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European Regional Development Fund project

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

WP2. "Development of Structural Health Evaluation Method"

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"Description of Numerical Model Calibration Method"

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Abstract

Structural health monitoring (SHM) is a process that aims at detecting, locating and quantifying damage in structures at an early stage in order to avoid unexpected failure. 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.

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.

The major issue of a supervised learning algorithm is that one would also need data from the structure of interest in all of damage states in order to train the algorithm. In

most applications it would be impossible or very time consuming and expensive to obtain data experimentally. To overcome this issue in this project it is proposed to use Finite Element simulations of composite structure in different damage states in order to obtain the necessary training data. For the training data to be accurate one must establish a physical-law based numerical model of structure and calibrate it in terms of features of interest according to the physical model. Thus, in this project, it is proposed to develop a numerical model calibration method based on the mixed numerical-experimental technique (MNET) and, this report presents description of the developed method.