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Data-driven models for strain-based damage identification in composite wind turbine blades

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Abstract. The increasing demand for renewable energy has led to the development of several wind energy projects. A rising concern is the aging of these structures that must keep their serviceability and integrity for a long lifetime. That is why recent studies have focused on monitoring systems for data extraction based on accelerometers, fiber optic sensors, and piezoelectric sensors among many other sensing technologies. One of the most promising approaches is the use of fiber-Bragg-grating-based systems taking advantage of their proven benefits such as electromagnetic immunity, low size and weight, and ability to embed numerous sensors in a single optical fiber line. However, most of the reported studies have addressed the operational assessment of the acquisition systems without further deepening the exploitation of the acquired data for structural health monitoring purposes. This work aims to data exploitation of strain measurements acquired by simulated fiber Bragg gratings (FBG) for damage identification in wind turbine blades made of composite materials. A FEM model of a 2.5-meter-long wind turbine blade with 40 virtual FBGs strain sensors was used to obtain strain data under normal operational conditions. Then, strain measurements were calculated after defining several damages to the blade. Once the data were obtained, different data processing techniques following the pattern recognition paradigm were tested comparing their performance in terms of accuracy. The results will contribute to designing real-time automatic damage identification systems using FBGs strain sensors for composite wind turbine blades.

Introduction

Wind turbine blades are preponderant in wind turbine performance. However, blades are prone to different types of damage which can generate imbalances affecting power generation efficiency, and operational and maintenance costs. 1 GW of installed generation capacity could cost between 0.5 to 1 USD million. In extreme cases, such damages can even cause catastrophic failures of turbines themselves or adjacent ones. In the worst scenario, a catastrophic failure can cause a safety hazard to persons. Therefore, early damage detection in wind turbine blades is of great importance to optimize maintenance planning and reduce operational costs while increasing safety.

Structural Health Monitoring (SHM) consists of a variety of strategies for early damage identification. These strategies can include machine learning algorithms which are used with the aim of “constructing” a baseline from a pristine structural element under regular operational conditions based on features related to data gathered from several types of sensors. Based on this baseline, newly gathered information can be “compared” to the baseline looking for outliers related to damage. This methodology based on physical measurements has been called data-driven SHM. In this way, SHM can be considered as the evolution of non-destructive testing, due to SHM techniques that can perform condition monitoring for diagnosis which can be performed online (real-time) or offline.

SHM tasks include signal processing from a structural system under dynamic loads, commonly using a variety of sensors embedded or placed on the structure for measuring physical variables such as strain, displacements, guided waves, and acceleration among others to identify damage occurrence. The availability of a record suggests that the user should make a most accurate and precise diagnosis of the structure, this for sure, could change the way that maintenance is made. The most common method of diagnosis as previously mentioned includes an unusual signal and prognosis of a section of interest.

There is reported much academic research related to damage detection methodologies, mainly based on guided waves, acoustic emissions, machine vision, thermography, vibration analysis, strain measurements, etc. [1]. However, according to Du et al [2], who published an exhaustive and comprehensive review of damage detection techniques for wind turbine blades, the discussion on fault indicators and research prospects of damage detection of wind turbine blades is still an open topic in the related research field.

This paper presents a data-driven general methodology for wind turbine blade damage detection based on strain field pattern recognition. First, the methodology is described in detail in the first section, in the second section experimental and numerical setup is described, results and discussion are presented in the third section and finally, a summary is presented in the fourth section.

Damage detection methodology

The fundamental premise behind strain mapping techniques is that damage occurrence produces a change in the local and global stiffness of a structure due mostly to damages producing an inertia variation promoted by discontinuities of several kinds of damages (i.e. holes, cracks, delamination, inclusions, etc.). Therefore, unitary strain changes in the near field of damage, and such changes can be detected through discrete or distributed strain measurements gathered using several types of sensors. According to Saint-Venant's principle, such slight changes in the strain field near to damage fade away at distances equivalent to a couple of times the damage size. In this way, it has been believed that damage detection is only possible if sensors are located very close to damage. However, it has been demonstrated that this is not necessarily true. By using adequate pattern recognition techniques global and local stiffness changes can be detected in sparse sensors arrays, for instance, in wind turbine blades it is possible to detect delamination of typical size for a big wind turbine blade by using strain sensors (FBGs) separated more than 1 meter among them [3].

An additional issue with the arguments mentioned before lies in the fact that not only damages can promote changes in the strain field in a structure, particularly in a wind turbine blade. The change in the operational conditions also promotes changes in the strain field. Think for example the pitch angle and the resultant aerodynamic forces in a wind turbine blade. For example, at fixed angular speed, as the incident wind speed increases the pitch angle of the wind turbine blade is increased and the resultant aerodynamic force changes in both direction and magnitude. In this way, the sectional inertia of the section changes, and therefore, the global stiffness changes. This change can be misconstrued as damage by many machine learning algorithms if these do not include information related to the operational conditions (wind speed, pitch angle, angular speed, etc.) that allows building different models (strain field models), each one representing a particular operational condition which can be used in a subsequent stage to compare against uncertain condition and discern if a change in the strain field has been promoted by damage occurrence, that is, uncoupling the changes in strain field promoted by damage from such promoted by operational conditions. This process has been called Optimal Baseline Selection (OBS) and is shown in Figure 1. The OBS can be performed in a "manual" way if operational conditions can be extracted from the wind turbine controller (i.e., pitch angle, angular speed, etc.) or can be extracted in an automatic fashion using clustering techniques when the operational conditions are not available.

As can be seen in Figure 1, the general proposed methodology consists of two stages. In stage A, a baseline is built for different operational conditions representing a specific strain field pattern.

This is done automatically by using a clustering technique of two-level clustering based on Self Organizing Maps (SOM) and a DBSCAN-based method. In a subsequent step, models are built for each baseline by using different dimensionality reduction techniques. In stage B, data for unknown operation conditions are classified according to their major similarities with baselines previously build in stage A, through a process we call "inverse OBS" and in a subsequent step, data is projected into the associated baseline model. Damage indices and detection thresholds are defined to perform the damage detection process.

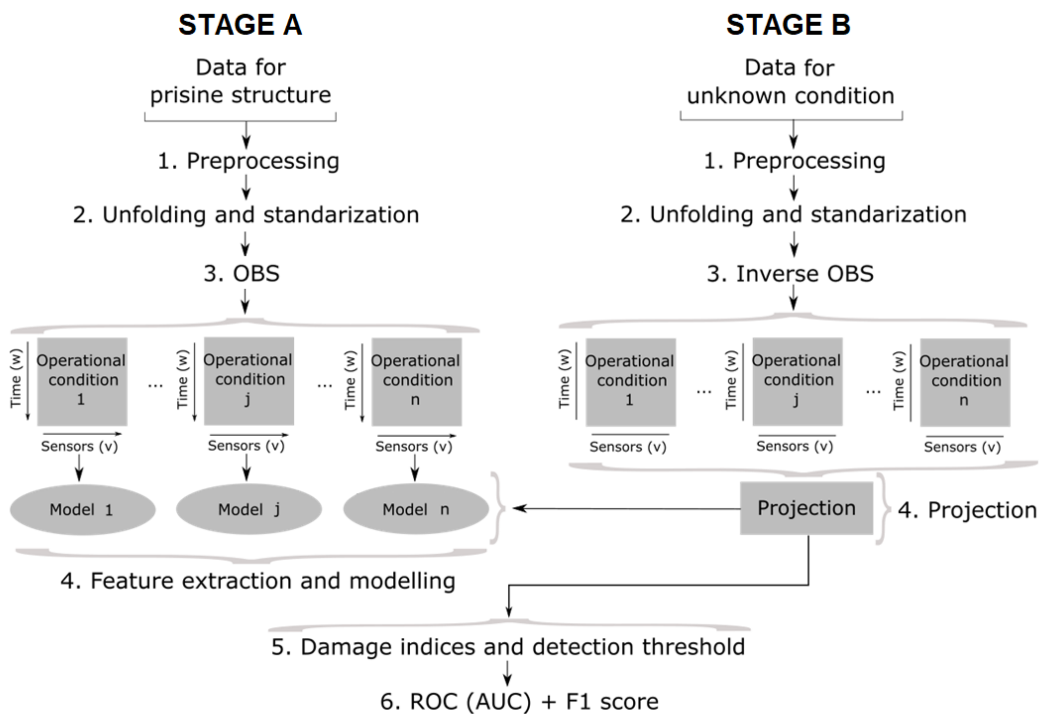

Figure 1. Scheme of data-driven based strain field damage detection methodology.

FA+GA-DBSCAN model

The use of unsupervised pattern recognition algorithms can be used for exploratory analysis to obtain specific clusters of data i.e., operational conditions. The model aims to unfold operational conditions from a randomized environment. The pattern recognition algorithm used to define these specific models is a modified version of Density-Based Spatial Clustering of Applications with Noise or DBSCAN.

DBSCAN has two particularities, the first is the fact that the algorithm is not automatized, it employs two parameters to define a cluster in a two-dimensional space, Eps which is related to a particular radius and MinPts can be considered as the minimum number of reachable elements in a cluster. A Genetic Algorithm GA is selected to define automatically DBSCAN parameters. The second is the computational cost of clustering, which is reduced when the dataset is evaluated in a two-dimensional space, therefore a two-dimensional projection using the Factor Analysis technique is applied to datasets before clustering, this methodology was defined as FA-DBSCAN. The previous also allows the identification of operational conditions in a simple visible way which is a two-dimensional representation of operational conditions.

The Factor Analysis model can be represented as $x_i = \Lambda f + e$, where x_i represents the original variables, Λ the factor loadings, f common factors and e the specific errors. Factor Analysis is also used to realize an outlier detection by a projection of new information to the generated baseline. The novel detection mechanism is an index which is represented as follows: $FA_{index} = x_i \times [I_{n\times n} - (\Lambda \times \Lambda')] \times x_i$, where $I_{n\times n}$ is the identity matrix.

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SOM-PCA model

One of the most successful clustering techniques is the SOM. In this work, a SOM-based technique is proposed to discriminate operational conditions automatically without any intervention of the user. SOM is considered an unsupervised method that allows the conversationally of nonlinear relationships among high dimensional data into simple relationships in an interpretable low dimensional space.

It is possible to use (learn) the information obtained with SOM to partition data in a discrete way (which is one of the main SOM's shortcomings). This algorithm has been called the two-level clustering technique.

On the other hand, another dimensional reduction technique used as a modeler (like Factor Analysis) is PCA. PCA is used to reduce complex data to a smaller dimension and to reveal simpler patterns in data hidden by noise, redundancies, or data complexity. The model is constructed through the linear transformation $T = \bar{X}P_r$, where $\bar{X}$ represents standardized data, P_r the first r retained principal components and T the scores. From this projection, it is possible to calculate different damage indices and thresholds. Perhaps one of the most successful is the so-called Q-index which denotes the difference between an observation and its projection into a PCA model. The index is given by $Q = \bar{X}(I - P_r P_r^T)\bar{X}^T$.

A detection threshold for Q-index can be defined as $\left(\frac{\upsilon}{2\varpi}\right)\chi^2_{2\varpi^2\upsilon^{-1}}(\alpha)$. Where $\chi^2_{2\varpi^2\upsilon^{-1}}$ is the upper 100α-th percentile of a chi-square distribution with $2\varpi^2\upsilon^{-1}$ degrees of freedom and at a significance level α, with ϖ and υ equal to the mean and variance of the Q-index respectively.

Numerical setup

A finite element model was made in ANSYS APDL and was cross-validated with experimental and numerical data obtained from a previous work made by Murray et al [4].

A mesh convergence study was made to select the appropriate mesh to use in the FE model for APDL. Two different element types were considered, the 4 node Shell 181 element and the 8 node Shell 281 element. The study showed that both elements can get results like those obtained by Murray et al with a margin of error of approximately 5%.

The FEM study was performed using a 2.5-meter-long wind turbine blade with a 40-thousand-element mesh to get good results according to the convergence study and the software configuration was established to simulate the blade at a macroscopic scale. So, several initial conditions were set to simulate the real blade operation, like:

- Rotational velocity of 40 rad/s, which represents the maximum operating velocity of the wind turbine blade.
- The blade base attachment was set rigid to fix the blade in the rotational disk.
- Blade lift was set as a pressure profile based on previous CFD analysis (See Figure 2).
- Drag force also was included in the FEM study with a force all over the body of 108.77 N.

The simulations were performed for 10 pitch angles starting from -5° to 40° with a 5° interval. These values are within the optimal and real blade operation.

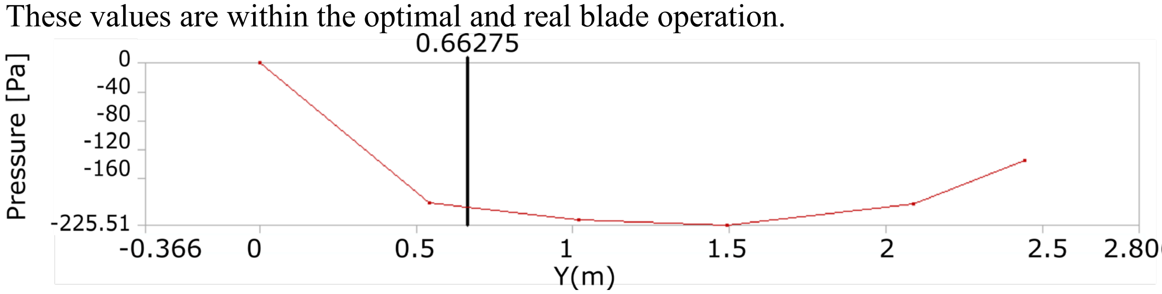

Figure 2. Wind turbine blade pressure profile.

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The value 0.66275 in the previous figure refers to where the mean aerodynamic chord (MAC) is. Regarding the virtual sensors, ten of them were located along the longitudinal axis of the blade at the extrados surface, approximately at 10% of MAC from the leading edge and trailing edge (See Figure 3 and Figure 4). At each sensor location, three strains of the blade were measured in their coordinate axis, the longitudinal (Y), transverse (X), and off the plane (Z), replicating a strain rosette.

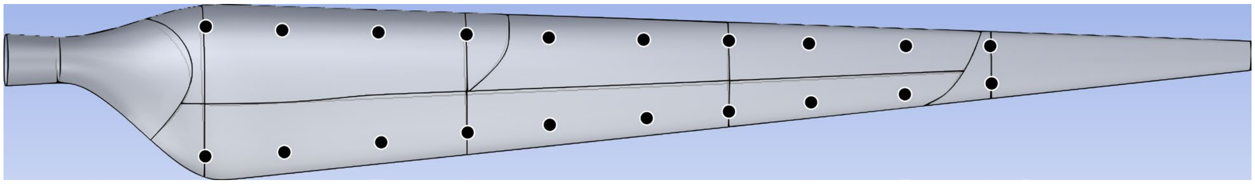


Figure 3. Strain sensor's location at intrados surface.

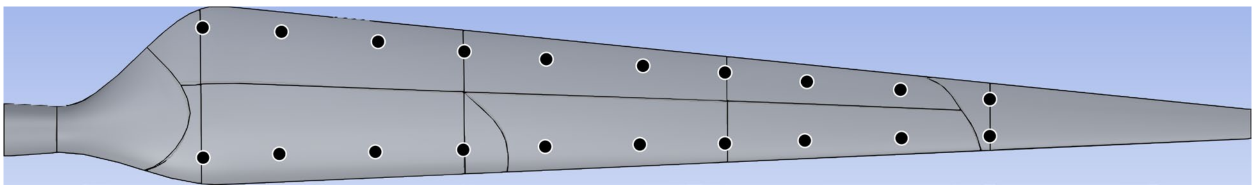
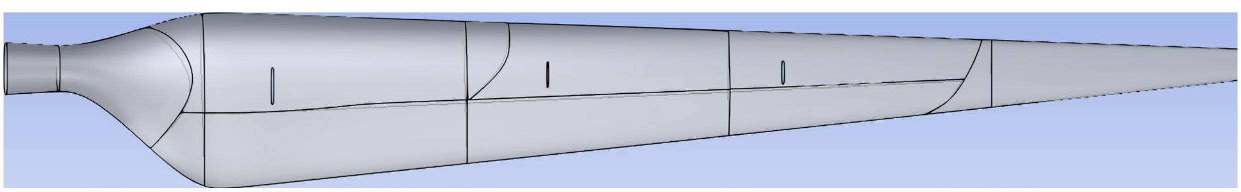


Figure 4. Strain sensor's location at extrados surface.

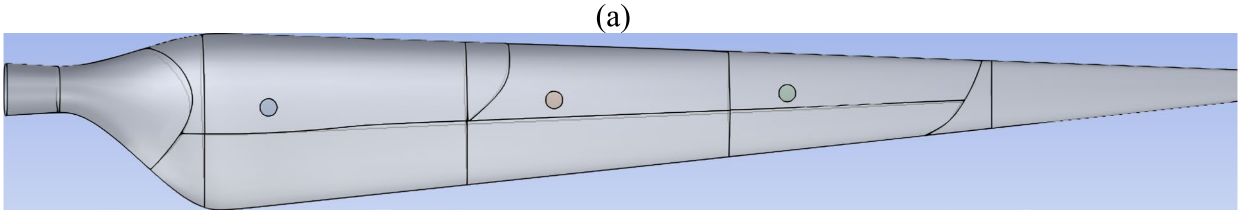
Each dot in Figure 3 and 4 represents a strain rosette, so in total there are 40 sensors and 120 strain values for each pitch angle. Sensors are distributed equally at both extrados and intrados surfaces and placed along the longitudinal axis; the tip zone was excluded for sensors since strain measurements are not representative of the damage detection methodology.

To evaluate the performance of the clustering model, six damages were proposed individually, and they are located along the intrados surface. The damages were proposed as three ovals and three circles, ovals were simulated within the fracture model that APDL has, and the circles were defined as damage that might show up during real blade operation [5].

The characteristic length of the damages was set as 10% of MAC and the location is distributed inside the sensor's area as shown in Figure 5.



(a)



(b)

Figure 5. Wind turbine blade damages: (a) Ovals and (b) Circles.

From the FEM model strains at virtual sensor locations were obtained for 10 pitch angles with and without different damages. To approximate a realistic data set, data should be grown artificially. Since a linear static FEM model was used, the first step in artificial data generation consisted of multiplying obtained data by random scalars between 2 to 10 and subsequently, by an artificial random gaussian noise which was selected to be ± 10% of the original strain values.

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Each operational condition defined (pitch angle) had a vector of $V_{1\times 120}$, with one time instant and 120 unitary strain measurements (40 virtual triaxial strain sensors). It was selected that each operational condition will have 1000 artificial replicas times 10 pitch angles, thus operational conditions matrixes will have a size of $D_{10000\times 120}$. A similar approach is given to the cases of the blade with induced damage under a specific load. In this way, a data set composed of 10000 strain measurements of 40 virtual sensors for baseline, 10000 strain measurements for validation data, and 10000 strain measurements for each damage condition, was built.

This baseline may guarantee a level of confidence for a condition diagnosis of structure which should be related to a damaged or undamaged system. The time steps of baseline virtually generated $D_{10000\times 120}$ are also randomly sorted as it should happen in real operation of a wind turbine blade due to external factors.

The damage assessment under the strain mapping technique includes a specific configuration of the strain information collected in a matrix form. The data collection method is defined considering the information of the pristine and damaged structure. The information is collected in a matrix of size $D_{m\times n}$, the rows m are time steps or the number of samples and, n are the number of sensors, which, in this case, measures the unitary strain.

Results and discussion

The pipeline methodology called FA+GA-DBSCAN is selected to automatically define operational conditions. The resultant baseline consisted of eight clusters. The representation is presented in Figure 6. The selection of these two parameters where automatized using a genetic algorithm, and then a dimensionality reduction was performed considering the well-known Factor Analysis method. The Factor Analysis model can be represented in terms of covariances according to the following equation:

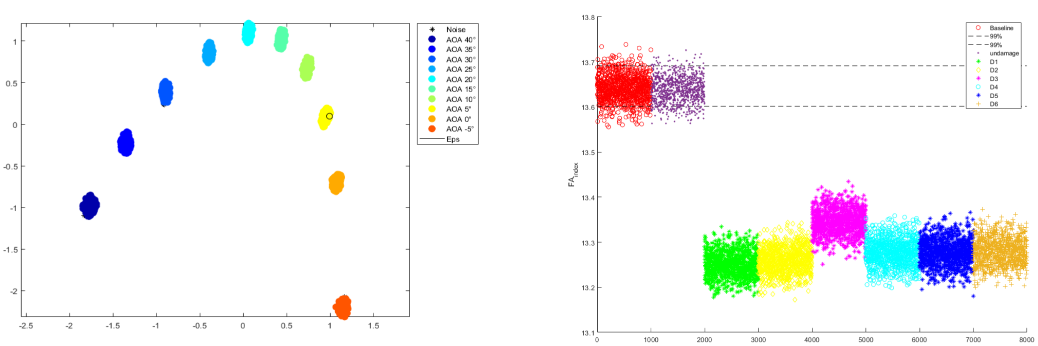

Figure 6. Left: Baseline artificially generated using Gaussian noise. Right: An example for damage detection using the FA index, six different levels of damage were detected using the generated baseline.

The use of Factor Analysis for damage detection is performed considering the specific factor loadings of the new information. These specific loadings are defined as a correlation number for the specific variable being analyzed. As presented in Figure 7 (right), new unknown information belonging to six levels of damage can be projected to the baseline, it is evident that these projections are far away from the baseline, thus, these can be considered as information related to damage on structure.

By using SOM-based unsupervised clustering it was possible to obtain 10 clusters, each one corresponding to one pitch angle. Each individual cluster was used to build a baseline model for such pitch angle. In a subsequent step, all damaged data were projected into the baseline models by performing an inverse SOM-based process, in which, damaged data are classified according to their similitude with baselines. Once damaged data are classified, PCA is used to project such

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damaged data into its respective model, and a Q index is obtained. This process is graphically explained in Figure 1.

Results are presented in Figure where the clusters segregation of SOM is presented at left (10 clusters can be observed). The result of the Q index for cluster number 2 (baseline model number 2) is presented at the center; it can be observed that the Q index for all damages is well separated from baseline and validation data. At the right of the figure, the performance of both clustering (SOM-based) process and Q index damage detection-based can be observed. For this example, the clustering technique serves to separate baselines and to assign the most similar baseline to damage data, however, it is not enough to perform a damage detection. On the other hand, by using PCA and Q index, the performance obtained for damage detection by using a specific baseline to project the most similar damage data into such baseline is remarkable (an accuracy of over 98%).

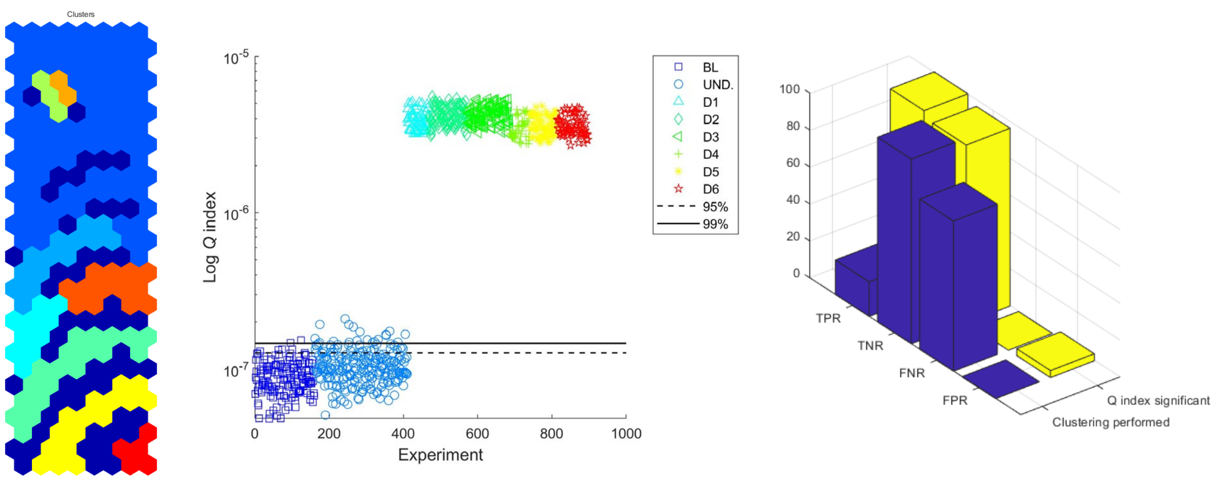

Figure 7. Left: SOM for baselines for all pitch angles. Center: example of Q index for baseline number 2. Right: performance results for cluster number 2.

Summary

In summary, the strain field of a virtual representation of the blade from a wind turbine under dynamic loads was evaluated using two different approaches of data-driven models. The pristine representation of the blade was used to define a baseline which was specified by applying Gaussian noise to strain measurements of the blade under static loads. This process will define a baseline with different time instants and slight variations in loads as it could happen in a structure under dynamic loads. Furthermore, six levels of damage were included and the strain information from these levels was also considered in a dynamic setting. Two data-driven models were taken into consideration for damage evaluation SOM and FA-GA+DBSCAN. These models were capable of automatically define the pristine operational conditions with a remarkable accuracy. The identification of damage on the blade was satisfactory projecting new information to the baseline created.

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