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"Development of New Structural Health Evaluation Method for Health Monitoring of Structural Components"

WP2. "Development of Structural Health Evaluation Method"

Deliverable 2.5

"Description of Structural Health Evaluation Method"

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Abstract

The aim of Structural Health Monitoring (SHM) system is to collect data from various sensor sources and carry out the necessary processing, including the extraction of key features, damage detection, and pre-diction. Depending on a type of damage, tested structure, environmental conditions, and several other factors, such systems can appear in various configurations. An additional difficulty in monitoring damage in structures appears when the tested structures are made of composite materials, which are heterogeneous by nature. This also implies the need to consider various types of damage, which do not appear in homogeneous structures, such as delamination, debonding, and other types of interface damage, which are weakly detectable, in general.

Most SHM methods are based on the identification of deviations from a “normal” or “healthy” condition. Ideally, deviations should be determined at an early stage of damage initiation and corrected by conducting suitable maintenance procedures, thereby improving structural integrity, reliability, availability and the overall life cycle of the structure [1]. In general, SHM prognostic modelling can be classified into two main approaches; physics-based and data-driven [1-4]. In SHM, a classic physics-based approach uses a numerical model (Finite Element Analysis (FEA) of the structure, which relates discrepancies between measured data and the data produced by the model to identify damage. This approach is computationally expensive due to an iterative analysis of a computer simulation model [4]. Compared to top-down modelling provided by the traditional physics-based models [3,4], data-driven health monitoring systems offer a new paradigm of bottom-up solution for detection of faults after the occurrence of certain failures (diagnosis) and predictions of the future working conditions and the remaining useful life (prognosis) [2,3]. Unlike a model-driven approach, a data-driven approach creates a model by learning from measured data and then performs a comparison between the model and measured responses in order to identify damage. With significant development of sensors, sensor networks and computing systems, data-driven health monitoring approaches have become more and more attractive.

Introduction

In data-driven structural health monitoring, damage detection can be regarded as a problem of pattern recognition. All pattern recognition methods offer two possible learning (training) schemes: supervised and unsupervised. The architecture and process of learning depend on which level of damage identification is required [5]. An unsupervised scheme leads to clustering analysis and in this case usually novelty detection methods (outlier analysis, kernel density methods, and auto associative neural networks) are used [5, 6]. These methods establish a description of normality using features representing undamaged conditions and then test for abnormality or novelty thus can only indicate presence of damage in structure. A supervised learning scheme, on the other hand can detect, locate damage and indicate severity of damage. In supervised learning, the training data consists of a set of feature vectors together with their known class labels. Thus, localisation of damage is achieved by dividing the structure into substructures and assigning a class label for data corresponding to damage in the given substructure. Similarly, for assessment of damage severity a class label is assigned to data corresponding to different damage extent. The output of such SHM algorithm might be a discrete class label representing Cartesian coordinates of damage location and damage extent, for example, in terms of loss of stiffness.

This report presents description of the developed data-driven structural health evaluation method based on supervised learning schemes. Five of the most typically employed machine-learning algorithms, namely, k-NN, discriminant analysis, decision trees, Naïve Bayes and Support Vector Machines within two supervised learning schemes are used to create classification models by learning from simulated response data. The first learning scheme involves building binary classifier models establishing a description of normality representing undamaged conditions and abnormality indicating presence of delamination damage in a composite structure. In the second learning scheme, the learning data representing the damaged state of the structure comprises also known class labels pointing to the geometrical location of the damage. Application of the developed method is shown on the example of a carbon fibre reinforced plastic (CFRP) rectangular plate.