FFT</td>
<td>Fast Fourier Transform.</td>
</tr>
<tr>
<td>FL</td>
<td>Fuzzy Logic</td>
</tr>
<tr>
<td>GA</td>
<td>Genetic Algorithms</td>
</tr>
<tr>
<td>GFRP</td>
<td>Glass Fiber-Reinforced Polymer</td>
</tr>
<tr>
<td>GWT</td>
<td>Guided Wave Testing.</td>
</tr>
<tr>
<td>IaaS</td>
<td>Infrastructure as a Service</td>
</tr>
<tr>
<td>IDE</td>
<td>Integrated Developing Environment</td>
</tr>
<tr>
<td>IoT</td>
<td>Internet of Things</td>
</tr>
<tr>
<td>IRT</td>
<td>Thermal Infrared Radiometer</td>
</tr>
<tr>
<td>LPI</td>
<td>Liquid Penetrant Inspection</td>
</tr>
<tr>
<td>LRUT</td>
<td>Long Range Ultrasonic Testing</td>
</tr>
<tr>
<td>MFC</td>
<td>Macro Fibre Composites.</td>
</tr>
<tr>
<td>MFL</td>
<td>Magnetic Flux Leakage</td>
</tr>
<tr>
<td>MLP</td>
<td>Multilayer Perceptron</td>
</tr>
<tr>
<td>MPI</td>
<td>Magnetic Particle Inspection</td>
</tr>
<tr>
<td>MSE</td>
<td>Mean Square Error</td>
</tr>
<tr>
<td>NDE</td>
<td>Non Destructive Evaluation</td>
</tr>
<tr>
<td>NDT</td>
<td>Non Destructive Test.</td>
</tr>
<tr>
<td>NN</td>
<td>Neural Network</td>
</tr>
<tr>
<td>O&amp;M</td>
<td>Operation and Maintenance</td>
</tr>
<tr>
<td>PaaS</td>
<td>Platform as a Service</td>
</tr>
<tr>
<td>PPM</td>
<td>Periodic Permanent Magnets</td>
</tr>
<tr>
<td>PTR</td>
<td>Parabolic Trough Receivers</td>
</tr>
<tr>
<td>PWT</td>
<td>Wavelet Packet Transforms</td>
</tr>
<tr>
<td>RAMS</td>
<td>Reliability, Availability, Maintainability and Safety.</td>
</tr>
</tbody>
</table>
List of Acronyms

<table>
<thead>
<tr>
<th>Acronym</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>RMSE</td>
<td>Root Mean Squared Error</td>
</tr>
<tr>
<td>S0</td>
<td>Symmetric mode zero (Lamb wave)</td>
</tr>
<tr>
<td>SaaS</td>
<td>Software as a Service</td>
</tr>
<tr>
<td>SCADA</td>
<td>Supervisory Control And Data Acquisition</td>
</tr>
<tr>
<td>SCC</td>
<td>Stress Corrosion Cracking</td>
</tr>
<tr>
<td>SH</td>
<td>Shear Horizontal (wave mode)</td>
</tr>
<tr>
<td>SHM</td>
<td>Structural Health Monitoring</td>
</tr>
<tr>
<td>SOFM</td>
<td>Self-Organizing Feature Maps</td>
</tr>
<tr>
<td>T(0,1)</td>
<td>Torsional mode</td>
</tr>
<tr>
<td>ToF</td>
<td>Time of Flight</td>
</tr>
<tr>
<td>UT</td>
<td>Ultrasonic Testing</td>
</tr>
<tr>
<td>VARMA</td>
<td>vector auto-regressive moving-average</td>
</tr>
<tr>
<td>VI</td>
<td>Visual Inspection</td>
</tr>
<tr>
<td>VLAN</td>
<td>Virtual Local Area Networks</td>
</tr>
<tr>
<td>VM</td>
<td>Virtual Machine</td>
</tr>
<tr>
<td>VPN</td>
<td>Virtual Private Networks</td>
</tr>
<tr>
<td>WECO</td>
<td>Wind Energy in Cold Climate</td>
</tr>
<tr>
<td>WT</td>
<td>Wind Turbine</td>
</tr>
</tbody>
</table>
Summary

The renewable energy industry is in a constant improvement in order to cover the current demands. Within the renewables energies, wind energy and concentrated solar power (CSP) are two of the fastest growing sources of renewable energy production.

Wind farms, in contrast to the conventional power plants, are exposed to the inclement and variability of weather. As a result of this variations, wind turbines are subjected to high mechanical loads, which require a high degree of maintenance to provide accost-effective power output and care the life cycle of the equipment [1-3]. Nowadays, the demand for wind energy continues raising at an exponential rate, due to the reduction in operating and maintenance costs and increasing reliability of wind turbines [4,5].

CSP is an alternative to onshore wind farms and photovoltaic which has received significant attention in recent years. Particularly, in southern countries, where the sunlight is and abundant resource. It is crucial to ensure that the solar receivers work properly to avoid failures, and to increase the reliability, availability, safety and maintainability.

Both renewable energies have some monitoring systems that allow to know the status of critical components, and to determine anomalous operating
Summary

situations. The power generation plants have incorporated a basic online monitoring control system. This system generally includes sensors for monitoring the machine parameters, such as temperature, speed, fluid levels, unbalance in the rotor, etc. [6]

The Condition Based Maintenance (CBM) is an advanced maintenance strategy based on monitoring data on the machine status. It can obtain measurements of condition monitoring of wind turbine or CSP components [7-10]. The main objective of CBM is to optimize maintenance activities and to reduce costs.

Non-Destructive Testing (NDT) is used in Structural Health Monitoring (SHM) systems for Fault Detection and Diagnosis (FDD). Within the CBM, some NDT techniques are used to prevent serious failures in critical components such as blades, gearbox, tower or receiver tubes. [11,12].

The techniques for condition monitoring employed in this work are based on the infrared radiometry and the ultrasonic guided waves. Infrared remote sensing techniques are based on the reception and analysis of the electromagnetic energy reflected or emitted by a surface. The Guided Waves are non-destructive techniques widely used for structural evaluation of plates or pipes.

The aim of this work is to develop new approaches for condition monitoring of wind turbines and concentrated solar plants based on infrared technology and guided waves.

**Keywords**

Maintenance management; Wind turbine; Concentrated solar power; Fault detection and diagnosis; Condition monitoring; Macro fiber composites; Guided Waves; Pattern recognition; Wavelet transform; Neural Networks.
1 Background

The challenge for the future is to get a cheap source of energy, non-polluting, renewable and accessible to all countries in the world, allowing to reduce dependence on fuels to households, industries and transportation. Current data on wind power and concentrated solar power place them as two of the main renewable energy sources globally. Its importance in the energy market is essential and all indicators are that this trend will continue in the near future.

This industry requires therefore of significant improvements in reliability, lifetime or availability that it is done by an efficient maintenance based on condition monitoring systems. Modern wind turbines need also an autonomous condition monitoring system because of the associated repair costs, especially for off-shore plants, where any repair actions can extend several weeks due to the difficult working conditions [13].

1.1 Wind turbines

Wind energy is nowadays being more competitive into the renewable energy sources [14]. Significant improvements in areas as reliability, lifetime and availability can be expected from efficient maintenance and repair strategies on the basis of condition monitoring systems (CMS). The new wind turbines
1. Background

require of CMS in order to reduce the maintenance and operations costs, especially in off-shore machines, where any corrective/preventive maintenance task can require several weeks due to the difficulties of the weather and sea conditions [15].

The evolution of wind energy over the past 15 years suggest that its importance will continue to grow in the future and will remain in a relevant position within renewable energy in the global energy scene [16].

The Figure 1.1 shows the annual installed wind power capacity in the world from 1997 to 2014.

![Annual installed wind power capacity in the world](image)

Figure 1.1 Annual installed wind power capacity in the world [17].

Wind Turbines (WT) are typically subject to high and varying loads, as well as extreme weather conditions. Consequently, the operational unavailability of Wind turbines reaches 3% of the lifetime of a Wind turbine. The operation and maintenance costs can account for 10%-20% of the total cost of energy for a wind farm, and it can reach 35% for a wind turbine at the end of life.

It is necessary a high degree of maintenance to provide a safe, cost-effective, and reliable power generation [18]. This is even more critical for offshore wind parks (Figure 1.2), where turbines cannot be reached during adverse weather conditions.
1. Background

Figure 1.2 Offshore Service of Vestas-MHI [17].

Condition monitoring (CM) is defined as the process of determining the condition of system [9,10,19]. The main propose of CM is to identify a significant change of this condition which is indicative of a developing fault. It is usually considered as part of a predictive maintenance strategy, in which maintenance actions, and therefore preventive maintenance tasks, are scheduled to prevent failure and avoid its consequences [12,20,21]. The objective is to extend the life cycle of the system analysed, and to avoid major failures, resulting in considerable cost and associated downtime reduction.

The 75% of the annual downtime in wind turbines is caused by only 15% of the failures [22]. It is more relevant to increase the condition monitoring in those parts that cause downtime bigger, not those having more failure rate [23].

The results published by Haln et al. [24] presents the average failure rate and average downtime per component. The Figure 1.3 shows the three groups
1. Background

that cause the more downtime, which are the blades, gearbox and drive train. Condition monitoring efforts should focus on these parts.

![Failure rates and downtime from two large surveys of European WTs over 13 years.](image)

Figure 1.3 Failure rates and downtime from two large surveys of European WTs over 13 years.

In the field of wind turbine, condition-monitoring is used to determine the optimum point between corrective and scheduled maintenance strategies [22,25,26]. Maintenance approaches in the wind turbine industry can be classified into three main groups:

- **Corrective maintenance:** The reaction is initiated after the failure occurs.

- **Preventive maintenance:** The operative period of a wind turbine is around 20 years [24,27] and most of the failures are predictable using time-based strategies.

- **Predictive maintenance.** This strategy is based on the condition of the wind turbine. By knowing the structural condition of the parts of the machine it is possible to detect defect in an early stage.
There are several non-destructive methods for SHM inspection for two wind turbine blades, such us the acoustic emission produced by a breakage of fiberglass [11,28,29] or conventional ultrasonic inspection [28,30-33].

1.1.1 Wind turbine blades.

Most existing blades are made with sandwich materials formed by composite skins and a core of lightweight materials and isotropic. The need to manufacture blades with a complicated geometry, low weight and adequate mechanical properties has driven the choice of these materials. One of the real highlight is its resistance to fatigue. Also these materials have low thermal expansion and low thermal conductivity.

A composite material is formed by long and straight fibers located within a matrix that surrounds and binds the fibers. Laminates are made by superimposed layers of fibers in the thickness direction. The material properties depend on orientation, stacking sequence and physical properties of these fibers. Sandwich structures are composed of two outer skins covering a material that is lightweight called core. The set results in a material of high rigidity and lightweight. The core is thick compared to the outer skins and it has a much lower density. The core function is to prevent relative movement of the skin.

Most manufacturers use blades with polymeric matrix composite. To lower prices while maintaining the structural properties being used fiberglass, e-glass being the most used. Epoxy resins are the most widely used thanks to its mechanical properties.

Another problem associated with the generation of wind energy is the icing blades.
1. Background

1.1.2 Icing blades problem.

Wind farms are located in areas with suitable wind characteristics, frequently prone to icing occurrence.

Icing blades have become an especially problem in regions where climatic conditions are prone to icing during almost all year. The ice affects to the aerodynamic efficiency increasing the surface roughness. It produces an imbalance of the rotor, which causes stress of both the blades and the drive train. The wind turbines require to be stopped until the de-icing, with a large loss production and costs.

A study conducted by IcingBlades research project [34] revealed that 517 wind turbines, with a total installed power output of 682 MW, failed to produce 18,966 MWh over a 29 month period solely due to ice on the blades in Spain, a country located in the Mediterranean Sea. This energy loss is practically equivalent to the sum of all major incidents: gear box replacement, generator replacement, etc.[35]. Extrapolating these figures to Spain, with more than 21,000 MW installed, this would be equivalent to a production loss of 550 GWh and, therefore, to some 45 million € every 29 months. The avoidance of these production losses would be equivalent to the consumption of 200,000 homes and a saving of 658,682 Ton of CO2.

Onshore wind farms are usually located in elevated areas in order to get the maximum wind velocity [36]. These locations are often exposed to freezing temperatures, i.e. it presents multiple problems due to the icing blades, leading to power generation losses and costs [37]. The WECO (Wind Energy in Cold Climate) project analysed the ice effects, energy generation and icing in wind turbines. It is estimated that 20% of the wind farms are installed in areas with high probability of icing [38].
1. Background

**Ice formation**

Parameters such as temperature, wind speed, relative humidity or air density, among others, condition the ice appearance (see Figure 1.4). A classification of different types of icing is presented in reference [39], discerning between in-cloud icing and precipitation and hoar frost. In-cloud icing appears when the atmospheric temperature is below 0ºC and the humidity is high. Super-cooled water droplets hit the surface of the structure and frozen at the time of impact. The major problem is the accumulation of different layers of this kind of ice.

Frost is the most common cause of ice appearance in wind turbines. It grows in all parts of the wind turbine but the onset occurs in the leading edge of the blades, owing the incident velocity [40].

![Figure 1.4. Illustration of icing blades.](image)

**Wind turbine phases during ice accretion**

Wind turbines do not operate properly when the ice accumulation is considerable and, consequently, the machines are necessary to stop. In the first stage, pre-icing, the wind turbine is working in optimal conditions. In a second stage, icing starts but the wind turbine can operate until it reaches
1. Background

the icing limit alarm. In the third stage, the ice accumulation continues and
the turbine needs to stop to prevent possible damages [41]. In the last stage,
post-icing, the turbine continues stopped until the ice is completing
removed.

The objective for the ice prevention or removal systems is the reduction of
the wind turbine downtimes. The mitigated wind turbines are those with a
system to deal with ice accretion. During the icing stage, the ice growth is
controlled by the system installed in order to avoid the alarm, reducing the
necessary downtimes to remove the ice from the turbine. When the
accumulation is significant, the alarm appears and the wind turbine is
stopped until the ice is removed. Downtimes are smaller than those in the
non-mitigated machines. During post-icing the wind turbine can operate
regularly [42].

**Icing and cold climate in wind turbines. Problems.**

The main problems due to icing blades can be summarised as [43]:

- *Power loss by the reduction of aerodynamic efficiency.* The presence of ice
  modifies the aerodynamics of the blades by increasing the coefficient of
  friction and making turbulences, vibrations and noise, as well as a
  reduction of revolutions.

- *Loads on turbines.* The icing on blades makes loads on the turbine. Icing
  causes an increasing of mass, drag coefficient, imbalance of the rotor and
  vibrations.

- *Influence in the lifetime of the components.* The fatigue due to loads
  reduces the life expectancy of the components of the wind turbine, e.g.
  blades, hub, gearbox, shafts, etc.

- *Increased noise generated by blades.* The drag coefficient of the blades
  increases due to icing blades.
1. Background

- **Changes in blade surfaces by ice accretion.** The frozen layer modifies the thickness of the boundary layer, and therefore the air transition characteristics on the blade.

- **Safety hazards.** A problem arises owing to that the ice fragments can break off of the blades and can impact against the ground or other objects.

- **Measurement errors.** During the icing process, the anemometers, temperature sensors and wind vanes are exposed to icing conditions, showing measurement errors higher than 40% [44].

Wind farms located in these areas present problems related to icing such as energy losses, mechanical failures, downtimes, problems to access for human resources, measurement errors or safety hazards among others (see Figure 1.5). An analysis carried out by the authors, as part of the research project *IcingBlades* [34], showed that 18966 MWh were lost over a period of 29 months as a sole consequence of blades icing up in a set of 517 wind turbines with a total installed power of 682 MW. This waste is practically equivalent to all the other major stoppages together (change of multiplier, turbine change, and so on). Extrapolating this to a national (Spanish State) level, with more than 21000 MW installed, this phenomenon would be equivalent to a loss larger than 550 GWh of power production and, thereby, to about 45 million € over every 29 months. Avoiding these production losses would be equivalent to the energy consumption of 200000 households and savings of 658682 tons of CO₂. Figure 1.5 shows the main causes of the production energy losses. Note that ice on blades is the principal one. These energy losses involve an increment of the operation and maintenance (O&M) costs.
1. Background

1.1.3 The mud and mosquito problem.

Often, the wind farms are in areas difficult to access, making it difficult to evaluate and clean the blades. The accumulation of dirt and mud on wind turbine blades represents a decrease in the performance of power generation. Stall on the blade is occurred due to changes in aerodynamic performance.
1.2 Concentrated solar Plants

Due to the continuous growth in electricity needs in the world, power production from renewable energy sources has been primarily used up to cover the energy demand. This need has caused significant growth and development of new Concentrated Solar Power. Figure 1.7 shows the growth of solar thermal power generation in Spain between 2007 and 2011.

Figure 1.7. Growth in installed solar thermal power generation capacity of Spain (projects in operation). An astounding total of 14,231 MW in potential solar thermal projects is currently under consideration in Spain [45].

Due to the continuous growth in electricity needs, power production from renewable energy sources has been primarily used up to cover the energy demand. CSP is an alternative to onshore wind farms and photovoltaic which has received significant attention in recent years particularly in southern countries.

The solar thermal energy industry is currently exhibiting rapid growth rates in an effort to meet the increasing environmental, societal and economic demands set for modern power generation production within the EU. The annual turnover of the European solar thermal power industry and its added
1. Background

Value was estimated to be 12 billion € for 2011 and it is expected that by 2020 the CSP market could be more than 55 billion €.

Solar thermal energy currently provides a small fraction (less than 0.2%) of the overall European electricity production. However, with the current growth trends exhibited the solar thermal energy industry is capable to supply more than 10% of the overall European power production by 2030, and over 25% by 2050. The solar thermal energy produced within Europe is expected to correspond to almost half of the solar thermal energy produced worldwide by 2020 [46,47]. Over the next decade the solar thermal industry is expected to experience almost double the annual growth rate of that of the wind energy industry [12], making it the strongest performer in the renewable energy market overall.

CSP requires to improve the operational and maintainability of this plants because a failure can halt production of an entire power plant [5,20,48]. A proper condition monitoring system [9] is necessary to analyse those critical elements of the plant, such as the absorber tubes and welds [12,26,49,50].
2 Non-Destructive Testing

2.1 State of the Art

Non-destructive testing has become an essential technique for the development of structure health monitoring systems. NDT use is increasing in many scientific and industrial fields, from wind energy production to the transportation of gases and liquids. The NDT progress depends on the continuous changes of the industry to suit the current scenarios. The benefits that these new techniques provide are related to the improvement of the product quality, public safety and especially the prevention of faults. The main consequence is the reduction of costs, since they can anticipate faults that involve both material and human losses to reduce the corrective/preventive maintenance tasks, and to increase the life cycle of the structure. Other advantages that they present are related to the forecasting analysis based on the data acquired in a real-time mode, as well as the establishment of FDD techniques.

Non-destructive testing are tests performed to detect materials for internal or surface discontinuities, or to determine properties of the same. It is also applied to view the properties of welds, parts and components or to determine the thickness of a material. The indications must be performed by qualified operators.
2. Non-Destructive Testing

Compared with the destructive testing, it provides less accurate data about the object to study but are usually less expensive because the part is not destroyed. The damage suffered by the piece is zero or almost zero and does not alter its physical, chemical, or mechanical dimensional properties.

**Application Areas:**

- **Quality control:** Are the tests performed to detect discontinuities, impurities and defects, characterization of materials and dimensional metrology.

- **Maintenance of facilities and equipment:** The purpose of these is to evaluate corrosion and deterioration caused by environmental agents, determining stresses, leak detection, etc.

- **Preservation and study of cultural heritage:** These tests look for defects and information about the structural state of historical monuments.

### 2.2 Classification

**Penetrating liquids**

It has a wide application. It is used to detect flaws or surface discontinuities on nonporous materials such as metals, glasses, ceramics ... it was introduced in the industry looking for an alternative method of magnetic particles, which requires materials with ferromagnetic characteristics.

It is acting on the principle of capillarity (ability of certain liquids to penetrate and be retained in the surface discontinuities). It depends on three properties: Wettability, surface tension and viscosity.

**Magnetic particles**
2. Non-Destructive Testing

It is used to detect cracks, surface or subsurface discontinuities in ferromagnetic materials. It is based on the physical principle of magnetism (attractiveness between metals).

This method involves to inspect the magnetized piece, then magnetic particles are applied subsequently and the results are studied according to the grouping of particles. Finally, the piece is demagnetized and cleaned.

**Eddy Current or Foucault**

It is based on the principle of electromagnetic driving. For that purpose, a AC generator is used. The generator is connected to a test coil that produces a magnetic field. If the coil is placed near a material which is electrically conductive, the field of the coil will induce an electric current in the material to be inspected. This current will produce a new magnetic field, which is called secondary field and will be proportional to the first field but opposite sign. As the induced current is alternating, whenever the current becomes zero, the secondary magnetic field will induce a new electric current in the coil. This occurs when the current changes phase.

**Industrial Radiography**

A body exposed to X- or Gamma rays absorbs energy in proportion to its thickness, density or configuration. This method involves bombarding an object with a beam of X or Gamma rays. Part of the radiation is absorbed by the object itself and the unabsorbed part is recorded by a printing plate. This is revealed displaying an image and it can be observed changes in tonality which are associated with changes in the material, like defects.

**Thermography**

When a material contains imperfections, they alter the rate of heat flow there around due to high temperature gradients and hot spots are formed. In this
2. Non-Destructive Testing

A coating which acts temperature is applied to the material surface. After the material is heated uniformly and then allowed to cool. The temperature around imperfections is higher than in other areas, so with the help of coating can be detected those points with different colour.

Among other applications with thermography they are: to detect faulty joints or delamination of layers that are part of composite materials.

**Acoustic Emission**

Acoustic Emission (AE) is a passive but dynamic Non-Destructive Evaluation (NDE) technique which is extensively used for SHM by the industry. The principle of AE is based on the detection of transient elastic waves emitted when the component under evaluation is loaded up to a sufficient level to cause damage growth. AE signals are high frequency events with very small magnitude. In order to detect AE signals very sensitive piezoelectric sensors are employed. The piezoelectric crystals convert the resulting displacement in the surface of the component to electric signals which are then suitably amplified using appropriate amplification.

AE signals can be generated from various sources including dislocation movement, plastic deformation, crack growth, corrosion, erosion, impact, friction and even phase transformation. In composite materials signals can arise from fibre deboning, delamination, matrix cracking and fibre failures. Depending on the type of damage evolution mechanism different wave types may appear. Crack growth in a metal will usually give rise to a burst type waveform. By analysing the different waveforms and other features of the AE signal it is possible to recognise the feature in the material that is giving rise to specific aspects of the recorded AE activity.

It is a method used to detect elastic waves occurring spontaneously. When a material is subjected to repetitive strain it is produced micro-cracks in the material releasing energy that is directed to the outside of the piece. This
energy is released as elastic wave that produces sound. Through sensors disposed on the surface it is possible to capture and record the sound. These sensors convert the mechanical energy of that sound into small electrical pulses that are often accompanied by amplifiers to record and analyse the signal more clearly.

**Ultrasonic Inspection**

Ultrasonic inspection is a non-destructive method where a set of mechanical high frequency waves (above 20 kHz) are applied to the material to be examined. These waves travel through the material, being reflected when it reaches the interface or a discontinuity. This beam is then analysed paying attention to three points:

- The Wave reflection on the interfaces
- The Transit time (Time of flight or ToF) of the ultrasound wave.
- The Attenuation of sound waves in the workpiece due to absorption and scattering within the workpiece.

Thus the presence, size and location of discontinuities is determined.

**Ultrasonic Inspection phased arrays**

Ultrasonic phased arrays consisting of several elements can increase the speed and accuracy of the inspection as well as remove some of the limitations related with the accessibility to the surface of the component since the interrogating beam can be scanned and steered in the direction of interest without having to move the probe itself. Furthermore, ultrasonic phased arrays can produce detailed C-scan images providing a useful visual record of the inspection. Two-dimensional images can be used to reconstruct three-dimensional images of the inspected component.
2. Non-Destructive Testing

2.3 Guided Waves

Inspection techniques using guided waves have gained popularity among structural monitoring techniques. This is due in large part to the drawbacks encountered in other non-destructive testing techniques, such as thermography and radiography. An example of one such drawback occurs when examining solar concentrator pipes. Thermography has a limited ability to identify internal defects if they are not outwardly manifested as temperature, and industrial radiography is dangerous for people who are close to the inspection site. Furthermore, the long range of the guided waves can inspect a greater distance than other techniques.

The inspection by guided waves consists of the excitation of an ultrasonic transducer, which generates ultrasonic waves that are propagated through the pipe [48]. The main advantage offered by this technique, compared with traditional ultrasonic methods, is the ability to inspect structures, such as plates or pipes, along several meters. This technique permits us to know the state of the pipe at a particular location. In some cases, hundreds of meters can be inspected without the relocation of the transducer. Novel methodologies in signal processing are being published [51], such as predictive analysis online, in order to be employed in structural health monitoring and ultrasonic waves. This waves can be generated in structures like plates or pipes.

2.3.1 Structures with two surfaces like plates.

In these structures Lamb waves and Shear Horizontal (SH) waves are generated. Lamb waves are guided waves propagating in plate or shell type structures. His interest has been growing for its ability to detect damage to these structures. In Lamb waves, energy is confined between the two surfaces and its attenuation is lower. Lamb waves are composed of two
different vibration modes (Figure 2.1), the symmetric and anti-symmetric modes (S0 and A0).

![Wave direction]

Figure 2.1. Propagation modes of Lamb waves (Symmetric and Antisymmetric) [52].

The SH waves, shown in the Figure 2.2, have a direction of propagation perpendicular to the particle movement direction. As Lamb waves, SH waves also have the symmetric modes or antisymmetric (SH0, SH1 ...). These waves are used to inspect plates are embedded, because hardly affected by external forces.

![Wave propagation]

Figure 2.2. Propagation of a Shear Horizontal wave in a plate.

### 2.3.2 Pipe type structure.

**Cylindrical Lamb waves**

Lamb waves are guided waves that propagate in thin plate structures or shell structures. The interest in using Lamb waves to identify structural damage
2. Non-Destructive Testing

has increased in recent years. Damage identification using Lamb waves is in an early stage of development compared with other techniques such as ultrasonic scanning. Lamb waves can also be generated in tubular structures such as in a pipe where thickness is much smaller compared to diameter. The propagation of Lamb waves in pipes is similar to those in thin plates with the addition of some peculiarities. Cylindrical Lamb wave’s modes are longitudinal, torsional and flexural, labelled with \( L \), \( T \) and \( F \) respectively. The cylindrical Lamb modes have two integers, \( L(n,m) \), \( T(n,m) \), and \( F(n,m) \), \((n,m=0,1\ldots)\). Specifically, \( n=0 \) indicates that the pipe is axially symmetric which is the case in most applications. The integer \( m \) indicates the mode number, in particular, \( L(0,1) \) propagates through the thickness of the pipe similar to the \( A_0 \) mode in flat plates, and \( L(0,2) \) mode propagates similar to the \( S_0 \) mode in plates. \( L(0,1) \) and \( L(0,2) \) are the most appropriate modes for damage identification because their axisymmetric properties facilitate the inspection along the circumference of the pipe.

- Longitudinal waves: This mode is very similar to the symmetric and antisymmetric modes which appear in plates

- Flexural waves: These modes are not symmetrical about the axis (Figure 2.3).

- Torsional waves: They are similar to the Shear Horizontal waves and are primarily used to inspect buried or embedded pipes, due to they suffer less attenuation. This mode has axial symmetry and the particles only have circumferential displacement.
2.4 Theoretical principles of the infrared thermography.

Infrared thermography is the technology that, using the physical principles described above, considers the use of optical-electronic devices to detect and measure the radiance emitted by a specific object or surface.

The beginning of the thermography can be attributed to the German astronomer Sir William Herschel, who conducted experiments with sunlight in 1800 [53]. Herschel discovered infrared radiation by passing sunlight through a prism and measuring the temperature in different colours obtained with sensitive mercury thermometer. Twenty years later, the German physical Thomas Seebeck discovered the thermoelectric effect [54], given the origin of the "thermomultiplier". Macedonio Melloni improved the thermomultiplier, creating the thermopile, a set of thermomultipliers in series, and concentrating the thermal radiation for detecting the body heat from a distance of 9 meters [55]. The thermography was used for non-military applications in the sixties in a variety of industrial applications [56,57], e.g. in the inspection of large electrical transmission and distribution systems, but the equipment employed were big, slow to data acquisition and
2. Non-Destructive Testing

with low resolution. Continuing advances in military applications in the seventies led to the first portable systems that could be used in industrial applications such as building diagnostics [58] and non-destructive testing of materials [59].

Remote sensing techniques are based on the reception and analysis of the electromagnetic energy reflected or emitted by a surface. Data collected by remote sensors can be used to retrieve features and parameters of the observed surface, without physical contact [60].

In the thermal infrared, the emitted energy is related to the kinetic temperature of the radiating body though the well-known Planck’s law (first assuming a perfect radiator or black body):

$$B_\lambda(T) = \frac{C_1}{\lambda^5(e^{C_2/\lambda T} - 1)}$$  \hspace{1cm} (1)

where $B$ is the spectral radiance (W m$^{-2}$ μm$^{-1}$), at wavelength $\lambda$ (μm), $C_1$ and $C_2$ are physical constants ($C_1=3.74 \times 10^8$, $C_2=1.439 \times 10^4$), and $T$ (K) represents the physical temperature of the object [61]. Thermal infrared is the region of the electromagnetic spectrum ranging between 3.0 and 100 μm. However, the spectral window 8-14 μm is traditionally used in remote sensing applications due to the low absorption of the water vapour and the neglected contribution of reflected sunlight in this range.

In practice, real objects are not ideal blackbodies and the radiance of a body at kinetic temperature $T$ is reduced by the emissivity ($\varepsilon_\lambda$) factor according to:

$$L_\lambda(T) = \varepsilon_\lambda B_\lambda(T)$$  \hspace{1cm} (2)

where $L$ is the emitted radiance. Emissivity depends on the substance and varies with wavelength, so that every single surface or body is characterized by its spectral signature.
This emissivity has an effect on the environmental radiance reflected by the surface and also measured by the remote sensor. According to the radiative transfer equation:

\[ L_\lambda(T_R) = \varepsilon_\lambda B_\lambda(T) + (1 - \varepsilon_\lambda)L_\lambda^d \]  

where \( T_R \) is the radiometric temperature corresponding the real temperature \( T \), and \( L^d \) is the down welling environmental radiance.
2. Non-Destructive Testing
3 Condition Monitoring System

3.1 Introduction

Condition monitoring is the process of determining the condition of system and its main propose is to identify changes between two states of the structure, damaged and undamaged. A change of its normal working condition is indicative of a developing fault. One application is in predictive maintenance, due to its ability to detect potential failures before they become fatal. The objective is to extend the life cycle of the system analysed, and to avoid major failures, resulting in considerable cost and associated downtime reduction. The goal is to extend the life cycle of the system analysed, avoiding fatal failures and resulting in a reduction of the cost and the downtime.

3.2 Condition monitoring for Wind turbines

Condition monitoring system has recently emerged as a new technique employed by the wind energy industry to improve the reliability, availability, maintainability and safety (RAMS) of the wind turbines reducing the O&M costs [14]. CMSs are installed in the wind turbine to monitor the state of the components by a set of sensors.
3. Condition Monitoring System

3.2.1 Condition monitoring for icing blades detection employing guided waves.

Traditional ice detection uses meteorological equipment that simply measures conditions for icing, but this does not detect ice on blades. It does not give operators enough information to take action such as shutting down the turbine to prevent damage.

Wind turbines should have a correct ice detection system to predict when the icing appears on the structure. Measurements are usually done on the nacelle, which generates false alarms when the ice volume varies radially and across the blade, or in a location into the wind farm. These measures are usually carried out in operating conditions providing overestimated values.

There are methods that detect certain parameters to find out the favourable conditions for the development of ice, e.g. the size of the droplets in suspension and the water concentration in the air, together with the temperature and wind speed. The main parameters that indicate the risk of freezing are the relative humidity and the air temperature.

Ice detection helps to increase the safety, reduce downtimes, increase reliability, availability and energy production, and decrease the costs associated with failures caused by icing blades. The ice detection techniques can be categorized as direct and indirect techniques as follow [13]:

Direct techniques are those in which the measurement of ice is carry out on the surfaces of the wind turbine analysed, being the most important:

- Measurement of the resonance frequency [13].
- Damping of ultrasonic waves [62].
- Measurement of amount of ice [63].
- Optical measurement techniques [64].
- Measurement of temperature change.
3. Condition Monitoring System

- Measurement of vibration damping of a diaphragm [65].
- Measurement of electrical properties.

The indirect techniques for ice detection include the data acquisition and comparison with historical data. This comparison is employed to determine the appearance of ice on the wind turbine. The most important indirect approaches are the following:

- Video monitoring.
- Measurement of noise [66].
- Difference in actual and expected power output.
- Comparison of heated and unheated anemometers.
- Dew point and air temperature.
- Change of the resonance frequency of the blade of a wind turbine.
- Prediction of ice and frost probability maps.
- Direct measurement of liquid water content and mean volume of raindrops.

Guided waves laboratory platform

The ultrasonic system used for ice detection (see Figure 3.1) consists of a data board able to acquire and generate signals at 4 MS/s. The channels are isolated and can work simultaneously in both differential and single ended mode. The platform is controlled by a computer, where experiments are programmed and the dataset are processed online. Firstly, the output signal is set and the experiment is defined. A signal is sent to the signal generator, then the signal is amplified by 50 using a high power amplifier in order to drive the piezoelectric transducer. Lamb waves are generated in blade section and the ultrasonic mechanic wave travel through the composite material. The ultrasonic wave is received by two ultrasonic transducer converting the mechanic waves in analogical electrical signals. This signals
3. Condition Monitoring System

are collected by the acquisition module and by an analogic digital converter is registered in the computer.

![Image of Icing detection system employing guided waves.](image)

Figure 3.1 Icing detection system employing guided waves.

This CMS are sensitive to the icing on the blade. The temperature affects the propagation velocity of the wave and ice build-up on the blade opposes the free movement of the particles in the surface [67].

The transducers used are macro-fiber composites (MFC). It is comprised of piezoceramic unidirectionally aligned fibers. The electrodes are interdigitated in a polyamide film, and are embedded in an adhesive polymer matrix composite. The use of MFC has become essential in different areas of research and development [68]. The main advantages of these sensors are the low cost, flexibility and adaptation to the. The MFC utilization is in SHM, but other applications are found, demonstrating the versatility of the composite, as in references [69], where it is shown applications where MFC was used for subsequent signal processing using wavelet transform.
3.2.2 Condition monitoring for icing blades detection employing an infrared radiometer.

This work presents a novel technique for operational icing detection based on thermal remote sensing. A thermal infrared sensor is used to measure the radiance emitted by the blade surface. The differences in terms of emissivity between ice and other materials allow the automatic and quick detection of ice formation by analysing the radiance values registered.

In this work, an Apogee SI-111 Thermal Infrared Radiometer (IRT) was used (Figure 3.2). This broad-band IRT derives the temperature by converting the thermal radiance within the range 8-14 µm, coming from the target defined by the circular field of view (22º), to electrical signals, with a response time of less than one second. The estimation error is 0.2 °C (calibrated temperature range from -30 to 65 °C). An anodized aluminium body and a radiation shield prevent the sensor from temperature changes of the sensor itself and reduce the noise in the measurements. It has a sensitivity of about 60µV per °C.

Figure 3.2. Thermal infrared radiometer, comprises a thermopile and a thermistor

This IRT has two analogy outputs, one gives the voltage from the thermopile radiation detector, which is proportional to the radiance received from the
3. Condition Monitoring System

target, and the other output gives the thermistor voltage, providing the temperature of the IRT body. The thermopile output is of the order of μV and requires a high measurement resolution in differential mode. The output voltage of the thermistor is measured in "single-ended" mode. This thermistor needs to be excited, and 2.5 V were applied.

An equation based on the Stefan-Boltzmann law is used to obtain the target temperature:

\[
T_R = \sqrt[4]{T_D^4 + m \cdot S_D + b} - 273.15
\]

where \(T_R\) is the radiometric target temperature (ºC), \(T_D\) is the detector temperature(K), \(S_D\) is the detector signal (mV), and "m" and "b" are the calibration parameters provided by the manufacturer. Note that \(T_R\) is not the kinetic temperature of the observed target, but the radiometric temperature. However, in this work we are not really interested in extracting absolute temperature values, since icing is not only determined by low temperatures as mentioned above. In the thermal infrared range, radiance from a surface comes from its first micrometres. Thus, the observed \(T_R\) temperature corresponds to the very thin layer on top of the blade. Emissivity of the white paint coverage of the blades does not differ significantly from ice emissivity. However, if a patch of some metallic material with a very low emissivity is used as a reference, a drastic change in \(T_R\) will be observed as soon as ice formation starts on it, according to equation (3).

The arrangement proposed for state inspection of the blade in actual working condition is showed in Figure 3.3:
3. Condition Monitoring System

Infrared Laboratory platform

The electronic device designed for this experiment consists of a datalogger provided with two acquisition modules and an infrared temperature sensor (see Figure 3.4). A piece of a wind turbine blade prototype was used in this work.

- NI cDAQ-9172: The NI cDAQ-9172 is an eight-slot NI CompactDAQ chassis that can hold up to eight C Series I/O modules (Figure 3.5). The chassis operates on 11 to 30 VDC and includes an AC/DC power
3. Condition Monitoring System

converter. The NI cDAQ-9172 is a USB 2.0-compliant device. The NI cDAQ-9172 has two 32-bit counter/timer chips built into the chassis. With a correlated digital I/O module installed in slot 5 or 6 of the chassis. Many devices can measure temperature, voltage, or bridge-based sensors. An NI CompactDAQ system can mix multiplexed voltage input signals and low-speed thermocouples.

Figure 3.5 Data acquisition system

- **NI-9211**: The NI 9211 thermocouple input module for use with NI CompactDAQ chassis includes a 24-bit delta-sigma analog-to-digital converter, anti-aliasing filters, open-thermocouple detection, and cold-junction compensation for high-accuracy thermocouple measurements. The NI 9211 features NIST-traceable calibration and a channel-to-earth ground double isolation barrier for safety, noise immunity, and high common-mode voltage range.

- **NI-9201**: The NI 9201 is a C Series module for 8-channel analog input at a maximum aggregate rate of 500 kS/s. The NI 9201 is protected from harmful voltage spikes of up to 2,300 Vrms. In addition to the absolute
3. Condition Monitoring System

protection from the isolation, the module features up to 100 V of overvoltage protection for errant signal connection or unexpected outputs to the individual channels.

3.3 Condition monitoring for Concentrated Solar Power.

The new technologies, communication systems and advances in mathematical models for signal processing aid in achieving that goal. The complexity of these devices causes a reduction of the RAMS and increases the maintenance costs due to the occurrence of non-monitored failures.

3.3.1 Structural degradation mechanisms.

The main CSP structural components, i.e. the solar absorber tubes, volumetric solar receivers and piping of coolant system are exposed to temperature and UV aging, thermomechanical fatigue, thermal shock, overheating, creep, hot corrosion, metal dusting, hydrogen embrittlement, and stress corrosion cracking.

Temperature and UV aging of the cermet coating is a common problem experienced in solar receivers used in CSP plants. Cermet coatings are generally designed to generally maintain their structural integrity as well as absorptivity and emissivity properties over the entire lifetime of the solar receiver under the design temperature range [11]. However, deviations in the operational temperature parameters due to temporary local overheating caused by variations in the flow of the working fluid as well as UV effects can have a detrimental effect on cermet coatings resulting in changes in the absorptivity and emissivity exhibited [11-13]. Furthermore, gradual
3. Condition Monitoring System

deterioration of the structural integrity of the cermet coating is possible particularly due to the continuous dilation and contraction of the substrate.

Thermomechanical fatigue of solar absorber tubes and CSP plant piping can be caused by turbulent mixing of hot and cold flow streams of the working fluid over time resulting in temperature variations across the tube or pipe wall [14]. Moreover, cyclic heating and cooling during normal operation can contribute further to the effect of thermomechanical fatigue of both the substrate metal as well as the cermet coating. Thermomechanical fatigue arises due to thermal expansion and contraction producing abnormal thermal stress loads on top of normal stresses associated with the flow of the working fluid. Thermomechanical fatigue can result in early initiation of thermal cracks followed by rapid propagation and subsequently final failure [15-17]. Plants based on Direct Steam Generation (DSG) are generally more prone to thermomechanical fatigue-related problems. Thermal shock can occur if rapid and significant changes occur in the temperature of the solar tubes or piping. Pressurised volumetric solar receivers may also exhibit thermomechanical fatigue and thermal shock. Although air pressures are relatively low (particularly in the case of open volumetric designs) the receiver is made of porous materials which can be fairly brittle. The presence of micro-cracks remaining after the complex manufacturing process of the honeycomb structure of the receivers can intensify the thermomechanical fatigue phenomenon. Furthermore, thermal shocks may also result in cracking. Accidental overheating can of course lead to damage of the volumetric solar receiver necessitating the replacement of the affected tiles.

Pitting and general corrosion of the solar receiver and insulated pipes is another common structural degradation mechanism. Solar absorber tubes and insulated pipes operating at a range of temperatures with repeated cycles may result in more aggressive forms of corrosion [18]. Corrosion and Stress Corrosion Cracking (SCC) can lead to sudden and catastrophic failure,
especially in DSG plants operating at high pressure [19-20]. Local pitting corrosion can cause initiation of stress corrosion cracking or result in small-scale leaks. Most stainless steel pipes are vulnerable to pitting corrosion and stress corrosion cracking [21].

Interrupted or poor flow of the working fluid can cause certain solar absorber tube sections to overheat [22]. This can lead to deterioration of the structural integrity of the cermet coating and its absorptivity and emissivity properties, accelerated creep damage, thermal oxidation, softening and stress rupture of the stainless steel tube. Obstruction of the working fluid can occur due to carbon (coke) or salt deposits on tube and pipe walls with time or due to corrosion debris travelling from the CSP pipework to the solar field. The solar absorber tubes have far smaller diameters than the rest of the pipelines of the CSP plant, Moreover, the pipework in CSP plants is not necessarily manufactured from the same steel grades and therefore pipes carrying working fluid to and from the solar field can experience different corrosion rates. Large corrosion debris particles can travel with the working fluid from the pipes to the solar field occasionally blocking the flow of working fluid and resulting in overheating. Overheating can result from the presence of carbon or salt deposits even if the flow of the working fluid is not obstructed by them. Carbon and salt deposits will form an insulating boundary between the working fluid and the tube wall causing gradual overheating and subsequently failure.

Metal dusting is a corrosion mechanism which affects stainless steels operating at temperatures between 300-850 °C under carbon-supersaturated gaseous environments [23-28]. Oil is currently the most common working fluid in CSP plants which operate between 300-400 °C. The use of oil as working fluid can result in carbon (coke) accumulating on tube and pipe sections. Metal dusting once it initiates will cause significant wall thickness reduction which can eventually result in failure.
3. Condition Monitoring System

Metal loss due to erosion can occur in CSP insulated pipes and solar absorbers due to internal-surface discontinuities or solid foreign objects lodged within tubes causing disturbance of the working fluid flow and increased turbulence leading to metal wasting. Erosion as a damage mechanism is of more significance to CSP plants using molten salts. However, in the case of oil-based CSP plants erosion can also influence the structural integrity of the solar absorbers tubes.

For most CSP plants, especially those using oil as working fluid, operational temperatures do not exceed 400°C under normal operational conditions. Hence, creep damage is not expected to be a problem unless local overheating is taking place. However, for CSP plants using molten salts or DSG as working fluids operating temperatures as high as 550 °C are possible. At this temperature creep damage becomes of importance. Thus, pipelines and solar absorber tubes will need to be evaluated for creep damage over time [30].

3.3.2 State-of-the-art of Non-Destructive Evaluation techniques for CSP plants.

The design of solar absorbers makes the inspection of the cermet coated stainless steel tube inside the evacuated borosilicate glass envelope very difficult with existing inspection techniques. Similarly, the inspection of insulated pipes widely used in CSP plants is very difficult unless insulation is removed.

Special inspection setups can be used to inspect the tubes and pipes without having direct contact with the surface of the component of interest. However, due to the significant lift-off involved in such inspection conditions, the maximum resolution achievable is fairly low and is only appropriate for the detection of defects of considerable size. In this section, the various
inspection techniques applicable for the non-destructive evaluation of key CSP structural components are shown.

3.3.2.1  **Visual Inspection (VI) including Automated Vision (AV).**
Visual Inspection (VI) of structural components in CSP plants can offer limited information for maintenance planning. The fact that there are several kilometres of tubes and insulated piping makes VI ineffective. Furthermore, only large visible defects can be detected using this technique. VI can help assess the amount of dust on the reflectors in order to determine cleaning requirements and restore solar ray reflectivity back to optimum levels.

3.3.2.2  **Liquid Penetrant Inspection (LPI).**
In the case of CSP plants the technique can be used to inspect welds of insulated pipes and storage tanks once the insulation has been removed as well as supporting structures of the heliostats or parabolic mirrors. The inspection is relatively fast but due to the large number of components to be inspected considerable time is required. Only surface-breaking defects are detectable with this technique.

3.3.2.3  **Magnetic Particle Inspection (MPI).**
Magnetic Particle Inspection (MPI) is another visual technique based on the use of ferrous particles which are sprayed over the surface of interest. As in LPI, MPI also requires cleaning of the surface of the component to be inspected, although it does not need to be as thorough. It should be noted that this technique is not appropriate for volumetric solar receivers due to the porous nature of the materials used as well as the absence of ferromagnetism.

3.3.2.4  **Magnetic Flux Leakage (MFL) Inspection**
Magnetic Flux Leakage (MFL) is an electromagnetic non technique applicable on ferrous materials only due to the requirement of magnetising the inspected component. The application of MFL in CSP plants is limited to
3. Condition Monitoring System

certain insulated ferrous pipelines, heat exchanger tubes and cold storage tanks. MFL is not suitable for inspecting absorber tubes or insulated piping manufactured of austenitic stainless steel alloy.

3.3.2.5 **Eddy Current (EC) Testing.**
In the case of volumetric solar receivers manufactured from a conductive porous material, in theory low frequency pulsed eddy current testing could be used to assess thermal ageing of the material giving potentially rise to some useful results.

3.3.2.6 **Alternating Current Field Measurement (ACFM).**
ACFM testing despite the similarity it has with eddy current inspection is not applicable for the inspection of volumetric solar receivers even if they are made of a conductive porous material.

3.3.2.7 **Radiographic inspection.**
Radiography is a particularly efficient NDE method for inspecting tubing, piping and storage tanks for the presence of corrosion and weld defects [56-59]. However, radiographic inspection requires access from both sides of the inspected component, is time consuming and inherently involves serious health and safety issues. However, it is possible to radiographically inspect components of interest where a defect is suspected or there is a risk of failure.

3.3.2.8 **Infrared (IR) Thermography.**
Inspection of CSP solar absorber tubes using infrared thermography can provide some insight regarding the overall condition of the solar field of the plant at least for identifying overheating. However, due to the presence of the glass envelope and cermet coating the use of infrared cameras is not straightforward and can be unreliable unless there is clear overheating in places. Due to the thickness of the volumetric solar receivers and their
3. Condition Monitoring System

porous nature, thermographic inspection would probably generate inconclusive results.

3.3.2.9 *Acoustic Emission (AE).*
In CSP plants AE can be used for SHM of storage tanks. High temperature AE sensors could be applied for the detection of corrosion debris flowing in the pipes and tubes and potentially for corrosion detection, crack initiation and propagation. Given the existing technical capabilities, it would be impossible to apply AE testing for the inspection or monitoring of volumetric solar receivers.

3.3.2.10 *Ultrasonic Testing (UT).*
In CSP plants UT can be applied for the evaluation of pipelines and storage tanks where the insulation has been removed for the presence of cracks and corrosion. Unfortunately, UT cannot be used for the evaluation of the solar absorber tubes due to lack of direct access on the surface of interest. It is highly unlikely due to the nature of volumetric solar receivers that UT techniques could be applied for their inspection due to the technical limitations that currently exist.

3.3.2.11 *Long Range Ultrasonic Testing (LRUT).*
Long Range Ultrasonic Testing (LRUT) is an inspection technique which can be used to evaluate long sections of welded pipes and tubes for the presence of large cracks and corrosion in a single inspection. The technique is particularly useful for the inspection of insulated or buried pipelines. The piezoelectric transducers can be fitted around the pipe using an inflatable ring within a small pipe length where the insulation has been removed. Thus there is no need to remove the insulation along the whole length of the pipe or excavate it if buried since only an area big enough to mount the transducer ring is required. The inflatable ring provides equal pressure on all transducers and assists ultrasonic coupling with the pipe inspected. The
3. Condition Monitoring System

number of transducers employed and ring size depend on the diameter of the pipe or the tube.

LRUT uses low operational frequencies in the range of 30-200 kHz to enable the interrogating ultrasonic waves emitted from the piezoelectric transducers to travel over a long distance with minimal attenuation. The interrogating waves are able to travel over several welds before the intensity of the signal drops below the detection threshold set. The piezoelectric transducers emit interrogating ultrasonic waves towards both directions from a single location. The technique has been reported to be capable of detecting several tens of metres in either direction in a single inspection. Piezoelectric transducers used in LRUT produce a large number of wave propagation modes travelling at different velocities. Thus, it is very important to use software which is capable of synchronising the different modes in order to produce meaningful results. Due to the low frequencies used the technique is sensitive to relatively large defects only, e.g. >5% wall thickness reduction or large transverse cracks that are able to reflect sufficient energy back to the transducers. Cracks running parallel to the direction of propagation of the ultrasonic waves are usually not detectable. In addition, LRUT inspection involves a considerably long dead zone. The dead zone is the area directly adjacent to the transducers from either direction. Since the wave front needs to become uniform in the first ~2 m of propagation due to the constructive and destructive interference of the wave fronts produced from each transducer the signal is too noisy and thus not usable. Any defects present within the dead zone will not be detectable and can interfere with the overall quality of the inspection. Another drawback in LRUT inspection is that due to the low frequencies used, interrogating waves will tend to leak in the surrounding insulation or ground reducing the signal to noise ratio and the maximum length which can be inspected in one go. If the pipe or tube is in operation during inspection, then the interrogating waves can leak in the working fluid decreasing further the signal to noise
ratio and subsequently the maximum resolution that can be attained becomes lower.

In CSP plants LRUT inspection can be used to assess insulated pipelines requiring insulation removal only in some locations. Furthermore, it can also be used to inspect solar absorber tubes provided that there are locations where the ring can be fitted. Unless the temperature of the tube or pipe to be inspected is below 100 °C then LRUT inspection can only be carried out during planned outages.

3.3.3 Test RIG.

A test rig has been designed and constructed in order to simulate the conditions of a PTR and/or LFR plant, and create similar temperature and thermo-mechanical fatigue conditions. The test rig consists of the following main components: oil heater, circulation pump, storage tank and control panel. The test rig consists of two 4m long stainless steel tube samples.

Description of Test Rig.

An experimental platform that simulates the concentrator solar plants operation has been designed and built. The purpose of the test rig is to allow non-destructive testing in a laboratory for the detection, localization and characterization of structural defects in pipes of CSP.

- Main features of Test Rig.

The test rig has been designed according to the main characteristics of the installations used in the CSP. It can be simulated for temperature conditions, cracks, welds faults, or flows. The main components of the test rig are:

- Special steel pipes and elbows designed for high temperature.
3. Condition Monitoring System

- Pumping and heating systems for working with different fluids: water or oil.

- Heating system

• Components

The schematic of the INTERSOLAR test rig is shown in Figure 3.6.

Figure 3.6 Schematic showing the design of the test rig

- Storage tank: A 120-liter storage tank is employed in order to store the thermal fluid when no tests are performed. The overall configuration allows the storage tank to be emptied by gravity. Filling and emptying is done through the available inlet and outlet valves.

- Heating system: An immersion thermostat digital control is used to provide heat to the fluid, for adjustable temperatures from ambient +5°C to 200°C. The thermostat has a circulation pump of 150 mbar supplying a flow of 5.6 l/min.

- Heating tank: The heating tank has a maximum volume of 30 liters and is made of stainless steel that is able to withstand high temperatures. The container is thermally insulated to prevent heat loss to the environment. It has an outlet valve connected to the feed pump, which allows the circulation of heated fluid to the pipe.
- Synthetic oil, Thermal fluid: Pirobloc HTF-BASIC is a fluid for heat transmission specially formulated from synthetic oils and additives. It can be heated up to a maximum of 330°C in a closed circuit. This oil has a high flammability point and an excellent resistance to oxidation. It provides a high service life under severe working conditions.

- Fluid pumping system: The fluid pumping system consists of an oil pump with adjustable flow, and a valve system that allows filling of the installation from the storage tank and continuous operation using only the heating tank.

- Thermal fluid circuit: The circuit along the thermal fluid is assembled from sections of austenitic stainless steel pipe Type 316 L, 3 mm thick. The sections are welded using TIG welding, which is one of the most common welding methods for this type of steel and widely used in thermal plants forms.

Figure 3.7 Test rig for CSP simulations
3. Condition Monitoring System

The test rig is compound by two sections of pipe, one for warming, which simulate the circuit portion that absorbs solar radiation in a CSP, and return section, being the tubes of austenitic stainless steel. The first section is where the ultrasonic waves are studied. The dimensions of the plant have been selected in order to reproduce at least two sections of solar collectors in actual installations, i.e. two 4.06 m tubes welded to a connector of the same type of steel. The connector space is used to support the pipe by metal arms attached to the pillars supporting the reflecting mirrors. This space is considered ideal to place the transmitter / receiver of ultrasonic waves.

![Figure 3.8](image1.jpg)  
(a) Detail of the junction of the collector tubes in the experimental platform (a) and in an actual concentrator solar installation (PSA) in Almeria, Spain.

The volume of thermal fluid in the pipe is 70 l. The test rig allows to study the influence of the welds on the transmission of ultrasonic waves, and the distance travelled by the waves over 8 meters.

The circuit which will travel the thermal fluid has a bleed valve to remove air bubbles in the oil return to the heating tank. The pipe is slightly tilted to prevent the formation of bubbles and to ensure complete emptying without pumping.
3. Condition Monitoring System

All pipes are thermally insulated to prevent heat loss with high density mineral wool blanket and 80 mm thick. The pipes are fixed to a metal frame with wheels that allow their displacement.

Table 1 Austenitic Stainless Steel Properties

<table>
<thead>
<tr>
<th>Type of steel</th>
<th>Austenitic stainless steel</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nomenclature</td>
<td>316l (AISI)</td>
</tr>
<tr>
<td></td>
<td>1.4404 (DIN)</td>
</tr>
<tr>
<td>Length</td>
<td>2m</td>
</tr>
<tr>
<td>Diameter</td>
<td>73mm</td>
</tr>
<tr>
<td>Thickness</td>
<td>3.05mm</td>
</tr>
<tr>
<td>Density</td>
<td>7.9 kg/dm³</td>
</tr>
<tr>
<td>Thermal Conductivity</td>
<td>15 W/m.K</td>
</tr>
<tr>
<td>Average thermal expansion coefficient</td>
<td>16e10⁻⁶</td>
</tr>
<tr>
<td>Electrical resistivity</td>
<td>0.75 Ω mm²/m</td>
</tr>
<tr>
<td>Magnetic permeability</td>
<td>1.005 a 0.8 kA/m DC or AC</td>
</tr>
<tr>
<td>Young longitudinal elastic modulus</td>
<td>200*10³ MPa</td>
</tr>
<tr>
<td>Poisson coefficient</td>
<td>0.3</td>
</tr>
</tbody>
</table>

3.3.4 Ultrasonic system

The platform (see Figure 3.9) consists of a device that is able to read and generate signals up to 4 MS/s. The device is connected to a PC for condition monitoring. The output signal from the device goes through an amplifier to drive the piezoelectric transducers. The high frequency amplifier is used to enhance the signal to noise ratio. Since the actuator is driven by the computer, different input signals can be generated as it will be shown later on.
3. Condition Monitoring System

The piezoelectric transducers used are MFC’s working as actuators and sensors. This type of elements has been successfully employed in wind turbine condition monitoring [14,70]

![Image](image.jpg)

Figure 3.9 Laboratory for ultrasonic NDT in pipes

3.3.5 A New Electromagnetic Acoustic Transducer for Condition Monitoring

The Electromagnetic Acoustic Transducer (EMAT) (Figure 3.10) is a transducer for non-contact sound generation and reception using electromagnetic mechanisms. It has been widely used in non-destructive testing in the generation of Shear and Lamb waves [71]. A new EMAT has been developed specifically for this purpose, with a specific configuration of coil and magnets.
3. Condition Monitoring System

Considering the dimension of the pipe (outer radius 35mm) and the review on EMAT configuration, a design of the EMAT transducer for this application is shown in Figure 3.11, using Periodic Permanent Magnets (PPM) and race track coil to generate SH0 mode in a plate or equivalent T(0,1) mode in a pipe. The dimension of each magnet is 15mm x 5mm x 5mm. The distance between magnets is 1mm. In addition, the magnetic strength of each magnet is 0.3T. The diameter of coil is 0.315mm and the width and length are 15mm and 35mm respectively with a lift-off distance 0.1mm to the sample.

Figure 3.11 EMAT transducers for CSP scheme
3. Condition Monitoring System

The type of EMAT configuration shown in Figure 3.11 is mainly to detect transversal defects (spiral cracking, blowout holes, circumferential cracking, bell splitting, etc.). In this case, Lorentz forces are generated normal to the tube wall, and so that the compressive forces produce ultrasound propagating along longitudinal direction through the tube/pipe for inspection.

![Figure 3.12 Principle of EMAT transmitter and receiver for longitudinal inspection](image)

Figure 3.12 Principle of EMAT transmitter and receiver for longitudinal inspection
4 Signal Processing and Pattern Recognition Approaches

4.1 Wavelet Transform

The approach for signal processing presented in this section is based on Wavelet transforms. It improves the limitations of resolution and the loss of information presented by the Short-Time Fourier Transform or the Fast Fourier Transform [72]. WT uses a variable window size, using large windows where it is required accuracy in low frequencies, and using small windows where the information is in the high frequencies. The resulting signal from low pass filter is the Approximations (A_i) (Figure 4.1), and the resulting signals from the high pass filter are the details (D_i) where “c” is the subsampling. For discrete signals it can be applied single-level or multi-level filters. The sum of the approximations and details should be given as a result the original signal.
WT are commonly categorized as continuous wavelet transforms (CWT), discrete wavelet transforms (DWT) or wavelet packet transforms (PWT), etc.[73]. The mother wavelet, which is given by the equation (5).

$$\psi_{s,\tau}(t) = \left(\frac{1}{\sqrt{s}}\right)\psi\left(\frac{t - \tau}{s}\right)$$  \hspace{1cm} (5)

where s is the scale factor, and \(\tau\) is the translational factor. The wavelet transform \(W_f(s,\tau)\) of a function \(f(t)\) is the decomposition of \(f(t)\) in a set of functions forming a base with the conjugate of the mother wavelet \((\psi^*s,\tau(t))\). It is defined by equation (6):

$$W_f(s,\tau) = \int f(t)\psi^*_{s,\tau}(t)dt$$  \hspace{1cm} (6)

The most recurrent families of wavelet transforms are Haar, Daubechies, Biortogonal, Coiflets, Morlet or Symlet transforms. The selection of a particular family can be set by the application where the wavelet is introduced.[74].

It was used a multi-signal analysis to study the three different cases together, and it is obtained the energy of each signal. It was also obtained the percentage of information of the decompositions in each signal. The Daubechies wavelet family were employed according to reference [75], where it is demonstrated that they are the most suitable for this type of signals because they are more sensitive to sudden changes. The number of
levels was set at seven, as this is the highest percentage of information contained. Figure 4.2 shows the seven levels of decompositions with their frequencies for the signals obtained in the experiments.

![Wavelet Decompositions Levels](image)

**Figure 4.2 Wavelet Decompositions Levels**

**Denoising filter**

The denoising of the signal is performed employing a multilevel 1-D wavelet analysis using Daubechies family. The wavelet decomposition structure of the signal to be de-noised is extracted. The threshold for the de-noising is obtained by a wavelet coefficients selection rule using a penalization method provided by Birgé-Massart. An overly aggressive filtering could eliminate data of interest, such as small echoes that come from defects. Figure 4.3 shows the original signal and the de-noised signal when it is applied the wavelet de-noised filter. In contrast to other digital filters, the Wavelet de-noising filter does not produce an unwanted signal delay.
4. Signal Processing and Pattern Recognition Approaches

It is observed that the filter removes noise significantly, and also does not eliminate information that is related to different structural features.

4.2 ARX

4.2.1 Models

ARX model is estimated to predict the output response for the baseline condition. This predicted output response can then be compared to the actual response measured during other experiments to determine whether a significant variation between both signals is present. In case that difference is important, the system is assumed to have changed in such a way that faults may be present [70].

Time series methods have been previously employed for failure prediction and detection. For instance, [76,77] utilize a VARMA (vector auto-regressive
moving-average) and harmonic regressions, respectively, for failure prediction in railway elements. Here, an ARX model is proposed to identify faults in wind turbines elements. Basically, an ARX model can be expressed by a linear difference equation (7):

\[ y_t + a_1 y_{t-1} + \cdots + a_{na} y_{t-na} = b_1 u_{t-nk} + \cdots + b_{nb} u_{t-nk-nb+1} + \epsilon_t \]

where AR refers to the autoregressive part and X to the extra input, sometimes called the exogenous variable. The parameters \( n_a \) and \( n_b \) are the orders of the ARX model, and \( n_k \) is the number of input samples that occur before the input affects the output, also called the delay in the system [78]. The variables \( y_t \) and \( u_t \) stand for the output and input responses, respectively. Model orders \( n_a, n_b \) and \( n_k \) have been chosen by minimizing the Akaike’s Information Criterion (AIC) [79]. Model selection and the estimation of the unknown parameters \( a_i, i=1,\ldots,n_a \) and \( b_j, j=1,\ldots,n_b \) have been done by means of the routines implemented in the MATLAB\textsuperscript{TM} System Identification toolbox [78].

### 4.2.2 Methodology

In order to detect potential faults, it is necessary to monitor a key variable, where changes of that variable are associated to a high fault probability. The procedure employed to detect such faults is described as follows:

**Selection of pulse frequency**

The inputs chosen to excite the system are white noise and Hanning pulses. The idea behind is to use white noise to excite the whole frequency bandwidth to investigate empirically which frequencies are better suited to carry out ultrasound tests. Here, a periodogram [80] of the resulting signals will be computed to determine which frequencies present resonant effects.
It should be considered that piezoelectric sensors have a high frequency limit, whose response is not reliable for frequencies that exceed that bound.

Therefore, once the working frequency has been chosen, the following experiments based on pulses will be set on the aforementioned frequency. Moreover, it is important to compute the dispersion curves to determine how many vibration modes are to be expected, as well as, their different associated group velocities.

**Delay estimation**

The delay between signals will be estimated by means of ARX models. Time series methods have been previously employed to failure prediction and detection. For instance, a VARMA [76] (vector auto-regressive moving-average) and harmonic regressions [77] have been employed, respectively, to failure prediction in railway elements.

where AR refers to the autoregressive part and X to the extra input, sometimes called the exogenous variable. The parameters \(n_a\) and \(n_b\) are the orders of the ARX model, and \(n_k\) is the number of input samples that occur before the input affects the output, also called the delay in the system. The variables \(y_t\) and \(u_t\) stand for the output and input responses, respectively. Model orders \(n_a\), \(n_b\) and \(n_k\) have been chosen by minimizing the Akaike's Information Criterion (AIC) [79], i.e.:

\[
AIC = 2k - 2\ln(L) \tag{8}
\]

where \(k\) is the number of parameters in the statistical model, and \(L\) is the maximized value of the likelihood function for the estimated model. The AIC includes a penalty for over fitting as a consequence of incorporating more parameters to the model in (7). To reduce the search space for potential
orders \((n_a, n_b, n_k)\) a cross-correlation [80] graph will be used, where the dimensionless cross-correlation coefficient at lag \(k\) is given by:

\[
\rho_{xy}(k) = \frac{\gamma_{xy}(k)}{\sigma_x \sigma_y}, \quad k = 0, \pm 1, \pm 2,
\]

(9)

Where \(\gamma_{xy}\) is the cross-covariance between the signal \(x\) and the signal \(y\) for \(k = 0, \pm 1, \pm 2, \ldots\) and \(\sigma_x\) is the standard deviation of signal \(x\).

Model selection and the estimation of the unknown parameters \(a_i, i = 1, \ldots, n_a\) and \(b_j, j = 1, \ldots, n_b\) have been done by means of the routines implemented in the MATLAB\textsuperscript{TM} System Identification toolbox [78].

### 4.3 Auto-correlations.

To perform the identification of the crack, it is necessary to adapt the signal using filters to remove noise. Other methods used are the Hilbert Transform and correction method.

#### 4.3.1 Envelope and smooth.

The Hilbert Transform is employed to obtain the envelope of the filtered signal. The Hilbert transform is an approach to study the energy distribution of a Lamb wave in the time domain [25]. It is useful to obtain the energy envelope, where local features can be extracted. It is necessary to smooth the envelope with the aim of finding events in the signal, which usually appear as peaks. An inadequate window size could produce distortions as “saw tooth” in the signal. A good result is achieved by again applying a Wavelet denoising filter and selecting the low frequency decompositions (approximations). This produces a smoothed function without significantly altering the signal.
4. Signal Processing and Pattern Recognition Approaches

4.3.2 Correction method.

Sometimes it is necessary to compare two states, ‘damage’ and ‘health’. To highlight the differences of a damage signal, a Lamb wave obtained is correlated with the benchmark signal [81]. Damage in the structure can thus be detected and quantified by pattern recognition considering as reference the healthy state.

$\lambda_{xy}$ is the correlation coefficient of two Lamb wave signals, $x_i$ and $y_i$. The length of the discrete signals is the same (N samples) [82,83]. The correlation coefficient is defined by equation (10).

$$
\lambda_{xy} = \frac{N \sum_{i=1}^{N} x_i y_i - \sum_{i=1}^{N} x_i \sum_{i=1}^{N} y_i}{\sqrt{N \sum_{i=1}^{N} x_i^2 - (\sum_{i=1}^{N} x_i)^2} \cdot \sqrt{N \sum_{i=1}^{N} y_i^2 - (\sum_{i=1}^{N} y_i)^2}}
$$

When the correlation coefficient reaches unity, this means that signal $x_i$ is very close to signal $y_i$. When a signal is correlated with itself it is called autocorrelation.

The pattern recognition approach is based on the autocorrelation of both signals, “benchmark” and “damage” signals. Then the autocorrelation of the signal with damage is divided by the autocorrelation of the benchmark signal in order to emphasize the differences and to obtain the ratio curve between them. The singularity contributed by the delamination-induced extra wave energy is more in the ratio curve, and its corresponding to the location of the damage.

The weakening of the boundary effect is another important advantage of this approach. The boundary reflections of the waves are produced regardless of the presence of damage, and these singularities do not appear in the ratio curve. The ratio curve is obtained by dividing the autocorrelations of two signals, to highlight the differences.
4.4 Defect Location

4.4.1 Triangulation method

This method has been developed to find the source of an acoustic emission in a plate employing three acoustic sensors. A graphical method is employed to obtain a system of non-linear equations that will be used for locating the emission source.

Three acoustic sensors A, B and C are placed as an equilateral triangle (see Figure 4.4). D is the location of the emission of the acoustic source.

![Figure 4.4](image)

Figure 4.4. Location of Vertices A, B and C and the defect D.

The nearest Sensor C is the first to be excited due to the wave front coming from the acoustic emission (Figure 4.5).
Figure 4.5 Wave front of the acoustic emission collected by the nearest Sensor C.

The delay between the excitation of the first Sensor C and the second closest Sensor B to the defect, D, is given by the distance from E to B (Figure 4.6). The delay time and the speed of the wave propagation on the blade is calculated by Equation (11):

\[ D_{EB} = v \times t_{CB} \]  

(11)

where \( D_{EB} \) is the distance between E and B, \( v \) is the propagation velocity of the wave (obtained experimentally) and \( t_{CB} \) is the time delay between the excitation of Sensors C and B.
Figure 4.6. Location of Point E, set by the delay between the excitation time in Sensors C and B.

The delay between Sensor C and Sensor A, the farthest one from Defect D, is given by the distance from F to A $D_{FA}$ in Equation (12).

$$D_{FA} = v \times t_{CA}$$  \hspace{1cm} (12)

where $t_{CA}$ is the time delay between the excitation of Sensor C and Sensor A. Figure 4.7 shows the scheme of the triangulation approach, the delay being represented by a circle.
4. Signal Processing and Pattern Recognition Approaches

In a real case study, Point D is unknown regarding the time and location, and the delays between the different sensors can be calculated. This condition is shown in Figure 4.8, where the circumferences represent the delays of the signal that comes to each sensor with respect to the first sensor (C).

Figure 4.7. Scheme of the acoustic emission delays for locating the source.
The objective is to find the source of the acoustic emission D mentioned above. This point is the center of a circle that is tangential to two given circles and passes through Point C (see Figure 4.7). The solution is obtained in this work employing a graphical method and an analytical method using a system of seven nonlinear equations.

### Triangulation Equations System

The seven nonlinear equations to solve this problem are given by Equations (3) to (9), considering the scheme shown in Figure 4.4, where the MFC sensors are located at Points A, B and C, and the defect is at Point D. The coordinates and radius are:

- $$x_c$$: x-coordinate at the top of the triangle.
- $$y_c$$: y-coordinate at the top of the triangle.
- $$x_a$$: x-coordinate at the left lower corner of the triangle.
- $$y_a$$: y-coordinate at the left lower corner of the triangle.
4. Signal Processing and Pattern Recognition Approaches

- \(x_b\): x-coordinate at the right lower corner of the triangle.
- \(y_b\): y-coordinate at the right lower corner of the triangle.
- \(r_a\): radius of the circle originated from A (delay of Sensor A).
- \(r_b\): radius of the circle originated from B (delay of Sensor B).

The data mentioned above are known. The unknown variables are \(x_1, x_2, x_3, x_4, x_5, x_6\) and \(x_7\) being:

- \(x_1\) and \(x_2\) the coordinates of the emission Source D.
- \(x_3\) and \(x_4\) the coordinates of the tangency of Point F.
- \(x_5\) and \(x_6\) the coordinates of the tangency of Point E.
- \(x_7\) is the radius of the circumference with the centre D.

The following equations define the method analytically.

Equation (13) considers a circle with the centre D and passing through C:

\[
F(1) = (x_c - x_1)^2 + (y_c - y_2)^2 - (x_7)^2
\]

Equation (14) represents a circle with the centre at D and passing through F:

\[
F(2) = (x_3 - x_1)^2 + (x_4 - x_2)^2 - (x_7)^2
\]

Equation (15) sets a circle with the centre at D and passing through E:

\[
F(3) = (x_5 - x_1)^2 + (x_6 - x_2)^2 - (x_7)^2
\]

Equation (16) represents a circle with the centre at A and passing through F:

\[
F(4) = (x_1 - x_a)^2 + (x_4 - y_a)^2 - r_a^2
\]

Equation (17) considers a circle with the centre at B and passing through E:

\[
F(5) = (x_5 - x_b)^2 + (x_6 - y_b)^2 - r_b^2
\]
4. Signal Processing and Pattern Recognition Approaches

\[ F(6) = \frac{(x_4 - y_a)}{(x_3 - x_a)} \times x_1 + \left( y_a - \frac{(x_4 - y_a)}{(x_3 - x_a)} \times x_a \right) - x_2 \]  \quad (18)

Equation (19) sets the straight line passing through Points B and E:

\[ F(7) = \frac{(y_b - x_6)}{(x_b - x_5)} \times x_1 + \left( y_b - \frac{(y_b - x_6)}{(x_b - x_5)} \times x_b \right) - x_2 \] \quad (19)

### 4.4.2 Paths convergence.

The approach identifies the events from the signals that are obtained from elements as boundaries or welds. This process consists of the following steps (see Figure 4.9):

- **Peak search**: It is important to select a proper threshold for this purpose.

- **Identify echoes from the edges**: The time of flight of each echo is obtained and compared with the distances of the sensor and actuator regard to the boundaries.

![Figure 4.9 Identification of edges echoes algorithm](image)

New Approaches on Fault Detection and Diagnosis for Structures  
Maintenance Management
4. Signal Processing and Pattern Recognition Approaches

Figure 4.10 Smooth of the envelope using Wavelet low pass filter

- Theoretical and experimental comparison for identification of the boundaries (Figure 4.11).

![Diagram](image)

Figure 4.11 Theoretical and experimental comparison for edges identification.

The vector $\mathbf{X}$ contains the position values of the peaks obtained experimentally, $\mathbf{Y}$ the height of the peaks of $\mathbf{X}$ of and $\mathbf{X}^*$ the position values of the peaks obtained theoretically.
4. Signal Processing and Pattern Recognition Approaches

\[ X = [x_1, \ldots, x_i, \ldots x_n] \]

\[ Y = [y_1, \ldots, y_i, \ldots y_n] \]

\[ X^* = [x_1^*, \ldots, x_j^*, \ldots x_m^*] \]

The matrix \( C \), given by equation (20) contains the absolute difference between each value of \( X \) and each value of \( X^* \)

\[
C = \begin{bmatrix}
|x_1 - x_1^*| & \cdots & |x_1 - x_j^*| & \cdots & |x_1 - x_m^*| \\
\vdots & \ddots & \vdots & \ddots & \vdots \\
|x_i - x_1^*| & \cdots & |x_i - x_j^*| & \cdots & |x_i - x_m^*| \\
\vdots & \ddots & \vdots & \ddots & \vdots \\
|x_n - x_1^*| & \cdots & |x_n - x_j^*| & \cdots & |x_n - x_m^*|
\end{bmatrix},
i = 1, \ldots n, \ j = 1, \ldots m \tag{20}
\]

The purpose of this approach is to select the real peaks having its homologous in the set of theoretical peaks. For each \( x_i \), the most similar value \( x_j^* \) is chosen if the difference between them is less than the tolerance \( \theta \), where an alarm could notice that the similitude has not been found. The minimum value of the components of each column \( C_j \) is given by a particular \( x_r \). \( X_{edges} \) is a subset of \( X \) that contains the minimum values of each column \( C_j \), i.e.:

\[ X_{edges} = [x_{edges_1}, \ldots, x_{edges_j}, \ldots, x_{edges_m}] \]

\[ x_{edges,j} = x_r, \ x_r \in X \ \forall \ r, j \ : \ c_{rj} = \min(C_j) \leftrightarrow c_{rj} < \theta, \ j = 1, 2 \ldots m \tag{21} \]

This method allows the determination of the absolute and relative error between the values obtained and expected for each event. The differences between the experimental and theoretical values are shown in Figure 4.12.
Figure 4.12 Boundaries location using an algorithm which compares theoretical (cross) and experimental (triangle) values of ToF.

The peaks that do not have their counterpart with the theoretical peaks are possible echoes that come from a defect \( \mathbf{X}_{\text{cracks}} \).

\[
\mathbf{X}_{\text{cracks}} \subseteq \mathbf{X} : \mathbf{X}_{\text{cracks}} \not\in \mathbf{X} \cap \mathbf{X}_{\text{edges}} \tag{22}
\]

\[
\mathbf{X}_{\text{cracks}} = \left[ x_{\text{cracks} 1}, \ldots, x_{\text{cracks} k}, \ldots, x_{\text{cracks} n-m} \right], \quad k = 1,2, \ldots n - m
\]

where the heights of \( \mathbf{X}_{\text{cracks}} \) are:

\[
\mathbf{Y}_{\text{cracks}} = \left[ y_{\text{cracks} 1}, \ldots, y_{\text{cracks} k}, \ldots, y_{\text{cracks} n-m} \right], \quad k = 1,2, \ldots n - m
\]

The potential crack detection and location (see Figure 4.13) is based on the echoes that are coming from the same crack, where they could come from different paths due to the EMAT generate forward and reverse shear waves.
4. Signal Processing and Pattern Recognition Approaches

Figure 4.13 Potential crack locations establishing relations between the two possible ways.

The algorithm considers that if the distance travelled is close, the defect is detected and therefore located. The scheme of this method is shown in Figure 4.14.

Figure 4.14 Location of the crack by two methods: Comparison with “as commissioned” and; location by convergence of different paths.
The pattern recognition approach is based on an automatic detection of cracks that compares the ToF employed by the same pulse to travel two different paths [21]. The two shortest paths for detecting a crack between the sensor and transmitter are the path “a” and path “b” shown in Figure 4.15. The distance travelled by an echo in the path “a”, for example $d_{echo_a}$, is used to determine the distance $d_{rc_a}$ between the crack and the receptor. Similarly, the distance travelled by an echo in the path “b” $d_{echo_b}$ is used to determine the distance $d_{rc_b}$. The distances $d_{rc_a}$ and $d_{rc_b}$ should be close. The method performs a comparison between the distances obtained for each component of $X_{cracks}$.

The paths are shown in Figure 4.15.

![Figure 4.15 Two shortest paths from Tx and Rx detecting the defect. The distance is given in centimeters.](image)

Path a:

\[
\begin{align*}
  d_{echo_{a,k}} &= dt_r + 2dr + 2d_{rc_{a,k}} \\
  d_{rc_{a,k}} &= \frac{d_{echo_{a,k}} - dt_r - 2dr}{2}
\end{align*}
\]
4. Signal Processing and Pattern Recognition Approaches

\[ \mathbf{D}_{rc_a} = [dr_{c,a,1}, \ldots, dr_{c,a,k}, \ldots, dr_{c,a,m-n}], k = 1, 2 \ldots n - m \]

Path b:

\[ d_{echo_{b,k}} = 3dtc + 2dt + dr_{c,b,k} \]  \hspace{1cm} (25)
\[ d_{tc} = dtr - dr_{c,b,k} \]  \hspace{1cm} (26)
\[ d_{echo_{b,k}} = 3(dtr - dr_{c,b,k}) + 2dt + dr \]  \hspace{1cm} (27)
\[ dr_{c,b,k} = \frac{3dtr + 2dt - d_{echo_{b,k}}}{2} \]  \hspace{1cm} (28)

\[ \mathbf{D}_{rc_b} = [dr_{c,b,1}, \ldots, dr_{c,b,k}, \ldots, dr_{c,b,m-n}], k = 1, 2 \ldots n - m \]

The distance \( dr_{c,a,k} \) is compared with all the echoes that come from the path 2 \( (dr_{c,b,k}) \). Therefore, the pair of echoes that provide the most similar distances \( dr_{c1} \) and \( dr_{c2} \) have the greatest likelihood to come from the same defect.

\[ \mathbf{D} = \begin{bmatrix}
|d_{rc,a,1} - d_{rc,b,1}| & \ldots & |d_{rc,a,1} - d_{rc,b,l}| & \ldots & |d_{rc,a,1} - d_{rc,b,n-m}| \\
\vdots & \ddots & \vdots & \ddots & \vdots \\
|d_{rc,a,k} - d_{rc,b,1}| & \ldots & |d_{rc,a,k} - d_{rc,b,l}| & \ldots & |d_{rc,a,k} - d_{rc,b,n-m}| \\
\vdots & \ddots & \vdots & \ddots & \vdots \\
|d_{rc,a,n-m} - d_{rc,b,1}| & \ldots & |d_{rc,a,n-m} - d_{rc,b,l}| & \ldots & |d_{rc,a,n-m} - d_{rc,b,n-m}| 
\end{bmatrix}, \quad (29) \]

where \( k = 1, 2, \ldots, n - m \) and \( l = 1, 2, \ldots, n - m \). In some cases could appear superposition between two echoes that came from paths a and b, and therefore they would present in the signal as a single peak. The main diagonal provides the solution for this cases. The component \( e_{crack.k,l} \) is the minimum difference between both paths, given by:

\[ e_{crack.k,l} = d_{kl}: \quad d_{kl} = \min(\mathbf{D}) \quad \leftrightarrow \quad d_{kl} < \tau, \quad \forall \ k, l. \]  \hspace{1cm} (30)

The solution to the problem of location is \( f_{crack.a} \), which is the distance of the crack from the sensor.

\[ f_{crack,a} = dr_{c,a,k}, \forall \ k : \quad d_{kl} = \min(\mathbf{D}) \quad \leftrightarrow \quad d_{kl} < \tau, \quad \forall \ k, l. \]  \hspace{1cm} (31)
4. Signal Processing and Pattern Recognition Approaches

For all other cases the main diagonal is not taken into account because it is assumed that there is no overlapping echoes. The difference between the $d_{rc_{a,k}}$ and $d_{rc_{b,l}}$ must be within the tolerance.

$$e_{crack} = d_{kl} : \quad d_{kl} = \min(D) : k \neq l \leftrightarrow D_{kl} < \tau, \forall k, l.$$  \hspace{1cm} (32)

$$f_{crack,a} = drc_{a,k} \forall k : \quad d_{kl} = \min(D) : k \neq l \leftrightarrow d_{kl} < \tau, \forall k, l.$$  \hspace{1cm} (33)

In some cases, there may be a need to consider the amplitude of each echo to perform the analysis. Theoretically an echo coming from a large transverse crack should have a greater amplitude than the echoes from smaller cracks, because more energy will be reflected.

The equation (34) weights the more similar distances with the amplitude of the two echoes of each path.

$$f^w_{crack,a} = drc_{a,k} \forall k : \quad d_{kl} = \min \left( \frac{|d_{rc_{a,k}} - d_{rc_{b,l}}|}{g(c_{k} + c_{l})} \right) : k \neq l, \forall k, l.$$  \hspace{1cm} (34)

In most cases the amplitude of the echoes is several orders of magnitude smaller than the ‘x’ axis.

The equation (35) shows a heuristic method gives more weight to the amplitude and corrects this problem.

$$f^w_{crack,a} = drc_{a,k} \forall k : \quad d_{kl} = \min \left( \frac{g|d_{rc_{a,k}} - d_{rc_{b,l}}|}{(c_{k} + c_{l})^{\theta}} \right) : k \neq l, \forall k, l, g$$  \hspace{1cm} (35)

4.5 Damage sizing

Damage sizing by the attenuation curve analysis.
4.5.1 Size damage determination

The approach presented in this work is based on comparing the energy of an ultrasonic pulse reflected from a crack with the attenuation curve of the pulse. Signal processing is performed in order to highlight important events in the collected signal, like reflected echoes from the edges. The applied signal processing consists of the Wavelet Transform and the Hilbert Transform. Wavelet Transform is used to decompose the signal into multiple levels according to different frequency ranges [73]. The Wavelet family employed for the signals has been Daubechies with seven levels of decompositions. The fifth detail decomposition “D5” contains more relevant information about the echoes and low signal noise ratio without delay regarding to the original signal.

The amount of energy of each echo can be quantified easily using a Hilbert Transform to generate the signal envelope [84]. The Hilbert transform is an approach to study the energy distribution of a Shear wave in the time domain.
4. Signal Processing and Pattern Recognition Approaches

[85,86]. It is necessary to smooth the envelope in order to avoid detecting false peaks in the signal, which usually is associated with an event.

The presented approach in this work identifies the events within the signals that are obtained from elements as boundaries or welds. The process shown in Figure 4.17 consists of the following steps:

- **Peak searching**: It is important to select the proper threshold for this purpose.
- **Identify the first event that indicates the instant when the actuator is excited.**
- **Identify the first pulse received by the sensors of each wave mode (direct pulses).**
- **Identify echoes from the edges**: The experimental Time of Fly (ToF) of each echo in the signal is obtained and compared with the theoretical ToF that they should have [87].
- **The ToF of each echo is identified to calculate the distances travelled.**
Figure 4.18 Edges reflections of echoes.

The numbers 1 through 5 in Figure 4.18 indicates the following:

1. The instant when the actuator is excited and emits the pulse.
2. The direct pulse, that is, the shorter distance between the actuator and the sensor.
3. The first reflection from the back edge.
4. The first reflection from the front edge.
5. The second reflection from the back edge.
6. The second reflection from the front edge.

4.5.2 Obtaining the attenuation curve

Attenuation is generally proportional to the square of sound frequency. There are two main attenuation mechanism: dispersion and absorption. Shear waves, are not dispersive. Absorption is produced by conversion of
4. Signal Processing and Pattern Recognition Approaches

mechanical energy in heat energy. Acoustic attenuation coefficient represents the amount of sonic attenuation per unit of length.

To determine the magnitude of the defect, it has been employed an approach that locate three events which come from the forward path. Attenuation often serves as a measurement tool that leads to the conclusion of the existence of a phenomenon that decreases the ultrasonic intensity.

In the case in which only two points of the curve are known, for example the amplitude of the direct pulse and the first forward reflection, the behaviour of the amplitude decreasing can be expressed as:

\[
P = P_0 e^{-\alpha d}
\]  

(36)

Where \(P_0\) is the amplitude of the signal in the direct pulse, \(P\) is the reduced amplitude after the wave has travelled a distance \(d\) (first reflection), and \(e\) is the Napier's constant. The quantity \(\alpha\) is the attenuation coefficient of the wave whose dimension are nepers/length.

Attenuation can be determined by evaluating the multiple backwall reflections seen in the signal.
The attenuation coefficient of the signal can be obtained as:

$$\alpha(\frac{N_p}{m}) = -\frac{\ln\left(\frac{P}{P_0}\right)}{d}$$  \hspace{1cm} (37)

The logarithmic unit Decibels is more common unit used to relating the amplitudes of two signals.

$$\alpha(\frac{dB}{m}) = -\frac{\ln\left(\frac{P}{P_0}\right)}{0.1151 * d}$$  \hspace{1cm} (38)

Equations (36)(37)(38) have been used to obtain the attenuation curve of this path [88]. When the crack is deeper, the echo coming from it has a higher amplitude. To assign an importance measure to the crack, the peak of the echo that comes from the crack is compared with the attenuation curve in this location. Since a total cut behaves similarly to an edge, the attenuation curve serves to provide a relevance percentage of each defect.

In the case in which three points of the curve are known, an attenuation curve can be generated more accurately. The Levenberg-Marquardt algorithm is employed for generating the attenuation curve. This method, also called the Damped least-squares method, generate the attenuation curve using three known points of the curve, which is the direct pulse, the first edge reflection and the second edge reflection, all the way forward. The equation (39) describes the behaviour of the curve:

$$S(\beta) = \sum_{i=1}^{m} [y_i - f(x_i, \beta)]^2$$  \hspace{1cm} (39)

where $x_i$ and $y_i$ are the location and amplitude of each point respectively and $\beta$ is the fitting parameter of the curve. The attenuation curve, see Figure 4.20,
4. Signal Processing and Pattern Recognition Approaches

drawn for this method shows the behaviour of the ultrasonic pulse traveling the forward way.

![Attenuation curve of the forward path using Levenberg-Marquardt method.]

Figure 4.20 Attenuation curve of the forward path using Levenberg-Marquardt method.

4.6 Obtaining the attenuation curve of the reflected pulse

In order to determine the relevance percentage of the defect, it is necessary to obtain two attenuation curves. The attenuation curve belonging to the pulse emitted directly by the transducer, and the attenuation curve belongs to the portion of the pulse that has been reflected due to the defect.

The identification of the echo from the crack provides the time when it is registered by the sensor \( t_{echo} \), and the height thereof \( h_{echo} \).
4. Signal Processing and Pattern Recognition Approaches

Figure 4.21 Time when the pulse is reflected from the crack and time when the echo is collected for the transducer.

In the previous section it was located exactly the crack position, and the distance from sensor is $d_{crack-sensor}$. The instant when the pulse passes through the crack ($t_{crack}$) can be determined as:

$$t_{crack} = t_{echo} = \frac{2 \cdot d_{crack-sensor}}{v} \quad (40)$$

Right at that moment, part of the energy of the ultrasonic wave through the defect and other portion of the energy is reflected. The echo has a smaller amplitude and it is necessary to adapt its attenuation curve. Echo height is sought in the attenuation curve obtained previously. The instant $t_{echo}'$ in which the attenuation curve has a height equal to the echo of the defect is defined as:

$$t_{echo}' = \frac{\ln\left(\frac{P_0}{h_{echo}}\right)}{v \cdot \alpha} \quad (41)$$
The echo attenuation curve is shifted to the instant when the pulse is crossing the crack. The curve after $t_{crack}'$ is shifted until the instant $t_{crack}$. The displacement of the curve is given by:

$$\Delta t_{curve} = t_{echo}' - t_{echo}$$  \hspace{1cm} (42)

Finally, the curve representing the behaviour of the ultrasonic pulse before and after of the crack reflection is shown in Figure 4.23.
4. Signal Processing and Pattern Recognition Approaches

Figure 4.23 Attenuation curve of an ultrasonic pulse that is reflected from a defect.

It can be expressed as a function piecewise:

\[
P = \begin{cases} 
P_0 \cdot e^{-\alpha v t}, & 0 \leq t < t_{crack} \\
P_0 \cdot e^{-\alpha v t} - \Delta t_{curve}, & t_{crack} \leq t < \infty 
\end{cases}
\]  
(43)

4.7 Determine the severity of the damage.

The degree of importance is analysed as a function of the position and height of the reflected echo from the defect. The attenuation curve establishes the amplitude of the echo along a distance and serves as a reference to compare the energy of a reflected echo.

The Figure 4.24 shows the portion of energy of an ultrasonic pulse that is transmitted when it crosses a defect, and the energy that is reflected from the defect.
The importance of the defect can be established relating the energy is transmitted to the energy that is reflected. This method allows to obtain an approximate percentage of the severity of the default, but there are other factors that can affect the results, such as the direction of the crack. The percentage of the severity of the damage can be expressed as:

\[
Relevance\ degree = \frac{E_{reflected}}{E_{reflected} + E_{transmitted}}
\]  \hspace{1cm} (44)

where \( E_{reflected} \) is the reflected energy from the crack, \( E_{transmitted} \) is the transmitted energy that cross the default and the \textit{Relevance degree} is the estimated percentage of the severity of the damage.
4. Signal Processing and Pattern Recognition Approaches

4.8 Neural Networks

4.8.1 Feature extraction from ultrasonic signal

110 signals are obtained for each temperature measurement and each signal contains 2000 samples. If each sample is considered an input of the neuronal network, in this case, to have a large number of inputs, would generate a high number of learning patterns and therefore, the error would be significant. Otherwise, it would be producing an overlearning network, which degrades the generalization ability of the neuronal network. This is called the *curse of dimensionality*, [89-91].

It is necessary to use a technique that allows reducing the number of inputs while maintaining the characteristic signal information. The characteristic coefficients of each ultrasonic signal were extracted by using the autoregressive model AR, by employing the Yule-Walker equations [92].

The ultrasonic signals provide different parameters, such as waveform, peaks, energy, amplitude, etc., that are used for pattern recognition. The knowledge in this field aids to select such parameters. The results obtained have been verified with trial and error.

Different classical approaches have been employed in order to achieve adequate results for neural networks, e.g. time domain (time of flight of the ultrasonic echoes of the signal, maximum amplitude, peak position, rise time and descent time, energy, etc.) or frequency domain (arithmetic mean, mode, standard deviation or variance). However, the outcomes of these methods are not accurate enough.

The autoregressive method of Yule-Walker is an example of parametric approaches. They calculate the power spectral density estimating the linear coefficients of a hypothetical system that generates the first signal. These...
methods tend to produce better results than conventional techniques, when the length of the available signal is relatively short.

In the spectral analysis used in this document a parametric estimator based on the model used Yule-Walker.

### 4.8.2 Pattern Recognition by Neuronal Network (Multilayer Perceptron).

For pattern recognition has been used a Neural Network Unidirectional supervised through a Multilayer Perceptron (MLP) with training by backpropagation algorithm [93]. The inputs of the NN are the AR coefficients of the ultrasonic signal and the outputs are the temperature ranges of the experiments. It has been established 11 ranges between 25°C and 55°C, whereby each range comprises 2.7 °C.

The structure is three layers of processing units (Figure 4.25) and mathematically expressed by:

![Multilayer perceptron scheme](image)

Figure 4.25 Multilayer perceptron scheme, where the inputs are the AR parameters, and the outputs are the temperature.

The equation 1 is the general equation of the neuronal network,
4. Signal Processing and Pattern Recognition Approaches

\[ z_k = \sum_j w'_{kj} y_j - \theta'_j = \sum_j w'_{kj} f \left( \sum_i w_{ji} x_i - \theta_j \right) - \theta'_j \]  

where:

- \( x_i \): Input neural network.
- \( x_i \): Output of the hidden layer.
- \( z_i \): Output final layer.
- \( t_k \): Output targets.
- \( w_{ji} \): Weight hidden layer.
- \( w'_{kj} \): Weight final layer.
- \( \theta_j \): Bias hidden layer.
- \( \theta'_k \): Bias final layer.

And the chosen activation function of the neuronal network is the sigmoid function. The sigmoid function is shown in equation 2, and plotted in Figure 4.26.

\[ f(x) = \frac{1}{1 + e^{-x}} \]
Figure 4.26 Sigmoid activation function.

The steps used to achieve the results with the neuronal network are described.

**Set of samples**

As mentioned in the previous section, in the input of the neuronal network is introduced the extracted characteristics of the signal. The architecture of the neuronal network, and the configuration of the hidden layer, depending on the structure of the input data. In this work it has been tested the following input parameter of the signal: AR (2), AR (5), AR (10), AR (15) and AR (20).

**Extraction of the training set, test and validation**

Samples the set of signals we performed in order to generalize the network (cross validation) apart in sets:

Training: 70%; Validation: 15%; Test: 15%

On the other hand, it was selected another set of signals (15%) to perform a check on the external network to test modes.
Architecture design of multilayer Perceptron

It has been designed a neural network with one hidden layer because it has been found empirically that networks with multiple hidden layers are more prone to getting caught in undesirable local minima. Therefore, we have proceeded to use with a single hidden layer.

It has tested different neural network architectures based on patterns obtained in the experimental phase. First it was tested with a Multilayer Perceptron 05/02/11 (first layer with two input neurons, hidden layer with five neurons and output layer of 11 neurons). Later we were increasing the number of inputs, the number of hidden neurons, to achieve the desired objectives.

Learning process

Backpropagation is one of the simplest and most general methods for supervised training of multilayer neural networks. Other methods may be faster or have other desirable properties, but few are more instructive.

We have used two training modes backpropagation algorithm:

1º Gradient descent with momentum and adaptive learning rate backpropagation and performance Mean Square Error (MSE) [94,95].

2º Scaled conjugate gradient and performance Cross Entropy [96,97].

In the second case we obtained best results with higher performance.

We have used a second-order analysis of the error in order to determine the optimal rate of learning through algorithm conjugate gradient based on performing gradient descent using also information provided by the rate of change of slope. It is the second derivative of the error:
4. Signal Processing and Pattern Recognition Approaches

\[ H = \frac{\partial^2 E(W)}{\partial w_{ij} \partial w_{kl}} \ (\text{Hessian matrix}) \] (47)

This algorithm uses different approaches that avoid the hard work that represents the direct calculation.

During the learning process, the MLP goes through stages in which the reduction of the error can be extremely slow. These periods of stagnation can influence learning times. In order to resolve this problem, we propose to replace the MSE by cross entropy error function. Simulation results using this error function show a better network performance with a shorter stagnation period.

**Early stopping.**

One way to dealing with the overfitting problem is to extract a subset of samples of the training set (note that the whole test previously extracted) and use of auxiliary way during training [98].

This subset is called validation set. The role of the validation set is to evaluate the network error after each epoch (or after every few epochs) and determine when this starts to increase. Since the validation set is left outside during training, the error about is a good indication that the network error will commit on the test set. Consequently, the procedure to stop the workout at the time the validation error and increase the values of the weights of the previous epoch are preserved.
5. Case Studies and Results

5.1 Infrared Radiometer

A piece of aluminium foil, with an emissivity of 0.05 (Table 2), was placed on top of the blade (Figure 5.1) and four different scenarios were considered. Firstly, measurements were conducted at room temperature; in a second scenario the blade was cooled down in a chest freezer during 24 hours, without accumulation of ice on the surface; the third scenario was similar but with partial accumulations of ice; in the last scenario the frozen blade was completely covered by a layer of ice. Three repetitions were conducted for each scenario.

Figure 5.1. Wind turbine blade with aluminum foil set up.
5. Case Studies and Results

Table 2 Lists a series of emissivity values for common materials and natural surfaces in the spectral range 8-14 \( \mu \text{m} \) (ASTER spectral library)

<table>
<thead>
<tr>
<th>Surface</th>
<th>Emissivity</th>
</tr>
</thead>
<tbody>
<tr>
<td>Asphalt</td>
<td>0.964</td>
</tr>
<tr>
<td>Cement</td>
<td>0.951</td>
</tr>
<tr>
<td><strong>Aluminium metal</strong></td>
<td>0.050</td>
</tr>
<tr>
<td>Galvanized steel metal</td>
<td>0.957</td>
</tr>
<tr>
<td>Copper metal</td>
<td>0.964</td>
</tr>
<tr>
<td><strong>White fiberglass</strong></td>
<td>0.956</td>
</tr>
<tr>
<td>Pine wood</td>
<td>0.946</td>
</tr>
<tr>
<td>Grass</td>
<td>0.984</td>
</tr>
<tr>
<td>Conifers</td>
<td>0.991</td>
</tr>
<tr>
<td>Water</td>
<td>0.983</td>
</tr>
<tr>
<td>Snow</td>
<td>0.986</td>
</tr>
<tr>
<td><strong>Ice</strong></td>
<td>0.970</td>
</tr>
<tr>
<td>Frost</td>
<td>0.985</td>
</tr>
</tbody>
</table>

5.1.1 Results and discussion

Temperatures were measured over both an original white painted blade spot and the aluminium foil (Figure 5.2).

The emissivity correction is necessary for accurately measuring the surface temperature, in other case the temperature measured at the body surface by the sensor is inaccurate if it is not taking into account the reflected infrared radiation.
The radiation detected by the infrared sensor includes two components, the radiation emitted directly by the body surface, and the radiation reflected coming from the entire environment (walls, ceiling, near objects, etc. if measuring inside a room). For this reason, target radiometric temperatures are always above zero in Table 3 although the icing.

The Table 3 shows the measurements over the blade and aluminium spots for the different scenarios. The measurements are the voltages (mV) registered by the germanium lens ($S_D$) and the internal body temperature ($T_D$) of the TIR sensor, together with the corresponding target radiometric temperature ($T_R$), over the blade and for the different scenarios. Kinetic temperature measured by a thermocouple has been also included.

The emissivity values of the protective lining of the wind turbine blade and the aluminium foil are 0.956 and 0.05, respectively, whereas a value of 0.97 corresponds to the ice. For this reason, $T_R$ values in the aluminium foil remain positive while no icing is observed although its real temperature (measured by a contact thermocouple) is close to -30 °C. However, as soon as icing starts $T_R$ drops in the aluminium, becoming closer to thermocouple values, as a consequence of the emissivity change in the surface, from 0.050 to 0.970.

This behaviour is illustrated in Figure 5.3, where measurements listed in Table 3 are now plotted. Note that difference in $T_R$ between the white paint...
and the aluminium gives us an insight of the icing status of the blade layer surface that the sole measurement of the thermocouple could not. The ice generates an abrupt change in the emissivity coefficient of the aluminium surface.

Table 3 Measured values of voltages registered by the sensor on a wind turbine surface and aluminium foil.

<table>
<thead>
<tr>
<th>Room temperature</th>
<th>Thermocouple [ºC]</th>
<th>T₀ [ºC]</th>
<th>S₀ [mV]</th>
<th>Tᵣ [ºC]</th>
</tr>
</thead>
<tbody>
<tr>
<td>white paint</td>
<td>19,9</td>
<td>21,4</td>
<td>0,35</td>
<td>26,3</td>
</tr>
<tr>
<td>aluminium foil</td>
<td>20,2</td>
<td>21,4</td>
<td>0,53</td>
<td>28,7</td>
</tr>
<tr>
<td>white paint</td>
<td>-29,4</td>
<td>18,7</td>
<td>-2,10</td>
<td>-17,8</td>
</tr>
<tr>
<td>aluminium foil</td>
<td>-28,5</td>
<td>16,2</td>
<td>-0,22</td>
<td>12,8</td>
</tr>
<tr>
<td>white paint</td>
<td>-30,8</td>
<td>21,5</td>
<td>-2,35</td>
<td>-20,0</td>
</tr>
<tr>
<td>aluminium foil</td>
<td>-27,8</td>
<td>21,3</td>
<td>-2,05</td>
<td>-13,7</td>
</tr>
<tr>
<td>white paint</td>
<td>-29,8</td>
<td>19,4</td>
<td>-2,07</td>
<td>-16,4</td>
</tr>
<tr>
<td>aluminium foil</td>
<td>-27,0</td>
<td>19,8</td>
<td>-1,94</td>
<td>-13,3</td>
</tr>
<tr>
<td>white paint</td>
<td>-29,2</td>
<td>18,6</td>
<td>-2,12</td>
<td>-18,4</td>
</tr>
<tr>
<td>aluminium foil</td>
<td>-28,8</td>
<td>17,8</td>
<td>-2,10</td>
<td>-19,1</td>
</tr>
</tbody>
</table>
5. Case Studies and Results

Figure 5.3. Radiometric temperatures measured by the IRT in both surfaces (white paint and aluminum foil.  

<table>
<thead>
<tr>
<th>Condition</th>
<th>Temperature (°C)</th>
</tr>
</thead>
<tbody>
<tr>
<td>White paint</td>
<td>-40</td>
</tr>
<tr>
<td>Aluminum foil</td>
<td>-30</td>
</tr>
<tr>
<td>Thermocouple</td>
<td>-20</td>
</tr>
<tr>
<td>Room Temperature</td>
<td>10</td>
</tr>
<tr>
<td>Frozen no icing</td>
<td>0</td>
</tr>
<tr>
<td>Frozen partial icing</td>
<td>-10</td>
</tr>
<tr>
<td>Frozen thin layer of ice</td>
<td>-20</td>
</tr>
<tr>
<td>Frozen thick layer of ice</td>
<td>-30</td>
</tr>
</tbody>
</table>

The state actual state of the blade can be determined by contrasting the observed temperature at the aluminium with the actual temperature.

Figure 5.4 shows the addition of the temperatures provided by the radiometer on the surface coating and the temperature obtained on the aluminium foil surface.
5.1.2 Conclusions

Icing blades is considered one of the main problems for wind turbines situated in cold regions. Ice accumulation on the blade surface leads to a reduction of the aerodynamic efficiency and increases the maintenance costs.

This work reports an operational technique based on thermal remote sensing to detect ice accumulation on the blade surface. This method takes advantage of the different radiative behaviour of surfaces with different emissivity values. Radiometric temperature of an aluminium foil assembled in the blade surface is measured by a thermal infrared sensor connected to a datalogger. Since aluminium and ice emissivity values are so different, 0.050 and 0.970, respectively, a drastic decrease in radiometric temperature is observed when icing starts and remains until ice melts.
5.2 Wavelet

5.2.1 Wavelet Transform in Wind Turbines for Ice Detection

Experiments

The experiments consider three different states of the blade: The first experiment was carried out at room temperature; the second was realized with the frozen blade but with no ice accumulation on the blade; the third experiment has been performed with the frozen blade and ice accumulations on the blade.

The ultrasonic transducers have been aligned, where the transducer (Tx) emits ultrasonic signals that will become into elastic waves having the same frequency. It will be collected by the sensor 1 (S1), and then by the sensor 2 (S2) (see Figure 5.5). It is expected that the elastic wave traveling through the blade, made of fiberglass with sandwich structure, changes its shape, amplitude, energy, phase, etc. and an attenuation appears between the sensor 1 and sensor 2 due to the properties of fiberglass that dissipates more energy than other composite materials, such as the carbon fiber. In addition, it is assumed to have the influence of temperature on Lamb wave propagation [99], i.e. when the temperature decreases the speed of the lamb wave propagation increases.
5. Case Studies and Results

The experiments consist of an excitation of the ultrasonic transducer with white noise that randomly excites all frequencies, in order to analyse the optimal frequency to do the experiments, where the wave is transmitted in this blade, analysing it in the frequency domain. In the same way it has proceeded to perform frequency sweep tests. Five cycles Hanning pulse will be emitted at 20 kHz, 30 kHz and 50 kHz to study the propagation of the pulse. The signal processing approach employed is the Wavelets techniques.

Every type of experiment has been repeated three times. The blade was introduced in a chest freezer for 24 hours with the sensors, and has been deposited on the surface water periodically until the formation of a layer of frost and ice to recreate the conditions that would have a real shovel frozen (Figure 5.6: a.- without ice, b.- with ice).
5. Case Studies and Results

Figure 5.6: (a) Wind turbine blade at room temperature and; (b) frozen blade with ice on the surface

Figure 5.7 shows the differences in the signal received in the sensor 1 at 30 kHz in the three experiments. At 20 and 30 kHz signal amplitude is greater due to the MFC works better as actuator at low frequencies. The sensor 1 receives a signal with more voltage because it is closer to the actuator. Three different types of signals were found, indicating that the CMS can find differences between the three states. The signal obtained with the sensors on the frozen blade without ice has bigger amplitude than the signals at room temperature as it was expected. However, when the blade has ice on its surface then the amplitude is lower. This is because the ice opposes the free displacement of the particles of the composite material. Figure 5.8 presents the signals received at the sensor 2 in the same cases.
5. Case Studies and Results

Figure 5.7 Signal in sensor 1 at 30 kHz in the three different scenarios.

Figure 5.8 Signal in sensor 2 at 30 kHz in the three different scenarios.

Results

Table 4 shows the results of the signal analysis for each scenario, showing energy for each signal according to the chosen wavelet decomposition. The percent of energy of each of the seven decomposition (approximation and details) is also presented in Table 4. D7 decomposition contains the highest
percentage of energy of the original signal in most of the cases. It is associated with the frequency range of 125.6 kHz – 31.25 kHz. It is consistent with the excitation frequencies of the Hanning pulse used in the actuator.

The composite material is highly dispersive, where the dispersion depends on the direction of wave propagation, the orientation and arrangement of the layers of fibre glass. Therefore, the waves received by the sensors contain frequencies that deviate from the centre frequency of excitation.

Table 4 Wavelet Decomposition of the received signal in the sensor 1.

<table>
<thead>
<tr>
<th>Sensor 1</th>
<th>A7 %</th>
<th>D7 %</th>
<th>D6 %</th>
<th>D5 %</th>
<th>D4 %</th>
<th>D3 %</th>
<th>D2 %</th>
<th>D %</th>
<th>Energy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Room T 20 kHz</td>
<td>25.6</td>
<td>47.4</td>
<td>19.5</td>
<td>5.51</td>
<td>1.42</td>
<td>0.36</td>
<td>0.09</td>
<td>0.03</td>
<td>16.49</td>
</tr>
<tr>
<td>Frozen</td>
<td>17.7</td>
<td>52.4</td>
<td>21.5</td>
<td>6.14</td>
<td>1.59</td>
<td>0.40</td>
<td>0.10</td>
<td>0.03</td>
<td>41.77</td>
</tr>
<tr>
<td>Frozen Ice</td>
<td>56.8</td>
<td>25.7</td>
<td>12.7</td>
<td>3.48</td>
<td>0.89</td>
<td>0.23</td>
<td>0.06</td>
<td>0.02</td>
<td>4</td>
</tr>
<tr>
<td>Room T 30 kHz</td>
<td>28.1</td>
<td>45.3</td>
<td>19.1</td>
<td>5.43</td>
<td>1.40</td>
<td>0.36</td>
<td>0.10</td>
<td>0.04</td>
<td>5.22</td>
</tr>
<tr>
<td>Frozen</td>
<td>20.3</td>
<td>49.0</td>
<td>22.0</td>
<td>6.32</td>
<td>1.63</td>
<td>0.41</td>
<td>0.10</td>
<td>0.03</td>
<td>16</td>
</tr>
<tr>
<td>Frozen Ice</td>
<td>49.0</td>
<td>28.3</td>
<td>16.0</td>
<td>4.77</td>
<td>1.24</td>
<td>0.34</td>
<td>0.12</td>
<td>0.10</td>
<td>0.85</td>
</tr>
<tr>
<td>Room T 50 kHz</td>
<td>24.1</td>
<td>47.8</td>
<td>20.2</td>
<td>5.73</td>
<td>1.49</td>
<td>0.38</td>
<td>0.11</td>
<td>0.05</td>
<td>0.69</td>
</tr>
<tr>
<td>Frozen</td>
<td>20.3</td>
<td>49.0</td>
<td>22.0</td>
<td>6.32</td>
<td>1.63</td>
<td>0.41</td>
<td>0.10</td>
<td>0.03</td>
<td>16</td>
</tr>
<tr>
<td>Frozen Ice</td>
<td>24.0</td>
<td>45.9</td>
<td>21.5</td>
<td>6.25</td>
<td>1.64</td>
<td>0.43</td>
<td>0.12</td>
<td>0.07</td>
<td>0.48</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Sensor 2</th>
<th>A7 %</th>
<th>D7 %</th>
<th>D6 %</th>
<th>D5 %</th>
<th>D4 %</th>
<th>D3 %</th>
<th>D2 %</th>
<th>D %</th>
<th>Energy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Room T</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Frozen</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Frozen Ice</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
The three scenarios can be identified by the energies shown in Table 4. Analysing the energy of the blade at room temperature, the frozen ice blade has a higher energy (more than doubled regarding to the rest of scenarios). However, when the blade has ice on the surface, the energy received by the sensor was about 25% of the energy received at room temperature.

In Figure 5.9, at 20 and 30 kHz are observed differences between the energies of each state. Considering 50 kHz, the energy of the signal at room temperature is very similar when the blade has ice, i.e. this frequency is not suitable for determining the state of the blade. In sensor 2 (Figure 10), the energy is smaller due to the attenuation of the signal by the ice on the surface. It is observed that the energy in each state of the blade has a similar relationship to that shown in the case of sensor 1, but at 20 kHz it is difficult
to distinguish between the cases at room temperature and with the frozen blade with ice. The optimal frequency for this experiment was at 30 kHz.

![Energy received in sensor 1](image1)

**Figure 5.9 Energy of each state and frequency received in sensor 1**

![Energy received in Sensor 2](image2)

**Figure 5.10 Energy of each state and frequency received in sensor 2**
5. Case Studies and Results

Figure 5.11 and Figure 5.12 show the energies of the original signal that each level of decomposition has in each experiment. The levels with more energy are: A7, D7 and D6. The signal has two peaks when blade has ice, in 20 and 30 kHz, while the details presence D7 and D6 have both energy decreases. This could be due by presence of ice on the surface of the blade. Other decompositions also present decreasing, but the percentage of signal information is very low. When the signals from sensor 2 are studied (Figure 5.12), D7 has period without peaks at 20 and 30 kHz, while the decomposition A7 has peaks in these cases.

Figure 5.11 Wavelet decompositions (Approximations and details), received by sensor 1
The optimal frequency to determine differences in the state of the wind turbine blade is 30 kHz. Sensors 1 and 2 have been able to identify clear differences of signals and the decompositions A7, D7 and D6 provide more information about the scenarios considered.

**Conclusions**

Ice accretion in the wind turbines blades affects the reliability, availability, maintainability and safety, and it is one of the biggest causes of energy losses. This research presents a new approach to detect the Ice accretion in a wind turbine blade using different ultrasonic technics. It has designed a condition monitoring system flexibly in order to generate and acquire Lamb waves in
the blade. Ultrasonic wave propagation is affected by changes in the material, such as temperature, ice accretion, delamination etc.

Experiments to detect ice on the blade have been carried out in three different scenarios: The first experiment was carry out at room temperature; the second was realized with the frozen blade but with no ice accumulation on the blade; the third experiment has been performed with the frozen blade and ice accumulations on the blade. The approach for signal processing chosen in this work is based on Wavelet transform.

It was used a multi-signal analysis, specifically, a Daubechies wavelet family with seven levels of decomposition, to analyse the three different cases together, and it is obtained the energy of each signal. The percentage of information of the decompositions in each signal is obtained to determine the most significant changes in the distribution of frequencies within the wave. A difference between the percentage of information of D7, D6 and A7 decomposition is observed in both sensors when the excitation is 30 kHz. This approach has proved useful to detect when the blade is unfrozen, frozen without ice, and frozen with ice.

5.2.2 Wavelet Transform in Concentrated Solar Plants

Experiments

An experimental platform that comprises a high power pulser-receiver and a condition monitoring system based on electromagnetic acoustic transducers placed on an austenitic stainless steel plate is designed in order to illustrate the results. The plate material is the same as that used in the solar concentration pipes (316Ti, standard carbon 3116 Type with titanium stabilisation). The properties of this material and the influence of temperature thereon is found in Table 5.
5. Case Studies and Results

Figure 5.13 Placement of the EMAT on austenitic steel plate.

Table 5 Physical properties of 316Ti steel and the influence of temperature.

<table>
<thead>
<tr>
<th></th>
<th>10^-6*Ke^-1</th>
<th>16</th>
<th>17</th>
<th>18</th>
<th>18</th>
<th>19</th>
</tr>
</thead>
<tbody>
<tr>
<td>Thermal expansion</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Modulus of elasticity</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Longitudinal Gpa</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Poisson number</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.3</td>
<td></td>
</tr>
<tr>
<td>Electrical resistivity</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Electrical conductivity</td>
<td>Siemen/mm²/m</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Specific Heat</td>
<td>J/(kg.K)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Density</td>
<td>kg/dm³</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Thermal conductivity</td>
<td>W/mK</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Relative magnetic permeability</td>
<td>μr</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Temperature (°C)</td>
<td></td>
<td>20</td>
<td>100</td>
<td>200</td>
<td>300</td>
<td>400</td>
</tr>
</tbody>
</table>
5. Case Studies and Results

The plate is heated with a heater pad for the tests of emission and reception of ultrasonic pulses by the EMAT from 40 °C to 180 °C (see Figure 4.14). Each test was performed when the temperature increased 10 °C. It has been used a 6 cycles Hanning pulse with a frequency of 256 kHz to excite the EMAT.

Figure 5.14 Heater pad on the plate

The Figure 5.15 shows the signals obtained at 40ºC (blue) and 180ºC (red).
Figure 5.15 Signals obtained by the EMAT with the plate at 40 °C and 180 °C

**Results**

Table 6 shows the results after the analysis of the signals for each temperature of the steel plate. It is showed the resulting energy for each signal according to the chosen wavelet decomposition, and it is also presents the percent of information of each of the five decompositions (approximation and details). In all cases the D4 decomposition contains the highest percentage of information of the original signal and it is associated with the frequency range 156 kHz – 312 kHz. And it is consistent with the excitation frequencies of the Hanning pulse used in the actuator (256 kHz). This allowed study the frequencies of interest from other frequencies.
5. Case Studies and Results

Table 6 Wavelet Decompositions and Energy of the signals at different temperature

<table>
<thead>
<tr>
<th>Temperature (ºC)</th>
<th>Wavelet Decompositions</th>
<th>Energy</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>D1</td>
<td>D2</td>
</tr>
<tr>
<td>40</td>
<td>0,48%</td>
<td>0,47%</td>
</tr>
<tr>
<td>50</td>
<td>0,10%</td>
<td>0,26%</td>
</tr>
<tr>
<td>60</td>
<td>0,13%</td>
<td>0,37%</td>
</tr>
<tr>
<td>70</td>
<td>0,14%</td>
<td>0,42%</td>
</tr>
<tr>
<td>80</td>
<td>0,17%</td>
<td>0,50%</td>
</tr>
<tr>
<td>90</td>
<td>0,20%</td>
<td>0,65%</td>
</tr>
<tr>
<td>100</td>
<td>0,24%</td>
<td>0,76%</td>
</tr>
<tr>
<td>110</td>
<td>0,28%</td>
<td>0,94%</td>
</tr>
<tr>
<td>120</td>
<td>0,35%</td>
<td>1,03%</td>
</tr>
<tr>
<td>130</td>
<td>0,37%</td>
<td>1,09%</td>
</tr>
<tr>
<td>140</td>
<td>0,38%</td>
<td>1,11%</td>
</tr>
<tr>
<td>150</td>
<td>0,40%</td>
<td>1,09%</td>
</tr>
<tr>
<td>160</td>
<td>0,39%</td>
<td>1,09%</td>
</tr>
<tr>
<td>170</td>
<td>0,49%</td>
<td>1,14%</td>
</tr>
<tr>
<td>180</td>
<td>0,49%</td>
<td>1,14%</td>
</tr>
</tbody>
</table>

The Figure 5.16 shows that D4 wavelet decomposition present the main percentage of energy of the signal in the frequency range of 156-312 kHz, which is consistent since the excitation ultrasonic pulse is 256 kHz. Finally, a multi-signal processing analysis employing wavelet transforms is done, providing a value of energy for each signal.
Figure 5.16 Percentage of signal information in each decomposition

Figure 5.17 shows that the energy decreases exponentially with increasing temperature. This is due to, although the frequency remains constant, the signal amplitude decreases as the temperature increases because it changes the parameters such as Young’s modulus and Poisson’s ratio and this affects the velocity of wave propagation.
5. Case Studies and Results

Figure 5.17 Energy of ultrasonic signals for each temperature.

Conclusions

The development of condition monitoring techniques together with the use of advanced signal processing approaches to reduce the failure rate of Parabolic Trough Receivers (PTR) has been done in order to increase the reliability, availability and investing returns in the generation of electricity by means of solar energy. PTR works at high temperatures where the properties of the ultrasonic inspection is affected. This work reports a novel methodology to control the condition of the PTR steel part by means of ultrasounds and digital signal processing. Particularly, a method for identifying changes in the ultrasonic signals due to changes in temperature is crucial to detect any anomaly in the pipes with greater efficiency.

Significant discrepancies between the energy measurements can work as an alarm signal to activate maintenance operations. Case studies based on laboratory experiments have been done in order to demonstrate this novel approach.
5.3 ARX for SHM in Concentrated solar plants.

5.3.1 Experimental results

According to the procedure previously described. The first step is to excite the system with a white noise input. Figure 5.18 depicts the periodogram of the signal measured by sensor 1. In that figure, it can be seen that the frequency that provides a maximum peak is around 30 KHz.

The emitted signal will be a Hanning pulse at 30 kHz, 2 cycles and a sampling frequency of 400,000 samples per second. Recall that the input frequency is set to 30 kHz to achieve a compromise between good response and MFC limitations when they work as actuators. Additionally, the pulse is composed of two cycles to create a narrow pulse and to avoid undesired overlaps between the emitted pulse and the first received echoes. Figure 5.19 shows the input signal (upper panel), the sensor 1 received signal (middle panel), and the sensor 2 measurements (lower panel). This picture shows clearly the delay between the input and both sensors. Since sensor 2 is located at a longer distance from the actuator the delay is also bigger.

![Figure 5.18. Periodogram of the sensor 1 signal measurements.](image-url)
5. Case Studies and Results

According to the previous section, the next step is to identify an ARX model between sensor 1 and sensor 2. To do that, we have to set the ARX model orders. It should be noted that the potential orders of the ARX model depend on the sample time. For instance, when the sample time decreases, the delay increases. In our particular case, since the sampling period is $2.5 \times 10^{-6}$ seconds ($1/400,000$ samples per second) and the delay should be around $0.2 \times 10^{-3}$ and $0.35 \times 10^{-3}$ seconds by inspecting the lower panel in Figure 5.19, the delay order $n_k$ should be around $80$ ($0.2 \times 10^{-3} / 2.5 \times 10^{-6}$) and $140$ ($0.35 \times 10^{-3} / 2.5 \times 10^{-6}$) lags. Another useful graph to identify the delay order is the sample cross-correlation graph. Figure 5.20 shows that the maximum cross-correlation coefficient should be between 80 and 140 lags, as it was deducted previously. Bearing in mind that information, the expected order values for the ARX model can be selected by minimizing the AIC criterion for delays ranging from 80 to 140 lags.
Figure 5.19. Actuator pulse input (upper panel). Sensor 1 measurements (middle panel). Sensor 2 measurements (lower panel).

The estimated ARX model is:

\[(1 - 1.764z^{-1} + 0.9685z^{-2})y_t = 0.2604z^{-100}u_t + \varepsilon_t \quad (48)\]

Where \( z \) is the \( Z \) operator, such as: \( z^{-1}y_t = y_{t-1} \). Thus, the delay is \( n_kT_s = 100 \cdot 2.5 \cdot 10^{-6} = 2.5 \cdot 10^{-4} \) seconds. In order to corroborate the results, the distance between sensors can be estimated. For instance, considering the delay (2.5 \cdot 10^{-4} \text{ seconds}) and the group velocity (3,100 \text{ m/s}), the estimated distance is approximately 3100 \cdot 2.5 \cdot 10^{-4} = 77.5 \text{ cm}, which matches with the distance between sensors.

Figure 5.21 shows the actual values measured by sensor 2 (solid lines) and the predicted output by using model in (4) and sensor 1 as input. Since the predicted output 100 steps ahead follow closely the harmonic behaviour of the ultrasound waves measured by sensor 2, the model is valid for condition monitoring. Note that significant deviations between the predicted output and the actual values may be consequence of a fault.
5. Case Studies and Results

Figure 5.20. Cross-correlation graph between sensor 1 and sensor 2.

Figure 5.21. Actual values and predicted output with 100 steps ahead.
5.3.2 Conclusions

The development of condition monitoring techniques together with the use of advanced signal processing approaches to reduce the failure rate of PTRs is of paramount importance to increase the reliability, availability and investing returns in the generation of electricity by means of solar energy. This work reports a novel methodology to control the condition of the PTR steel part by means of ultrasounds and digital signal processing. Particularly, a methodology to identify models capable of predicting the fault-free output sensor signals has been proposed. In that sense, significant discrepancies between the predicted output and the actual measurements can work as an alarm signal to activate maintenance operations. Case studies based on laboratory experiments have shown promising results.

Further research might address the following issues: i) implementation of the proposed methodology for serially connected PTRs; ii) Categorization of different faults depending on the predicted output error pattern in conjunction with the incorporation of other exogenous variables as, for example, steel temperature; and iii) the use of different sensors/actuators to enhance the signal to noise ratio yielded by the MFCs.

5.4 Auto-correlations: Wind turbines: Fault detection employing guided waves

5.4.1 Properties of the employed wind turbine blade.

The structures under consideration are two glass-fibre composite wind turbine blades, one of them with 3 disbond areas between skin-honeycomb. The wind turbine blades were built by the manufacturer Encocam. The blades are identical (Figure 5.22), but in the manufacturing process of one of
5. Case Studies and Results

them, some elements were introduced to generate debonding between two layers. The purpose of the introduction of these elements is to simulate delamination and debonding between layers, which entails a reduction in the performance of the blade.

![Figure 5.22 Wind turbine blades (damaged and undamaged)](image)

The dimensions of both blades, as well as the sandwich area (limited by red lines) are represented in the Figure 5.23.

![Figure 5.23 Structural scheme of the wind turbine blade](image)

The layers configuration is shown in Figure 5.24. The composite is Glass Reinforced Plastic (GRP), which is a composite of tough resilient, durable plastic resin, and glass fibres of high strength. The resin employed is Epoxy resin. The laminate thickness is 4.6 mm with a tolerance of ± 0.5 mm. The layers number used varies according to the area of the blade. The latching
zone has 18 layers for increased strength, the transition zone (widening) has 12 layers and the rest of the structure has 6 layers of fiberglass.

![Layers configuration of the composite material. E-glass twill fiber (yellow) and E-glass biaxial fiber (grey).](image)

The physical properties of the laminated configuration are shown in Table 7.

Table 7. Laminated physical properties used in the wind turbine blades

<table>
<thead>
<tr>
<th>IN-PLANE</th>
<th>Panel</th>
<th>Units</th>
</tr>
</thead>
<tbody>
<tr>
<td>Longitudinal Modulus</td>
<td>1.612E+04</td>
<td>[MPa]</td>
</tr>
<tr>
<td>Transverse Modulus</td>
<td>1.612E+04</td>
<td>[MPa]</td>
</tr>
<tr>
<td>Poissons Ratio - Vxy</td>
<td>0.129</td>
<td></td>
</tr>
<tr>
<td>- Vyx</td>
<td>0.129</td>
<td></td>
</tr>
<tr>
<td>Shear Modulus</td>
<td>2.516E+03</td>
<td>[MPa]</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>FLEXURAL</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Longitudinal Modulus</td>
<td>1.604E+04</td>
<td>[MPa]</td>
</tr>
<tr>
<td>Transverse Modulus</td>
<td>1.604E+04</td>
<td>[MPa]</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>STIFFNESSES</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Longitudinal Stiffness - E*T</td>
<td>7.425E+04</td>
<td>[N/mm]</td>
</tr>
</tbody>
</table>

New Approaches on Fault Detection and Diagnosis for Structures Maintenance Management
5. Case Studies and Results

<table>
<thead>
<tr>
<th></th>
<th>Value</th>
<th>Unit</th>
</tr>
</thead>
<tbody>
<tr>
<td>Transverse Stiffness - E*T</td>
<td>7.425E+04</td>
<td>[N/mm]</td>
</tr>
<tr>
<td>Shear Stiffness - G*T</td>
<td>1.159E+04</td>
<td>[N/mm]</td>
</tr>
<tr>
<td>Longitudinal Bending - El</td>
<td>1.307E+05</td>
<td>[N mm^2/mm width]</td>
</tr>
<tr>
<td>Transverse Bending - El</td>
<td>1.307E+05</td>
<td>[N mm^2/mm width]</td>
</tr>
<tr>
<td>Torsional - GJ</td>
<td>2.063E+04</td>
<td>[N mm^2/mm width]</td>
</tr>
</tbody>
</table>

**NEUTRAL AXIS**

<table>
<thead>
<tr>
<th></th>
<th>Value</th>
<th>Unit</th>
</tr>
</thead>
<tbody>
<tr>
<td>Longitudinal Bending</td>
<td>0.00</td>
<td>[mm] above mid-plane</td>
</tr>
<tr>
<td>Transverse Bending</td>
<td>0.00</td>
<td>[mm] above mid-plane</td>
</tr>
</tbody>
</table>

**LAMINATE**

<table>
<thead>
<tr>
<th></th>
<th>Value</th>
<th>Unit</th>
</tr>
</thead>
<tbody>
<tr>
<td>Weight</td>
<td>7.49</td>
<td>[kg/sq.m]</td>
</tr>
<tr>
<td>Core Thickness</td>
<td>0</td>
<td>[mm]</td>
</tr>
<tr>
<td>Total Thickness</td>
<td>4.61</td>
<td>[mm]</td>
</tr>
</tbody>
</table>

The honeycomb employed is Aluminium honeycomb 4.5 1/8 5052 (Figure 5.25). The honeycomb thickness is 15 mm and the overall sandwich panel thickness is 23 mm.
Introduction of defects in the manufacture process of the blade.

In order to simulate defects in the manufacture process, that can lead potential failures and large economic costs, three defects were introduced during the manufacture of the blade. The manufacturer Encocam inserted three Teflon PTFE non-stick tapes in the zones shown in Figure 5.26 to create the delamination and disbanding. The dimensions of the disbonds of A, B and C are 150x150 mm, 100x100 mm and 50x50 mm respectively.

Figure 5.26. Wind turbine blade scheme (mm). A, B and C areas are the disbonds between the honeycomb and the skin.

The dimensions and details of the disbonds are shown in Table 8.

Table 8 Disbands dimensions.

<table>
<thead>
<tr>
<th></th>
<th>Disbond A</th>
<th>Disbond B</th>
<th>Disbond 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>area (mm²)</td>
<td>50x50</td>
<td>100x100</td>
<td>150x150</td>
</tr>
<tr>
<td>Thickness (microns)</td>
<td>25</td>
<td>25</td>
<td>25</td>
</tr>
<tr>
<td>Type</td>
<td>Teflon PTFE</td>
<td>Teflon PTFE</td>
<td>Teflon PTFE</td>
</tr>
</tbody>
</table>

Figure 5.25 Composite and honeycomb sandwich (left) and aluminum honeycomb structure (right).
5. Case Studies and Results

5.4.2 Data analysis and signal processing.

5.4.2.1 Collection data process.
The method employed to collect the ultrasonic signals is pitch and catch. The transducers used were MFC [67,100], specifically, the model M2814-P1 from Smart Material, and they were attached on the surface (Figure 5.27). A transducer serving as transmitter is located on the tip of the blade. The position of the transmitter does not change, while the receiver is placed at different distances along the blade. The first position of the receiver is 100 mm from the transmitter, and the following measures have been taken by increasing the distance 100 mm until the 3800 mm (38 different locations).

Figure 5.27 Scheme of the damages introduced in the manufacture process (mm).

The signal generated by the emitting transducer, was a 5 cycles sinusoidal shaped signal, modulated by a Hanning window. At each position, a frequency sweep was deployed from 10 kHz to 100 kHz, with steps of 5 kHz. The aim of this work is to find evidence in the signal that may determine that there is a defect in the blade, when the guided waves travel through the defects.
5.4.2.2 Signal processing.
It was found that the signals containing more information were the 50 kHz signals. The 50 kHz signals of the 38 distances were pooled to analyse the correlation between them. Figure 5.28 shows the displacement of the wave front as the sensor moves away from the transmitter.

Figure 5.28 ultrasonic signals at different distances (50 kHz).

5.4.2.3 Wavelet Denoising.
The number of levels was set at seven, as this is the highest percentage of information contained.

The Daubechies wavelet family were employed according to reference [101], where it is demonstrated that they are the most suitable for this type of signals because they are more sensitive to sudden changes.

In order to remove from the signal, the trend and other components that appear in the low frequencies, the lower wavelet approximation is removed from the original signal.
5. Case Studies and Results

5.4.3 Defect detection and location.

The following signal processing is applied for all the 50 kHz signals of the 38 distances from the tip of the blade. Each signal is compared with the immediately preceding signal. Thus, the received signal at a distance of 20 cm from the transmitter is compared with the received signal at 10 cm, and the signals at 30 cm is compared with the signal at 20 cm, and so forth.

The damage in the wind turbine blade should affect to form of the ultrasonic Lamb waves. Hence, if there is a damage between two adjoining measures, the correlation between both signals should be different than the correlations between signals in areas without damage.

The Figure 5.29 shows the filtered signals at a distance of 200 and 210 cm from the transmitter.

![Figure 5.29 Received signals at 200 cm (green signal) and 210 (blue signal) cm from the tip of the blade.](image)

Envelope and smooth.
The signals were normalized and their envelopes were obtained by using the Hilbert Transform. The Hilbert transform is an approach to study the energy distribution of a signal in the time domain. It is useful to obtain the energy envelope (Figure 5.30) to identify local characteristics of the signal. A new Wavelet denoising filter is applied to smooth the envelope, and the low frequency decompositions (approximations) are selected [102].

Figure 5.30 Envelopes of the signals employing Hilbert Transform and

Figure 5.31 Autocorrelation of the signals at 200 cm (green signal) and 210 (blue signal) cm from the tip of the blade.
5. Case Studies and Results

The pattern recognition approach is based on the autocorrelation of both signals. Then the autocorrelation of one of the signals is divided by the autocorrelation of the other signal in order to emphasize the differences and to obtain the ratio curve between them (Figure 5.32). The singularity caused by the induced disbonds in the wind turbine blade, it is more recognizable in the ratio curve, and its corresponding to the location of the damage.

![Figure 5.32 Ratio curve of the pair of signals at 200 cm and 210 cm.](image)

5.4.4 Results.

The maximum values of the ratio curve correspond to the maximum differences between signals. An algorithm of automatic identification of peaks for each pair of signals has been used. The values of the higher peaks have been registered and they are shown in the Table 9.
### Table 9 Maximum discrepancy between signals.

<table>
<thead>
<tr>
<th></th>
<th>Distance from tip (cm)</th>
<th>Maximum of Ratio Curve</th>
<th>Zone</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>10 – 20</td>
<td>3,99</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>20 – 30</td>
<td>4,06</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>30 – 40</td>
<td>1,09</td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>40 – 50</td>
<td>1,22</td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>50 – 60</td>
<td>3,76</td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>60 – 70</td>
<td>1,50</td>
<td></td>
</tr>
<tr>
<td>7</td>
<td>70 – 80</td>
<td>4,56</td>
<td></td>
</tr>
<tr>
<td>8</td>
<td>80 – 90</td>
<td>21,44</td>
<td>Start of Honeycomb</td>
</tr>
<tr>
<td>9</td>
<td>90 – 100</td>
<td>1,34</td>
<td></td>
</tr>
<tr>
<td>10</td>
<td>100 – 110</td>
<td>12,75</td>
<td></td>
</tr>
<tr>
<td>11</td>
<td>110 – 120</td>
<td>1,14</td>
<td></td>
</tr>
<tr>
<td>12</td>
<td>120 – 130</td>
<td>3,43</td>
<td></td>
</tr>
<tr>
<td>13</td>
<td>130 – 140</td>
<td>4,99</td>
<td></td>
</tr>
<tr>
<td>14</td>
<td>140 – 150</td>
<td>4,02</td>
<td></td>
</tr>
<tr>
<td>15</td>
<td>150 – 160</td>
<td>1,24</td>
<td></td>
</tr>
<tr>
<td>16</td>
<td>160 – 170</td>
<td>6,43</td>
<td></td>
</tr>
<tr>
<td>17</td>
<td>170 – 180</td>
<td>2,53</td>
<td></td>
</tr>
<tr>
<td>18</td>
<td>180 – 190</td>
<td>13,58</td>
<td></td>
</tr>
<tr>
<td>19</td>
<td>190 – 200</td>
<td>7,47</td>
<td></td>
</tr>
<tr>
<td>20</td>
<td>200 – 210</td>
<td>1,46</td>
<td></td>
</tr>
<tr>
<td>21</td>
<td>210 – 220</td>
<td>6,12</td>
<td></td>
</tr>
<tr>
<td>22</td>
<td>220 – 230</td>
<td>1,36</td>
<td></td>
</tr>
<tr>
<td>23</td>
<td>230 – 240</td>
<td>19,87</td>
<td>Disbond A</td>
</tr>
<tr>
<td>24</td>
<td>240 – 250</td>
<td>8,77</td>
<td></td>
</tr>
<tr>
<td>25</td>
<td>250 – 260</td>
<td>6,63</td>
<td></td>
</tr>
<tr>
<td>26</td>
<td>260 – 270</td>
<td>3,53</td>
<td></td>
</tr>
<tr>
<td>27</td>
<td>270 – 280</td>
<td>4,74</td>
<td></td>
</tr>
</tbody>
</table>
5. Case Studies and Results

<p>| | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>28</td>
<td>280 – 290</td>
<td>2,34</td>
</tr>
<tr>
<td><strong>29</strong></td>
<td><strong>290 – 300</strong></td>
<td><strong>22,62</strong></td>
</tr>
<tr>
<td>30</td>
<td>300 – 310</td>
<td>1,63</td>
</tr>
<tr>
<td>31</td>
<td>310 – 320</td>
<td>2,77</td>
</tr>
<tr>
<td>32</td>
<td>320 – 330</td>
<td>12,69</td>
</tr>
<tr>
<td>33</td>
<td>330 – 340</td>
<td>2,21</td>
</tr>
<tr>
<td><strong>34</strong></td>
<td><strong>340 – 350</strong></td>
<td><strong>19,48</strong></td>
</tr>
<tr>
<td>35</td>
<td>350 – 360</td>
<td>1,33</td>
</tr>
<tr>
<td>36</td>
<td>360 – 370</td>
<td>9,29</td>
</tr>
<tr>
<td>37</td>
<td></td>
<td>8,27</td>
</tr>
</tbody>
</table>

The following graph (Figure 5.33) present the final results of the experiment. Both blades, damaged and undamaged, have a discontinuity in common, which is the start of the sandwich zone. The three induced disbonds in the “damaged blade” are clearly shown in the sections: 230-240; 290-300 and 340-350 cm. This proves the effectiveness of the method used, where the ultrasonic waves are sensitive to these changes in the e-glass material, even at a distance of almost 4 meters.
5.4.5 Conclusions.

Wind energy has undergone a rapid expansion over the past 15 years, where a proper maintenance plays a crucial role in their life cycle. The WT blades are critical elements that are subjected to high loads and stresses. The continued subjection to stress of the WT blades can cause the disbond between the layers of the composite material. These defects are points of stress concentration and often trigger breakage of the blade. A failure in the wind turbine blades could cause great downtimes, especially in wind farms located in remote areas with difficult access or off-shore wind turbines, providing considerable economic losses.
5. Case Studies and Results

The work proposes a solution for an optimal structural health monitoring of the WT blade. The approach presented in this work is able to detect defects in the blade in an early state and potential failures employing ultrasonic guided waves.

In order to test the method, two WT blades were manufactured, including three defects in one of them in the manufacturing process. An ultrasonic transmitter MFC is located in the tip of the blade, and the sensor is moved along the blade. Then a signal processing approach is employed to analyse the guided waves. In the experiments, the method could detect the start of the honeycomb within the blade in both blades, and the three disbonds in the damaged blade. This shows that the ultrasonic guided waves, despite the large attenuation in these composite materials, can determine the structural health of the blade at least 4 meters between transmitter and sensor. The works demonstrate that would be possible to implement in actual WT blades a network of MFCs strategically arranged to cover the blade, or areas with higher probability of appearing defects, cracks or disbonds.

5.5 Defect Location

5.5.1 Wind turbines: Acoustic emission in wind turbine blades.

5.5.1.1 Introduction

The SHM on wind turbine blades is employed to detect the defect online and to locate it with accuracy. The wind turbine blades are becoming larger and more complex, and this requires setting the exact location of a fiber breakage to reduce the maintenance cost and the productivity.

Three MFC sensors are strategically located along a blade section to detect incipient breakages in the structure. The case study involves some considerations, e.g., the appearance of the scattering phenomena, the
orientation of the sensors when the excitation is received, etc. However, it will be demonstrated that the proposed method can set the location with high accuracy. The analysis identifies a single point obtained from a graphical method that is analytically set by nonlinear equations.

The accuracy of this method depends on the transducer sensitivity, the type of composite material, irregularities in the material, the environmental noise, etc. The localization precision of the emission source will be affected by the type of composite material, the sensitivity of the materials, environmental noise, false positives due to impacts on the piece, etc. Moreover, in real working conditions, considering environmental conditions, e.g., rain or hail, or impacts on the blade, it can cause false alarms.

In working conditions, it would be possible to distinguish between the frequencies associated with the vibration of the blade (low frequencies) and the frequencies associated with the acoustic emission of the fiber breakage (frequencies within the audible range and the ultrasonic range). It is possible to filter the frequencies associated with the vibration from the collected signal.

5.5.1.2 Experiments

The experiments were performed in a section of the wind turbine blade. The fragment, shown in Figure 5.34, is made of Glass Fiber-Reinforced Polymer (GFRP), with dimensions of 100 × 79.5 cm. The section is composed of a honeycomb central layer embedded between two fiberglass layers made of polyester resin. This type of material has good structural properties, resistance to fatigue and other advantages. The attenuation of the acoustic emission in the blade is high, and it depends on the material, wave frequency and travelling distance between the failure source and the sensor location.
The waves with the same velocity form a circular wave front when they propagate through an isotropic material. The velocity generally does not depend on the direction of propagation, but in anisotropic materials, e.g., the composite materials of the wind turbines, the velocity depends on the direction of propagation. A slowness factor could be introduced in order to consider the propagation direction, e.g., it has been observed that the configuration of layers (+45/−45) for a composite has a strong dependency of the direction of propagation. However, it has been demonstrated that the direction of propagation does not affect the velocity in the blade section studied in this work. Therefore, the slowness factor has not been introduced in these experiments.
5.5.1.3 Location of the Fiber Breakage by the Triangulation Methodology.

The glass fiber breakages of a wind turbine blade have been simulated in the laboratory on a real blade. A novel location method by triangulation has been developed. The aim of the work is to locate the acoustic emission source in four different points on the blade section. The acoustic emission produced by the division of the glass fibers is simulated by breaking the tip of the lead from a mechanical pencil [103]. Three MFC transducers (A, B and C) were used to detect the acoustic emissions (Figure 5.35). The three transducers are used as sensors that collect the wave front of the mechanical wave produced by the acoustic emission.

![Wave front propagation from the acoustic emission source.](image)

These signals received by the sensors present a low amplitude, and therefore, they need to be pre-amplified before being acquired by the oscilloscope. In working conditions, there are many factors that could influence the configuration of the arrangement of the sensors on a blade, for example the length of the blades, the intensity of the acoustic emission, the accuracy of
5. Case Studies and Results

the sensors, the background noise, attenuation, *etc.* Depending on these factors, many groups of three sensors would be established, as they are required to cover the entire blade.

The propagation velocity of the acoustic emission (see Figure 5.36) has been experimentally calculated by breaking a pencil lead and measuring the delays in the excitement of the sensors S1 and S2 (Figure 5.37).

![Diagram of sensor setup](image)

*Figure 5.36. Measuring the experimental propagation velocity in the composite material.*
Figure 5.37. Peak detection of the acoustical emission collected by Sensor 1 (blue) and Sensor 2 (green) to obtain the experimental propagation velocity in the composite material.

The delay between Signals 1 and 2 is 271 µs (542 samples), and the propagation velocity for the composite material is 2583 m/s.

Four experiments have been conducted at four different locations of the acoustic emission. Twelve tests have been done applying the same force, angle of inclination and length (1 mm approximately). The main objective is to get similar signals for all of the case studies. The data are also filtered for the signal processing, where undesired frequencies are filtered. The peak detection algorithm identifies the wave front of each signal. This process is complex because the waves are compounded by a large number of frequencies. Moreover, there are multiple elements in the blade that could affect the scattering of the acoustic signal, such as the edges of the geometry, the junction with the beam, adhesives, etc.

The signal processing consists of a pass band filter that eliminates low and high frequencies and carries out a comparison of the peaks of the wave front in the same frequency range of Signals A, B and C, generated by the above-mentioned MFC sensors, A, B and C (Figure 5.38).
5. Case Studies and Results

Figure 5.38. Pre-processing of the signal. Wave front collected by Sensors C (blue), B (green) and A (red).

5.5.1.4 Experimental Procedure and Results.

The time of flight and distances are set in this section for Sensors B and A regarding C, C being the first sensor to receive the acoustic signal of the breakage. The experiments are repeated four times to take into account the deviations of the results. The algorithm gives the exact location of the defect, as well as a graphic outline, knowing the radius of the circles with centres at B and C. The dimensions of the blade section, the distribution of the sensors and the emission source (star) in the wind turbine blade are shown in Figure 5.39. The mathematical results obtained with the algorithm are given in Tables 10–17.
The methodology shown in the section 4.4.1 based on triangulation algorithm has been employed to generate the results in the following 4 cases.

Table 10 First case study: detection time; delay with C; delay; theoretical distance; experimental distance

<table>
<thead>
<tr>
<th>Sensors</th>
<th>Detection Time (Samples)</th>
<th>Delay with C (Samples)</th>
<th>Delay (Seconds)</th>
<th>Theoretical Distance (m)</th>
<th>Experimental Distance (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>C</td>
<td>1152</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>B</td>
<td>1381</td>
<td>229</td>
<td>1.15 × 10⁻⁴</td>
<td>0.30</td>
<td>0.30</td>
</tr>
<tr>
<td>A</td>
<td>1528</td>
<td>376</td>
<td>1.88 × 10⁻⁴</td>
<td>0.49</td>
<td>0.49</td>
</tr>
</tbody>
</table>

Table 11 Initial data of the first case study

<table>
<thead>
<tr>
<th>Locations</th>
<th>x-Coordinate (m)</th>
<th>y-Coordinate (m)</th>
<th>Radius (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>0</td>
<td>0</td>
<td>0.49</td>
</tr>
<tr>
<td>B</td>
<td>0.8</td>
<td>0</td>
<td>0.30</td>
</tr>
<tr>
<td>C</td>
<td>0.4</td>
<td>0.69</td>
<td>-</td>
</tr>
<tr>
<td>1</td>
<td>0.55</td>
<td>0.495</td>
<td>-</td>
</tr>
</tbody>
</table>
5. Case Studies and Results

Table 12 Second case study: detection time; delay with C; delay; theoretical distance; experimental distance.

<table>
<thead>
<tr>
<th>Sensors</th>
<th>Detection Time (Samples)</th>
<th>Delay with C (Samples)</th>
<th>Delay (Seconds)</th>
<th>Theoretical Distance (m)</th>
<th>Experimental Distance (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>C</td>
<td>912</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>B</td>
<td>1063</td>
<td>151</td>
<td>$7.55 \times 10^{-5}$</td>
<td>0.20</td>
<td>0.20</td>
</tr>
<tr>
<td>A</td>
<td>1296</td>
<td>384</td>
<td>$1.92 \times 10^{-4}$</td>
<td>0.50</td>
<td>0.50</td>
</tr>
</tbody>
</table>

Table 13 Initial data of the second case study.

<table>
<thead>
<tr>
<th>Locations</th>
<th>x-Coordinate (m)</th>
<th>y-Coordinate (m)</th>
<th>Radius (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>0</td>
<td>0</td>
<td>0.50</td>
</tr>
<tr>
<td>B</td>
<td>0.8</td>
<td>0</td>
<td>0.20</td>
</tr>
<tr>
<td>C</td>
<td>0.4</td>
<td>0.69</td>
<td>-</td>
</tr>
<tr>
<td>2</td>
<td>0.65</td>
<td>0.495</td>
<td>-</td>
</tr>
</tbody>
</table>

Table 14 Third case study: detection time; delay with C; delay; theoretical distance; experimental distance.

<table>
<thead>
<tr>
<th>Sensors</th>
<th>Detection Time (Samples)</th>
<th>Delay with C (Samples)</th>
<th>Delay (Seconds)</th>
<th>Theoretical Distance (m)</th>
<th>Experimental Distance (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>C</td>
<td>962</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>B</td>
<td>1298</td>
<td>336</td>
<td>$1.68 \times 10^{-4}$</td>
<td>0.43</td>
<td>0.43</td>
</tr>
<tr>
<td>A</td>
<td>1087</td>
<td>125</td>
<td>$6.25 \times 10^{-5}$</td>
<td>0.17</td>
<td>0.16</td>
</tr>
</tbody>
</table>

Table 15 Initial data of the third case study.

<table>
<thead>
<tr>
<th>Locations</th>
<th>x-Coordinate (m)</th>
<th>y-Coordinate (m)</th>
<th>Radius (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>0</td>
<td>0</td>
<td>0.16</td>
</tr>
<tr>
<td>B</td>
<td>0.8</td>
<td>0</td>
<td>0.43</td>
</tr>
<tr>
<td>C</td>
<td>0.4</td>
<td>0.69</td>
<td>-</td>
</tr>
<tr>
<td>3</td>
<td>0.2</td>
<td>0.445</td>
<td>-</td>
</tr>
</tbody>
</table>
Table 16 Fourth case study: detection time; delay with C; delay; theoretical distance; experimental distance.

<table>
<thead>
<tr>
<th>Sensors</th>
<th>Detection Time (Samples)</th>
<th>Delay with C (Samples)</th>
<th>Delay (Seconds)</th>
<th>Theoretical Distance (m)</th>
<th>Experimental Distance (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>C</td>
<td>1155</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>B</td>
<td>1650</td>
<td>495</td>
<td>$2.48 \times 10^{-4}$</td>
<td>0.64</td>
<td>0.64</td>
</tr>
<tr>
<td>A</td>
<td>1385</td>
<td>230</td>
<td>$1.15 \times 10^{-4}$</td>
<td>0.29</td>
<td>0.30</td>
</tr>
</tbody>
</table>

Table 17 Initial data of the fourth case study.

<table>
<thead>
<tr>
<th>Locations</th>
<th>x-Coordinate (m)</th>
<th>y-Coordinate (m)</th>
<th>Radius (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>0</td>
<td>0</td>
<td>0.30</td>
</tr>
<tr>
<td>B</td>
<td>0.8</td>
<td>0</td>
<td>0.64</td>
</tr>
<tr>
<td>C</td>
<td>0.4</td>
<td>0.69</td>
<td>/</td>
</tr>
<tr>
<td>4</td>
<td>0.05</td>
<td>0.645</td>
<td>/</td>
</tr>
</tbody>
</table>

**Case Study 1**

The breaking of the lead is made in the following coordinates from Sensor A at Point 1 (star); see Figure 5.39. Sensor A is the coordinate origin.

- Coordinate x: 0.55;
- Coordinate y: 0.495.

The location of the source employing the algorithm is: Point 1: (x: 0.5533, y: 0.4920). The error in the location is: x: 3.3 mm; y: 30 mm

**Case Study 2**

In this case, the emission source was generated at Point 2 (star), shown in Figure 5.40:

- Coordinate x: 0.65.
- Coordinate y: 0.495.
Case Studies and Results

Figure 5.40. Scheme for Case Study 2.

The location of the source employing the algorithm is: Point 2: \((x: 0.6502, y: 0.4950)\). The errors in the location are: coordinate \(x\): 0.2 mm; coordinate \(y\): 0.00 mm.

Case Study 3

In this case, the emission source was generated at Point 3 (star); see Figure 5.41:

- Coordinate \(x\): 0.20.
- Coordinate \(y\): 0.445.
5. Case Studies and Results

New Approaches on Fault Detection and Diagnosis for Structures

Maintenance Management

Figure 5.41. Scheme for Case Study 3.

The location of the source employing the algorithm is: Point 3 (x: 0.1914, y: 0.4434). The errors in the location are: coordinate x: 8.6 mm; coordinate y: 1.6 mm.

Case Study 4

In this case, the emission source was generated at Point 4 (star), and it is shown in Figure 5.42:

- Coordinate x: 0.05.
- Coordinate y: 0.645
5. Case Studies and Results

Figure 5.42. Scheme for Case Study 4.

The location of the source employing the algorithm is: Point 4: (x: 0.050, y: 0.6495). The errors in the location are: coordinate x: 0 mm; coordinate y: 4.5 mm.

Different waves with different speeds appear as a result of the scattering phenomena when a large number of frequencies are excited by the breakage. This makes the identification of peaks to measure the delays of the signals complicated. The orientation of the sensors, when they receive the excitation, can affect the shape of the signal collected.

It is observed that the algorithm provides correct and coherent results. It detects the location of the acoustic emission with an accuracy of two decimals (millimetres). The maximum error registered was 9 mm.

Finally, the algorithm shows the position of the acoustic emission point with the real dimensions of the blade. Figure 5.43 shows the location of the acoustic emission for the first case study.
5. Case Studies and Results

5.5.1.5 Conclusions

The development of a localization approach presented in this work is set using macro-fiber composites to detect cracks in blades in an SHM system. This approach, based on NDT, automatically identifies and locates an acoustic emission source coming from a fiber's breakage in a wind turbine blade section by a novel signal processing method. It can be extrapolated to other similar structures, e.g., airplane wings.

Three sensors are strategically located in the blade. It is demonstrated that the approach is able to detect the location of the simulated defect accurately employing acoustic emissions signals. The signal processing is based on a graphical method of triangulation and seven nonlinear equations. The signals are previously filtered. Different experiments are performed to demonstrate the effectiveness of the proposed method.

![Diagram](image.png)

Figure 5.43. Scheme of the location of the acoustic emission for the first case study.
5. Case Studies and Results

The approach detects the location of the acoustic emission with high accuracy, 9 mm being the maximum error registered. There are conditions that affect the accuracy of the emission source location, e.g., the type of composite material, the sensitivity of the transducers, environmental noise, false positives due to impacts on the piece, etc. The method shows the position of the acoustic emission point with the real dimensions of the blade.

5.5.2 Concentrated solar plants: Defect Location.

Experimental procedure.

The aims of the experiment are to test the approach “Paths convergence” developed in the section 4.4.2. The objective is to use the method to detect changes in the thickness of the pipe and to locate them. Cylindrical Lamb waves (see section 2.3) were activated in the 316L austenitic stainless steel. The experimental platform described in section 3.3.4 for ultrasonic inspections was used to carry out the experiments.

The frequency used to activate the guided waves in the actuator were 200 kHz and 6 cycles pulses (to find a compromise between the excitation of this frequency and avoid the overlapping of the echoes), and the guided waves were received by three sensors. To perform the identification, location and size determination of defects a cut was made as shown in Figure 5.44.
Figure 5.44 Location of the crack in the pipe and location of the MFCs.

The first experiments were carried out in the pipe without any defect in order to have benchmarking signals. Subsequently, measurements were performed by making a cut with six different depths. The increment of each cut is 0.5 mm.

5.6 Edges location.

The presented approach in this work identifies the events within the signals that are obtained from elements as boundaries or welds. The process shown in Figure 4.9 consists of the following steps:

Figure 5.45 Identification of edges echoes algorithm.

- Peak searching: It is important to select the proper threshold for this purpose.
- Identify the first event that indicates the instant when the actuator is excited.
- Identify the first pulse received by the sensors of each wave mode (direct pulses).
- Identify echoes from the edges: The experimental ToF of each echo in the signal is obtained and compared with the theoretical ToF that they should have. The comparison sequence for identification of the edges is shown in Figure 4.11
5. Case Studies and Results

- The ToF of each echo is identified to calculate the distances travelled.

Echoes which are bounced from the pipe edges allow us to identify false cracks. It also provides information such as the attenuation of the ultrasonic pulse. The algorithm uses the distance of the sensors from the edges to perform a self-identification of signal events. The event is located theoretically when the two possible ways of propagation of ultrasound (forward and back), are analysed together, taking into account the ToF of each echo. Then, the algorithm correlates the theoretical events with the potential events detected in the signal. Next, the measurement accuracy is checked and validated or not, and each specific event is experimentally located, obtaining the experimental propagation velocity.

The purpose of this approach is to select the real peaks having its homologous in the set of theoretical peaks. This method detects the absolute and relative error between the values obtained and expected for each event. Figure 5.46 shows the edges location of the L(0,2) whose propagation velocity is 5020 m/s, where the “X” markers are the theoretical location of the echoes that come from the edges. The numbers 1 through 6 in Figure 5.46 and Figure 5.47 indicates the following:

1. The instant when the actuator is excited and emits the pulse.
2. The direct pulse, that is, the shorter distance between the actuator and the sensor.
3. The first reflection from the back edge.
4. The first reflection from the front edge.
5. The second reflection from the back edge.
6. The second reflection from the front edge.
5. Case Studies and Results

Figure 5.46 Edges reflections of $L(0,2)$ mode by comparing the theoretical and experimental values of ToF.

The approach analyses both longitudinal modes. Analogously Figure 5.47 shows the edges reflection of the $L(0,1)$ mode with a velocity of 2807m/s.

Figure 5.47 Edges reflections of $L(0,1)$ mode by comparing the theoretical and experimental values of ToF.
5. Case Studies and Results

5.7 Crack location.

To obtain the location of the damage it is more appropriate to analyse the longitudinal Lamb mode \(L(0,2)\) which is most similar to the symmetric Lamb mode in thin plates. This mode is more sensitive to the changes in the section of the thickness; therefore, hereinafter, only this propagation mode will be taken into account.

The potential crack detection and location method proposed is based on the search for two echoes that come from the same crack, but have different routes. The algorithm considers that if the time employed to traverse a common section is almost equal, the defect is detected and therefore located.

The pattern recognition approach is based on an automatic detection of cracks that compares the ToF employed by the same pulse to travel two different paths. The two shortest paths for detecting a crack between the sensor and transmitter are the path “a” and path “b” shown in Figure 4.15.

The distance travelled by an echo in the path “a”, for example \(d_{echo_a}\), is used to determine the distance \(d_{rc_a}\) between the crack and the receptor. Similarly, the distance travelled by an echo in the path “b” \(d_{echo_b}\) is used to determine the distance \(d_{rc_b}\). The distances, \(d_{rc_a}\) and \(d_{rc_b}\), should be close. The method performs a comparison between the distances obtained for each component of “X”

The paths are shown in Figure 5.48:
5. Case Studies and Results

New Approaches on Fault Detection and Diagnosis for Structures

Maintenance Management

Figure 5.48 Two shortest paths from actuator to sensor detecting the crack.

The ‘path convergence’ through the following results.

Figure 4.13 shows the echo coming from the crack by the path a.

Figure 5.49 Echo coming from the crack via path a.

Finally, when the location is determined the crack is shown in a schema with the actual dimensions of the plate and the position of the sensors (Figure 5.50)
5. Case Studies and Results

Figure 5.50. Crack location relative to the left edge in meters

Conclusions.

A new advanced signal processing approach for cylindrical Lamb waves has been developed. The method provides more precise information about the structural state of the pipe, which leads to an increase in safety, reliability, availability and investing returns. This work presents a new approach based on signal processing to automatically identify, locate and determine the severity of a defect in a pipe, given certain conditions. The algorithm developed combines two different techniques. The first identifies the time of fly of both longitudinal Lamb modes and it is used to automatically identify the edges or welds of the pipes. Time of Fly of the echoes are calculated theoretically and then compared with the experimental times to determine which echoes come from the edges. The second technique uses the correction method in order to identify the differences between the signals with defects and the benchmark signals. Then, the position in the time domain of these differences is compared with the echoes obtained in the first technique and the location of the defect is obtained. Echoes from the same defect traveling different paths are compared and the defect is located, considering each
amplitude. The second technique allows knowing the severity of the defect by analysing the changes in the ratio curve between the autocorrelations of the different signals.

5.8 Damage sizing

5.8.1 CSP: Autocorrelations and Ratio curve for Damage Sizing

Damage sizing.

To obtain the damage size of the case study 5.5.2 of each cut, the correction method explained in section 4.3 is performed. The ratio curve is obtained by dividing each autocorrelation with the autocorrelation of the benchmark signal. Figure 5.51 shows the ratio curves and the behaviour of the curves in the instant when the echo coming from the damage is captured. The height variations of the curves are proportional to the damage.

Figure 5.51 Ratio curve between the autocorrelations of each signal with the benchmark signal.

The predicted damage can be obtained using the equation:
5. Case Studies and Results

\[
P_{\text{Predicted_dmge}_i} = \frac{\text{Highest_point}_i \cdot \text{Tested_dmge}_i \cdot \text{Predict_dmge}_n}{\text{Highest_point}_n \cdot \text{Tested_dmge}_n};
\]

\[i = 1, 2 \ldots n.
\]

The ratio curve is computed by dividing the autocorrelation curve of the damage signal by the autocorrelation of the benchmark signal. The highest point in each ratio curve is called \textit{Highest_point}. The \textit{Tested_dmge} is the ratio of depth of the cut by the thickness of the pipe (3.05mm). The predicted damage (\textit{Predicted_dmge}) is the proportional expected percentage of damage computed by taking the highest Ratio Point (1.3) divided by the highest base point (2.09) multiplied by 16%. The error is the difference between the tested damage and predicted damage.

Table 18 Predicted damage by comparison of ratio curve with benchmark

<table>
<thead>
<tr>
<th>Depth of the cut (mm)</th>
<th>Highest Point</th>
<th>Tested damage (%)</th>
<th>Predicted damage (%)</th>
<th>Error (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.5</td>
<td>1.30</td>
<td>16</td>
<td>10</td>
<td>6</td>
</tr>
<tr>
<td>1.0</td>
<td>1.45</td>
<td>33</td>
<td>23</td>
<td>10</td>
</tr>
<tr>
<td>1.5</td>
<td>1.59</td>
<td>49</td>
<td>38</td>
<td>11</td>
</tr>
<tr>
<td>2.0</td>
<td>1.83</td>
<td>66</td>
<td>58</td>
<td>8</td>
</tr>
<tr>
<td>2.5</td>
<td>1.96</td>
<td>82</td>
<td>77</td>
<td>5</td>
</tr>
<tr>
<td>3.05</td>
<td>2.09</td>
<td>100</td>
<td>100</td>
<td>0</td>
</tr>
</tbody>
</table>

5.8.2 CSP: Damage sizing by analysing the attenuation curve.

5.8.2.1 Experimental procedure

A defect has been induced in the plate in order to visualize the automatic location of the events. Figure 5.52 shows the placement of the EMAT and the crack location. EMAT transducer is excited by a 256 kHz and six cycles pulse.
Shear waves are generated in both directions. The EMAT (R) receives echoes from the edges and from the crack.

Shear waves are non-dispersive, i.e. the propagation velocity of these waves is not frequency dependent. The propagation velocity of Shear Waves depends on the material properties \[104\]. The propagation velocity for the 3 mm austenitic steel plate (316Ti) is 3020 m/s. This is an advantage to locate events on the plate with high accuracy.

The method employed to achieve these results is explained in section 4.5.2.

There have been several tests on the steel plate where cuts have been made with different depths.

Table 19 Depths and relevance degree of each cut.

<table>
<thead>
<tr>
<th>Cut Depth</th>
<th>Relevance degree</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.00 mm</td>
<td>18.68 %</td>
</tr>
<tr>
<td>1.50 mm</td>
<td>21.70 %</td>
</tr>
<tr>
<td>2.00 mm</td>
<td>25.05 %</td>
</tr>
</tbody>
</table>
5.8.2.2 Conclusions

The development of a new electromagnetic acoustic transducer for condition monitoring together with the use of advanced signal processing approaches, provide more precise information about the structural state of the system, which leads to increase the reliability, availability, safety and investing returns. This work presents a new approach based on signal processing to automatically identify, locate and determine the severity of a defect in a plate. Similarly, could be used to detect defects and welding in pipes. Particularly, this approach comprises a pre-filter and denoising using Wavelet methodologies and the Hilbert Transform to detect relevant peaks. Time of Fly of the echoes are calculated theoretically and then compared with the experimental times to determining which echoes come from the edges. Any other echo represents a potential crack. Echoes from the same defect traveling different paths are compared and the defect is located considering each amplitude. Finally, the attenuation curve of the ultrasonic echoes is determined to provide an importance measure of the defect.

5.9 Neural Networks

5.9.1 Wind turbines: Detection of mud in WT blades

5.9.1.1 Methodology for the detection of mud on WT blades

The patterns recognition and classification techniques by Neural Networks (NN) are being used in the field of health structural materials (Section 4.8). Multilayer Perceptron neural network has been used to carry out the classification of five levels of mud on the blade. In order to check the effectiveness of the NN for the employment of multiples frequencies, two test were performed. The first experiment was carried out employing only a
single frequency for all the cases, and the second one employing several frequencies for the same cases.

1º Classification levels with ultrasonic signals of the same frequency (25,000 Hz)

2º Classification levels with ultrasonic signals of different frequencies (18,000 Hz, 20,000 Hz, 25,000 Hz, 30,000 Hz, 40,000 Hz and 50,000 Hz)

It has been followed the schematized process in Fig 2.

![Process flow for determining the level of mud and dirt on the blade.](image)

Sand mixed with a solution of water and glue is used to generate a paste of mud. It is added to the surface of the blade and then, to simulate the different levels of mud, the layer is gradually reduced with sandpaper. The ultrasonic signals are generated employing the Pitch and catch technique for each level.

- Level 1: 5 – 6,5 mm of mud.
- Level 2: 3,5 - 5 mm of mud.
- Level 3: 2 - 2,5 mm of mud.
- Level 4: 0,5 - 1,5 mm of mud (Figure 5.54).
- Level 5: no mud.
5. Case Studies and Results

![Image](image.png)

Figure 5.54 Mud on the wind turbine blade section.

The signal is emitted from a MFC transmitter and received by a MFC sensor. The tests were performed employing different excitation frequencies. The frequencies were: 18.000 Hz, 20.000Hz, 25.000 Hz, 30.000Hz, 40.000 Hz y 50.000 Hz (fig 4)

![Graph](graph.png)

Figure 5.55. Set of signals for level 1 of mud. Signals collected by the sensor for different frequencies.
5.9.1.2 Results

**Experiment 1:** Classification levels with ultrasonic signals of the same frequency (25,000 Hz).

The established NN architecture (05/05/05) has been trained with the results shown in Figure 5.56 (left).

**Experiment 2:** Classification levels with ultrasonic signals of different frequencies (18,000 Hz, 20,000 Hz, 25,000 Hz, 30,000 Hz 40,000 Hz and 50,000 Hz).

It has been tested with different NN to obtain better results (Figure 5.56 right) with the architecture: 15/15/05.

![Neural Network Result for 25 kHz](image1)

![Neural Network Results for 18, 20, 25, 30, 40 and 50 kHz](image2)

Figure 5.56. Neural network results for ultrasonic signals at 25 kHz (left) and signals at 18, 20, 25, 30, 40 and 50 kHz (right).

Figure 5.57 shows the histogram of error of the neural network is detailed noting that the high degree of accuracy.
5.9.1.3 Conclusions

This work shows a methodology that allows to evaluate the levels of mud on the wind turbine blades using guided waves. The methodology is able to differentiate between 5 different levels of mud on the blade. The signals were experimentally obtained in an actual wind turbine section and with simulated mud. A neural network was designed for that purpose and the training of the network determines the different levels of mud with a 1-1.5 mm accuracy. Other advantage is that it can avoid the redundancy of sensor, because the same ultrasonic sensor could inspect the structural health of the blade and to determine the amount of mud on the blade surface.

5.9.2 CSP: Pattern recognition for temperatures.

In this work, a type of neuronal network has been used to train and recognize temperatures ranges in a test rig that simulates the working conditions of a CSP.
This work presents a novel approach based on signal processing employing neuronal network to determine effectively the temperature of pipe, using only ultrasonic transducers. The main novelty presented in this work is to determine the temperature of CSP without requiring additional sensors. This is achieved by using existing ultrasonic transducers which is mainly designed for inspection of the absorber tubes.

5.9.2.1 Experimental procedure

The aim of this work is to determine the temperature of the tubes only by using piezoelectric sensors. It can lead to cost savings and to optimize the number of structural health monitoring sensors of a CSP. It was carried out emissions of ultrasonic short pulses at different temperatures, and the signals were processed to train a neuronal network. The output of the neuronal network allows knowing the temperature of the pipe.

The experiment was carried out in a test rig (Figure 3) consisting in 316L austenitic stainless steel tubes, four meters long, similar to those used in CSP, whereby oil is circulated at high temperature.

Two Macro Fiber Composite (MFC) transducers were placed in the test rig (Figure 5.58), where one acts as a transmitter and the other as receiver (pitch and catch). The transmitter transducer generates short pulses (6 cycles) of 250 kHz. The receiver transducer collects the ultrasonic wave, by converting the mechanical movement of the wave into electrical signal. Also the temperature is collected by using a thermocouple on the pipe, in order to train the neuronal network.
Figure 5.58 Use of ultrasonic pulses for detecting the temperature of the test rig pipes.

The oil that circulates inside the pipes was heated from 25°C to 75°C and the external surface of the pipe reached 55 °C. During the heating of the experimental platform were collected 1100 ultrasonic signals with their respective temperatures.

5.9.2.2 Results

During the design of the architecture of neural network, it has been determined the following parameters:

1. Number of inputs to define the neural input layer: The original signals with the relevant information of the received ultrasonic pulses is composed by 2000 samples: The number of inputs is significantly reduced after extracting the characteristics of the signal through the method of autoregression (AR). Network has been tested with different inputs as can be seen in Figure 5.59, and the AR-10 method provides better results.
2. Numbers of outputs. A neuronal network with fewer outputs have better results that with more outputs. It was decided to have more outputs for the range of temperature range were lower. Thus, each range has a range of 2.7 °C, corresponding to eleven outputs elected.

3. The numbers of neurons in the hidden layer is treated by many authors problem. There are criteria based on the number of inputs and training patterns. This is one of the main problems of MLP. For the calculation of the hidden neurons we've had on one hand the network performance through the mean square error and on the other the number of patterns to train. In this study we have trained, validated and tested with ultrasonic 990 signals, leaving 110 signals for further test in order to generalize the neural network.

4. Scaled conjugate gradient and performance Cross Entropy has been training mode chosen as the best performance.

The established neural network architecture has been trained with the following results (Figure 5.60):

![Success Rate Chart](image)

Figure 5.59 Success rate of the AR employed
5. Case Studies and Results

5.9.2.3 Conclusion

The work presents a novel methodology that allows increasing the reliability of a condition monitoring system analysing the temperature of the absorber tubes employing ultrasonic waves in a Concentrate Solar Plant (CSP). The approach can detect a temperature due to potential failures, such as hot spots in defects in welds. This technique allows avoiding redundancy of sensors, since a specific number of ultrasonic transducers can determine the structural condition of the tube and its temperature, using guided waves. A test rig, that simulates the working conditions of the absorber pipes of a CSP, was built to carry out the experiments. The oil inside the pipes was heated and circulated in the installation, while the pitch and catch of ultrasonic pulses were carried out. A neuronal network has been designed for signal processing and pattern recognition in order to identify the conditions. In order to reduce the inputs of the neuronal network, the ultrasonic signals have been pre-processed and their characteristic parameters have been extracted employing autoregressive methods. The trained neuronal network can determine the temperature of the test rig with an accuracy of 2.7 Celsius degrees.

Figure 5.60 Success rate of the neural network to determine the temperature range.
6 Big Data for Condition Monitoring

6.1 Big Data for Wind turbines maintenance

6.1.1 State of art

In addition to onshore wind farms, wind farms are built in the sea (offshore), several kilometres from the coast, to take advantage of the best wind conditions to overcome the negative relief effects. In these installations it is common to find much more powerful machines than which are installed onshore. The diameter of the turbine is a crucial parameter: longer blades, more swept area and more energy produced.

This trend to building ever larger blades carries out certain problems. The blades have to bear more and more weight and strength due to its greater sweep area. This means an increased fatigue in the blade structure, and therefore any blade failure entails very high costs. It has been estimated that the time between failures in wind turbine blades is 5 years. The time spent in repairing one of these blades is 2 days on average in onshore wind
6. Big Data for Condition Monitoring

turbines. However, in the case of offshore wind turbines the downtime could increase up to a month.

The repair costs of a wind turbine blade may vary between 20000€ to 50000€ depending on the required operations, e.g. if it is necessary to take it down and if it can be repaired in the field or it has to be carried back to the factory. These costs can be multiplied by 10 if the turbine is located offshore due to the associated costs of transporting the new blade and difficult working conditions for replacement [105]. In addition to these costs, is necessary to add lost profits caused by the downtime.

To deal with these problems companies have invested great resources to develop reliable preventive maintenance. This was responsible of ensuring the adequate working of wind turbines by means of periodic reviews, which consisted on oil changes on the gearbox, visual inspections of blades, retighten screws, etc. Nowadays has emerged a new form of maintenance, called predictive maintenance, in order to avoid the defects as far as possible, whose function is to try to detect a potential failure before it occurs, to avoid triggering a fatal error. For this reason, this approach requires a system capable of providing real-time status of the machine, independently, safely and accurately.

6.1.2 Big Data in Structural Health Monitoring.

The non-destructive inspection tests are used with the purpose of detecting superficial or even internal discontinuities of a certain material, as well as assessing its properties. SHM is the process of implementing a damage detection strategy in a given structure. By SHM is possible to detect structural changes. It is commonly used for checking welding points and components, or for assessing the density of a material. Most of the times, the obtained data on these tests are not directly understandable, and may require the analysis of qualified professionals.
The implementation of such a system for predictive maintenance purposes represents a big challenge, and many factors contribute to make it harder. Some of them are related with the nature of the data, as they primarily consist on time-domain signals while data mining techniques have traditionally focused on cross-section data (with no time dimension). Another concerning fact is the problem of integrating the result of multiple signal analysis in a unified and consistent framework. But probably the most challenging fact is the problem of dealing with huge amounts of data, as the traditional algorithms are not specially designed for being scalable over terabytes or even petabytes of data.

The problem this large amount of data to analyse is mainly due to the development of new types of sensors at a low cost, and the possibility of transmitting tons of data everywhere. These factors let to build a 'digital projection' of the machines' life, consisting on all the data that have been collected about them, including their surrounding working conditions. for example, the health monitoring of a machine should focus on the more critical components, not only on those that will cause a larger failure rates, but also those that would produce longer down-time failures. In wind turbines it is known that the highest failure rates of structural components are caused by the blades, especially the pitch system, and the drive system. At this light, it would be reasonable to have a number of at least 16 sensors on each blade and 48 sensors on the tower. These sensors are commonly MFC transducers that work at ultrasonic frequencies, in the range of MHz. A typical signal sampled at 4MHz during one second will represent 9.72MB of data. Having 96 sensors in a single turbine, it would represent the amount of 933 MB of data in just a matter of a second. These dimensions get even bigger when we consider the tracking of multiple wind turbines, e.g. a wind farm with 80 turbines would generate 72.9 GB of data each second. In addition, it must to be add all the information about environmental working conditions,
6. Big Data for Condition Monitoring

which usually come from the Supervisory Control and Data Acquisition (SCADA) systems.

Even though Big Data has become one of the most popular buzzword, the industry has evolved towards a definition around this term on the base of three dimensions: volume, variety and velocity [106].

Data volume is normally measured by the quantity of raw transactions, events or amount of history that creates the data volume. Typically, data analysis algorithms have used smaller data sets called training sets to create predictive models. Most of the times, the business use predictive insight that are severely gross since the data volume has purposely been reduced according to storage and computational processing constraints. By removing the data volume constraint and using larger data sets, it is possible to discover subtle patterns that can lead to targeted actionable decisions, or they can enable further analysis that increase the accuracy of the predictive models.

Data variety came into existence over the past couple of decades, when data has increasingly become unstructured as the sources of data have proliferated beyond operational applications. In industrial applications, such variety emerged from the proliferation of multiple types of sensors, which enable the tracking of multiple variables in almost every domain in the world. Most technical factors include sampling rate of data and their relative range of values.

Data velocity is about the speed at which data is created, accumulated, ingested, and processed. An increasing number of applications are required to process information in real-time or with near real-time responses. This may imply that data is processed on the fly, as it is ingested, to make real-time decisions, or schedule the appropriate tasks.
6.1.3 Proposed methodology

The approach proposed in this chapter is based on the use of three sources of information. These sources are not independent, because they provide information about the same physical event. The signals picked up by the transducers will be processed in the very first step by three parallel filters. They will be responsible of extracting the useful information to be used in the condition monitoring. The results are three set of signals: vibrations, acoustic emission and ultrasonic signals, each of them analysed by an independent 'line' of the system.

Figure 6.1 Wind turbine condition monitoring for blade and tower
Vibrations

The first approach analyses only low frequencies that are characteristics of vibrations. It is possible to get valuable information related with the integrity of a blade structure analysing the vibrations in dynamic conditions \[107\]. The extracted information shows the natural frequencies of a blade, and their respective harmonics. These vibrations are registered on a model that analyses the amplitude and frequency. Because the manufacturing of the blade is manual, and blades are not identical, the system will create a unique model for each blade. The model will learn from these two parameters over a period of time, and these parameters will be associated to a free fault model. Therefore, these signals are processed online in the time domain and in the frequency domain. In the time domain is applied an upper and lower limit amplitude for signals, based on what it has learned in the previous period, which correspond to very strong vibrations that can trigger broken fibres due to the fatigue of these large vibrations, then trigger an alarm. Same data are analysed in the frequency domain, and the natural frequencies and
their harmonics are compared with the learned in the model. If there is a new energy peak in the frequency domain, which may be due to a failure in its structure has altered the natural frequency of the blade, and then an alarm should be triggered.

Employing the Big Data approach is possible to analyse large amounts of information, even coming from different sensors and places. In this sense, the information obtained from meteorological sensors on the turbine becomes highly profitable and valuable. These data are usually extracted from SCADA systems, and should include wind speed and direction which definitely determine the blade vibrations in its natural frequencies. That information is also taken into account in the design of the trained model, thus making possible to predict the blade vibration for different wind directions and speeds.

**Acoustical emissions:**

The second approach is focused on the detection of acoustic emission. When repetitive loads are applied on a certain material, it is known that they produce micro-breaks which liberate energy out of the material [28]. This energy takes the form of elastic wave which produce sound. With the help of sensors properly disposed it is possible to capture and record this sound. These sensors translate that mechanical energy in small electrical signals, which usually are pre-amplified in order to obtain a clearer signal. During the installation of the system is important to adequately locate the sensors, and to fix them to the material by good coupling. The signals are captured, amplified and recorded in a computer for posterior analysis. The frequency of the signal produced by the micro-breaks depends on several factors, e.g. the nature of the material, the type of discontinuity and the source of the emission. On this base it is possible to characterize the source of the emission by isolating certain frequencies with the help of appropriate filters. In many
works it is common to use three sensors, which are properly located to determine the source of the emission with high accuracy, usually with the help of triangulation algorithms.

In wind turbine blades domain, the acoustic emission is a major way to detect micro-breaks between the glass fibers of a blade in real time.

![Sensors](image)

Figure 6.3: Sensor location in a wind turbine blade

The method proposed in this chapter consists on the use of 16 MFCs on each blade. Most of the sensors are located in the first third of the blade, where breaks commonly occur.

These sensors are constantly recording data. When a fiber break occurs, the elastic waves reach the MFC and the signal is recorded. Knowing the distance between the MFCs, and measuring the time delay between the activation of every sensor, it is possible to accurately compute the location of the break and its characteristics, depending on the type of wave issued, (amplitude, frequency ...).
Figure 6.4: Crack delay signal simulations. The source is located by triangulation algorithms.

The large amount of data generated by all the sensors, as well as the meteorological data, are processed by the Big Data system, and a specific model for each blade is generated. It is important to note that when meteorological data predict rain or hail, acoustic emission detection should be disabled, because each impact of each raindrop produces similar sound waves, which can be confused with those issued by a fault. The system will create a proper model for each blade, will record the detected acoustic-emission source locations and the most probable types of defect. In parallel, when an acoustic emission is detected, the ultrasonic inspection is activated in order to corroborate the possible damage.

The last approach is an active search for defects using the technique of pulse-echo ultrasound. In this case the transducer is excited with a short pulse with frequencies above 20 kHz. These signals are applied to the material, and the received echoes are studied. In order to strengthen the ultrasound analysis,
the signals will be emitted in the form of white noise. This line could be subdivided into two parts. The first one would perform a general periodic monitoring: when a failure event is detected; the second part is initiated to perform a more exhaustive analysis which verifies the actual existence of a break and its location.

**Ultrasonic inspection**

This approach is an active search for defects using ultrasonic inspections and ice detection. For fault detection, in contrast to acoustical emissions, ultrasonic short pulses are applied on the material to be examined. A combination of the pulse-echo and pitch-catch techniques is used. The ultrasonic short pulses produce waves that travel through the material, and these waves are reflected when reach the interface or a discontinuity [108]. These echoes give information such as the break location by measuring the arrival time of the echo, as well as the type of defect.

![Figure 6.5: Crack source location by triangulation algorithms](image)

Figure 6.5: Crack source location by triangulation algorithms
For ice detection on blades, meteorological data from SCADA systems are also used. It is known that the ice on the blade changes the properties of wave propagation, especially the velocity. If the meteorological information predicts the presence of frost, and ice build-up on the blades, the ultrasonic transducer will emit the short pulses and the system will compare the collected signals with the ones coming from normal (previous) conditions.

### 6.1.4 Big data and cloud computing

The large amount of data generated by sensors will require a powerful computing architecture that ingests such volumes of data with no problems of saturation neither response delays. Nowadays, the concept of Cloud Computing has got popularity in the industry as well as in the academic community. It introduces the idea of 'elastic resources' which expand and contract according to the system load dynamics [109]. In this way, computational resources can be shared across applications, resulting in great reduction of costs and latency [110]. Even though this is a novel trend in industry, it is well founded in rather known concepts like parallel computing, concurrent computing and operating system architecture. They all have more than four decades in academic and research community, and have been raised now under the name of Cloud Computing. There are various reasons for this resurgence, e.g. the penetration of Internet in any sector and industry of economy, the increasing power of computers at a lower price, the advent of embedded systems and definitely the evolution of software industry. But more importantly, this new paradigm has opened the door to an immense quantity business models. Some of them are included in one of the following service models:

**Infrastructure as a Service (IaaS)**
6. Big Data for Condition Monitoring

They are the most architectural layer of a computing system. The services that users can access include storage, load balancers, firewalls, Virtual Private Networks (VPN) and Virtual Local Area Networks (VLAN), but the most generally consumed service at this level is computing power: the user is provided with network access to an operating system, which can be executed either by a real machine or by an emulator. The latter has crystalized in the industry with the name of Virtual Machine (VM), and many products have extended these techniques not only for infrastructural services, but also for final users. Some of them are VMware, VirtualBox, Xen, Hyper-V. Most of the tools provided by a IaaS cloud are focused on managing such virtual machines in software containers called pools. VM pools are able to run large numbers of virtual machines, and scale up and down the resources according to the whole charge in the system [106]. From the customer point of view, the services provided in this layer will require considerable technical knowledge and expertise because they involve installing, patching and maintaining operating system images as well as the actual final application software and its dependencies.

Figure 6.6: Hierarchy of Service Models in Cloud Computing Industry
Platform as a Service (PaaS)

The technical complexity involved in IaaS products became a barrier for their adoption in many domains. For that reason, the cloud providers started to build up a new layer of services, which will be closer to the customer requirements. The users will not have to worry about infrastructure issues, they should be able to focus on the concrete business requirements. PaaS is conceived to make it possible: the user is provided with a computing platform that ideally fits all his requirements: an operating system, a programming language execution environment, database and http servers, and even an Integrated Developing Environment (IDE). The underlying resources are automatically scaled by the infrastructure so that the users do not have to allocate resources manually. These features allow programmers the development of large and complex software solutions, deploy them in the cloud and reach the production stages much easier than using traditional server development techniques.

Software as a Service (SaaS)

The successful and rapid adoption of platform services in the cloud made the industry to evolve towards a new layer of services, those oriented to final software consumers. As programmers were endowed with cloud developments platforms and tools, the most foreseeable evolution was indeed a remarkable increment in the volume of cloud solutions targeting final consumers. And these services were quickly and massively adopted in software industry: by one hand, software developers install and operate applications and do not have to deal with the infrastructure’s complexity, and by the other hand, the final users receive additional benefits because they do not have to install and run the application in local machines, but simply use cloud clients to access the application. These changes dramatically reduce the tasks of support and maintenance, and unify the
user’s experience in a single interface. The application is completely executed in the cloud, allowing the implementation of new valuable features and functionalities that were unfeasible in local software solutions. This is possible mainly by the hardware scalability provided by the infrastructure at lower levels, but some techniques have been designed to optimize time and resources also at the software layer. A software optimization technique that has become very popular among SaaS providers is multitenancy, which consists on grouping several logic instances of an application in a single bunch which is served by a single shared resource.

Another big sub product in this trend is the so called Internet of Things (IoT) which is becoming more and more popular these days. It is a natural consequence of the previous developments, since it consists on the interconnection of uniquely identifiable embedded computing like devices with the existing Internet infrastructure. Companies like Xively, AT&T, Axeda, Cisco and others are offering solutions specifically targeted to this new growing market.

6.1.5 Proposed Infrastructure

The sensors are controlled by a node (in some domains it is called waspmote), which is a device capable of receive streams of data from sensors, split them in packages, and send them through the network with the appropriate metadata. Several considerations should be done in this point. With respect to the volume of data generated, it is important to make the accurate estimations in order to acquire the correct hardware which supports it. For example, if it is need to install forty MFC sensor on a wind turbine, and capture data at 25 kHz, it would mean approximately 360MB of data every second. Would the node support this? Is its data bus enough for ingesting such a stream? These all are factors that should be considered when hardware options are being evaluated.
Once the data has been properly collected by the node, it is time to transmit them to the computing centre. This process is usually done by mean of REST web services, which work over the HTTP requests and responses layer; nevertheless, some alternative technologies have recently emerged, like WebSockets and other streaming solutions. Some of these efforts have crystallized in the HTML5 standard that web browser must accomplish. Even these all alternatives, it is important to select the most appropriate data transmission technology. Some criteria will help for this:

Granularity. The granularity of the requests (bunches of data send) from the node to the server has to allow the latter to scale their resources as needed. In other words, it is necessary to balance the trade-off between small and big queries. Small queries will let the server scale smoother, but at the price of a higher number of queries. As certain amount of protocols related bytes is attached to each query, the total efficiency of the system could decrease when the size of the queries is arbitrarily reduced.

Responsiveness. One of the strongest requirements in industrial applications is the responsiveness of the whole system. It is true also for monitoring systems, where no real time decision is made, but streams of data has to be continuously processed to guarantee safe working conditions. This is the case of wind turbines condition monitoring. In the next sections we are going to present how it could be achieved in a cloud computing environment.

**Task Queues**

Regardless the cloud provider selected, the system should be designed to scale and balance the resources as needed, otherwise the system much probably will collapse at demand picks. The most common approach for doing so consists on splitting the load in a proper way: by doing so, some tasks are processed 'in the background' by some worker threads, and some other tasks are directly dispatched in the "main thread". The correct
separation depends on several factors, like the quantity of expected requests, the volume of the received data and the computing cost of processing each request. In all cases, the incoming requests are organized in small and discrete units of work, called 'tasks', and are pushed into a queue, at the time that some 'worker' processes dispatch them as soon as possible. The scalability of the system comes when the 'workers' are replicated to timely consume the processes in the queue, and this is done dynamically and according to the current system load.

In today's cloud industry this approach is widely used, though using different names according to the specific provider. For example, in Google Cloud Platform it is called 'Task Queues', while in Amazon Web Services (AWS) it is named 'Simple Queue Service'. In Windows Azure Cloud Platform it is a bit trickier to match this functionality. It will be a combination of the 'Service Bus' and 'Scheduler' functionalities both provided in Azure platform. The Scheduler provides a mechanism for multiple process orchestration, integrating them all in a single logical base, but it needs the help of the Service Bus, which provide the messaging and buffering tools for making possible such integration.

**Processing algorithms**

The algorithms executed by these tasks depend on the concrete application to build. In wind turbine condition monitoring with MFC sensors, task processing will probably consist on analysing the received raw signal, first making a sort of feature extraction. Feature extraction is a form of dimensionality reduction where the data is transformed into a reduced representation set of features. The objective of this step is twofold: reduce the redundancy in the data, and spotlight the relevant information contained in the data.
6. Big Data for Condition Monitoring

Once this information is computed, the following common step is to compare them with the previously stored data. The most elegant and efficient way of doing it is by means of statistical modelling techniques. A statistical model is an abstract formalization of the relationships between the principal variables in a certain phenomenon. By using a model, it is possible to condense huge amounts of data in just few values. These values usually correspond to the parameters of the model. The process of optimizing the value of the parameters is called model training, because the model is fitted to the data according certain restrictions [111]. There are lots of different approaches to modelling data. For signal analysis it is very common the use of the Fast Fourier Transform (FFT) and Wavelet Transform (WT).

Using the appropriate modelling technique, and having a set of well-trained models, it is possible to detect novelties in the data by just testing the new data against the models. Depending on the case, the appropriate system message has to be triggered (warning, error, fault...).

**Data logging**

The following step consists on storing the relevant data in a proper way. For the case when the stream of received data is extremely big, it would be good to consider the possibility to design a feature extraction process targeted to reduce dimensionality in data for storing purposes. In these cases, instead of storing the full set of data receive, it will store only a representation. Part of this process would imply re-training the stored models, in order to update them according to the newest system’s state.

Conventional relational databases are not well suitable for this kind of applications, firstly because of the huge volume of the data gathered, and secondly, due to the nature of the data itself: relational databases were designed mainly for enterprise applications, where the data is definitely transactional and relational. In the big data applications, it is very common
6. Big Data for Condition Monitoring

to work with unstructured data, even with dynamic formats and relationships. For that reason, many efforts were devoted to build schema-less databases which are better suited for these new kind of applications. MongoDB is probably the most popular product in this sector, which usually is referred with the general name of 'NoSQL' databases. They were rapidly adopted by cloud providers as one of the key infrastructure components. Some examples are 'Cloud Datastorage' from Google and Amazon S3 from AWS.

6.1.6 Conclusions

The proposed model is used to cover the most important requirements of the structural health monitoring and vibration monitoring in a wind turbine blade. The system analyses the received signals online and acts depending on different events. After the signal processing stages, the system records the status of each wind turbine to predict future failures and to get failure patterns between different wind turbines. The advantages of the proposed methodology include the exploitation of large volumes of data online, as well as the integration of continuous parallel analysis in a unified framework. Additional advantages come from the fact that the system uses the same transducers for three different purposes, which implies that the whole system is simplified and costs are reduced.

6.2 Big Data for Concentrated Solar Plants

Big Data is becoming the most powerful tool to analyse the huge amount of data around us. Cloud Processing is among the benefits offered by the Big Data, which allows to analyse data in real time from different parts of the world. These technological advances in mass data processing can be exploited to treat information from thousands of sensors. In this work it is
proposed a new approach for and optimal condition monitoring and control of Concentrating Solar Plants spread over different geographical locations. The information from the condition monitoring sensors (ultrasonic guided waves) and the data for the optimal control of the plants need a cloud platform to analyse jointly with forecast data (meteorological, demand of other plants, etc.). The main processing tool used are neural networks, responsible for correlating the obtained signals in real time, to determine anomalous results and generate alarms.


In the current era, where the satisfaction of the energy demands of the growing world population reaches very high limits, it becomes imperative to develop alternative sources of energy [20,41]. The alternative sources must be economic, non-polluting, inexhaustible and technologically applicable to satisfy the demand of society [11].

Solar energy is one of the most important alternatives for use as an alternative energy source and it can be technologically exploited by photothermic conversion. This need has caused significant growth and development of new Concentrated Solar Power (CSP)[8]. There are a large number of solar fields using this technology for generating heat and electricity. The parabolic through concentrator are solar concentrating collectors of linear focus, which transform the direct solar radiation into thermal energy. This is achieved by heating a thermal oil that can reach 400 °Celsius.
6. Big Data for Condition Monitoring

That is why the CSP require to improve the operational and maintainability of this fields because a failure in the system can halt production of an entire power plant [25,26,67,100,112]. Therefore, the need arises to implement a condition monitoring system to analyse those critical elements of the plant, such as the absorber tubes and welds [9,12,21,23].

One of the major advantages of the cloud computing is the introduction of the ‘elastic resources’ idea which expand and contract according to the system load dynamics. In this way it is possible to reduce the latency by the shared across applications. The great penetration of Internet in all the industry sectors, the increasing power of the computational systems and the advances in software have made possible that this new computing architecture emerge as a real solution.

In this chapter a new system for condition monitoring and control for CSPs is proposed based on the cloud computing. The main objective is to jointly benefit data processing, cooperative work between different power plants, optimization of resources, and increasing the performance of CSP plants.

Figure 6.7 Storage of the CSP power plants in Spain. The Spanish Association of Solar Thermal Power Industry (PROTERMOSOLAR)
For this purpose, there are two mainly groups of input data to the system:

- **Endogenous Data**: This group encompasses all those variables and parameters that are intrinsic to each CSP plant. On the one hand, there are the fixed parameters. These parameters are not modifiable values of the characteristics of the CSP plant. These parameters are, for example, the collection surface, the reflectivity of the mirrors, the storage limit, etc. These parameters will be considered for later compare performance of different plants to obtain conclusions which are more efficient. On the other hand, there are the endogenous variable data, which have to be continuously optimized. They are all those values that come from sensors of CSP plant. Examples of endogenous variables are the temperature on the absorber tubes, the ultrasonic signals and the generated MW. It is crucial to analyse all these variables, in order to optimize the operational performance of the CSP plant. All these sensors will be connected to the central station of the CSP plant and it will send signals so the provider of online cloud services.

Table 20 Endogenous Data of the CSP plant.

<table>
<thead>
<tr>
<th>Endogenous Data CSP plant (Parameters and variables)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Solar Collection</strong></td>
</tr>
<tr>
<td><strong>Optic Efficiency</strong></td>
</tr>
<tr>
<td><strong>Storage</strong></td>
</tr>
<tr>
<td><strong>Circulation</strong></td>
</tr>
<tr>
<td><strong>Re-circulation index</strong></td>
</tr>
<tr>
<td><strong>Performance</strong></td>
</tr>
</tbody>
</table>
6. Big Data for Condition Monitoring

<table>
<thead>
<tr>
<th>Condition Monitoring</th>
<th>Ultrasonic signals</th>
<th>Temperature sensors</th>
</tr>
</thead>
</table>

- **Exogenous Data**: This group includes all the parameters which are independent of the CSP plant. The Exogenous data are part of an indirect way in the las purpose of the CSP plant, the energy generation. Although they are not directly involved they have an important role. They are, for example, the meteorology, the cloud cover, the market demand and the company strategies.

Table 21 Exogenous Data of the CSP plant.

<table>
<thead>
<tr>
<th>Exogenous Data</th>
<th>Anemometer</th>
<th>Pluviometer</th>
<th>Hygrometer</th>
<th>Thermometer</th>
<th>Barometer</th>
<th>Pyrometer</th>
<th>Cloud cover</th>
<th>Radiance index</th>
<th>Power Demand of CSP (MW)</th>
<th>Power Demand of others CSPs</th>
<th>Storage Forecast</th>
<th>Energetic Strategy</th>
<th>Condition monitoring strategy</th>
<th>Performance Strategy</th>
<th>Watt current price</th>
<th>Watt price forecast</th>
</tr>
</thead>
</table>

The Figure 6.8 shows a scheme of the information flux proposed in this chapter for a condition monitoring and management of a CSP plant. Where the inputs are the variables and parameters above mentioned and the outputs are the optimal maintenance and the CSP plant control. The optimal maintenance comprises a proper condition monitoring of the plant within a specific maintenance strategy. The CSP plant control will manage the production as a function of the power production strategy, which comprises the current energy demand and the status of other CSPs.
Specifically, if we focus on inspecting the absorber tubes, according to National Laboratory of the U.S. Department of Energy (NREL), a common 50 MW power plant has 22464 concentrating solar receiver pipes. The Spanish Association of Solar Thermal Power Industry (PROTERMOSOLAR) would comprises a total of 1.035.000 absorber pipes.

The European project ‘Intersolar’ [19] proposes to inspect the absorber receiver tubes employing ultrasonic guided waves in order to detect defects such as cracks or corrosions in the pipes [5,19,49]. This project proposes to inspect the pipes employing 4 ultrasonic transducers. A unique ultrasonic signal is approximately 100 kb, therefore it multiplied by all installed sensors would generate 41 Petabytes each sweep. By sweeping hourly, it would be generated 1 Exabyte daily. This is only information from ultrasonic signals for condition monitoring, so this should be added the signals from all other sensors.

Figure 6.8 Flux data Scheme of the proposed processing data system based on Cloud Computing.
6. Big Data for Condition Monitoring

Proposed Infrastructure for Cloud Computing.

A node controls the information collected by the sensors with the metadata, and organizes them in packages to send them through the network. The above estimations of the amount of data collected by the sensors will determine the characteristics of the hardware employed. This will define the optimal choice of the IaaS. Then the data will be transmitted to the computing center. The standard HTML5 is the proposed technology to carry out this process due to its integration to work in a web browser.

![Cloud Computing Platform Diagram]

Figure 6.9 Proposed Cloud Computing platform to jointly analyse and control a group of CSP plants. The example shows the Spanish Association of Solar Thermal Power Industry (PROTERMOSOLAR).

The most appropriate data transmission technology will be selected depending on the granularity of the data and the responsiveness of the system. For the granularity it is necessary to balance the trade-off between small and big queries. The responsiveness is a strong requirement for the condition monitoring.
In order to avoid the system collapse at demand picks, the system should be designed to scale and balance the resources as need. It is recommendable to split the load of work by processing some tasks ‘in the background’ and others ‘in the main thread’. It depends on several factors, like the volume of data, the request frequency and the computing cost of each request. It is necessary a high scalability of the system, where the processes of each task are dynamically replicated according to the system load.

The processing algorithms executed by these tasks depend on the concrete application. In CSP plants, the condition monitoring with the ultrasonic sensors will consist on reduce the amount of data of the signal by the extraction of the characteristic of the signal. Then the following methods are proposed to process the data and to determine the structural health of the absorber tubes.

### 6.2.2 Neural Networks Techniques and Fuzzy Logic Controllers.

Prognosis and prediction of solar radiation are stochastic processes due to the variability of solar resources. As a consequence, numerous mathematical techniques have been developed to model these processes. Among these techniques, Artificial Neural Networks (ANN), Fuzzy Logic (FL), Genetic Algorithms (GA) and hybrid systems (GA / ANN ANN-FL) are widely employed. Further information about these techniques can be found in references [113-123].

Figure 6.8 shows some parameters (Solar Collection, Storage, Circulation, ...) which are considered as inputs of the system to obtain useful information for establishing maintenance and control schedules of the plant. In this chapter, it will be show an example of a condition monitoring application based on ultrasonic inspection employing neural networks.

**Ultrasonic Inspection.**
6. Big Data for Condition Monitoring

The inspection by guided waves consists of the excitation of an ultrasonic transducer, which generates ultrasonic waves that are propagated through the pipe. The main advantage offered by this technique, compared with traditional ultrasonic methods, is the ability to inspect structures, such as plates or pipes, along several meters. This technique allows to know the state of the pipe at a particular location. In some cases, hundreds of meters can be inspected without the relocation of the transducer. Novel methodologies in signal processing for these applications are being published [51], such as online predictive analysis to be employed in structural health monitoring.

An unsupervised neural network Self-Organizing Feature Maps (SOFM) [124,125] which will serve as a tool of grouping patterns for ultrasonic signal and data mining [126]. It will also serve as a tool for process monitoring and data mining.

Initially it has proceeded to remove noise in the ultrasonic signals through wavelet transform to. Then the filtered signals are inputted to the neural network. The architecture of this model consists of two layers: an input or sensory layer consisting of m neurons (a neuron for each signal), distributing the information to the second layer. The processing is done in the second layer with a linear structure. First each neuron calculates the similarity between the input vector x(t) (ultrasonic signal) and reference vector (vector of synaptic weights) according to established criteria. The winner neuron is called Best Matching Unit (BMU), whose weight vector is more similar to the input. Therefore, each winning neuron (BMU) indicates the pattern detected in the input vector. In the learning phase the winning neuron modifies its weights to make it more similar to the input vector. On the other hand, the neighborhood function causes neurons belonging to the environment of the winning neuron modify their weights similarly. This implies nearby neurons tune in with similar patterns. After a sufficient number of iterations, the network adapts to the form of data or input.
distribution. The neural network has an associated cost function that the map attempts to minimize during their learning. This function in our case is

**Temperature**

When corrosion occurs in the tubes, for example near welds, hot spots are generated. The hot spots may not be detected by temperature sensors if they are far from the hot spot. A solution here is planted, which employ guided waves to sweep the total pipe and to obtain the pipes temperature. The guided waves are sensitive to changes not only in the material, also to changes in temperature. Knowing the temperature by guided waves can be very useful to avoid redundancy of sensors, or for redundancy in safety, making that the condition monitoring system makes relations between the temperature data and the guided waves signals.

To explore the idea of the condition monitoring in a CSP plant establishing a relationship between temperature of the pipes and the guided waves it has been performed tests in a platform which simulates a CSP plant. The results are shown in section 4.2.

This section delves into the establishment of a hybrid control system (ANN-FL) using as main parameters the temperature in the solar absorber tubes. The ultrasonic transducers will be used to determine the temperature of solar absorber tubes by analysing the guided waves. Short ultrasonic pulses were emitted at different temperatures, and the signals were processed to train a neuronal network. The output of this neuronal network allows to know the temperature of the pipe.

Once the temperatures have been obtained by these neural networks, a fuzzy logic controller provide the state of the CSP plant regard to the temperatures.

**Fuzzy Logic Controller (FLC).**
6. Big Data for Condition Monitoring

Data interconnected from different sensors (temperature, oil flow, ...) are often disordered and therefore it is necessary to establish a relationship which allows to obtain an output, for example, an alarm. Fuzzy logic controller emerges as a solution to this problem and it has been used in many fields. The structure of a FLC is formed by three blocks: Fuzzifier, Fuzzy Inference System, Defuzzier.

The Fuzzifier converts the numerical values of the input variables into linguistic variables (fuzzy sets). In this case it has been used a Singleton Fuzzifier.

The Fuzzy Inference System interprets the type of rules 'IF-THEN' of a set of rules, in order to obtain the output values. This values are based on the current values of the linguistic variables which are the inputs of the system.

Defuzzifier is the function that transforms a fuzzy set, which is the typical output of a Fuzzy Inferring System in a non-Fuzzy value. It usually is converted into a continuous signal.

The advantage of this system is the computational efficiency and ease of adaptation.

In this case it has been used a FLC with triangular functions including, Fuzzifier of Singleton type and Defuzzifier by mean centers successfully.

The FLC operation can be summarized as:

- Outputs of different neural networks will be FLC inputs. Each neural network will be interpreted by different signals from multiple sensors.
- The FLC expert system will establishes the status of the plant according to the input, and if necessary, it will activate the corresponding alarms.
6.2.3 Case study: Results

Detection of cracks and corrosion in absorber tubes.

The aims of the experiment are to develop a technique able to detect changes in the thickness of the pipe, to locate them and to determine the size of the damage. Cylindrical Lamb waves were activated in the 316L austenitic stainless steel.

The first experiments were carried out in the pipe without any defect in order to have benchmarking signals. Subsequently, measurements were performed by making a cut with six different depths. The increment of each cut is 0.5 mm (Figure 6.10).

Ultrasonic signals obtained are processed in a neural network SOFM order to classify them into six groups. Each pattern will reflect the status of damage. The process followed is collected in the previous section. In Figure 6.11 the clustering results it is shown in six groups. It can be appreciated that there are a group samples twice in the rest. This is because the healthy tube and the first damage is barely noticeable grouped.
6. Big Data for Condition Monitoring

6.2.4 Conclusions

A new system for condition monitoring and control for CSP plants is proposed based on the cloud computing. The main objective is to jointly benefit data processing, cooperative work between different power plants, optimization of resources, and increasing the performance of CSP plants.

In this chapter it has been studied the application and implementation of Big Data techniques for monitoring a CSP plant. The proposed technique for processing the data is a hybrid system which consists in Artificial Neural Network and Fuzzy Logic Controller, also known as Neuro-Fuzzy (ANNS-FLC). It has been shown that, based on data obtained through ultrasonic signals in the solar absorber pipes, it is possible to obtain parameters such as the temperature or the structural state of the pipe. A fuzzy logic expert system employ processing with ‘SOFM’ and ‘MLP’ neural networks in real time to determine the state of the plant and sets alarm.
The idea presented in this work proposed an autonomous and optimal management of CSP plants. It is possible thanks to recent advances in hardware and software which are based on Big Data and Cloud Computing techniques. By using these resources, it is possible to intelligently manage and control a large number of similar CSP plants dispersed around the world.
6. Big Data for Condition Monitoring
7 Conclusions

Wind and solar energy powers have become the most important renewable energies in the worldwide in recent years. The reduction in operating and maintenance costs of the turbines has been identified as one of the biggest challenges to establish this energy as an alternative to fossil fuels. Predictive maintenance can detect a potential failure at an early stage reducing operating costs, especially in areas of difficult access.

Non-destructive tests have emerged as an effective method to detect defects and failures in those crucial pieces for the proper functioning of the plant. Guided ultrasonic waves offer possibilities as NDT to inspect structures of reduced thickness, e.g. wind turbine blades or tubes.

This work proposes approaches for different problems related with the generation of wind energy and Concentrated Solar Plant.

The avoidance of wind turbine shutdowns during times of ice or snow represents considerable financial and energy savings. This research work proposes a NDT method that includes different techniques to inspect materials in order to detect the icing blades. It is considered a technique based on ultrasonic method called guides waves. Lamb waves are guided waves propagating in plate or shell type structures.
7. Conclusions

A common defect in wind turbine blades is delamination and disunion between layers, which results in a stress concentration area (potential failure). This work presents a new methodology for the detection disunity between layers using a real blade.

This work introduces a novel design of a Fault Detection and Diagnosis model based on ultrasound technique. The FDD model will be able to detect fault/failures via the pulse-echo technique. The pulse-echo is got via piezoelectric transducers that are also employed as sensors.

This thesis also discusses the NDT evaluation techniques that can be employed to inspect solar receivers and insulated pipes as well as relevant research and development work in this field. The following approaches has been designed and used in real case studies:

- Wavelet Transform.
- Autoregressive exogenous models.
- Acoustic emission location by triangulation method.
- Ultrasonic echoes convergence by different paths.
- Damage sizing by ratio curve.
- Damage sizing by analysing the attenuation curve.
- Neural Networks for damage sizing.
- Neural Networks for determining temperature.

The techniques above mentioned has been employed with conclusive results, which provide new solutions and possibilities to the field of condition monitoring.
8. References


8. Gómez Muñoz, C.Q.; García Marquez, F.P.; Liang, C.; Maria, K; Abbas, M.; Mayorkinos, P. A new condition monitoring approach for


34. Investigación de técnicas avanzadas de deshielo y prevención de la acumulación de nieve en palas de un aerogenerador (icingblades). 2012.


41. Pinar, J.M.; Gómez Muñoz, C.Q.; Segura, E.; García Márquez, F.P. In A novel study of life cycle cost model of ice in blades condition monitoring systems for a wind turbine, The Energy and Environment Knowledge Week Congress, Toledo, Spain, 30/10/204, 2014; Toledo, Spain.


49. Gómez Muñoz, C.Q.; Trapero Arenas, J.R.; García Márquez, F.P. In Structural health monitoring for concentrated solar plants, 11th
8. References


60. Lega, M.; Ferrara, C.; Persechino, G.; Bishop, P. Remote sensing in environmental police investigations: Aerial platforms and an innovative application of thermography to detect several illegal activities. Environmental monitoring and assessment 2014, 186, 8291-8301.

61. Slater, P.N. Remote sensing: Optics and optical systems. 1980.


8. References

8. References


92. de Lautour, O.R.; Omenzetter, P. Damage classification and estimation in experimental structures using time series analysis and


8. References


118. Mellit, A. Artificial intelligence technique for modelling and forecasting of solar radiation data: A review. *International Journal of Artificial intelligence and soft computing* **2008**, *1*, 52-76.


8. References


