Novelty detection applied to vibration data from a CX-100 wind turbine blade under fatigue loading.

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Abstract. The remarkable evolution of new generation wind turbines has led to a dramatic increase of wind turbine blade size. In turn, a reliable structural health monitoring (SHM) system will be a key factor for the successful implementation of such systems. Detection of damage at an early stage is a crucial issue as blade failure would be a catastrophic result for the entire wind turbine. In this study the SHM analysis will be based on experimental measurements of Frequency Response Functions (FRFs) extracted by using an input/output acquisition technique under a fatigue loading of a 9m CX-100 blade at the National Renewable Energy Laboratory (NREL) and National Wind Technology Center (NWTC) performed in the Los Alamos National Laboratory. The blade was harmonically excited at its first natural frequency using a Universal Resonant Excitation (UREX) system. For analysis, the Auto-Associative Neural Network (AANN) is a non-parametric method where a set of damage sensitive features gathered from the measured structure are used to train a network that acts as a novelty detector. This traditionally has a highly complex “bottleneck” structure with five layers in the AANN. In the current paper, a new attempt is also exploited based on an AANN with one hidden layer in order to reduce the theoretical and computational difficulties. Damage detection of composite bodies of blades is a "grand challenge" due to varying aerodynamic and gravitational loads and environmental conditions. A study of the noise tolerant capability of the AANN which is associated to its generalisation capacity is addressed. It will be shown that vibration response data combined with AANNs is a robust and powerful tool, offering novelty detection even when operational and environmental variations are present. The AANN is a method which has not yet been widely used in the structural health monitoring of composite blades.

1. Introduction
New generation offshore wind turbines are introducing a demanding increase in the blade size which has brought together a chain of structural challenges. Reliability remains on issue for such structures and it is apparent that the making of a robust and online system of Structural Health Monitoring (SHM) is a dominant concern in the successful implementation of such alternative systems in the energy arena. Reinforced composite materials such as carbon fibre reinforced polymer (CFRP) or
glass fibre reinforced polymer (GFRP), are leading the industry in the manufacture of blades as they are characterised by high strength-to-weight and stiffness-to-weight ratio [1].

The purpose of this study is to examine a damage detection approach for a 9m CX-100 blade under fatigue loading such as may be used for new generation wind turbine blades. The overall approach taken is to apply auto-associative neural networks with different architectures to FRF data.

2. Novelty detection analysis methods

The premise of novelty detection techniques is to seek the answer to a simple question; given a newly presented measurement from the structure, does one believe it to have come from the structure in its undamaged state? The objective of this study is to demonstrate the technique of novelty detection in the context of auto-associative neural networks (AANNs). Artificial Neural Networks (ANNs) offer a holistic, nonlinear parameterised mapping between a set of inputs and a set of outputs [2, 3].

The AANN is a type of multilayer perceptron whose target outputs are the same as the inputs. Generally, the auto-associative neural network consists of five layers including the input, mapping, “bottleneck”, de-mapping and output layers. Also, here for comparison reasons outlier analysis based on the Mahalanobis-Squared Distance (MSD) and monte-carlo simulation, is used as a robust and simple statistical method. The theoretical analysis behind these methods is not described in this study. For this, as well as the critical issue of calculating the thresholds, the reader is referred to previous works [4, 5, 6, 7, 8, 9, 10] in turn, the definition of MSD is briefly given by the following equation:

\[
D_i^2 = (x_i - \mu_x)^T \Sigma^{-1} (x_i - \mu_x).
\]  

(1)

where \(x_i\) is the potential outlier, \(\mu_x\) is the mean of the samples observations and \(\Sigma\) is the sample covariance matrix. The mean and covariance matrix could be inclusive or exclusive measures.

In order to find the best network architecture the training data was tested for several different architectures, by applying at the same time an early-stopping criterion in order to avoid over-fitting problems and achieve a better generalisation. For this purpose a percentage of the input data was used for validation purposes and testing purposes in order to implement the early-stopping criterion.

3. Experimental overview of the testing blade

The full-scale fatigue test was performed between 11/08/2011 and 9/11/2011. The test was running continuously for approximately 8.5 million cycles until a visible crack was observed on 9/11/2011. The crack nature was a through-thickness crack appeared on the surface of the blade in the root area near to the leading edge. The blade is made of a fibre glass body (shell) and a carbon fibre spar cap with balsa wood core (small percentage of spar cap of root section is made of glass fibre with some carbon fibre layers in the thick skin). The specimen was excited at its first natural frequency at 1.8 Hz. Two saddle positions were implemented at 1.6 m and 6.75 m from the root and on 13/09/2011, 10/10/2011 and 18/10/2011 extra mass was added on the first saddle at 1.6 m, leading to increase of mass from 582.4 Kg initially to 642.3, 702.16, 762.04 Kg respectively. The structural health monitoring sensor system consisted of several different systems implementing active sensing and passive sensing [21], [22].

In this study active sensing measurements are used for the novelty detection methods. Using this active sensing system (LASER sensing system) two different sensor arrays were implemented (figure 2) called the INNER and OUTER sensor arrays; they consisted of 6 and 7 sensors respectively and an actuator was used in each of them (thick blue dot). The excitation frequency bandwidth was between 5 KHz and 40 KHz with a sampling rate of 96 KHz giving a resolution of 7200 spectral points for the FRFs that were measured and used for this study. The observations are between 11/08/2011 and 9/11/2011 corresponding to 565 for the INNER sensors and 534 for the OUTER sensors (crack observed at observation 560 for INNER and 529 for OUTER array).
4. Feature selection

In order to implement the novelty detection methods and overcome the “curse of dimensionality” a classification of features according to their ability to separate the normal from any other condition was assumed. For the purpose of this work only “strong” 50 dimensional features were selected. For a detailed analysis the reader is referred to the previous work [10, 15, 18, 19]. As was described in Section 3, the boundary conditions regarding the added mass were changed. During the analysis it was found that this change had influenced a limited number of the features (peaks) in the FRF spectrum. For this reason, a method to overcome the influence of external factors on normal conditions is introduced in Section 6.

5. Novelty detection results

After selecting the training, validation and testing data for each of the 13 sensors labelled INNER and OUTER, a well-trained AANN was used via unsupervised learning to generalise the normal condition of 50 dimensional features. Then a novelty distance (Euclidean distance [7,10]) was calculated by feeding the network with testing data [10]. In Figure 3, there is representative image of two sensors in the INNER and OUTER families showing the novelty results and in Figure 5, there is a summary graph of all sensors results. The blue bar shows when initially novelty was observed like Figure 4 and in some sensors there is a red bar that represents a monotonic different pattern as the days pass indicating a noticeable novelty change about 10 days before a visible crack was observed as in Figure 3.
6. Features affected by change in boundary conditions

Through an extensive analysis of the FRF data it was found that a limited number of specific features (peaks on FRF) were affected by the mass change on the saddle during the fatigue test. Figure 6, represents an outlier analysis where the normal/trained data was selected directly after the 13/09/2011 which is the first added mass condition up to 05/10/2011 before the change of the second added mass, in order to visualise how the boundary conditions (black arrows) influenced this specific feature, see Figure 6 (left). In Figure 6 (right), are the results of a well-trained AANN and this shows the ability in overcoming the difficulties of the boundary changes by “learning” how to adapt on these external factors using only one node in the hidden bottleneck layer [9]. For this reason the trained data was selected so as to include some data after the second added mass on 10/10/2011. For comparison reasons with the same trained data as the AANN, the results from auto-association with only three layers with linear and non-linear transfer functions are presented in Figure 7.

Figure 4. AANN novelty Index for INNER sensor 6 (on the left) and OUTER sensor 5 (on the right).

Figure 5. Summary of all sensor novelty results in INNER array (on left) and OUTER array (on right).

Figure 6. Outlier novelty index (on the left) and AANN novelty improved index (on the right).
Figure 7. AANN with only three layers with linear (on the right) and non-linear (on the left) transfer functions.

7. Conclusion
In this paper a novel approach applied to wind energy systems was addressed. The ability of autoassociation of a three layer network with nonlinear and linear transfer function and their difference to generalise on simple changes in boundary conditions was investigated. The use of the AANN as a novelty detection algorithm has been shown to be effective in detecting alternate mechanisms during the continuous fatigue test. Differences between the sensors were noticeable in detecting the fault mechanisms. Active sensing measurements combined with novelty detection methods point out that the integration of AANN enables a quantitative and qualitative damage detection even when the system exhibits a range of normal conditions. The paper demonstrated the differences between linear and nonlinear activation function. It is noticeable that the one layer auto-association is doing a better classification than the linear auto-association, as it is able to generalise better. Feature selection was found not to be a trivial process and the number of dimensions of each feature warrants further discussion.

The authors believe that the initial damage was introduced internally and started from the main carbon spar. In the experiment, the excitation of the fatigue test was the first bending moment with a natural frequency at 1.8 Hz. This specific load is carried from the main spar and in high proportion at the blade root. If a failure occurs in the spar components then the blade’s shell is not able to carry the high loading and usually damage will appear inevitably to the shell’s body (as it happened). The shell mainly is for aerodynamic reasons but also its design is playing a small structural role by "helping" in stiffening and strengthening the spar.

The results are very encouraging for classification and pattern recognition purposes. The study raised many issues that warrant further attention. As discussed above, further considerations include factors such as variability, structure of the real blade, loading and environmental conditions, boundary conditions, feature selection and AANN architecture that will all affect the performance of the classifier.

Acknowledgments
The research was funded by the Department of Energy through the Laboratory Directed Research and Development program at Los Alamos National Laboratory. The authors would also like to acknowledge Scott Hughes and Mike Desmond from the National Renewable Energy Laboratory, and Mark Rumsey and Jon White from the Sandia National Laboratory for their support and guidance on this study. The authors gratefully acknowledge the support of the EU Marie Curie scheme through the Initial Training Network SYSWIND.
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