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“Maintenance management based on Machine Learning and nonlinear features in wind turbines”

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Abstract: Delamination is a common problem in wind turbine blades, creating stress concentration areas that can lead to the partial or complete rupture of the blade. This paper presents a novel delamination classification approach for reliability monitoring systems in wind turbine blades. It is based on the feature extraction of a nonlinear autoregressive with exogenous input system (NARX) and linear auto-regressive model (AR). A novelty in this paper is NARX as a Feature Extraction method for wind turbine blade delamination classification. Further, the NARX feature is demonstrated to be significantly better than linear AR feature for blade damage detection, and NARX can describe the inherent nonlinearity of blade delamination correctly. A real case study considers different levels of delamination employing ultrasonic guided waves that are sensitive to delamination. Firstly, the signals obtained are filtered and de-noised by wavelet transforms. Then, the features of the signal are extracted by NARX, and the number of features is selected considering the Neighbourhood Component Analysis as main novelties. Finally, six scenarios with different delamination sizes have been performed by supervised Machine Learning methods: Decision Trees, Discriminant Analysis, Quadratic Support Vector Machines, Nearest Neighbours and Ensemble Classification.

Index Terms: Wind Turbine Blade, Delamination, NARX, Machine Learning, Guided Waves.
1. INTRODUCTION.

A common problem in composite structures, such as wind turbine blades (WTB), is the appearance of delamination. The delamination is the disunion of one or more layers of the
composite material, which leads to a deterioration of the structural properties of the whole structure.

When a structure with any delamination is subjected to tensions and forces, e.g. in work regimen, stress concentration is generated at the edges of the disunion. It can generate the total breakage of the structure [1]. Due to the risks and large economic costs involved in the breakage of a WTB, a proper maintenance management based on predictive maintenance is required.

Structural health monitoring (SHM) is employed to analyse the condition of a structure. It is usually considered in a predictive and preventive maintenance strategy [2-4]. It is often used to detect failures in real time, or at fixed intervals by analysing the signals collected from sensors and using signal processing methods.

SHM systems have become an important research topic to reduce operation and maintenance cost. In the last decade, due to advances in the computational capacity of electronic systems and digital signal processing, SHM is having more relevance [5,6]. New SHM techniques and approaches have been developed for inspecting WTBs [7-9]. SHM is also employed to measure and evaluate the structural integrity in the new concept of “smart-blade”, that involves the life cycle of the blade including design, operation, maintenance, repair and recycling [10]. Figure 1 shows the methodology of an “smart-blade”.

Techniques, such as Pattern Recognition from Machine Learning (ML), are applied to detect the different stages in the cycle of a WTB. Pattern recognition by ML has been used in many different issues. Pérez-Ortiz et al. perform a comprehensive review of problems and classification

![Fig. 1. Life stages of a wind turbine blade: “smart-blade” [10].](image-url)
algorithms with ML in the field of renewable energies [11]. Joshuva and Sugumaran present a
compressive review on failure diagnosis methods and SHM for wind turbines [12]. N. Dervilis et al. applied pattern recognition to diagnose the failure of a WTB employing Principal Component Analysis (PCA), Non-Linear Principal Component Analysis (NLPCA) and Artificial Neural Networks (ANN) with Radial Basis Functions [13]. Panu Pratumnopharat et al. carried out a new approach using Meyer's Mexh, Daubachies, Morlet and Discrete Wavelets to obtain the historical stresses over the time in a wind turbine using vibration signals [14]. Altabey and Noori show a review of methodologies based on Lamb wavelets and ANN developed for the detection of damage in composite structures [15]. Feklistova and Hein identify the size and location of delamination in homogeneous and composite laminates using an aggregated approach that combines Haar wavelets, Support Vector Machine (SVM) and ANN [16]. Pavlopoulou et al. developed a work based on the SHM online of adhesive composite repairs, using ultrasonic guided waves (UGW) with post-processing techniques by Features Extraction (FE) and selection by PCA and NLPCA [17].

A general procedure in pattern recognition using ML is to filter the original signal, extract and select the relevant features, and classify the extracted features [18]. The classified results are used to identify WTB conditions or levels of damage severity [7,19,20]. SHM can reduce maintenance costs by preventing serious WTB failure, and can also increase profitability by reducing downtime [21,22].

There is extensive literature on the filtering and analysis of UGW. Standard statistical techniques have been employed for filtering [23]. Yu et al. [24] reduced noise using averaging techniques and Daubechies Wavelet Transform, filtering the high-frequency perturbations. Denoising and compression signal of UGW, based on the Discrete Wavelet Transform, was performed by Rizzo and di Scalea [25]. Hamming [26] presented a study about low-pass filters available for data smoothing.

FE techniques aims to create representative characteristics with lower dimensionality than the original data. FE can be extracted from models, such as Markov models and Autoregressive (AR) models [27,28]. The AR model is one of the most popular methods for FE of time-series dataset [29]. However, AR is a linear method, and a nonlinear relationship presented in the signal cannot be represented, and this may limit classification performance due to the lost nonlinear information.

This paper presents as novelty a Nonlinear Autoregressive with Exogenous input method (NARX) utilised as FE for detection and classification different delamination states in WTB. The features extracted by NARX presents better accuracy in the case study than linear AR features. The behaviour of Lamb waves propagation through defects is complex and nonlinear when they are
transmitted in anisotropic materials, e.g. WTB. NARX is a robust, simple and versatile algorithm for identifying non-linear dynamic systems, considering also Gaussian noises.

NARX was introduced by Leontaritis and Billings to describe a wide class on nonlinear systems [30]. NARX predicts the output value $y_t$ by a non-linear function $F$ from the input $x_t$, i.e. $y_t = F(y_{t-1} \cdots y_{t-n_y}; x_{t-1} \cdots x_{t-n_x})$. $F$ is defined by regression approaches, e.g.: multinomial regression, non-parametric model forms based on automatic learning (Multi-layer Perceptron neural networks, MLP, Radio Basis Function, Gaussian Process, NARX models, etc.) [31].

NARX has been developed as a methodology in ML by applying a data-driven approach to prediction through the NARX Neural Network with exogenous inputs [32], e.g. predicting faults in gearboxes, bearings [33,34], predictive control [35] and forecast of wind speed and power [36]. The NARX model is often formulated as a linear combination of nonlinear functions to reduce computational costs referred as the linear-in-the-parameters model [37]. NARX models are properly structured for adaptive learning, and its structure setting is complex due to the number of terms grows rapidly.

The main selection methods are the Forward Regression Orthogonal Estimator, Randomized Model Structure Selection, Randomized Features Selection and Classifier, etc. PCA, Multidimensional Scaling, Kernel PCA, and Neighbourhood Component Analysis (NCA) are employed to reduce the dimensionality in classification learning [38]. NCA is proposed by Goldberger et al. for learning the Mahalanobis distance measurement for KNN classification algorithm [39]. Zhou et al. established a condition monitoring and fault diagnosis system to prevent abrupt bearing breaks during operation using NCA as a feature selection method [40].

Training process with supervised learning is employed to perform the classification [41]. Then, the trained classifier can be used for new data classification the classification performance is dependent on the choice of features and classifier models.

In this paper, five classifiers are employed to identify the delamination: Decision Trees, Discriminant Analysis, Support Vector Machines, Nearest Neighbours and K-Ensemble Classification. The results are compared with the AR-FE model that is obtained using the Yule-Walker method to verify the performance of the NARX features. Two conventional methods were used to evaluate the precision of the classifiers: Analysis Receiver Operating Characteristic (ROC) and Confusion Matrix. The classification of the different levels of delamination of the WTB has been performed employing: Wavelet Filtering, FE NARX, FS NCA and ML classifiers. Figure 2 shows the scheme of the proposed methodology.
Fig. 2. Proposed Methodology.

Appendix B shows a summary of the state of the art showed in this paper.

2. CASE STUDY

2.1 Experimental procedure.

The experimental system is composed of a WTB section, an ultrasonic pulser-receiver system and ultrasonic transducers. This WTB is usually installed in wind turbines model G80-2.0 MW, being the Gamesa NACA 63.XXX + FFA-W3 model. It is made with fiber glass with a PVC foam core, and it is 39 meters length.

SHM of the WTB was done by UGW, transmitted through the composite material. The transmitter was excited with a sweep of frequencies to experimentally determine the best frequencies.

The transducer is Macro Fibre Composite (MFC) and it is composed of interdigitated piezoelectric fibers [42]. It can easily adapt to curved surfaces, e.g. the WTB surface. Figure 3 shows the sweep signals in the frequency domain, where the frequency range from 47 to 57 kHz provided better results. The ‘y’ axis is the power spectral density in decibels.
The frequencies employed in this paper were: 25, 37, 55 and 100 kHz, being 37 and 55 kHz the frequencies that provided better results.

Six different case studies were carried out: the first case of study consists of transmitting UGW in the WTB without inducing any damage; the second is to induce internal damage of one centimetre in length and one centimetre in deep with a sharp instrument. The following cases are increased the depth of the defect in one centimetre up to 5 centimetres (Table 1). Table 1 shows all the scenarios considered in the experiments.

<table>
<thead>
<tr>
<th>Scenario</th>
<th>‘x’ (cm)</th>
<th>Delamination Area (cm²)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0 (Undamaged)</td>
<td>0</td>
</tr>
<tr>
<td>2</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>3</td>
<td>2</td>
<td>2</td>
</tr>
<tr>
<td>4</td>
<td>3</td>
<td>3</td>
</tr>
<tr>
<td>5</td>
<td>4</td>
<td>4</td>
</tr>
<tr>
<td>6</td>
<td>5</td>
<td>5</td>
</tr>
</tbody>
</table>

Figure 4 shows the transducer locations in the blade Gamesa NACA 63.XXX + FFA-W3 type, usually installed in wind turbines model G80-2.0 MW. The ultrasonic technique used was ‘pitch and catch’, where a short ultrasonic pulse is emitted by the MFC transmitter (Tx), and then it is collected by the MFC sensor (Rx). The ultrasonic pulse was a six-cycle Hanning pulse for each frequency.
Fig. 4. Scheme of MFC location for delamination detection.

Six hundred experiments for each frequency were done. Figure 5 shows the signal for 55 kHz in each scenario with a sample rate of four million of samples per second.

Fig. 5 Set of signals for different scenarios, collected for 55 kHz (Filtered).
2.2 Novel approach.

The signals are firstly filtered and de-noised by Wavelet transforms [43,44]. The signals contain noise that appears at high frequencies (random noise).

The Wavelet transform is a powerful method that allows to identify the local characteristics of a signal in the time and frequency domain. It presents some advantages that improves the limitations of resolution and the loss of information presented by the Short-Time Fourier Transform or the Fast Fourier Transform [45]. The Wavelet transform has several level decompositions. Each level decomposition is essentially a combination of two filters, where one is low pass filter, generating the filtered results that are called approximations, and other is high pass filter, producing the results called details [7].

In the case of the multi-level filters, they repeat the filtering process with the output signals from the previous level, leading the wavelet decomposition trees. Additional information is obtained by filtering at each level. However, more decompositions levels do not always mean better accurate results.

The Daubechies wavelet family were employed according to reference [46], where it is demonstrated that they are the most suitable for this type of signals because they are more sensitive to sudden changes, and they handle with boundary problems for finite length signals. The number of levels was set at seven after several experiments, where it was obtained the highest percentage of information. The lower wavelet approximation is removed from the original signal to avoid the trend and other undesirable components that appear in the low frequencies.

The denoising of the signals is performed employing a multilevel 1-D Wavelet analysis using the Daubechies family [47]. An overly aggressive filtering could eliminate information about the condition, e.g. small echoes that come from defects. The threshold for the de-noising is obtained by a wavelet coefficients selection rule using a penalization method provided by Birgé-Massart, which produces good results [48]. In contrast to other digital filters, the Wavelet de-noising filter does not produce an unwanted distortion of the signal characteristic parameters, e.g. time of flight.

Section 4 and 5 describes the FE of each ultrasonic signal extracted by AR and NARX. Section 5.B indicates the FS by AIC. The pattern recognition was done by ML through supervised learning. The results from the following classifiers were compared: Decision Trees, Linear Discriminant Analysis, Support Vector Machines, K-Nearest Neighbours and Ensemble Classification. The ROC and confusion matrix analysis has been employed to evaluate the classification and obtain the precision.
3. LINEAR FEATURES.

An AR system of extraction is employed to compare the linear and nonlinear regressive methodology. The current output is a linear combination of the past $p$ outputs, considering also a white noise input, and it is set as an AR model of order $p$. The objective is to minimize the mean-square prediction error by setting the weights on the $p$ past outputs of the auto-regression. If $y(t)$ is the current value of the output with a zero-mean white noise input, the AR($p$) model can be written as equation (1),

$$ y(t) = \sum_{i=1}^{p} \phi_i y(t-i) + \xi(t) $$

(1)

where $y(t)$ is the time series to be modelled, $\phi_i$ are the model coefficients, $\xi(t)$ is white noise that is independent from the previous points, and $p$ is the order of the AR model.

Modified covariance method (forward-backward approach), correlation method (Yule-Walker approach), or covariance method, are widely used in AR [49]. In this paper, Yule-Walker has been applied to estimate the unknown model coefficients $\phi_i$ [50].

4. NONLINEAR FEATURES.

The NARX model is introduced in this section and then the details of the nonlinear FE procedure are discussed, followed by the feature number determination using NCA.

4.1 NARX model

A polynomial NARX model is used as the nonlinear function. The polynomial NARX model with an order up to 3 is given by equation (2) [51].

$$ y(t) = \sum_{i_1=1}^{M} y(t - i_1) \theta_{i_1} + \sum_{i_2=1}^{M} \sum_{i_1=1}^{M} y(t - i_1) y(t - i_2) \theta_{i_1 i_2} + \sum_{i_1=1}^{M} \cdots \sum_{i_{n-1}=1}^{M} y(t - i_2) \cdots y(t - i_2) \theta_{i_1 \cdots i_n} + \xi(t) $$

(2)
where $y(t)$ are data sample at time $t$, $t=1,...,N$, and $y(t-i_k)$ are the delayed data with lagged $i_1, i_2 = 1, ..., r$. The coefficient $\theta$ are the features. Nonlinear AR (NAR) is a special case of NARX where the input coefficients are zeros, i.e. the input has no contribution to the model.

Given a set of $N$ training samples, equation (2) can be expressed in the matrix form as equation (3),

$$ y = P\Theta + \Xi $$

where $y = [y(1), \ldots, y(N)]^T$ is the coefficient vector, $\Theta = [\theta_1, \ldots, \theta_M]^T$ is the unknown parameter vector, $\Xi = [\xi(1), \ldots, \xi(N)]^T$ is the residual vector, and $P = [p_1, \ldots, p_i, \ldots, p_M]$ is a $N$-by-$M$ matrix, being $p_i = [p_j(x(1), v_j), \ldots, p_j(x(N), v_j)]^T$ [52].

### 4.2 Features Extraction

The coefficients of NARX, given in equation (4), are obtained as:

**Step 1.** The matrix of first-order terms ($\sum_{i=1}^{M} x_{i_1}(t) \theta_{i_1}$) is

$$ A(M) = \begin{pmatrix} y(t) & y(t-1) & \cdots & y(t-M) \\ \vdots & \vdots & \ddots & \vdots \\ y(N-1) & y(N-2) & \cdots & y(N-M) \end{pmatrix} $$

when $M = 3$, then:

$$ A(3) = \begin{pmatrix} y(t) & y(t-1) & \cdots & y(t-2) \\ \vdots & \vdots & \ddots & \vdots \\ y(N-1) & y(N-2) & \cdots & y(N-3) \end{pmatrix} $$

**Step 2.** The matrix of second-order terms ($\sum_{i_1=1}^{M} \sum_{i_2=i_1}^{M} x_{i_1}(t) x_{i_2}(t) \theta_{i_1 i_2}$) is:

$$ B(M) = \begin{pmatrix} y(t)y(t-1) & \cdots & y(t)y(t-M) \\ y(t+1)y(t-1) & \cdots & y(t+1)y(t-M) & y(t)y(t) \\ \vdots & \vdots & \ddots & \vdots \\ y(N-1)y(N-2) & \cdots & y(N-1)y(N-M) & y(N-2)y(N-M) & \cdots & y(N-M)y(N-M) \end{pmatrix} $$
For $M=3$,

$$B(3) = \begin{pmatrix} y(t)y(t-1) & y(t)y(t-2) & \cdots & y(t)y(t-M+1) \\ y(t+1)y(t) & y(t+1)y(t-1) & \cdots & y(t+1)y(t-M+1) \\ \vdots & \vdots & \ddots & \vdots \\ y(N-1)y(N-M+2) & y(N-1)y(N-M+1) & \cdots & y(N-1)y(N-M+1) \end{pmatrix}$$

(7)

There are two reasons for choosing the model with order $M=3$: The first reason is that the higher order terms have much less contributions than lower model terms. This can be illustrated using Taylor expansion, where the contributions of higher order model terms are negligible. Moreover, the higher order terms can easily approximate noises; the second reason is that the higher orders introduce significant model complexity. According to parsimonious principle, a simple model is always preferable to a complex one when they have similar model performance. Sometime, a model with higher order terms could be too complex and performs poorer than the simpler models. Therefore, majority practical application only used model order up to 3.

**Step 3.** For matrix of $N$ variables, each term is the product of the $N$ values

$$\sum_{i=1}^{M} \cdots \sum_{i=M-N}^{M} x_{i1}(t) \cdots x_{iN}(t) \theta_{i1} \cdots \theta_{iN}.$$ For example, for a polynomial of 3 variables and $M = 4$, the terms are shown in Table 2.

<table>
<thead>
<tr>
<th>N°</th>
<th>TERMS</th>
</tr>
</thead>
<tbody>
<tr>
<td>1-5</td>
<td>$y(t-1), y(t-2), y(t-3), y(t-4), y^2(t-1)$</td>
</tr>
<tr>
<td>6-8</td>
<td>$y(t-1)y(t-2)y(t-3)y(t-4)y(t-5)y(t-6)$</td>
</tr>
<tr>
<td>9-12</td>
<td>$y^2(t-2)y(t-3)y(t-4)y(t-5)y(t-6)y^2(t-3)$</td>
</tr>
<tr>
<td>13-16</td>
<td>$y^2(t-3)y(t-4)y^2(t-4)y^3(t-1)y(t-2)$</td>
</tr>
<tr>
<td>17-19</td>
<td>$y^2(t-1)y(t-3), y^2(t-1)y(t-2)y(t-3)y^2(t-2)$</td>
</tr>
<tr>
<td>20-21</td>
<td>$y^2(t-1)y(t-2)y^3(t-3)y(t-1)y^2(t-4)$</td>
</tr>
<tr>
<td>22-23</td>
<td>$y^2(t-1)y(t-2)y(t-3)y(t-4)y(t-5)$</td>
</tr>
<tr>
<td>24-25</td>
<td>$y(t-1)y(t-2)y(t-3)y(t-4)y^3(t-2)$</td>
</tr>
<tr>
<td>26-28</td>
<td>$y^2(t-2)y(t-3)y^3(t-2)y(t-4)y(t-5)y^2(t-3)$</td>
</tr>
<tr>
<td>29-31</td>
<td>$y(t-2)y^2(t-4)y(t-2)y(t-3)y(t-4)y^3(t-3)$</td>
</tr>
<tr>
<td>31-34</td>
<td>$y^2(t-3)y(t-4)y(t-3)y^2(t-4)y^3(t-4)$</td>
</tr>
</tbody>
</table>

**Step 4.** $P$ matrix consists of the matrices involved ($A$, $B$),

$$P = (A) (B)$$

(8)
Step 5. The solution of equation (3) is given by equation (8).

\[ \Theta = P^{-1}y \]  

(9)

where \( \Theta = [\theta_1, \ldots, \theta_d]^T \) is the extraction features parameter vector. The direct inverse of \( P \) matrix can be used to solve the model parameters. Alternatively, least squares methods are often used to compute the model coefficients by using the equation \( \Theta = (P^TP)^{-1}P^TY \). The least squares method tends to be more popular as it is more numerically robust than direct inverse operation.

4.3 Feature Selection

NCA has been applied to reduce the dimensionality in AR and NARX [38, 40]. Let \( Y = \{y_1, y_2, \ldots, y_n\} \) be labelled features set, where \( y_i \in \mathbb{R}^d \), where the corresponding class labels are \( \{c_1, c_2, \ldots, c_n\} \). The objective is to find a vector of weighting \( w \) to select the subset of characteristics optimizing the classification of nearest neighbours. \( w \) is the weighted distance between two samples \( y_i \) and \( y_j \), given by equation (10):

\[ D_w(y_i, y_j) = \sum_{l=1}^{d} w_l^2 |y_{il} - y_{jl}| \]  

(10)

where \( w_l \) is a weight associated with the \( l \)th feature.

The reference point in NCA is chosen randomly, where all points in \( X \) have a probability of being selected as the reference point. The point \( x_i \) selects the point \( x_j \) as its neighbour with a probability \( p_{ij} \), receiving the class label from the neighbour selected. \( p_{ij} \) is defined by equation (11):

\[
\begin{align*}
    p_{ij} &= \frac{\mathcal{K} \left( D_w(y_i, y_j) \right)}{\sum_{k \neq i} \mathcal{K} \left( D_w(y_i, y_k) \right)}; \text{ if } i \neq j \\
    p_{ij} &= 0; \text{ if } i = j
\end{align*}
\]  

(11)

where \( \mathcal{K}(z) = \exp(-\frac{z^2}{\sigma}) \) is a Kernel function, and the Kernel with \( \sigma \) is an input parameter that influences the probability of each point to be selected as the reference point. The probability of the query point \( x_i \) to be correctly classified, \( p_i \), is given by equation (12):

\[ p_i = \sum_j c_{ij} p_{ij} \]  

(12)
being $C_{ij} = 1$ if the class label $C_i = C_j$, and $C_{ij} = 0$ if the class label $C_i \neq C_j$

The true leave-one-out classification accuracy $\xi(w)$ is calculated by equation (13):

$$\xi(w) = \sum_i \sum_j C_{ij} p_{ij} - \lambda \sum_{l=1}^{d} w_l$$  (13)

where $\lambda$ is a regularization parameter set by cross validation. The regularization term $\lambda \sum_{l=1}^{d} w_l^2$ is introduced in equation (12) to improve the feature selection and avoid overfitting.

A gradient rule is applied by differentiating $\xi(w)$ regarding to $w_l$ in equation (14):

$$\frac{\partial \xi(w)}{\partial w_l} = 2 \left( \frac{1}{\sigma} \sum_i \left( p_l \sum_{j \neq l} p_{lj} |y_{il} - y_{jl}| - \sum_j C_{lj} p_{ij} |y_{il} - y_{jl}| - \lambda \right) w_l \right)$$  (14)

5. CLASSIFICATION METHODS

ML multiclass with supervised learning is employed to classify the scenarios of the WTB conditions. The classifiers used are: Decision Trees (DT); Quadratic Discriminant Analysis (QDA); Support Vector Machines (SVM); K-Nearest Neighbours (KNN), and; Ensemble Classification.

DT is a classifier used because of a complex decision process is segregated in simpler decision processes [53]. DT consists in three stages: Construction of the maximum tree using a binary partition procedure; tree pruning, and; selection of the optimal tree by means of a cross-validation procedure. A classification tree is graphically represented by nodes and branches. The tree is initially represented by the root node.

Construction of the maximum tree is based on the cyclic decomposition of an initial data group, called the parent group, into two mutually exclusive subgroups, namely daughter groups. The subgroups are configured to increase the homogeneity of the new group using the impurity function.

The impurity function determines the quality of a node. The impurity, or partition criterion, is given by Gini's Diversity Index (GDI), equation (15):

$$GDI = 1 - \sum_i p^2(i)$$  (15)

being $p(i)$ the observed fraction of classes with class $i$ that has the node. A node with only one class, named pure node, $GDI = 0$, being $GDI > 0$ in other cases.
The optimal tree generally presents overfitting [54]. The second phase of the process is to reduce the size of the tree, that consists of cutting off terminal nodes until the optimal size. The tree is divided in different subtrees, that are compared to find the optimal, considering the measure of cost complexity \( R_a(T) \), given by equation (16):

\[
R_a(T) = R(T) + \alpha |\hat{T}|
\]  

(16)

being \( R(T) \) the average within-node sum of squares, \( |\hat{T}| \) is the tree complexity, i.e. the total number of nodes of the subtree, and \( \alpha \) the complexity parameter employed as a penalty for each additional terminal node. \( \alpha \) is gradually increased from 0 to 1 in the pruning procedure, and it is considered the value that minimize \( R_a(T) \). The optimal subtrees are selected according to the minimal predictive error models employing cross validation. The advantage of this classifier is the flexibility and ability to be applied to nonlinear relationships between features and classes.

QDA is a common technique for multivariate analysis, based on finding the quadratic combination of variables, optimising the classification of differentiate classes by means of a discriminant function [55].

The classification of a discriminant analysis process can be summarized as:

a) To calculate the prior probability \( \pi_i \) of the class \( i \), i.e. the expected proportion of observations belong to each group.

b) To determine if the variance or covariance matrix is homogeneous in all groups. It is assumed that the vector of feature variables \( X \) is multivariate normally distributed in the group with mean \( \mu_i \) and covariance matrix \( \Sigma_i \).

c) To estimate the necessary parameters for the conditional probability functions by equation (17),

\[
f_i(X) = \frac{1}{(2\pi)^{P/2} |\Sigma_i|^{1/2}} \exp \left[ -\frac{1}{2} (X - \mu_i)^T \Sigma_i^{-1} (X - \mu_i) \right]
\]  

(17)

where \( P \) is a dimension factor (2 for QDA), and \( T \) is a transpose operator.

d) To calculate the result of the discriminant function by equation (18) to set the group assigned

\[
g_i(X) = -\frac{1}{2} (X - \mu_i)^T \Sigma_i^{-1} (X - \mu_i) - \frac{1}{2} \log(|\Sigma_i|) + \log(\pi_i)
\]  

(18)

e) To use cross-validation to estimate the probabilities of misclassifications.
SVM considers each feature as a point in a high-dimensional space, where the number of dimensions is equal to the number of rating levels [56]. An optimal hyperplane is defined to separate the dataset based on class membership. The Kernels function $K(x_i, x') = (\phi(x_i), \phi(x'))$ is used to transform the input data to a higher dimensional space, where a decision boundary can be designed. Given $n$ training vectors, $x_i \in \mathbb{R}^p; i = 1, \ldots n$, defined by a set of $p$ descriptive variables $x_i = \{x_{i1}, \ldots, x_{ip}\}$, by the class label $y_i \in \{-1, +1\}$, and using the Lagrange function, the optimization problem is solved by the decision function (19),

$$D(x) = w\phi(x_i) + b$$

(19)

where $w$ and $b$ are the SVM parameters, and $\phi(x)$ is a kernel function, and the quadratic function Kernel is $K(x_i, x') = ((x_i, x') + 1)^2$.

The hyperplane is defined by equation (20), and the distance between the hyperplane and pattern $x$ is given by equation (19).

$$D(x) = \frac{\|w\|}{\|w\|}$$

(20)

A training classifier is used to find the value $w$ that maximizes the margin between the class boundary and the training patterns [56]. The objective function, $J$, of the training algorithm is given by equation (21).

$$J = \frac{\|w\|^2}{2}$$

(21)

One vs one is a method used in pattern recognition when multiple patterns exist [57].

KNN classifier has been used for pattern classification and ML [58]. KNN is based on the determination of the nearest neighbours and to set the class using the neighbours. Given a set training observations $X$ of $n$ feature measurements, $X = (x_1, \ldots, x_N)^T$, and the class label $Y = 1, \ldots, C$, a KNN classifier allows to find the $K$ nearest neighbours of a query point $x_0$ in $X$, and then it predicts the class label of $x_0$. Given a query $x_0$, its unknown class $y_0$ is assigned by two steps: Firstly, a set of $k$ similar labelled target neighbours for the query $x_0$ is identified. The Euclidian distance is given by equation (22) for a set $T' = \{x_i^{NN}, y_i^{NN}\}_{i=1}^K$, set in a growing order in terms of Euclidean distance $d(x_0, x_i^{NN})$ between $x_0$ and $x_i^{NN}$.
\[ d(x_0, x_i^{NN}) = \sqrt{(x_0 - x_i^{NN})^T (x_0 - x_i^{NN})} \]  

Secondly, the class label of the query point is predicted by the majority of voting of its nearest neighbours, given by equation (23)

\[
y_0 = \arg \max_y \sum_{(x_i^{NN}, y_i^{NN}) \in T} \delta(y = y_i^{NN})
\]

where \( y \) is the class label, \( y_i^{NN} \) is the class label for \( i \)-th nearest neighbour among its \( k \) nearest neighbours. The Dirac delta function is expressed by equation (24),

\[
\delta(y = y_i^{NN}) = \begin{cases} 1 & \text{if } y = y_i^{NN} \\ 0 & \text{otherwise} \end{cases}
\]

Weighted KNN (WKNN) classifier has been used in this paper, where the nearest neighbours outweigh the farthest. The nearest neighbours have a higher weight than the farther ones in WKNN. Consequently, the weighted distance function shall be used, where the \( \omega_i^0 \) weight for the \( i \)-th nearest neighbour of the query \( x_0 \) is defined by equation (25).

\[
\omega_i^0 = \begin{cases} \frac{d(x_0, x_i^{NN}) - d(x_0, x_k^{NN})}{d(x_0, x_k^{NN}) - d(x_0, x_i^{NN})}, & \text{if } d(x_0, x_i^{NN}) \neq d(x_0, x_k^{NN}) \\ 1, & \text{if } d(x_0, x_k^{NN}) = d(x_0, x_i^{NN}) \end{cases}
\]

where the result of the classification of the vote, based on the weighted majority vote, is obtained by equation (26)

\[
y_0 = \arg \max_y \sum_{(x_i^{NN}, y_i^{NN}) \in T} \omega_i^0 \times \delta(y = y_i^{NN})
\]

Equation (26) indicates that a neighbour with less distance has a weight greater than one with more distance. Therefore, the nearest neighbour will have a weight of 1, and the furthest neighbour will have a weight of 0. The neighbours between these distances will have linear scaled weights.

Ensemble classification methods are learning algorithms that construct a set of classifiers whose individual decisions are combined generally by weighted, or unweighted voting, to classify the set of features of each pattern [59].

Bagging, boosting, and random subspaces are general techniques that can be used with any type of base classifier. In this case, Ensemble Bagged Tree (EBT) was the ensemble with the best
results. EBT depends on the number of splits and the number of learners. The complexity of the
tree increases with the number of splits. An overfitting is done when the number of splits is not
correct. The accuracy is proportional to the number of learners, but it can be time consuming to
fit. A high predictive power can be got by a few hundreds of learners. It is necessary to carry out
different tests to set the hits percentage for each algorithm. EBT uses the Breiman's “random
forest” algorithm [60], i.e. a combination of tree predictors, where each tree depends on a random
vector sampled independently. The distribution of the trees in the forest is the same. The size of
the trees in the forest is limited by the generalization error for forests convergence. This error
depends on the correlation between the trees and their strength.

5.1 Evaluation

ROC, as the confusion matrix, has been employed to evaluate the classifications, obtaining the
precision of classifier, or tape rate, $P$, by equation (27),

$$P = \frac{tp}{(tp + fn)}$$  \hspace{1cm} (27)

where $tp$ are true positives correctly classified, and $fn$ are false negatives in the confusion matrix.

Macro-averaging and micro-averaging are used to evaluate the performance average.

*Macro-average* ($P_{Ma}^i$): $P_{Ma}^i$ is obtained by the average over all $P_{Ma}^i$, where $Ma$ denotes
Macro-average, and $i$ the scenario. They are then calculated for each category, i.e. the
values precision is evaluated locally $P_{Ma}^i$, and then globally $P_{Ma}$.

*Micro-average* ($P_{\mu}^i$): The precision value is obtained as: i) $tp$, $fp$, $fn$, are calculated for
each scenario, where $fp$ are false positives in the confusion matrix; ii) the value of $tp$, $fp$
and $fn$ are calculated as the sum of $tp$, $fp$, $fn$, and; iii) to apply the definition of the
measure that corresponds to it.

There are several indices extracted from ROC to evaluate the classifier efficiency. Area Under
Curve (AUC) [61] is the area between the ROC curve and the negative diagonal [62]. AUC is
optimized by equations (28) and (29).

$$AUC = \frac{(P - fp rate) + 1}{2}$$ \hspace{1cm} (28)

$$fp rate = \frac{fp}{(fp + fn)}$$ \hspace{1cm} (29)

5.2 Comparative analysis of classifiers

The Friedman test, recommended by Demšar [63], or its modification made by Garcia and Herrera
[64], are employed to perform the comparative analysis of different classifiers. The Friedman test
assumes that all classifiers can achieve the same performance with the same classification accuracy. It is called the null hypothesis [65]. The Bonferroni-Dunntest [66] is used to determine any significant differences between the top-ranked classifiers, and, finally, the Holm Test [67] is applied to contrast the results. The T-test [68] has been applied to confirm the null hypothesis and validate the results.

6. RESULTS

6.1 Selection Features

The signal has been analysed where it provides more information about the fault, i.e. in the second third. The feature parameter vector \( \Theta \) has been obtained to reduce the number of features, i.e. to avoid “the curse of the dimensionality”. 15 features have been used for AR and Yule Walker, and 30 for NARX (the first 15 features are of the first order). The number of features has been selected by NCA, and the results for NARX are shown in Figure 7.

![Fig. 6 NCA Features.](image)

According to the results given by NCA, the value \( p = 15 \) has been selected.

6.2 Analysis of the results in terms of measurement precision

The classification is done when the FE is obtained by NARX and AR methods and the features number is selected. The FS vector of each signal has been introduced in different classifiers. The FS number \( p = 15 \) is the number of inputs in the classifier. The NARX and AR methods are compared with different classifiers, see section VI, and the results are shown in Table 3. The first
main column describes the scenarios and the precision parameters; the remaining columns show
different classifiers, and each column is subdivided into three sub-columns. The first sub-column
shows the FE results employing AR by Yule-Walker. The second corresponds to the NARX
results. The last sub-column indicates an improvement in the NARX results compared to the
results given by AR. The values of micro and macro precision accuracies are given in the seven
and eighth rows. The coefficient given by the Friedman tests and their classification are shown in
the last rows.

The FE provided by NARX gives better results than AR in all scenarios, see Table 3.
The Demšar method has been employed to identify the significant difference between the
classifiers and to establish the ranking between them.
The test results for significant differences between classifiers and for each experiment show that
the Friedman test for AR did not reject the null hypothesis (p-value = 7.8894^{-4} ≤ 0.05). The
Bonferroni-Dunn test, see Figure 8, rejects the null hypothesis for \( p \leq 0.05 \), with a confidence
value \( \alpha = 0.05 \) for the classifier 1 (DTC). The Holm test does not reject the null hypothesis for the
classifier.
The NARX Friedman test did not reject the null hypothesis because no significant differences
were found (\( p\text{-value}=0.0042 ≤ 0.05 \)). The Bonferroni-Dunn test rejects the null hypothesis with \( p \leq 0.05 \), with a confidence value \( \alpha = 0.05 \) for classifier 1 (DTC), while the test Holm does not reject
the null hypothesis.

![Bonferroni-Dunn test](image.png)

**Fig. 7** Bonferroni-Dunn test for AR and NARX with \( \alpha = 0.05 \).

The t-Test is applied for NARX (Table 3) to validate the results between the classifiers. The test
rejects the null hypothesis in the cases of the DT-QDA, DT-QSVM and DT-EBT classifiers.
Consequently, DT can be discarded for this purpose. For QDA-QSVM, QDA-WKNN, QDA-
EBT, QSVM-WKNN, QSVM-EBT, WKNN-EBT, the p-value is \( \geq 0.05 \), i.e. validating these methods.

### TABLE 3 T-TEST: NARX.

<table>
<thead>
<tr>
<th></th>
<th>DT</th>
<th>QDA</th>
<th>QSVM</th>
<th>WKNN</th>
<th>EBT</th>
</tr>
</thead>
<tbody>
<tr>
<td>DT</td>
<td>0.02911</td>
<td>0.03264</td>
<td>0.77067</td>
<td>0.01856</td>
<td></td>
</tr>
<tr>
<td>QDA</td>
<td>0.02911</td>
<td>0.36089</td>
<td>0.09865</td>
<td>0.07600</td>
<td></td>
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<tr>
<td>QSVM</td>
<td>0.03264</td>
<td>0.36089</td>
<td>0.11716</td>
<td>0.09254</td>
<td></td>
</tr>
<tr>
<td>WKNN</td>
<td>0.77067</td>
<td>0.09865</td>
<td>0.11716</td>
<td>0.17900</td>
<td></td>
</tr>
<tr>
<td>EBT</td>
<td>0.01856</td>
<td>0.07600</td>
<td>0.09254</td>
<td>0.17900</td>
<td></td>
</tr>
</tbody>
</table>

Table 4 shows the T-Test for AR. It does not reject the null hypothesis for QDA-QSVM, QDA-WKNN, QDA-EBT and EBT-WKNN classifiers. The t-Test indicates concordance of results between QSVM-QDA regarding to the classifiers. DT is also discarded in AR due to its low concordance with the classifiers.

### TABLE 4 T-TEST: AR.

<table>
<thead>
<tr>
<th></th>
<th>DT</th>
<th>QDA</th>
<th>QSVM</th>
<th>WKNN</th>
<th>EBT</th>
</tr>
</thead>
<tbody>
<tr>
<td>DT</td>
<td>0.00442</td>
<td>0.00478</td>
<td>0.00027</td>
<td>0.00044</td>
<td></td>
</tr>
<tr>
<td>QDA</td>
<td>0.00442</td>
<td>0.41848</td>
<td>0.10283</td>
<td>0.17127</td>
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</tr>
<tr>
<td>QSVM</td>
<td>0.00478</td>
<td>0.41848</td>
<td>0.02674</td>
<td>0.03711</td>
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<tr>
<td>WKNN</td>
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<td>0.10283</td>
<td>0.02674</td>
<td>0.16222</td>
<td></td>
</tr>
<tr>
<td>EBT</td>
<td>0.00044</td>
<td>0.17127</td>
<td>0.03711</td>
<td>0.16222</td>
<td></td>
</tr>
</tbody>
</table>

QSVM is the best classifier for AR (Table 5). Finally, the t-Test indicates that the QDA classifier is the best classifier for NARX. The classifiers for NARX FE do not present significant difference in terms of precision according to the evaluation tests, i.e. they present accuracy and robustness.

### 6.2 Analysis of the results employing AUC.

Table 4 shows the AUC results, where all scenarios exceed 0.87 (87%) of successes in the AR FE, and 0.92 (92%) in the NARX FE. Furthermore, it is observed that QSVM and LDA are close to 1 (100%) in all scenarios.

Figure 9 shows the results of the best classifier with AR FE (a) and NARX FE (b). It shows that, for LDA NARX, all the curves are closer to one compared to the curves for LDA AR.
The test results for AUC are close to the previous sections, i.e. the Friedman test, as in post-hoc tests, shows that the QDA classifier is the best for the E-1; the Holm test confirms that the QDA classifier gives better results.

7. CONCLUSIONS

The paper shows a novel approach to determine delamination in a wind turbine blade employing ultrasonic guided waves and classifiers. A Nonlinear Autoregressive with Exogenous input system (NARX) method has been introduced for Feature Extraction.

The FE NARX method is set by Receiver Operating Characteristic curves, with the measure of the Area Under Curve and the Precision Measure values, where a set of features is selected considering the Neighbourhood Component Analysis method. Each scenario has been performed by Machine Learning through supervised learning. The classifiers used were: Decision Trees, Quadratic Discriminant Analysis, Quadratic Support Vector Machines, K-Nearest Neighbours and Ensemble Classification. Macro-averaging and micro-averaging are employed to evaluate the performance average across categories. FE by NARX improves the performance of all classifiers with respect to Autoregressive, according to the Precision Measure and Area Under Curve parameters.

The approach is able to differentiate between 6 different levels of delamination. The ultrasonic signals were experimentally collected in an actual wind turbine section. Different classifiers were used to identify the delamination size. The recommendations for comparative analysis of
classifiers by Demšar, and the extensions by García and Herrera, have been employed. The Friedman test was used to confirm the null hypothesis. The Bonferroni-Dunn test was applied to determine any significant differences between the top-ranked classifier and, finally, the Holm Test was employed to contrast the results. The NARX method improves the AR between 3.5% and 7.6%.

Acknowledgement

The work reported herewith has been financed by the Spanish Ministerio de Economía y Competitividad, under Research Grant Ref.: DPI2015-67264-P.
### Table 5. Results Precision

<table>
<thead>
<tr>
<th>SCENARIO</th>
<th>DECISION TREE COMPLEX</th>
<th>QDA</th>
<th>QSVM</th>
<th>WEIGHTED KNN</th>
<th>ENSEMBLE BAGGED TREE</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$P_{\Delta}$ (AR)</td>
<td>$P_{\Delta}$ (NARX)</td>
<td>IMPROVE (%)</td>
<td>$P_{\Delta}$ (AR)</td>
<td>$P_{\Delta}$ (NARX)</td>
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<tr>
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<td>0.915</td>
<td>8.8</td>
<td>0.857</td>
<td>0.995</td>
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<tr>
<td>2</td>
<td>0.813</td>
<td>0.900</td>
<td>8.7</td>
<td>0.982</td>
<td>0.992</td>
</tr>
<tr>
<td>3</td>
<td>0.767</td>
<td>0.867</td>
<td>10.0</td>
<td>0.873</td>
<td>0.953</td>
</tr>
<tr>
<td>4</td>
<td>0.92</td>
<td>0.987</td>
<td>6.7</td>
<td>0.997</td>
<td>1.000</td>
</tr>
<tr>
<td>5</td>
<td>0.963</td>
<td>0.97</td>
<td>0.7</td>
<td>1.000</td>
<td>1.000</td>
</tr>
<tr>
<td>6</td>
<td>0.893</td>
<td>1.000</td>
<td>10.7</td>
<td>1.000</td>
<td>1.000</td>
</tr>
<tr>
<td>$P^\delta$</td>
<td>0.864</td>
<td>0.940</td>
<td>7.6</td>
<td>0.951</td>
<td>0.990</td>
</tr>
<tr>
<td>$P^\delta_{\Delta}$</td>
<td>0.864</td>
<td>0.940</td>
<td>7.6</td>
<td>0.951</td>
<td>0.990</td>
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<td>RANKING</td>
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<td>4.17</td>
<td>4.41</td>
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<td>CLASSIFIC.</td>
<td>5</td>
<td>5</td>
<td>2</td>
<td>1</td>
<td>1</td>
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</table>

### Table 6. Results by AUC

<table>
<thead>
<tr>
<th>SCENARIO</th>
<th>DECISION TREE COMPLEX</th>
<th>QDA</th>
<th>QSVM</th>
<th>WEIGHTED KNN</th>
<th>ENSEMBLE BAGGED TREE</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$P_{\Delta}$ (AR)</td>
<td>$P_{\Delta}$ (NARX)</td>
<td>IMPROVE (%)</td>
<td>$P_{\Delta}$ (AR)</td>
<td>$P_{\Delta}$ (NARX)</td>
</tr>
<tr>
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<td>0.917</td>
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<td>0.940</td>
<td>0.993</td>
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<tr>
<td>2</td>
<td>0.876</td>
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<td>6.10</td>
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<tr>
<td>3</td>
<td>0.903</td>
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<td>4</td>
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<td>5</td>
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<td>-0.90</td>
<td>0.998</td>
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<td>4.90</td>
<td>1.000</td>
<td>1.000</td>
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<td>4.25</td>
<td>4.16</td>
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<tr>
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<td>5</td>
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<td>1</td>
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### Appendix B. Signal, Feature and classification processing

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<td>[14]</td>
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<td>Meyer's Mekh, Daubachies, Morlet and Discrete Wavelets</td>
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<td>Digital Filters</td>
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<td>Approach for detecting and identifying faults in railway infrastructure components</td>
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<td>Feature Extraction and Selection</td>
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<td>Pattern recognition to diagnose the failure of a WTB</td>
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<td>AR</td>
<td>Structural health monitoring techniques of pattern recognition of two different structural conditions of a boat.</td>
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<td>AR and Variational mode decomposition</td>
<td>Seizure detection techniques for epileptic electroencephalogram</td>
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<td>GP-NARX framework by providing a means of converting the GP prediction bounds in the time domain into bounds on the hfrfs</td>
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<td>Feature selection and Classification</td>
<td>NCA, KNN classification</td>
<td>A novel method for learning a Mahalanobis Distance measure to be used in the KNN classification algorithm</td>
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<tr>
<td>[40]</td>
<td>Feature selection and Classification</td>
<td>NCA, Hidden Markov model</td>
<td>Bearing fault diagnosis and fault severity classification</td>
</tr>
</tbody>
</table>
REFERENCES


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