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NullSpace and AutoRegressive damage detection: a comparative study

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Abstract

In this paper we present the application of two damage detection methods to a laboratory tower. The first method is based on subspace identification. The second one is based on AutoRegressive modeling of the signals involved. Both methods are tested in a tower demonstrator simulating a wind turbine. They are able to correctly detect damage in the structure that is simulated by loosening some of the bolts in the joints. The results show that the first method is computationally more efficient, but the results are more stable with the second method.

1 Introduction

Structural health monitoring (SHM) aims to give, at every moment during the life of a structure, a diagnosis of the 'state' of the constituent materials, of the different parts, and of the full assembly of these parts constituting the structure as a whole. The state of the structure must remain in the domain specified in the design, although this can be altered by normal aging due to usage, by the action of the environment, and by accidental events. The time-dimension of monitoring makes it possible to store the full history database of the structure. Owing to the evolution in the data of the database, SHM, apart from detecting and locating damage, can also provide a prognosis (evolution of damage, residual life, etc).

Figure 1: Broken wind turbine.

Damage to structures has caused many disasters in the course of history. Figure 1 shows a broken wind turbine. The fact that these disasters can involve human lives has attracted the attention of the community dealing with construction techniques and the maintenance of structures.

Among the different fields of application for SHM, wind turbines can be considered as an important current example. The current trend in this field is to locate the wind power plants offshore. The advantage of this idea is that the wind is stronger off the coasts, and unlike wind over the continent, offshore breezes can be strong in the afternoon, matching the time when people are using the most electricity. Offshore turbines can also be located close to the power-hungry populations along the coasts, eliminating the need for new overland transmission lines. However, offshore plants have some drawbacks: costs, including maintenance and operations, increase significantly compared to onshore ones, and in addition to the usual difficulties associated with wind turbines (high towers, great forces generated at the edge, and the requirements of long life of the structure and a minimum percentage of time out of service), the demanding conditions of the marine environment have to be taken into account. These drawbacks have increased the level of interest in the implementation of different concepts of SHM in these structures.

Table 1: Levels of damage detection.

Level	Description
1	Determination of the existence of structural damage
2	Level 1 plus identification/localization of the damage
3	Level 2 plus quantification of the injury
4	Level 3 plus prediction of the remaining life (prognosis)

The main objective of a SHM system is to determine the state of the structure under study. Detection methods can be classified into four levels (see Rytter [1]), which are summarized in table 1.

On many occasions, the first of these levels (detection) is enough, and in many applications this is the most important one. For this level, there are different types of methods. Some local non-destructive testing tools have been developed based on ultrasound, acoustic, eddy current or thermal field principles [2]. The main problem with these methods is that they require access to a vicinity of the potentially damaged area, so some information regarding the possible location of the damage is needed, which is not always available. Moreover, most of these techniques are expensive and time consuming. An alternative approach that tries to overcome these difficulties are vibration based methods [3]. The idea of these methods is that small variations in a structure cause changes in the vibrational response which can be detected. Among these, statistical time series for SHM form an important category. They use the output response signals to some random excitations (and sometimes also the input excitation) measured with sensors as time series. Among the vibration based methods, there are parametric and non-parametric methods. Non-parametric time series methods for SHM are based, for example, on power spectral estimates [3, 4], or on frequency response function methods [5], although these types of methods have received limited attention in the literature. Parametric methods are based on corresponding time series representations and will be described later.

Some of the vibrational methods are based on natural frequencies [6, 7], others on modal shapes [8, 9] or on modal strain energy [10, 11]. Worden et al [12], for example, developed a method having the above mentioned characteristics for damage detection. Principal component analysis (PCA) was used in [13, 14] for the detection and localization of structural damage. A novel analysis method based on the Kalman model was recently proposed in [15]. The Kalman model is based on the fact that there is a significant increase in the residual errors when a Kalman model identified from the undamaged system is used to predict responses of the damaged system.

In this paper we present two implementations of level 1 algorithms applied in a tower similar to the one of a wind turbine. Both methods described are examples of vibration based methods, based on the statistical analysis of output-only measurements from structures. None of the methods needs a finite element model, since they are data based instead of physics based. The efficiency of both methods has been checked by applying them to a tower demonstrator, which simulates a wind turbine.

The first method that will be used in this paper is the NullSpace method. The method applied is based on the work by Fritzen [16], which is also based on that of Basseville et al [17], who proposed a subspace identification based fault detection algorithm. The key idea of the method relies on the concepts of subspace identification and null subspace. The response data (accelerations in our case) collected from the monitored structure are used to construct the Hankel matrices. If no structural damage occurs, the orthonormality assumption between the subspaces of the Hankel matrices corresponding to different datasets remains approximately valid according to small residuals; if not, these residues increase, indicating damage.

The second method to be used is an example of a parametric based method for SHM. The representation selected is an AutoRegressive model [18] which will characterize the data in the healthy state. The damage will be detected by comparing a characteristic feature in an unknown state with the corresponding one in the healthy state. These types of methods have received considerable attention in the literature [3, 19]. A more general case using AutoRegressive moving average (ARMA) models or AR with eXogenous inputs (ARX) is analyzed in Sohn et al [20] and in Liu et al [21].

The rest of the paper is organized as follows. In section 2, we explain the details of the two algorithms that will be used for damage detection, and in section 3, the experimental setup is presented. Section 4 shows the results obtained with both methods, comparing both the quality of the results and the computational efficiency. Finally, in section 5, the conclusions and future work are presented.

2 Description of the methods

2.1 NullSpace method

As indicated before, the algorithm used is inspired by the concept of subspace identification but it does not require modal identification. Let us consider the discrete-time state-space model of a structure in the form:

$$x_{k+1} = Ax_k + w_k \tag{1}$$

$$y_k = Cx_k + v_k \tag{2}$$

Here x_k is the state vector at time step k, and y_k the output vector. The matrices A and C are called, respectively, the state and output matrices. The vectors w_k and v_k denote, respectively, the state noise and measurement noise processes, which are assumed to be Gaussian white-noise sequences with zero mean. The concept of subspace identification for linear systems is based on the definition of the Hankel matrix:

$$H_{p,q} = \begin{bmatrix} \Xi_1 & \Xi_2 & \cdots & \Xi_q \\ \Xi_2 & \Xi_3 & \cdots & \Xi_{q+1} \\ \vdots & \vdots & \ddots & \vdots \\ \Xi_{p+1} & \Xi_{p+2} & \cdots & \Xi_{p+q} \end{bmatrix}; \quad q \geq p \tag{3}$$

Here p and q are user-defined parameters and Ξ_i represents the output covariance matrix, which may be estimated from a set of N output data samples y_k as:

$$\Xi_i \simeq \left(\frac{1}{N-i-1}\right) \sum_{k=1}^{N-i} y_{k+i} y_k^t \tag{4}$$

From the point of view of damage detection, we are not concerned with identifying the modal parameters of the structure. Instead, only relative changes of characteristic features are necessary for structural damage assessment. For this purpose, a method based on the null subspace concept of these Hankel matrices is used. Performing the singular-value decomposition (SVD) on the weighted Hankel matrix, we obtain:

$$H_{p,q} = U_H S_H V_H^t \tag{5}$$

In this moment, U_{H0} must be found. This matrix is the one that makes the next property true:

$$U_{H0}^t H_{p,q} = 0 \tag{6}$$

U_{H0} contains the maximum number of independent column vectors that span the column nullspace of $H_{p,q}$. The size of this matrix is not fixed; it varies depending on the input signal. In order to find it, we have to find which singular values (S_H) are equal to zero, and take the left-hand singular vectors (U_H) corresponding to those null singular values. This way the nullspace analysis of the Hankel matrix is performed.

If the structure is undamaged, the multiplication between the nullspace (U_{H0}) and the new Hankel matrix should be equal or very close to zero (as seen in equation (6)), because both should have the same (or, at least, a similar) nullspace. If damage occurs, this multiplication should be different from zero. We will call the result of that multiplication the residue matrix, and it can be defined as:

$$R = U_{H0}^t H'_{p,q} \tag{7}$$

Once this residue matrix is calculated, we apply a vectorization operator, which rearranges the columns of the R matrix into one column vector.

$$\zeta = \mathrm{vec}(R) \tag{8}$$

The residual (ζ) contains the information about how the structure has changed. This information needs to be quantified, so that we can deduce whether the structure is damaged or not. For that, we need a damage indicator. In [22], we introduced different types of damage indicators. For this paper, we used the 'covariance matrix' damage indicator, because of its good sensitivity. This indicator is used by Fritzen [23]. Using the different residuals (ζ) of the undamaged structure, we construct the residual covariance matrix estimate; this way we are able to know how the structure works in the undamaged state.

$$\hat{\Sigma} = \left(\frac{1}{n-1}\right) \sum_n \zeta_n \zeta_n^t \tag{9}$$

where n is the number of residuals we have for the undamaged structure. Next, we calculate the residual vector for the structure being monitored. Subsequently, we apply the next formula to detect whether damage exists:

$$DI = \zeta_{n+1}^t \hat{\Sigma}^{-1} \zeta_{n+1} \tag{10}$$

This damage indicator will be small if the structure is healthy, while it will be larger when the structure is damaged. The larger the damage indicator, the more severe the damage in the structure.

2.1.1 The algorithm

The schema in Figure 2 show the different phases of the algorithm in a visual way. Before describing the learning and detecting phases of the algorithm, we will explain the different parts of the schema: the H block means that the Hankel matrix is built in that block, and the U_{H0} calculates the nullspace of the Hankel matrix, whereas the ζ is able to compute the residual vector. With those residuals, the Σ block calculates the covariance matrix, which is used in order to estimate the damage indicator in block DI.

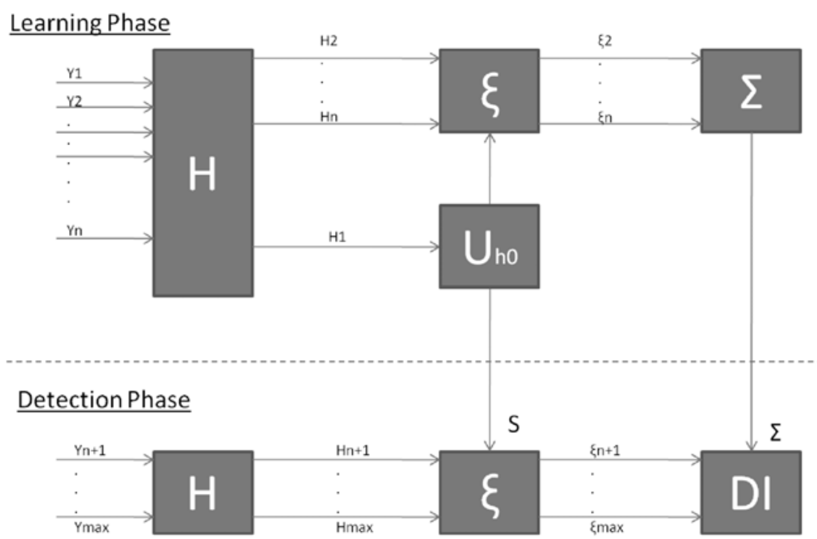

Figure 2: Schema of the NullSpace method.

2.1.2 Learning phase

First of all, we have different healthy datasets, n in this case. As will be shown in section 3, in our laboratory tower we will have eight different points of measurement, and in some of them more than one direction, giving a total of 16 channels of measurement. Each dataset has the information of the 16 sensors. With the first dataset $[Y_1]$, its Hankel matrix is found, and also its NullSpace (U_{H0}). With the other undamaged data $[Y_2 \dots Y_n]$ we calculate the Hankel matrix for each of them, and using the NullSpace of the first one, the residuals for each one are extracted. With these residuals we are able to determine the covariance matrix Σ. The Nullspace and the covariance matrix will be used in the detection phase in order to determine whether the structure is healthy or not.

2.1.3 Detection phase

The evaluation of the incoming data is performed to determine whether it corresponds to a damaged structure or not. Thus, for each new piece of data, it calculates the residuals in the same way as in the learning phases and it applies the Σ to this residual so as to calculate the damage indicator.

2.1.4 Application notes

The algorithm uses all of the 16 channels rearranged in one matrix. In order to construct the Hankel matrix, data transformation is carried out. The original data are transformed into output covariance matrices, between different time samples. A lot of memory resources are needed in order to handle the matrix and the transformations between data. In this application, the Hankel matrix is composed using the p and q indices $p = q = 30$. In order to learn how the structure behaves, the NullSpace method needs many datasets, 50 in this case.

As can be seen in the schema of Figure 2, the NullSpace is estimated only with the first dataset. This means that this first dataset is important, because every residual is calculated using this first NullSpace. This means that the results may vary if we select a different dataset as the first input.

Apart from the dataset number, the longer the time series are, the more stable the algorithm is. In this case, the datasets used are only 2 s long. With this duration, the output indicator in a particular state varies greatly from one realization to another. This is why we analyzed different datasets from each state, and took a mean value of them in order to obtain a significant value for the damage indicators.

2.2 AutoRegressive method

Let $\{x[n]\}_{n=1}^{N}$ be a time series. In an AutoRegressive model the signal is approximated by the linear difference equation with complex coefficients given by:

$$x[n] = u[n] - \sum_{k=1}^{p} a[k]x[n-k] \tag{11}$$

where $x[n]$ is the output sequence of a filter (of order p) which models the observed data, and $u[n]$ is the conducting noise, which is assumed to be a white noise with zero mean and variance σ_u^2. We denote by θ, the vector of p parameters:

$$\theta = \begin{bmatrix} a[1] \\ a[2] \\ \vdots \\ a[p] \end{bmatrix} \tag{12}$$

To obtain the coefficients $a[k]$, with $k = 1, \ldots, p$ and the variance of the white noise σ_u^2 from a finite series of data we must solve the so called Yule-Walker equations, which are a linear system. In principle we would need $O(p^3)$ operations to solve it, but its particular structure allows us to solve it in $O(p^2)$ operations by the Levinson algorithm. Note that this order p will be related to the length of the signal, but will not be higher than half this length and in general will be much lower (see [18]).

The selection of this order is not an easy task and it is a critical aspect for building an appropriate model. The optimum filter order is not known a priori, which is why in practice, various orders are postulated. Based on this, some kind of error criterion is defined to indicate which order to select. An intuitive approximation would be to construct a series of AutoRegressive models with increasing orders, until the error level reaches a minimum. The problem is that, in general, the higher the order, the better the approximation (except in cases where the time series is exactly an AR signal), so we need to penalize the inclusion of a new parameter, since this produces spurious behavior and a very high computational cost. In Kay et al [24], the authors outline different criteria for selecting this order. Some examples of error criteria are the first prediction error (FPE) or the Schwartz's Bayesian criterion (SBC). What is done is to postulate a minimum and a maximum order between which the optimal order must be. After this, all of the intermediate models are obtained and the value of the corresponding error is calculated. Finally, the order is chosen as the one that minimizes the selected criterion.

2.2.1 The algorithm

The damage detection will be performed by comparing a parametric feature of the structure in an unknown state with the corresponding one in the healthy state. The method used in this paper is an algorithm of level 1, based on AutoRegressive methods (see Fassois et al [3]) that uses only output data for the structure.

The method has two different steps. In the first one the behavior of the structure in the healthy state will be modeled, in a form that will be described later. After that, given a new unknown state, the method will determine whether it has any failure or not by using statistical hypothesis testing. Let us describe how both phases of the method work.

2.2.2 Learning phase

Given one representative time series of the healthy structure we build an AR model of the form in (11) to characterize it, namely:

$$x_{\mathrm{ref}}[n] = u_{\mathrm{ref}}[n] - \sum_{k=1}^{p} a_{\mathrm{ref}}[k] x_{\mathrm{ref}}[n-k] \tag{13}$$

where $u_{\mathrm{ref}}[n]$ is a white noise with variance σ^2_{ref}. When estimating the vector of parameters in the reference state θ_{ref}, we also calculate the variance matrix, P_{ref}, of this estimation (see Ljung [25]). In this step, the model order needs to be chosen for the time series given.

2.2.3 Detection phase

Damage detection will be based on testing for statistically significant changes in the parameter vector θ_{ref}.

Given a new time series of an unknown state, we build an analogous model to the reference one:

$$x_{\mathrm{new}}[n] = u_{\mathrm{new}}[n] - \sum_{k=1}^{p} a_{\mathrm{new}}[k] x_{\mathrm{new}}[n-k] \tag{14}$$

with a new vector of parameters θ_{new}, where $u_{\mathrm{new}}[n]$ is a white noise with variance σ^2_{new}. It should be noted that in this step the model order obtained in the previous step is used.

Let us specify the statistical hypothesis test used (see [3]):

$H_0 : \delta\theta = 0$, null hypothesis (healthy state)

$H_1 : \delta\theta \neq 0$, alternative hypothesis (damaged structure),

where $\delta\theta = \theta_{\mathrm{ref}} - \theta_{\mathrm{new}}$ is the difference between the new parameters obtained and the reference ones. The estimation of this difference follows a normal distribution with the following mean and variance:

$$\delta\hat{\theta} = \hat{\theta}_{\mathrm{ref}} - \hat{\theta}_{\mathrm{new}} \sim N(\delta\theta, \delta P) \tag{15}$$

with $\delta P = P_{\mathrm{ref}} + P_{\mathrm{new}}$. Under the null hypothesis:

$$\delta\hat{\theta} = \hat{\theta}_{\mathrm{ref}} - \hat{\theta}_{\mathrm{new}} \sim N(0, 2P_{\mathrm{ref}}) \tag{16}$$

and the quantity

$$DI = \delta\theta^T (2P_{\mathrm{ref}})^{-1} \delta\theta \tag{17}$$

follows a χ^2 distribution with p degrees of freedom. This quantity DI is the damage indicator in the AutoRegressive case.

By using the estimated version of the covariance matrix, $\hat{P}_{\mathrm{ref}}$, we can then construct the following test:

$$DI \leq \chi^2_{1-\alpha}(d) \Rightarrow H_0 \text{ is accepted} \tag{18}$$

$$\text{Else} \Rightarrow H_1 \text{ is accepted} \tag{19}$$

where α is the chosen (type I) risk level for the test, and $\chi^2_{1-\alpha}(p)$ is the $\chi^2(p)$ distribution's $1-\alpha$ critical point.

2.2.4 Application notes

It is important to note that the methodology presented here refers to just one time series, i.e. the healthy state is supposed to be characterized with the signal measured in just one point. As has been introduced in section 2.1.1.1 and will be discussed later, we have a total of 16 channels.

To deal with the different monitoring channels, two alternatives could be used. The first one consists of analyzing with the previously described method each channel in an independent way. The second option corresponds to considering all of the signals as a group and using multivariate AutoRegressive models.

In this work we have used the first option; the second one will be analyzed in a future work. We have to take into account that with this technique it is possible that not all of the types of damage are detected by all of the channels. As a conservative approach, we may say that there is damage if at least one channel indicates it. Another alternative is to sum all of the metrics for each channel and all of the thresholds and say that there is damage if the sum of the metrics is greater that the sum of the thresholds. From both alternatives, in the results presented we have chosen the second one.

With the first approach of separated channels we can imagine extending the presented method to a level 2 algorithm by analyzing the specific behavior of the different channels in each type of damage. One thing that must be taken into account is that a learning process needs to be performed for each particular type damage, so we need a priori knowledge of all the possible types of damage to be encountered, which is not always possible, especially when dealing with real structures.

3 Experimental setup

The tested structure is a tower model, similar to those of a wind turbine (see Figure 3). The structure is 2.2 m high; the top piece is 1 m long and 0.1 m wide. The tower is composed of three sections joined with bolts. Each joint has four connecting bolts. Damage is simulated by acting on these bolted joints. As can be seen in Figure 3, there is a modal shaker placed on top of the structure. This shaker simulates the nacelle of a wind turbine and it creates vibrational movement. To detect the structural response, some accelerometers are placed on the tower; in order to find the best location for these sensors, FemTools (by Dynamic Design Solutions) has been used. The pretest analysis made through the finite element model (FEM) of the tower resulted in 8 accelerometers, 4 triaxial and 4 uniaxial (see Figure 4).

Let us give some additional details of the FEM modeling used for the sensor location. The model has three major parts. The horizontal rectangular tube is represented using solid elements. The vertical cylindrical tube is represented using shell elements, element shell181 specifically. Finally, the shaker is represented as a point mass element type (mass21). It has been assumed that the material properties are isotropic. Finally, the joint between the floor and the tower has been assumed to be ideal.

In order to have a good quality FEM, we carried out an operational modal analysis and updated the FEM. In this case, we analyze the first 10 modes, which are located under 500 Hz.

The optimal sensor location is found using the sensor elimination by the modal assurance criterion (SEAMAC) pretest method implemented in FemTools. The modal assurance criterion (MAC) is commonly used to compare mode shapes. Each term in the MAC matrix measures the squared cosine of the angle between two mode shapes i.e. $\mathrm{MAC}_{i,j} = \cos^2\theta_{i,j}$ and is calculated as

$$\mathrm{MAC}_{i,j} = \frac{|\{\Psi_i\}^t\{\Psi_j\}|^2}{(\{\Psi_i\}^t\{\Psi_i\})(\{\Psi_j\}^t\{\Psi_j\})} \tag{20}$$

where Ψ_r is the modal shape for mode r.

When $\mathrm{MAC}_{i,j} = 0$, the ith and jth mode shapes are orthogonal to each other. Hence, the mode shapes are most linearly independent when all off-diagonal terms of MAC are zero.

The SEAMAC algorithm is a sensor elimination algorithm. This method attempts to find a measurement point configuration that minimizes MAC values in off-diagonal terms. The method SEAMAC is based on eliminating iteratively one by one those degrees of freedom that show a lower impact on the MAC values. This iterative process stops when a default MAC matrix is reached, high values in the diagonal terms and low values in the off-diagonal terms.

The structure is excited with a modal shaker which stimulates the structure using a white noise. The data are acquired using an OROS OR36 system with an acquisition frequency of 1024 Hz, and 2 s long time series. In this test, each dataset consists of 2048 $\times$ 16 points. Nine levels of damage are created by loosening, respectively, one, two, or three connecting bolts on each level of the tower.

3.1 Inputs and damage

First, the data acquired in the undamaged state are introduced into the algorithms implemented in Matlab. At this point, they learn how the healthy structure behaves.

The shaker introduces a white noise with a frequency range between 3.125 and 500 Hz. We have acquired the structural response, getting several datasets corresponding to an undamaged state of the structure. These data will be used to learn how the structure behaves.

Subsequently, different areas of structural damage are introduced by acting on the bolted joints. There are four different bolts in each joint of the tower. The torque of each bolt in a healthy state is 125 N m^{-1}. In order to produce damage, the bolt is loosened until the torque value is 50 N m^{-1}. Three levels of damage severity are introduced in each joint. We will consider the damage shown in Table 2.

Table 2: Definition of the damage.

Damage name	Description
D1	One loosened bolt in joint 1
D2	Two loosened bolts in joint 1
D3	Three loosened bolts in joint 1
D4	One loosened bolt in joint 2
D5	Two loosened bolts in joint 2
D6	Three loosened bolts in joint 2
D7	One loosened bolt in joint 3
D8	Two loosened bolts in joint 3
D9	Three loosened bolts in joint 3

Next, using the same type of excitation, the response of the accelerometers is acquired in each damage case. The obtained damaged and healthy series are introduced into the algorithm. Finally, the algorithms provide the damage indicator values, representing the existence of structural damage. The comparison of this metric with a threshold determines whether structural damage exists or not.

4 Results and comparison

Let us show the obtained results with both methods. Figure 5 shows the results with the NullSpace method, while Figure 6 shows the results with the AutoRegressive method. In both figures, each bar corresponds to a different time series. In the y axis, we represent the value of the damage indicator, on a logarithmic scale. This indicator is given by (10) in the NullSpace method and by (17) in the AutoRegressive case; specifically, we represent the sum of the metrics for all of the different channels. The first three white series correspond to healthy signals, and then there are three time series from each type of damage. The darker the bar, the more severe the damage (one, two or three loosened bolts). Each bar corresponds to the resulting damage indicator of a time series. In each time series all of the information of all sensors for 2 s is stored. Each time series dataset is defined as an $N_{\text{sensors}} \times N_{\text{data}}$ matrix, 16×2048 in this case.

In the NullSpace method results, it can be seen that the damage is well detected. Between the threshold and the highest healthy damage indicator there is a big gap. For each type of damage, we can see that the results of the algorithm are logical, because the damage indicator values for the damage with more loosened bolts are greater than the ones with fewer loosened bolts. The threshold is calculated with the datasets used in the learning phase. The damage indicators of those datasets are determined. The mean value and the variance is then extracted from those damage indicators. The threshold is set to be the mean value plus three times the variance value.

In the results from the AutoRegressive method, it can be seen that the first type of damage has a metric which is very near to the threshold and to the healthy states. We show here just the result from the sum of the metrics for all of the channels and of all the thresholds. The threshold used is that obtained with an alpha value of $\alpha = 10^{-3}$. If we choose a smaller value of alpha, it is possible that we will not detect this first type of damage, while by choosing a greater value we may find some false alarms. It is observed that, in general, the values for series of the same type of damage are similar, and that if more bolts are loosened, a greater value of the metric is obtained.

Considering the results, it can be seen that both methods correctly detect all the damage considered, although in the case of the AutoRegressive method the first damage D1 has a metric that is very close to the metric of the healthy time series, which makes it difficult to detect. It should be noted that a learning process with many healthy signals, 50 in this case, is required for the NullSpace method, whereas for the AutoRegressive method a single time series is enough.

Moreover, the results we obtain with the AutoRegressive method are more stable; the values of the metric for time series from the same damage are similar. In the NullSpace case, when the time series are short the metric varies, but with long time series the results are stable. In this case, it is necessary to take averages between some time series to obtain this stability.

Another difference between the methods is that the AutoRegressive one works with each channel separately. In some cases this may help us to identify a strange behavior of a particular sensor or direction of measurement.

Concerning the execution time, the first method is faster than the second one, particularly when considering longer signals. When short signals are considered, for instance, below 10 s signals sampled with a 1024 Hz sampling frequency, the differences are not so big, but once the input signals are above this value, the performance of the AR solution falls down in the learning part, while the detection part is still good. In Figure 7 the performances are compared, using different sized signals, both for the learning phase and the detection process. These tests were carried out using a Dell workstation with the specifications shown in Table 3.

Table 3: Workstation specifications.

Component	Description
CPU	Intel(R) Core(TM) i5-2400 CPU @ 3.10 GHz
RAM	8Gb DDR3
Hard Disk	7200RPM

It can be seen that the NullSpace is faster than the AR method, needing, in general, half as much time as the AR method.

5 Conclusions and future work

Both damage detection methods, when applied to a laboratory tower, have been able to correctly detect damage in the structure. The metric indicating failure has higher values in the cases where more bolts are loosened, as expected, since a greater level of damage is related to a higher value of the metric.

Both methods are valid for damage detection, but the NullSpace method needs to be implemented with longer datasets so as to be as stable as possible. The AR method has the advantage of being able to detect damage in each channel, such that basic localization of the damage is possible. Concerning the execution time, the NullSpace method is faster for the same time series. On the whole, both methods are valid for damage detection.

It would be useful to be able to identify the type of damage in each case. If all of the possible types of damage are a priori known and series representative of all of them are available, a learning process for each damage state could be carried out. The feasibility of such a method should be discussed with the manufacturers, because they know which are the usual types of damage in the structures they manufacture.

A future application for the methods described in this paper is their adaptation to yield reliable results in different environmental and operational conditions. For this purpose, we will simulate a wind turbine using BLADED [26] software with different wind speeds and different nacelle directions on an offshore wind turbine. Depending on the environmental conditions, the response of the structure may not be exactly the same. It will be useful to have different learning models in different environmental conditions. In order to achieve this, different clustering methods can be used.

We have also built an offshore jacket for the tower model, and we will work on damage detection and we will simulate different environmental and operational conditions in order to be able to detect damage correctly.

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Figure 3: T[illegible]

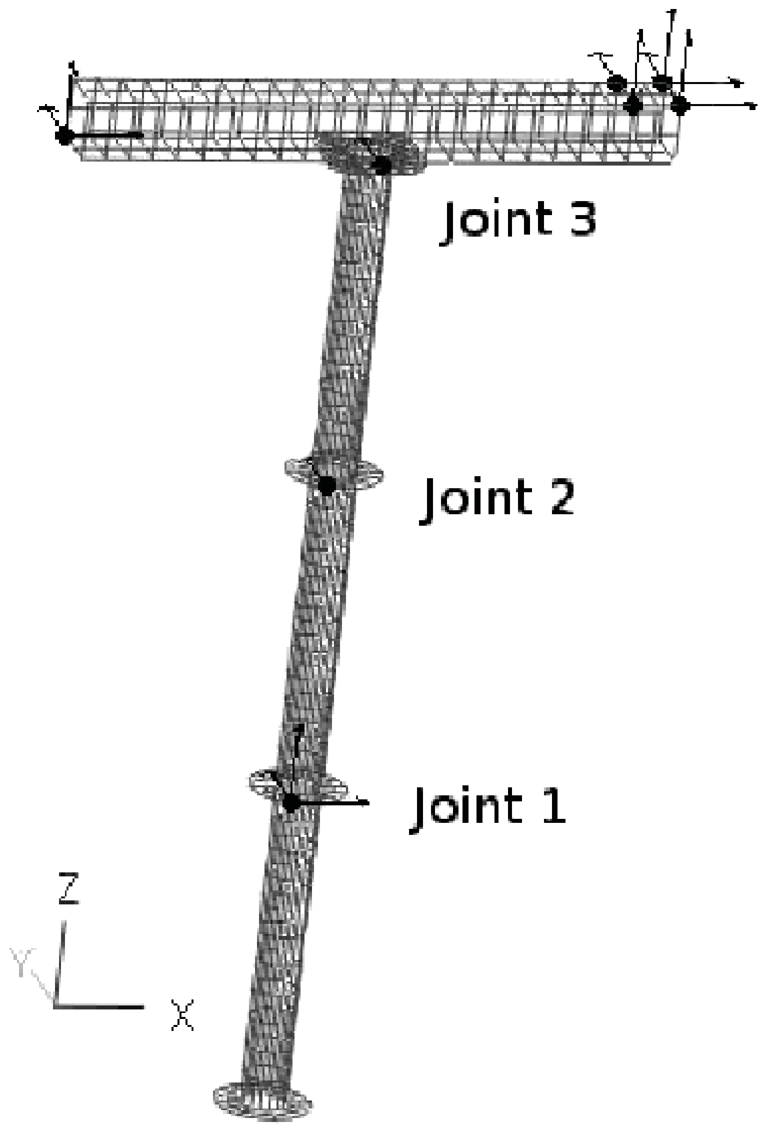

Figure 4: Location of sensors.

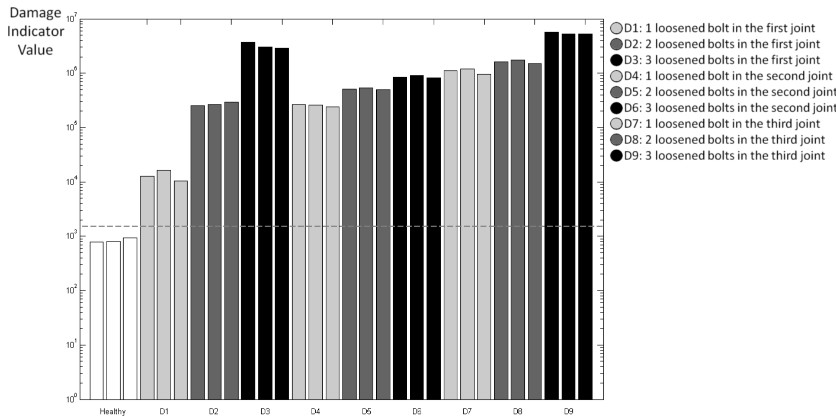

Figure 5: Results obtained with the NullSpace method.

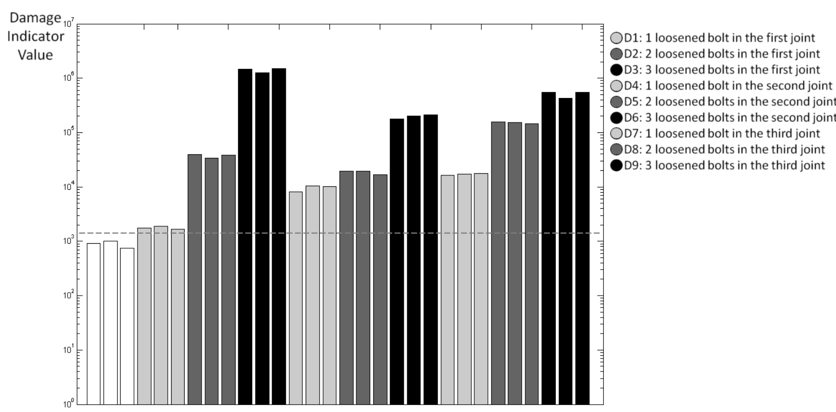

Figure 6: Results obtained with the AutoRegressive method.

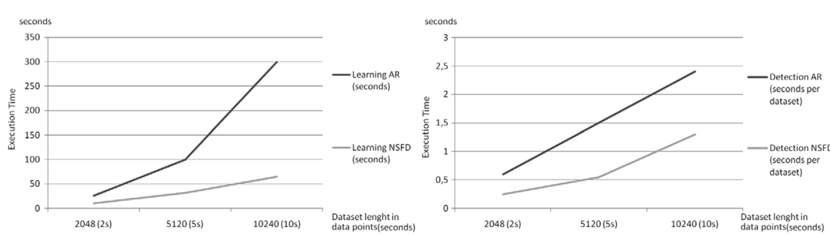

Figure 7: Performance of the algorithms.