Introduction

Structural Health Monitoring (SHM) defines a well-known engineering area whose main issue is the verification of the state or the health of structures in order to ensure proper performance using non-destructive tests, involving sensors permanently attached to the structure and computational algorithms. SHM brings different benefits such as: knowledge about the structural behavior under different loads and different environmental changes, knowledge on the current state in order to verify the integrity of the structure and determine whether a structure can work properly or whether it needs maintenance or replacing, with the corresponding maintenance cost saving. Basically, the use of SHM can be extended to any system with structures, this means, a wide range of applications in engineering areas such as civil, aerospace, aeronautics, mechanical and others.

As an example, it is possible to mention aeronautics, where the currently daily passengers flow, merchandise and operations in airports in a global scale suggest increasing the safety in the daily operations in all the elements involved. According to the International Civil Aviation Organization (ICAO), in 2012 the total world volume of scheduled commercial flights began to edge over 31 million per year (ICAO, 2013) and still increasing. However, despite this trend, the global accident rate (accidents per million departures) has changed compared with the year 2011, when it was of 4.2, decreasing in 2012 up to 3.2. This result implies an improving safety and the implementation of best solutions for monitoring. To ensure safety, the ICAO promotes the systematic implementation of Standards and Recommended Practices (SARPs) for the aviation safety through the following activities:

- Policy and standardization initiatives;
- Safety monitoring;
- Safety analysis;
- Regional safety;
- Implementing programs to address safety issues.

At airports level, Safety Management Systems (SMS) are defined in order to contribute to the airports to detect and correct safety problems before they result in aircraft accidents or incidents (FAA, Federal aviation administration, 2012; International Civil Aviation Organization, 2013). These management systems are very important because the risk and the probability of an accident are present in the daily tasks. In addition, there is an increment in this factor due to the higher number of operations, which are significant and still rising. As example, in Spain airports during 2011, the total number of passengers was 204,373,288 and the number of merchandise transportation was 671,722,190 according to AENA (“Aeropuertos Españoles y Navegación Aérea”) (AENA, 2012). These quantities associated with the
value of what is transported daily, provide important reasons for increasing the safety in airport operations and in the involved elements (airplanes, helicopters, etc.). In a low level, each flight company requires to ensure the reliability of its aircrafts during the different phases of the flight (pre-flight, departure and climb, route, cruise, descent and landing). To do that, the company needs to guarantee the proper performance of their aircraft structures, navigation systems, communication systems, among other elements. According to (FAA, Aircraft inspections, 2012): “when an aircraft is being designed and produced, the aviation authority, the manufacturer, and selected industry participants form groups called Maintenance Steering Groups (MSG) and industry steering committees (ISC). These groups, through numerous meetings determine the frequency and scope of aircraft inspections to be performed. This information is provided to another group called the Maintenance Review Board (MRB) which will issue their final recommendations to the manufacturer on how an aircraft should be maintained”. In general, the inspection of any civil aircraft is determined by operation type. The aircraft must also be maintained in an airworthy condition (referred to as continued airworthiness) between those required inspections (Bureau, 2015). Additionally, a preflight inspection is conducted before each flight in ramp, which consists of checking the aircraft by visual examinations and operational tests to detect defects and maladjustments (Navyaviation, 2012). Many times these inspections have revealed faults and damages in the structures. Recently, for instance some small cracks were discovered in the world’s biggest passenger aircraft (Airbus A380) during a routine inspection. To correct this possible problem 20 aircrafts were inspected and according to the vice-president of AIRBUS (Tom Williams): “This is not a fatigue problem, but a problem during the manufacturing process” (Staff, 2012). Unfortunately, failures of this type have traditionally been detected during routine inspection periods and normally with the use of various non-destructive techniques, but in the case of visual inspections, it is sometimes impossible to detect small structural damages (for instance between each flight). In this sense, Structural Health Monitoring (SHM) has appeared as a solution to provide tools for early structural damage detection using non-destructive techniques and algorithms.

In a general way, it is possible to compare a SHM system with the human nervous system as in Figure 1. In both cases a sensor network is connected to a central system, which allows apply excitation signals and measure the responses from the sensors distributed along the structure. Additionally there is a system for processing the data, which defines the state or the health of the structure.

In SHM different classes exist for damage diagnosis (Ryutter, 1993) in a general way, which can be grouped in four levels (Figure 2). The first level corresponds to the damage detection. In this level it is important to know whether there is any change in the structure and if this change is due to damage. In the second level, after detecting damage, using proper techniques, the position of the damage can be determined. The third level considers the definition of the type of damage and its size. Finally, in the level 4, the remaining lifetime is determined. Recently, an extra level is considered in order to include the capability of auto-healing in smart structures (Inman & Grisso, 2007).

Most common applications in SHM are concentrated in the first three levels and there are many applications using different techniques. The majority of these implementations include the use of Non-Destructive inspections by means of sensors attached to the structure. These experimental setups normally require knowing the structure in order to define which sensors can be used and their distributions in the structure. The variety of sensors and configurations for data acquisition is quite broad as will be shown in the literature review.
Introduction

In aeronautic and astronautic areas, it is very common the use of aluminium and composite materials for building the structures (Ye, Lu, Su, & Meng, 2005). Since some years ago (probably since the first introduction into commercial use in 1944 as fuselage skin for Vultee BT-15 trainer plane (Hoskin & Baker, 1986; Ye, Lu, Su, & Meng, 2005), the trend in the design of the structures has been directed towards the use of composite materials because the advantages compared with traditional materials as the aluminum allowing the weight-saving among others benefits. There are many examples useful to show the diversity of the materials currently used in military and commercial applications among, others.

Figure 1. Analogy of a SHM system and the human nervous system

Figure 2. Levels in SHM
**Introduction**

Figure 3a. Fighter aircraft F-18 E/F: F/A-18F Super Hornet (Daily, 2012).

![Diagram of F/A-18F Super Hornet with material percentage](image1)

**PERCENT OF STRUCTURAL WEIGHT**

<table>
<thead>
<tr>
<th>Material</th>
<th>F/A-18C/D</th>
<th>F/A-18E/F</th>
</tr>
</thead>
<tbody>
<tr>
<td>Aluminum</td>
<td>49</td>
<td>31</td>
</tr>
<tr>
<td>Steel</td>
<td>15</td>
<td>14</td>
</tr>
<tr>
<td>Titanium</td>
<td>13</td>
<td>21</td>
</tr>
<tr>
<td>Carbon Epoxy</td>
<td>10</td>
<td>19</td>
</tr>
<tr>
<td>Other</td>
<td>13</td>
<td>15</td>
</tr>
</tbody>
</table>

Figure 3b. Fighter aircraft F-18 E/F: schematic diagram with the percentage of structural weight (Baker, 2004).
Introduction

Figure 4. Utility of composite structures on A380: monolithic CFRP and thermoplastics (Ye, Lu, Su, & Meng, 2005).

For instance, in the U.S. Navy, the F-18 E/F fighter has 31% of aluminium of the total weight, while the carbon epoxy has the 19% as can be seen in the Figure 3. Other example can be found in the AIR-BUS A380, which is one of the biggest commercial aircraft. Although the use of composite materials has increased, the aluminium is still widely used (Figures 4 and 5).

The SHM systems are currently in a development stage and the majority of the applications are available in a research level, especially in the aeronautic and astronautic areas. To perform the inspection of the structures in the majority of applications, the structure is isolated and the monitoring is performed under special conditions. In areas as aeronautical and aerospace it is really important to evaluate the health of the structures in normal operational conditions when the element is integrated into the system (aircraft, helicopters, satellites, space shuttle, among others). This reason has motivated the development of new methodologies. An additional motivation is the reduction in the cost of maintenance to avoid that the aircraft goes out of operation for periodical maintenance and to increase the safety in the normal operation of the structures.

Other examples about the need of SHM systems can be found in civil engineering. This area presents big interest since large infrastructures imply big quantity of humans that use daily these civil developments. One example in this area can be found in the building called SPACE in Medellin-Colombia, where a bad design and the lack of effective state inspection, resulted in loss of life and the destruction of one of its buildings (Figure 6).
Figure 5. Utility of composite structures on A380: materials distributions (weight breakdown) (Ye, Lu, Su, & Meng, 2005).

![Materials distribution (weight breakdown) on A380 structure](image)

- Aluminum (61%)
- Surface protections (2%)
- Composite materials (22%)
- Miscellaneous (2%)
- Glare (3%)
- Titanium & Steel (10%)

Figure 6. Building Space, Medellín-Colombia (Tiempo, 2014).

![Building Space, Medellín-Colombia](image)
A BRIEF REVIEW OF STRUCTURAL HEALTH MONITORING AS A PATTERN RECOGNITION APPROACH

The problem of structural monitoring can be tackled from different points of view. Some authors have built mathematical and numerical models based on physical laws to describe the characteristics of the structure. In this kind of approaches, a high-fidelity model of the structure is required to perform a reliable damage identification. On the other hand, other authors use techniques based on data gathered by experiments or by numerical simulations. These approaches usually require a statistical model representation of the system to perform the structural state analysis (Worden & Manson, 2007). In this case, the system does not use physically based models and the problem of damage identification can be approached as a pattern recognition application, where some features of the collected signals are used as reference pattern. In general, it exploits the fact that the vibrational response of a structure is deferent when it is healthy or damaged. In this way, if some defect exists in the structure, its vibrational response will change and these changes can be analyzed.

Several reviews have been carried out in Structural Health Monitoring (SHM). Among them, Chang, Flatau, and Liu (2003) presented a review of SHM for civil infrastructures. Fritzen (2005) presented an overview of the developments of vibration based methods in the year 2005, also in 2006, Lynch and Loh (2006) presented a summary review of wireless sensors and sensor networks. Farrar and Worden (2007) performed a brief historical review of SHM technology development. The same year, Brownjohn (2007) presented a review of SHM applications to various forms of civil infrastructure, including a discussion about the damage diagnosis procedure in terms of instrumentation, data acquisition, communication systems and data mining. The next year, Chiang, Lee, and Shin (2008) presented a review focused in damage detection methods for a wind turbine system. In 2010, Mujica, Rodellar, and Vehí (2010) performed a review of impact damage detection in structures using strain data, which included sensors, specimens and impact sources used for developing and testing strategies. Recently, in 2011, Fan and Qiao (2011) presented a review and comparative study of vibration-based damage identification methods. The review included methods based on modal parameters, natural frequencies, mode shapes as well as curvature/strain mode and shape-based methods. These reviews have proved that the interest in the development of algorithms and methodologies in SHM has been growing. As result of this interest, SHM has been applied in different areas, which include applications in civil, aeronautics and astronautics structures. Many works has been reported for more than three decades (Chang, Flatau, & Liu, 2003) with promising results, for instance, tests in bridges (Azevedo, et al., 1996; Lee, Kim, Yun, Yi, & Shim, 2002; Riveros, 2007; Kawano, Mikami, & Katsuki, 2010; Panetos, Ntotsios, Papadimitriou, Papadioti, & Dakoulas, 2010), buildings (Garziera, Amabili, & Collini, 2007; Serino & Spizzuoco, 2010), wind turbine blades (Park, Taylor, Farinhaot, & Farrar, 2010), and other structures (Law & Sohn, 2000; Mujica et al., 2005; Sohn, Farrar, Hunter, & Worden, 2001; Jaques, Adams, Doyle, & Reynolds, 2010).

The next subsections give a brief overview of the SHM levels in order to show from a general point of view the wide range of methods and applications developed in SHM.

Brief Review of the Structural Health Monitoring Levels

As it was mentioned, SHM includes different levels starting by the detection of the damage and following with the localization, classification, identification and the prognosis of damages (prediction) (Worden & Manson, 2007).
Damage Detection

The damage detection corresponds to the first level in SHM, whose goal is to detect defects or damages in structures when they are still in their nascent state using non-destructive techniques and algorithms. As was previously introduced, damages can be defined as changes in the structure when it is compared with a baseline obtained from the structure in a healthy state. These changes include variations in the material or in the geometric properties.

The need of damage detection to prevent an accident is an essential factor to ensure the proper work of a structure in service. There are many applications in different areas, but it is important to note that in some areas as aeronautical and aerospace engineering the continuous monitoring of the structural health is very important to guarantee its proper performance. Probably, the use of SHM in these two areas is more important than in other areas since, normally, in areas like civil engineering, some damages are really dangerous when they start to have a considerable size. However, in aeronautical and aerospace engineering, some damages that are imperceptible when are subjected to extreme changes in their working conditions can cause catastrophes. In the aeronautical industry, for instance, the majority of inspections are performed visually (Brand & Boller, 1999; Mujica et al., 2010). However, many research groups around the world are focusing efforts to develop techniques that allow the inspection of structures in service. These investigations are focused on developing techniques for making the best detection of the different possible damages. Some developments at the damage detection level are reviewed below.

In 1992, Kudva, Munir, and Tan (1992), in 1993, Gunter, Wang, Fogg, Starr, Murphy, and Claus (1993), and Hann, Wilkerson, and Stuart (1994), Sirkis, Berkoff, Kersey, Fribelle, and Jones (1994) in 1994, and Schindler, May, Claus, and Shaw (1995) in 1995 worked on impact damage detection by using advanced signal processing with Artificial Neural Networks (ANN). Friswell, Penny, and Garvey (1998) in 1998 used a genetic algorithm for damage detection based on vibration data in order to identify the position of one or more damage sites in a structure and to estimate the extent of these damages. Yap and Zimmerman (1998) used genetic algorithms for damage detection. In difference with the classical coding of the genetic algorithm, this work proposed the use of two coding enhancement strategies. In 2001, Ganguli (2001) proposed a fuzzy logic system for health monitoring of a helicopter rotor blade when this is on ground. The rules of the fuzzy system were defined in order to consider four different levels of damages in the output. The measurements used were the first four flap (transverse bending) frequencies of the rotor blade. Hao and Xia (2002) in 2002 used a genetic algorithm with real number encoding to identify the structural damage by minimizing the objective function, which directly compares the changes in the measurements before and after damage. They used three different criteria, namely, the frequency changes, the mode shape changes and a combination of both. This methodology was tested in a cantilever beam and a frame. The same year, Staszewski, Biemans, Boller, and Tomlinson (2002) used passive acousto-ultrasonic sensors to impact damage detection in composite structures. In this work, a study of different signal processing methods for passive damage monitoring was performed. In 2004, Sun and Chang (2004) presented a methodology to classify some statistical patterns using the Wavelet Packet Transform (WPT). The vibration signal collected from the structure was decomposed into wavelet packets. Later on, the signal energy of the packets were calculated and ordered according to the magnitudes. The most important magnitudes were considered and the rest were rejected, using these magnitudes and defining some thresholds and confidence limits to detect abnormal behaviors. This methodology was tested in a beam and four damage cases were studied involving line cuts of different severities in the flanges at one cross section. In 2006, Menendez, Fernandez, and Guemes (2006) used
an active piezoelectric system and Fibre Bragg Grating (FBG) to detect de-bonding of subcomponents in monolithic composite parts. In the methodology, the power spectrum was used to find the damage. In the piezoelectric active system the maximum amplitude of every piezoelectric sensor is used in order to measure the energy loss of the input pulse. The same year, Fernandez, Guemes, Fritzen, and Mengelkamp (2006) performed a comparison between the use of FBG and piezoelectric sensors for damage detection.

To do that, the Hankel matrix was used to obtain the damage indicator values. They proposed, as an alternative, the use of combined hybrid piezoelectric/FBG sensors. Wildy, Kotousov, and Codrington (2007) in 2007 proposed a passive method of damage detection based on the concept of strain field. Huang, Ghezzo, Rye, and Nemat-Nasser (2008) used acoustic emission in thin glass/epoxy composites plates in order to detect damages. The same year, Mujica, Vehi, Staszewski, and Worden (2008) used a hybrid methodology which combined Case Base Reasoning (CBR), wavelet transform and Self Organizing Maps (SOM) in order to detect impact damages in a wing flap. Piezoceramic sensors attached over the surface of the flap were used to collect time varying strain response data. In 2009, Chandrashekhar and Ganguli (2009) applied a fuzzy logic system with a sliding window defuzzifier using modal curvatures for damage detection. The methodology fuzzified the changes due to a damage in modal curvature using Gaussian fuzzy sets and mapped to damage location and size. This methodology was applied to a cantilever beam. Recently, Dervilis, Barthorpe, Staszewski, and Worden (2012) presented a scheme for damage detection in carbon fiber materials using novelty detection methods. These methods were applied to FRF measurements from a stiffened composite plate, which was subjected to incremental levels of impact damage.

**Damage Localization**

The localization of damages is the next task after damage detection. Its complexity depends on the structure, the type of sensors and their distribution. Some of the most common strategies for the location of damages include triangulation processes (Mujica et al., 2010). According to Salehian (2003), three sensors are enough for determining impact location for isotropic materials, but in anisotropic materials as composite materials these approaches must be different (Mujica et al., 2010). Other researches have combined different strategies combined with the processing of sensor data for locating damages. Some of them are discussed below.

Staszewski et al. (2000) and Worden and Staszewski (2000), used ANNs as regressor to predict the impact location and energy in composite materials. The approach used a multilayer perceptron which was trained with experimental data using back propagation.

Additionally, these works presented the combined use of the genetic algorithms and ANN to find near-optimal sensor distributions for damage detection.

In 2001, Chou and Ghaboussi (2001) presented a methodology based on genetic algorithms, which uses static measures of displacement for damage localization. In 2003, Coverley and Staszewski (2003) proposed a methodology for damage location using triangulation methods and genetic algorithms. Gorinevsky, Gordon, Beard, Kumar, and Chang (2005) presented a design as a subsystem to the Integrated Vehicle Health Management (IVHM) system of an aircraft. This system used SMART Layer sensors from Acellent Technologies. Using the signals obtained from the sensors, the mean signal amplitude was calculated and compared with the scatter signal to obtain a damage index for each actuator-sensor path. Using these values, they obtained a representation of the location structural changes and one measure of the damage size. In 2010, Mujica, Tibaduiza, and Rodellar (2010) used Principal Component Analysis
and some statistic indices to localize different damages using contribution plots in an aircraft turbine blade. Recently, Hackmann, Sun, Castaneda, Lu, and Dyke (2012) in 2012 presented a holistic approach for damage localization, which integrated a decentralized computing architecture using wireless sensor networks. In the approach the damage localization algorithm used post-processed natural frequency data.

**Damage Classification**

The damage classification corresponds to the level which, according to some characteristics obtained from the structure in different structural states and some algorithms, a classification of each state can be performed according to their features. In general, a typical classifier is used to define which damage is present in the structure. Some examples are shown below.

Using a combination of time series analysis, neural networks and statistical inference techniques, Sohn, Worden, and Farrar (2002) in 2002 classified damages under environmental changes. First, an AR-ARX model was developed to extract damage-sensitive characteristics, then a neural network was used to normalize the data and to separate the effect caused by the environmental changes. Finally, a sequential probability ratio test was performed to define the state of the system. The methodology was tested using a numerical example of a computer hard disk and an experimental study of an eight degree-of-freedom spring-mass system. In 2007 and 2008, Mujica et al. (2007) and Mujica, Vehi, Staszewski, and Worden (2008) used Wavelet Transform in a hybrid methodology to detect, quantify and localize damages. This methodology used the wavelet transform in order to extract different characteristics from the measured signal and subsequently applied a neural network to classify the damages. Zhou, Chakraborty, Kowali, Papandreou, and Cochran (2007) proposed an algorithm for the classification of structural damage based on the use of continuous Hidden Markov Modeling (HMM) technique. It was used to model time-frequency damage features extracted from structural data using the matching pursuit decomposition algorithm.

Many works have shown the usefulness of neural networks for classification (Bakhary, Hao, & Deeks, 2007). For instance, clustering algorithms based on Self-Organizing Maps -SOM- (attempting to organize feature vectors into clusters) have been used for the classification of acoustic emissions (Yan, Holford, Carter, & Brandon, 1999; Godin, Huguet, Gaertner, & Salmon, 2004) and for active sensing damage classification (Tibaduiza, Mujica, Gemes, & Rodellar, 2010). Dua, Watkins, Chandrashekhara, and Akhavan (2001) in 2001 used an ANN with backpropagation algorithm and Finite Element Analysis (FEA) to classify impacts on composite plates. A 503,10,3 ANN was used for training and simulating the data: 503 elements in the input layer which were excited by strain profiles obtained from FEA, 10 neurons in the hidden layer and 3 neurons in the output layer. A total of seven classification groups were performed inspecting the composite plates and the kinetic energy of the falling mass. This classification was coded using Gray Code.

In 2006, Kolakowski, Mujica, and Vehi (2006) presented two approaches for damage identification. One of them was based on Virtual Distortion Method (VDM). The other methodology involved the use of Case Based-Reasoning (CBR) applying wavelet transform in order to extract features and reduce the variables to introduce into a Self-Organizing Map (SOM) for damage identification. These techniques were tested in an aluminum beam. In 2007, Bakhary, Hao, and Deeks (2007) applied a two-stage ANN system for damage location and damage severities. In the first stage, an ANN was used to identify the substructures with damage and the secondary ANN identified the damaged elements and its severity. Inputs in the first ANN were modal frequencies and mode shapes of the full structure and the outputs were modal
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frequencies of substructures, these were the inputs to the second ANN where the final analysis to locate the damage was performed. For testing the approach, a numerical example was used which consisted of a two-span concrete slab. Dobrzanski, Sroka, and Dobrzanski (2007) used a multilayer perceptron 9-6-5 for the classification of internal damages in steel during creep services using metallographic images. Also in 2007 and 2008, Mujica et al. (2007; Mujica, Vehi, Staszewski, & Worden, 2008) presented a methodology to detect, quantify and localize damages and impacts in several structures, among them a wing aircraft section and an aluminum beam. This methodology used wavelet transforms to extract different characteristics from the collected signal and a SOM to classify them. In 2008, Kabir, Rivard, and Ballivy (2008) presented an algorithm for damage classification using a multilayer perceptron. The methodology included the use of analysis of texture of surface deterioration using optical imagery in concrete structures. The data in the perceptron included three different datasets: spatial, spectral and a combination spatial-spectral dataset. Iskandarani (2010) in 2010 applied neural networks to classify composite structure conditions. Resin injection molded (RIM) samples response to impact damage was carried out using low frequency tapping, visual imaging, low temperature thermo imaging and tensile strength. Recently, Zhou, Tang, Zang, and Zhou (2012) presented an Artificial Immune Pattern Recognition (AIPR) approach for the damage classification in structures. The approach included the development of an immune learning algorithm and a ARX algorithm to compress the data.

Type and Extent of Damage

The knowledge of the type of damage is a task that provides information about the severity of damage. This is performed after the detection and localization and provides information on whether the structure can still do its job or must be replaced. Some works related to the definition of the damage type and extent are outlined next.

Mares and Surace (1996) in 1996 presented a strategy based on genetic algorithms and residual force method (modal analysis theory) to detect, quantify and obtain the extent of damages in elastic structures. Friswell, Penny, and Garvey (1998) in 1998 used a genetic algorithm for damage detection in vibration based data to identify the position of one or more damages in a structure and to estimate their length. Hao and Xia (2002) in 2002 used a genetic algorithm with real number encoding to identify the structural damage by minimizing the objective function, which directly compares the changes in the measurements before and after damage. They used three different criteria, namely, the frequency changes, the mode shape changes, and a combination of them. This methodology was tested in a cantilever beam and a frame. In 2003, Mujica et al. (2003) showed the use of Case Based Reasoning as tool for damage diagnosis. A wavelet transform was also used to obtain some characteristics and a Self-Organizing Map (SOM) was used as method for handling the case base. This methodology was tested in a cantilever truss. The same year, Chang and Sun (2003) proposed a novel structural condition index for locating and quantifying structure damage based on Wavelet Packet Signature (WPS). This year, Shan and King (2003) presented a methodology to locate impacts and estimate impact magnitude on smart composites using fuzzy clustering for feature selecting and adaptive neuro-fuzzy inference system for impact locating and magnitude estimation. In 2005, Mujica et al. (2005) extended the methodology presented in 2003 to define the severity and the dimension of the damage. Recently in 2011, Gul and Catbas (2011) presented a time series methodology to detect, locate and estimate the extent of the structural changes. The approach used ARX models, which were obtained for different sensor clusters by using the free response of the structure. The approach considered also obtaining the ARX model fit ratios or the ARX coefficients as damage features.
Damage Prognosis (DP)

Damage prognosis is the last level in SHM, which includes the quantification of the damage to determine the useful lifetime remaining for the structure and the conditions to continue operating. The publications in this kind of applications are lesser in number than those existing for the previous SHM levels. Some of them are discussed below.

Staszewski, Worden, Wardle, and Tomlinson (2000) presented a discussion focused on extraction and data pre-processing in pattern recognition procedures for the diagnosis of location and severity of damage. In 2003, Farrar, Park, Robertson, Sohn, and Williams (2003) presented an approach for damage prognosis by integrating advanced sensing technology, data interrogation procedures for state awareness, novel model validation and uncertainty quantification techniques, and reliability-based decision-making algorithms. Later on, in 2007, Farrar and Lieven (2007) presented some general concepts of damage prognosis, such as the problem definition, the motivation and the process of DP. Also a review of emerging technologies with potential impact on the damage prognosis process was included. In 2010, Zhang, Zhou, and Li (2010) presented an approach that included the use of flexible piezo paint sensor and a probabilistic fracture mechanics based framework for on-line assessment and updating of the remaining fatigue life of steel bridges. In 2012, Ling and Mahadevan (2012) presented a Bayesian probabilistic methodology to integrate model-based fatigue prognosis with online and offline SHM data, considering various sources of uncertainty and errors. The methodology was tested in a numerical example, considering the surface cracking in a rotorcraft mast under service loading.

ORGANIZATION OF THE BOOK

This book aims to cover the SHM levels above discussed, considering different applications. The book is divided into 14 chapters, starting with this introduction. Chapter 2 presents an experimental investigation on self-healing properties of conventional and fly ash cementitious mortar exposed to high temperature. The study shows the self-recovery of significant physical properties to micro cracks generated in the material. Chapter 3 considers new features for damage detection in the presence of temperature uncertainties, using fuzzy similarity and wave clustering. The stability of these features is tested on different experimental case studies with increasing complexity. Chapter 4 approaches the problem of damage detection under varying operating conditions using wavelet transform, in particular the modulus maxima decay lines. The proposed methodology is evaluated on both simulated and experimental case studies under varying temperatures. Chapter 5 lies within the context of ultrasonic based non-destructive welding inspection. A prototype and a methodology for detection of weld failures are presented and tested. Chapter 6 presents a methodology for structural damage classification using an artificial immune system. The approach is implemented to an aircraft skin panel equipped with active piezoelectric devices. Chapter 7 provides a practical comparison of several learning machine algorithms for impact localization in structures. Both accuracy and execution time are considered in the experimental evaluation, where the so-called extreme learning machine exhibits a good potential for impact detection due to the fast learning speed. Chapter 8 contributes with a case based reasoning scheme to detect stiffness changes in structures. The approach is validated through numerical experiments using finite element models. Chapter 9 proposes a statistical methodology to structural damage diagnosis (detection, localization and estimation) under uncertainties such as physical variability, measurement noise and modeling errors.
Introduction

The proposed methods are illustrated using two types of example problems, a structural frame and a hydraulic actuation system. Chapter 10 discusses on nonlinear ultrasonic approaches for early damage detection, considering fundamentals, experimental techniques, damage evaluation methods and future trends. Chapter 11 is devoted to analysis of fatigue crack growth and damage prognosis in structures. The effect of different types of uncertainty – physical variability, data uncertainty and modeling errors – on crack growth prediction is investigated.

Chapter 12 deals with prognostics design for structural health management. Using physics-based mathematical models, the authors propose methods to estimate the remaining life of structures to failure thresholds using fatigue data. Chapter 13 describes a complete methodology for health monitoring of wind energy structures. It includes sensor location, data selection, classification of environmental and operational conditions, damage detection and sensor fault detection. Only output data are used to implement the methodology, which is experimentally tested on a laboratory tower model. Finally, Chapter 14 closes the book with some concluding remarks.

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