Impact Damage Detection for Composite Material Typical of Wind Turbine Blades Using Novelty Detection

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ABSTRACT

Offshore wind turbines are gaining a leading role in the electric energy market. The wind turbine blade plays a vital role in the lifetime operation of the turbine. Key challenges such as robust Structural Health Monitoring (SHM) of the blades is crucial for the economic and structural efficiency of the new generation of wind energy. In this study intelligent fault diagnosis methods are adopted such as novelty detection techniques. The methods used are a statistical outlier analysis which allows a diagnosis of deviation from normality, an Auto-Associative Neural Network (AANN) and an Artificial Neural Network (ANN) classification technique. Vibration responses combined with a novelty approach provide a robust statistical method for low-level structural damage detection. It will be shown that a neural network is a powerful tool, offering on-line and real time damage prediction and classification. This paper is adopting vibration data such as FRFs by exploiting multilayer neural networks and outlier detection. The outcomes of these approaches are demonstrated for a blade composite structure subject to gradually increased levels of impact damage.

INTRODUCTION

New generation offshore wind turbines are the subject of an intensive and dramatic increase of technological development which has introduced a continuous chain of structural challenges. Among these, reliability is an outstanding factor for such structures and it is apparent that the making of a robust, accurate and online system of Structural Health Monitoring (SHM) will be a leading factor in the successes of such energy systems. Reinforced composite materials such as carbon fibre reinforced polymer (CFRP) or glass fibre reinforced polymer (GFRP), are dominant in the manufacture of wind turbine blades as they are characterised by high strength–to-weight and stiffness-to-weight compared to conventional metallic alternatives [1].

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The call for an accurate and robust low level damage detection system may be answered in several ways, one of which is by adopting a novelty detection approach. This fault analysis method proceeds by using experimental measurements to develop a statistical representation of the structure in its "normal" state. Damage detection is achieved by assessing whether subsequent measurements from the structure deviate from this normal state. This class of algorithms offers the advantage of requiring an unsupervised learning approach, with no requirement for data from non-normal states [2,3].

The purpose of this case study is to examine a damage detection approach for CFRP materials such as may be used for new generation wind turbine blades. The approach taken is to apply auto-associative neural networks with different architectures and multivariate outlier analysis to vibration response data gathered from an experimental structure.

ARTIFICIAL NEURAL NETWORKS

Multi-Layer Perceptron (MLP)

Artificial Neural Networks (ANNs) offer a holistic, nonlinear parameterised mapping between a set of inputs and a set of outputs. For the purposes of this paper a brief description of the most common network paradigm, the Multi-Layer Perceptron (MLP) is given; for a more detailed analysis the reader is referred to the following work [4,5,6]. The MLP consists of a series of connected elements called nodes (or neurons in biological terms), organised together in layers. Signals pass from the input layer nodes, progress forward via the networks hidden layers and finally reach the output layer.

Auto-Associative Neural Network (AANN)

The AANN is a type of MLP whose target outputs are the same as the input. Generally, the auto-associative neural network consists of five layers including the input, mapping, "bottleneck", de-mapping and output layers [6]. A restriction of the mentioned topology is that the "bottleneck" layer must have less neurons than the input and output layers. This neural network architecture was motivated by Non Linear Principal Component Analysis (NLPCA) which is a robust and powerful statistical method for feature extraction and dimension reduction. As investigated in [7,8,9] the NLPCA idea can be used also for novelty detection; an approach which is adopted in the current study. Similar to linear Principal Component Analysis (PCA) the NLPCA, by adopting arbitrary nonlinear functions, seeks a mapping following the equation (5) [6, 9]:

$$X=G(Y). \tag{5}$$

Where Y represents the original input data with size $p \times n$, with p number of variables and n number of data sets, X is the scores matrix and G is a nonlinear vector function consisting of a different number of individual nonlinear functions. The original data reconstruction is performed by the inverse of equation (5) using a nonlinear function H:

$$\hat{Y}=H(X). \tag{6}$$

The information loss of the mapping procedure is calculated in the reconstruction error matrix:

$$E=Y-\hat{Y}. \tag{7}$$

As indicated in the introduction, 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 case study is to demonstrate the technique of novelty method in the context of auto-associative neural networks (AANNs) and outlier analysis, which is a robust and simple statistical technique [3]. One of the great challenges of novelty methods is their ability to detect damage independently of the operational and environmental fluctuations that may alter the natural dynamic characteristics and indicate wrongly a fault signal.When a trained AANN is fed with an input data set coming from an unprecedented state of the structure, such as a damage state in this paper, the novelty index n described from Euclidean distance will increase:

$$n(y) = \|y - \hat{y}\|. \tag{8}$$

Where y and $\hat{y}$ are each row of Y and $\hat{Y}$ of equation (7). If the neural network learning was successful then $n(y) \approx 0$ for all the training data set. Later on testing, $n(y)$ may significantly depart from zero indicating the presence of novelty.

It is common in SHM and condition monitoring to introduce a threshold in order to visualise clearly the presence of abnormal readings. In the case of a novelty index calculated from AANN the *warning level* [7] (the procedure is described in [10] is the threshold value after which a reading value can be considered as an abnormal quantity to involve further investigation).

PRINCIPAL COMPONENT ANALYSIS (PCA)

PCA is a well-known and established method of linearly mapping multidimensional data sets into lower dimensions with the minimum reconstruction error, a statistical tool which is not described analytically in this study. The reader can refer for details of the method on the following references [6,9,11]. The basic idea is the same as NLPCA as it was described but instead of a nonlinear G vector function there is a linear loading matrix T.

$$X = TY. \tag{9}$$

$$\hat{Y} = TT^T X. \tag{10}$$

Where $TT^T \approx I$.

AUTO-ASSOCIATIVE NEURAL NETWORKS AND SINGULAR VALUE DECOMPOSITION (SVD)

A common claim in the published literature is that for autoassociation with a single hidden layer with linear output units, the optimal weight values can be derived by standard linear algebra, and therefore that the usage of nonlinear transfer functions at hidden layers may be pointless [6, 12, 13]. On the other hand, nonlinear auto-associators were widely used for their ability to solve problems that cannot be solved by SVD because of the singularity of the PCA characteristic. In this study an analysis based on experimental data is performed in order to demonstrate the ability of nonlinear auto-associators for multimodal classification problems and novelty detection supporting the results derived from [14]. A close look at a particular condition was assumed in [12]. For the nonlinear transfer function F(x) it is observed that if the values of input x are small enough then the nonlinear processing function $F(x)$ can be approximated from by the linear part $F(x) \rightarrow a_0 + a_1 x$ arising from its power series expansion. This approximation automatically leads to a result where the hidden unit activation prior to their transformation must be in the linear range of the $F(x)$ function. This assumption automatically leads to the suggestion that when the net inputs to do not fall in range of the transfer function they do not inevitably react as PCA. Furthermore, while SVD-PCA represents a unimodal reconstruction error surface by calculating a global solution to the problem, the nonlinear transfer functions can “comprehend” local valleys to the problem [14].

MULTIVARIATE DATA OUTLIER ANALYSIS

Multivariate data can be described as *n* observations in *p* variables, i.e. may be symbolised as n points in a p-dimensional feature space. Outlier detection is accomplished by establishing a model of the normal data in *p*-dimensions and defining a discordancy measure that indicates deviation from the model. The discordancy measure used in this study is the Mahalanobis Squared-Distance (MSD), which is given by the following equation [3],

$$D_i^2 = (x_i - \mu_x)^T \Sigma^{-1} (x_i - \mu_x). \tag{11}$$

where x_i is the potential outlier, μ_x is the mean of the samples observations and Σ is the sample covariance matrix. The mean and covariance matrix can be inclusive or exclusive measures. Setting an appropriate threshold in the absence of any damage state data, as is the case in this study, is a non-trivial task. In many studies presented in the published literature, the assumption made is that the multivariate data are normally distributed, with the MSD subsequently approximated by a chi-squared distribution in p-dimensional space. Because of the critical shortcomings of the chi-squared distribution as they were described in [10, 16], for the purposes of this study another method for setting the threshold was followed is proposed as in [3]. A Monte Carlo simulation based on extreme value statistics was used.

THE COMPOSITE EXPERIMENTAL PLATE AND DATA EXTRACTION

The structure to be tested was a carbon fibre plate with a stiffening element. The geometry of the plate was 60cm x 14.8cm x 4mm. The carbon plate was suspended using soft springs to approximate free-free boundary conditions. It was decided to use frequency response function (FRF) data in order to monitor the specimen [17]. The sensors used were single-axis piezoelectric accelerometers. The accelerometers were fixed with wax. The plate was excited using an impact hammer. The FRFs were measured using an LMS-DIFA SCADA III acquisition system controlled by LMS software. FRFs were measured in the range of 0-10240 Hz and processed using 4096 spectral lines, giving a frequency resolution of 2.5 Hz. FRFs from a specific position were obtained with 5 averages for each of them. Next, 180 measurements were repeated successively. Of these, the first 120 would be used to establish the statistics of the patterns for the training set for the outlier analysis and 60 would be used for testing data. The second series of tests involved introducing damage into the structure, and gathering data from the structure in its subsequent 'damaged' conditions. An impact rig was used to apply three different levels of impact (15, 30 and 40 Joules) to the centre point of the plate. After each impact the specimen was removed from the impact rig and again placed in an approximation of a free-free condition. The same procedure of excitation with an impact hammer was applied in order to extract 60 repeated measurements of each faulty condition.

FEATURE SELECTION FOR NOVELTY DETECTION

The initial stage is to set up which features of the FRF spectrum will be used to individually detect damage in the specimen. As described in [15], in order to separate the possible features, a classification into degrees: weak, fair or strong was assumed. In a previous work [10] another path of choosing the training data was followed. From the 180 normal condition samples was used a random distribution of collecting the undamaged training set. As an addition because of the data variability, it was decided to add plus and minus three times the standard deviation σ for the "raw" representation of the FRF around the mean in order to introduce an updated definition of feature selection compared to the previous one. The features are shown in Fig. 1 where FRF magnitude is plotted. The x-axis corresponds to the spectral lines (sample). In the figures the blue, black and green lines represent the 15 Joule, 30 Joule and 40 Joule impacts respectively and the red line the normal condition.

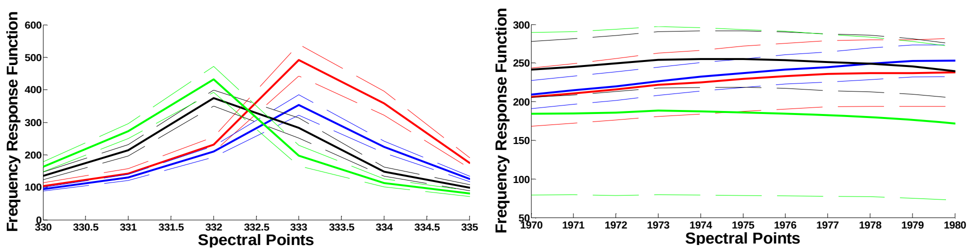

Figure 1. Strong feature (left) and Weak feature (right).

NOVELTY DETECTION RESULTS

The results shown in Fig. 2 and 3 are reasonably good; they not only detect the damaged situation by introducing a monotonic novelty detector but also, respond clearly to the characterisation of normal condition. Fig. 4 and 5 show the results for the weak feature, indicating the better generalisation of AANN, Fig. 4 (right) but also indicates the better mapping of one layer nonlinear autoassociator, Fig. 5 (left) regarding the 15 Joule damage detection.

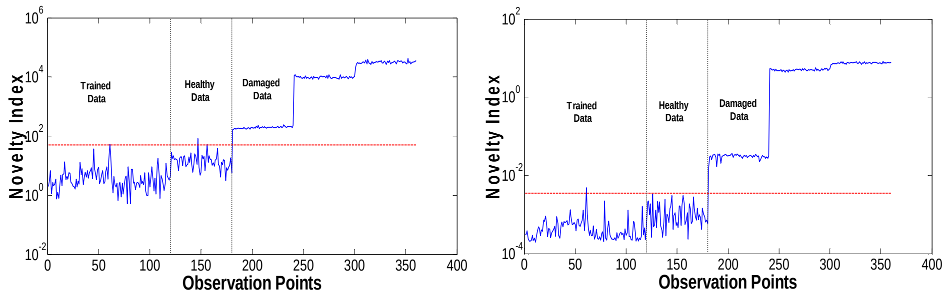

Figure 2. Strong feature Outlier (left) and AANN (right) novelty detection.

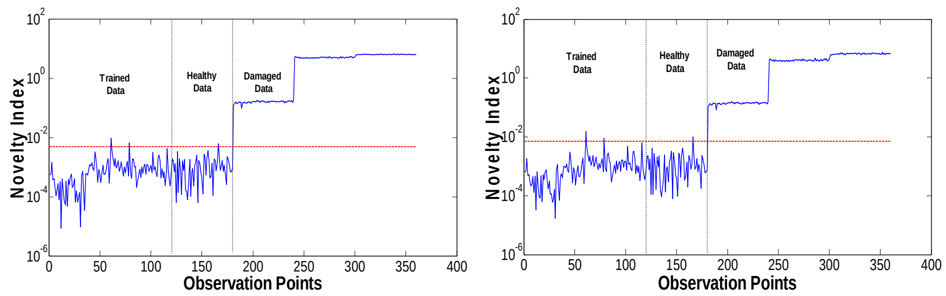

Figure 3. Strong feature AANN with one hidden layer of non linear (left) and linear (right) transfer function.

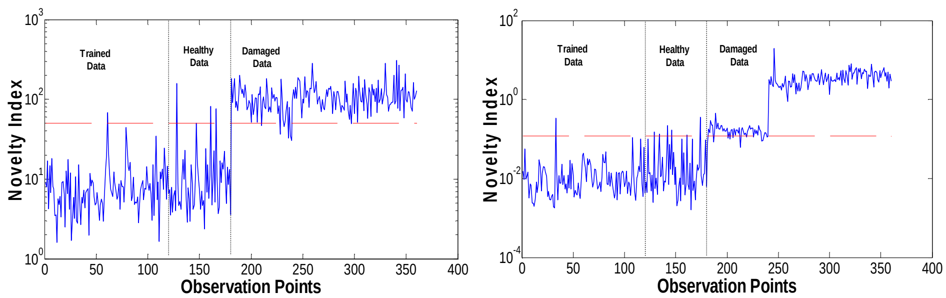

Figure 4. Weak feature Outlier (left) and AANN (right) novelty detection.

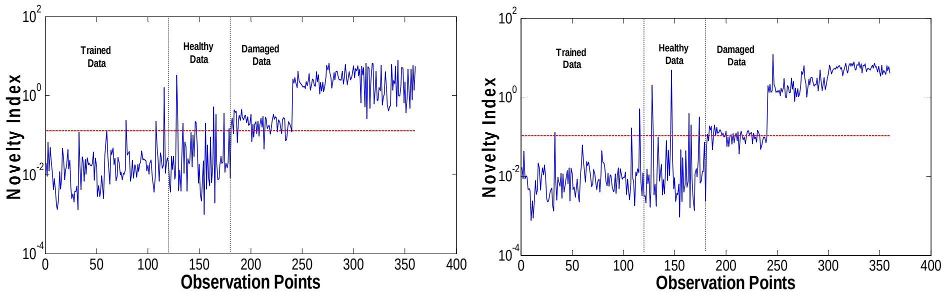

Figure 5. Weak feature AANN with one hidden layer of non linear (left) and linear (right) transfer function.

DAMAGE DETECTION USING ARTIFICIAL NEURAL NETWORKS VIA REDUCED DATA DIMENSION

The dimension of FRF measurements remains a big challenge as the novelty detection technique suffers from the “curse of dimensionality”. Even if technologically the power was available for such performance when the number of observations is much smaller than the dimensions, then over-fitting would be the dominant problem as the neural network could focus only on local regions of the training data. As demonstrated in previous parts of the current study, one can introduce subset of the data by introducing features which are sensitive to damage. In this section an alternative approach is presented by reducing the dimension of FRF data using PCA, [18]. It was decided to retain 96% of the data variance around the mean response which is reflected at the first 10 principal components, Fig.6. As was mentioned in previous sections the total FRF matrix was 360 (observations)×4096 (spectral lines). As an input to the neural network a 10 dimensional space was fed consisting of 120 observations of the healthy condition, and 30 observations for each damage condition consisting a matrix of 10×240. As an output, a two dimensional [1,0] (healthy)-[0,1] (damage) and one dimensional space [1] (healthy)-[0] (damage) was introduced for comparison of two different cases of output. The use of two outputs was assumed because theoretically it could result in a better nonlinear mapping. In order to find the best network architecture the training data was tested for several number of hidden layer nodes varying from 1 to 30 for the same number of iterations (Fig. 6 (right)), and 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. Briefly, the training data is used for calculating the gradient and updating the network weights and biases. The mean square error on the validation set is examined during the training procedure. In the case of over-fitting the validation error normally begins to rise compared to the training set error. Also, it has to be mentioned that when the error in the test data touches a minimum value at a noticeably different epoch compared to the validation error, this could point out a poor separation of the data set. The results are presented in Fig. 7.

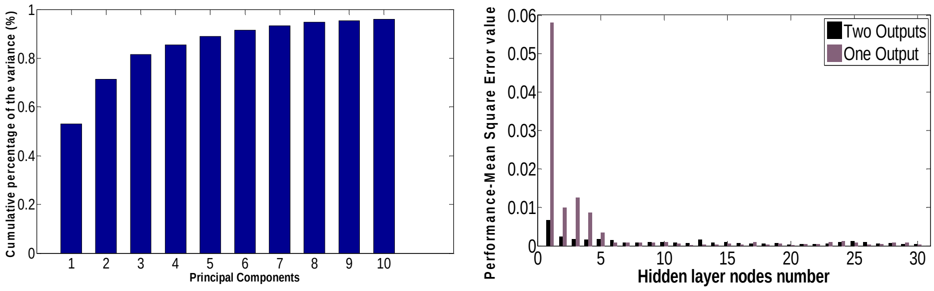

Figure 6. Variance (%) of first 10 PC (left) and Mean Square Error performance comparison for the 30 different node cases (right) for one and two outputs.

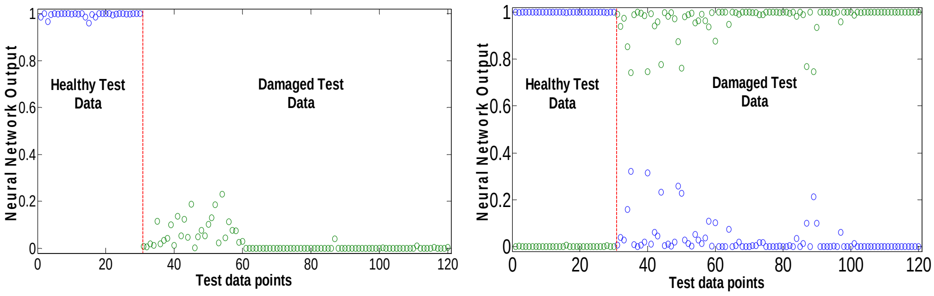

Figure 7. Comparison of damage detection for the different number of outputs, one output (left) and two outputs (right).

DISCUSSION AND CONCLUSION

The main objective of this paper was to investigate the effectiveness of two novelty detection methods with different characteristics by comparing a strong and weak feature. The second objective was to investigate the capability of autoassociation of a three layer network with nonlinear and linear transfer function and their difference in novelty detection. The use of the AANN as a novelty detection algorithm has been shown to be effective in detecting alternate mechanisms after three different levels of introduced impact. Results point out that the integration of AANN and outlier detection with a novelty measure enables a quantitative and qualitative damage detection even when the system exhibits a range of normal conditions. Furthermore, an attempt to address the paradox described in section 4 is introduced. We demonstrated the two sides of the coin. For the strong feature the comparison shows no differences between linear and nonlinear activation function. But for the weak feature it is noticeable that the one layer auto-association is doing a better classification regarding the 15 joule impact than the linear auto-association, as it is able to generalise better. In both novelty algorithms, in order to minimise the false indication of damage and implement a robust and reliable system, the training data set which plays a vital role must be collected over a wide range of different operational and environmental conditions. Feature selection was found not to be a trivial process and the number of dimensions of each feature warrants further discussion. For this reason in section 7 another definition is applied. In section 9 it was shown that the combination of data dimension reduction and neural network classifications provide a useful technique for damage detection. The differences between one and two output layer classes are negligible.

In this current study the bottleneck layer architecture was known *a priori* but is essential that different topologies be tested based on Akaike's information theoretic criterion (AIC), Akaikes's final prediction error criterion technique (FPE) or an early-stopping technique for avoiding overtraining, and maybe Bayesian regularisation method. 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.

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