



Model-based Data-driven Structural Health Monitoring of a Wind Turbine Blade

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ABSTRACT: The development of structural health monitoring algorithms for wind turbines is an emerging need because of the aging issue in wind farm facilities. An emerging field of data-driven machine learning schemes has resulted in the development of new means in structural health monitoring. Although, these approaches are inclined to errors in the absence of good insight into the physics of the system. Therefore, a comprehensive model of the structure, as well as its uncertainties, could be a good complement to these approaches. In the current article, an algorithm is developed for autonomous health monitoring of a wind turbine blade, which is one of the most expensive parts of the turbine, based on acceleration measurements taken from several points on the blade. The data are acquired based on a close-to-reality finite element model of the blade. The acceleration signals are gathered from five nodes along with the wind turbine model, which act as vibration sensors in a common similar test setup. Advanced algorithms of system identification are used for extracting damage sensitive features. Moreover, a one-class kernel support vector machine (SVM) is trained to find the data associated with a damaged state of the structure. Finally, the success of the procedure in the detection of the existence and location of the damage is depicted.

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1. INTRODUCTION

Considering the environmental impacts and sustainability problems of conventional energy resources, renewable energies are attracting ever-increasing attention all around the globe [1]. Among all available renewable resources, wind energy plays a pivotal role in meeting energy demands through renewable and sustainable means [2]. Wind turbines are employed to harness this vast energy potential [3]. To be more efficient and cost-effective, structures of the wind turbines have been designed and developed in larger sizes rendering more difficult maintenance and catastrophic consequences in the case of failure than before [4]. These problems are further exacerbated when dealing with off-shore turbines [5]. It should be noted that the operation and maintenance costs over the lifetime of the turbine are believed to be 75%- 90% of the initial investment [6]. Therefore, special care should be taken to detect damages in early stages and take corrective actions to minimize the potential consequences. For this purpose, Structural Health Monitoring (SHM) of the system is introduced that contains damage detection strategies and characterization schemes. Combining SHM systems with novel sensor technologies, wind turbine turns out to be a more economical and reliable means to harness wind energy [7]. Within the SHM approach, there are various techniques based on the sensor technology utilized, among which vibration-based monitoring systems are desirable due to their ma-

turity and long history of utilization in condition monitoring of rotary machines [8].

A wide array of features could be extracted from the measurements and utilized to serve as indicators of damage, such as modal parameters, dynamic spatial parameters, wavelet packets, and time series, which are broadly explored in the literature and are briefly reviewed in reference [9]. One of the most applicable methods utilized for Vibration-Based Structural Health Monitoring (VB SHM) of the wind turbine blade is the statistical pattern recognition paradigm. Farrar *et al.* introduced this paradigm [10, 11]. It is a mature procedure for implementing a fully automated monitoring system to detect changes in the system condition, which can be interpreted as damage. This algorithm can be applied in an embedded computer that is installed in situ, and the machine will alarm the operators whenever there is a change in the condition of the system.

Several efforts have been made by researchers all over the world to either develop new SHM techniques or improve the existing ones in monitoring the health of different parts of a wind turbine. A significant number of works have been dedicated to the health monitoring of blades as the most expensive components of the wind turbine. For instance, in 2000, Flotow *et al.* surveyed different sensor technologies, such as capacitive, inductive, optical, microwave, infrared, eddy-current, pressure, and acoustic, which can be used in health monitoring of the blade [12]. They analyzed and discussed

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data quality and the complexity of the systems under each sensor technology. Their study covers many practical aspects of SHM implementation. The data analysis challenges are also addressed by Yang *et al.* in 2013 [13]. In 2011, Adams *et al.* analyzed the effect of damage on modal features of a blade. They compared the variations in response along different directions due to the damage [14].

Numerous researchers have employed finite element simulation to develop SHM schemes. Accurate Finite Element Method (FEM) models can contribute greatly to the process as they can provide the researchers with the training data necessary for feature extraction and statistical modeling. This advantage is particularly more valuable when the structure is hard to access for real data acquisition, as in offshore turbines. In 2007, Kumar *et al.* utilized a FEM approach to analyze a wind turbine blade for its low-frequency fatigue damage [15]. Based on the conducted study, they illustrated that it is possible to detect damage before the failure occurs. In another study in 2007, a group of researchers developed an SHM oriented FE model of the Tsing Ma bridge tower [16]. They could show that the developed model can represent the dynamic features of the structure very well. In 2018, Xiang *et al.* developed an FE model of a transmission tower in China [17]. Applying model updating techniques and using the test data, they concluded that the FE model can capture global features of the model with an acceptable computational load. However, they stated that exploring the local features deserves more accurate FE modeling.

Usually, some general concerns must be considered when initiating an actual SHM project. Although the current project is not a commercial one, there has been an attempt to address some of the more critical concerns. A 1.5 MW wind turbine, which is pretty similar to the one modeled in this project, costs up to several million Euros [18]. The blades of the turbine are of the most expensive components which contribute to about 20% of the whole expenses [19]. Furthermore, failure of the blades may introduce damage to other components such as nacelle and tower and cause more financial loss. Thus, it is thoroughly justifiable from an economic perspective to design, develop, and implement an SHM system for a wind turbine blade.

In the current article, an accurate finite element model of a wind turbine blade is utilized so that the acquired data from the blade will be close to the values corresponding to the real system. The FE model, if accurate enough, can capture many of the signatures and behaviors of the system well. This modeling makes it possible to design, develop and validate SHM algorithms before real-time implementation in a system. This can make significant economic value by reducing the cost of trial and error. According to the author's best knowledge, this is the first time that the whole process of health monitoring is being done utilizing an FE model of the wind turbine blade.

The current paper consists of four sections. A description of the whole method is presented in section 2. This section includes some explanations on the FE model of the blade, data collection scheme from FEM, pattern recognition, and statistical modeling of the data. The results are demonstrated

in section 3. The last section is devoted to a discussion on the simulation results. The final section of the paper is dedicated to the concluding remarks.

2. METHODOLOGY

Considering the challenges and costs involved in experimental data collection and its inflexibility in studying different ambient and structural conditions, a physics-based model, such as a FE model, could offer many benefits by providing a virtual platform for the development of different parts of the SHM system. Mainly, the model output under different simulation conditions can be used as training data, which is a crucial element of any SHM system. The FE model presented by Cornell University [20] is taken and then customized promptly to be usable for dynamic transient analysis and to model damages. Thereafter, the SHM scheme is exerted on the data obtained by this model.

There is a wide array of possible damage scenarios that can happen to a wind turbine, e.g., composite delamination, crack formation, and fracture. Accurate modeling of these damages is complicated and can be the subject of another study, but the consequence in most of the damage scenarios is a reduction in stiffness that results in the change of the structure's static and dynamic responses and thus, changes the modal properties [21]. Hence, in this project, the damage has been modeled merely by reducing the stiffness of the blade at different locations.

Wind turbine blades are exposed to high wind speeds while rotating about a center at a high altitude above the ground. These special conditions result in some difficulties in accessibility of the blades for measurement purposes during the operation. Therefore, some sensing devices must be installed on the blades before triggering the process in an actual wind turbine. In the current project, maximum effort has been made to model these actual operational and environmental conditions, by considering the wind speed and blade rotation. Some measurement points are specified on the blades as the sensors to have vibration signals on them.

In order to have a comprehensive SHM paradigm, after an initial operational evaluation, some principal steps must be implemented [1], which are: (1) Data collection and preprocessing, (2) Feature extraction and feature selection, and (3) Statistical modeling for feature discrimination. In this work, the steps are implemented one by one as described below.

2.1. Data Collection And Preprocessing

As stated before, the data are provided from several FE simulations on a close-to-reality model, in its healthy and damaged conditions. An existing CAD model corresponding to a blade of 1.5XLE GE wind turbine, as shown in Fig. 1, has been imported to the ANSYS® software. The details corresponding to the simulated blade including its spar specifications, dynamic properties, and geometric features can be found in reference [22]. Some specifications of the turbine blade and the operating conditions used in this study can also be found in Table 1.

Five virtual sensors are considered to be placed in the mid

Table 1. Specifications and operating conditions of the wind turbine blade [20].

Parameter	Value
Rated power	1.5 MW
Cut-in wind Speed	3.5 m/s
Rated wind speed	11.5 m/s
Cut-out wind speed	20 m/s
Length	82.5 m
Tip speed	81 m/s
Material	GFK

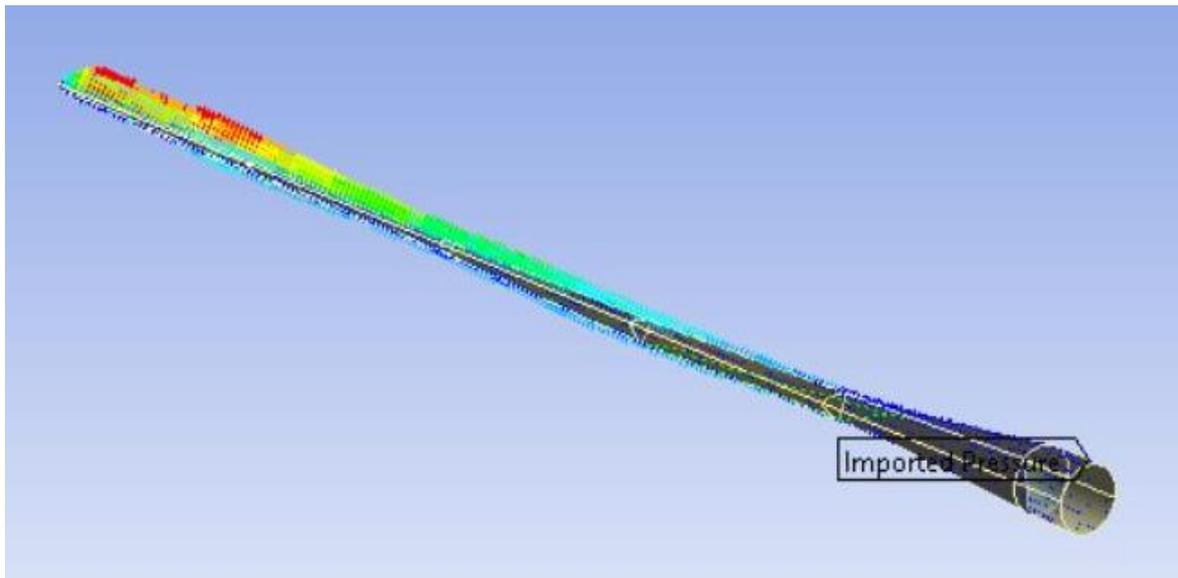


Fig. 1. Imported wind pressure on the blade

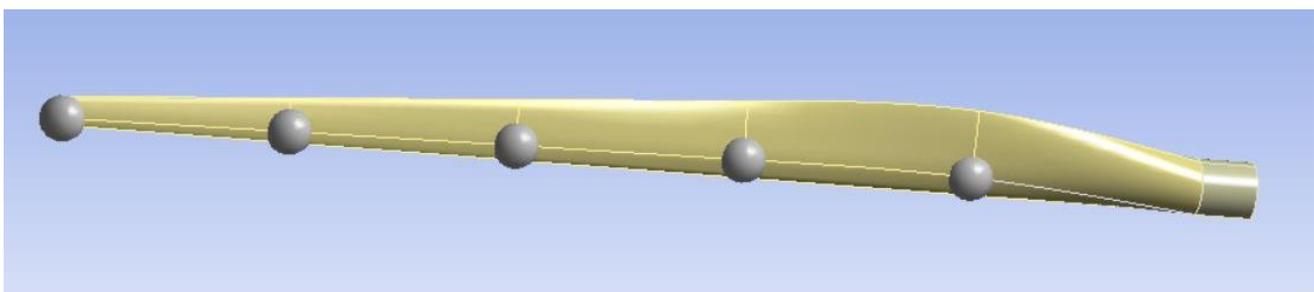


Fig. 2. Sensors and their placement on the blade.

part of the blade FE model, as illustrated in Fig. 2. Acceleration signals corresponding to each of these locations are obtained during simulations and used in the feature extraction phase of the study.

The existence of noise on the signals in real systems lessens the clarity of signal with respect to the ones obtained from the simulations and may lead to different outcomes in

the system identification process. To minimize this difference, synthetic noise should also be added to the data collected through simulations. The addition of the noise also makes the process of statistical model development more effective as recommended in the literature [23]. This is due to the fact that the size of the training data increases and randomness is added to each data point. As such, Gaussian white noises

with a specific Signal-to-Noise Ratio (SNR) are added to the original data before moving on to the feature extraction phase of the study.

2.1.1. Finite Element Simulations

Two main simulation stages should be implemented on the model. At the first stage, employing CFD analysis of FLUENT component in ANSYS, the blade is exposed to several wind speeds. In this study, it is assumed that the rotor speed is constant at 2.2 rad/sec and the wind speed varies for different Tip Speed Ratios (TSR). The wind speed also differs from 10 m/s to 20 m/s, these amounts have been chosen from the optimum TSR which is considered to be around 5 [24] and the nominal wind speed which is given to be about 11 m/s. The nominal rotational velocity has been considered around a remote point set to be at the center of the hub. Then Navier-Stokes equations are solved for a moving frame placed on the blade using a CFD-optimized tetrahedral mesh. $k-\omega$, SST (Shear Stress Transport) viscous model, which is a hybrid turbulence model, a combination of $k-\omega$ model which is suitable for near the boundary condition and $k-\varepsilon$ which is a good choice for the free stream, is utilized to model the behavior of wind accurately both near the boundary layer and in the mainstream. The results obtained from the CFD part correctly models the fluid flow properties expected such as the wake behind the blade and the increment of the wind velocity over the blade surface from the hub to the tip. Detailed analysis of the CFD results is not within the scope of the current study and the interested readers can refer to reference [20]. Then the profile of wind pressure on the blade can be obtained.

In order to use the CFD results in the structural analysis, the resulting wind pressure is to be transferred into the structural component of the software. This practice is known as one-sided Fluid-Solid interaction. Therefore, at the second stage, the calculated pressure is imported to the transient structural component of ANSYS, to get the dynamic response of the blade due to the wind loading and rotor speed. The density and the stiffness of the blade are set at this point as given in reference [20]. The transient analysis is conducted over 10 seconds, logging 2500 acceleration data along the Z-axis which is perpendicular to the blade surface. This means that each run of the study yields 2500 data, taken with a sampling frequency of 250 Hz, to be utilized in the feature extraction part. The results obtained from the finite element modeling are independent of the mesh size and features such as aspect ratio and orthogonality of the mesh all fall within an acceptable range.

Reducing stiffness is a method commonly employed in the literature as in reference [25] to impose the damage in the FE method. In this study, the stiffness of the spar is reduced by specific values to model the damage in the blade. For this purpose, three damage scenarios are considered: (1) The stiffness of the spar along the whole blade is reduced by 50 percent, (2) the stiffness of the third one-fifth of the spar is reduced by 50 percent and (3) the stiffness of two-fifths of the spar is reduced by 50 percent. Employing these scenarios,

the damage is implemented in the model and the data from the structural analysis are transferred for further process to be sent to the machine learning scheme in the next stage.

2.2. Feature Extraction And Feature Selection

Feature engineering is about creating a low-dimension set of parameters from the original high-dimension data which best characterizes the system. If the engineered features represent inherent characteristics of the system, then the features are invariant to operating conditions and they may serve as indicators for the occurrence of probable damage in the structure. Damage-sensitive features that can be used for this purpose are comprehensively discussed by Farrar and Worden [9].

In this work, modal analysis is employed for feature extraction from primary time signals of FE simulations. Modal analysis characterizes the system in terms of its natural frequencies, mode shapes, and damping ratios, which are representative of the inherent system properties. This approach formulates feature engineering as a system identification problem where the plant parameters are determined. This model-based approach, unlike signal-based methodologies, could consistently provide information about the changes in the system even under various operating conditions [9].

2.2.1. Modal Parameters

Since in this case, excitor is the operational force induced by wind velocity and blade rotation, it is needed to employ an Operational Modal Analysis (OMA) approach to invoke the natural frequencies, mode shapes and damping ratios of the system. Among various frequency-domain and time-domain OMA approaches, in this article, the Stochastic Subspace Identification (SSI) method is employed due to its clear advantages over other methods. Using linear algebra manipulations to reach the state-space matrices of the system directly, SSI approach is computationally more efficient and assures convergence of the analytical procedures. Another advantage of the SSI method which makes it a better choice is its robustness against noise.

The state-space formulation describes the system in terms of discrete state matrix $[A]$, discrete input matrix $[B]$, discrete output matrix $[C]$, and direct transmission matrix $[D]$ as [26]:

$$\begin{cases} \{s_{k+1}\} = [A]\{s_k\} + [B]\{u_k\} \\ \{y_k\} = [C]\{s_k\} + [D]\{u_k\} \end{cases} \quad (1)$$

where s_k , u_k and y_k represent state of the system, system input and measured data at time step k , respectively.

There are mainly two types of SSI methods: covariance-driven and data-driven. The first approach is used in this work due to its efficient computational load, which makes it suitable for real-time implementation in situ. Covariance-driven stochastic subspace identification (CD SSI) is a parametric, time-domain method that identifies the stochastic

state-space realization of the system, using only output data. The algorithm starts by forming the block Toeplitz matrix,

$$[T_{1|i}] = \begin{bmatrix} [\hat{R}_i] & [\hat{R}_{i-1}] & \dots & [\hat{R}_1] \\ [\hat{R}_{i+1}] & [\hat{R}_i] & \dots & [\hat{R}_2] \\ \vdots & \vdots & \ddots & \vdots \\ [\hat{R}_{2i-1}] & [\hat{R}_{2i-2}] & \dots & [\hat{R}_i] \end{bmatrix} \quad (2)$$

where subscript i stands for time delay in covariance matrix and $[\hat{R}_i]$ is the autocorrelation of the output,

$$[\hat{R}_i] = \frac{1}{N-i} [Y_{1:N-i}][Y_{i:N}]^T \quad (3)$$

where $[Y_{l:m}]$ is a partition from the total data matrix $[Y]$ by removing elements from beginning up to l th element and also from m th element to the end (N th element). Here, the data matrix $[Y]$ consists of the acquired data arranged in 5 rows which represents the number of utilized sensors, and 2500 columns which is the number of logged data in each measurement. The Toeplitz matrix can be decomposed into observability $[O_i]$ and reversed controllability $[RC_i]$ matrices as,

$$[T_{1|i}] = [O_i][RC_i] \quad (4)$$

The state matrix $[A]$ can be computed by decomposition of the one-lag shifted Toeplitz matrix as,

$$[T_{2|i+1}] = \begin{bmatrix} [\hat{R}_{i+1}] & [\hat{R}_i] & \dots & [\hat{R}_2] \\ [\hat{R}_{i+2}] & [\hat{R}_{i+1}] & \dots & [\hat{R}_3] \\ \vdots & \vdots & \ddots & \vdots \\ [\hat{R}_{2i}] & [\hat{R}_{2i-1}] & \dots & [\hat{R}_{i+1}] \end{bmatrix} \quad (5)$$

$$= [O_i][A][RC_i]$$

Therefore,

$$[A] = [O_i]^+[T_{2|i+1}][RC_i]^+ \quad (6)$$

where $+$ sign stands for pseudo-inverse operation. Once the state matrix $[A]$ is obtained, $[C]$ matrix will be calculated using the observability matrix,

$$[O_i] = \begin{bmatrix} [C] \\ [C][A] \\ \vdots \\ [C][A]^{i-1} \end{bmatrix} \quad (7)$$

Having the state space matrices $[A]$ and $[C]$ known, the mode shapes can be computed using eigenvalue decomposition:

$$[A] = [\Psi][\mu][\Psi]^{-1} \quad (8)$$

where $[\Psi]$ is the eigenvectors matrix of $[A]$ and $[\mu]$ is the diagonal matrix corresponding to the eigenvalues. Having column j of the eigenvector matrix as $\{\psi_j\}$, the mode shape vector $\{\phi_j\}$, which is the observable part of the eigenvector is obtained by utilizing the observability equation as:

$$\{\phi_j\} = [C]\{\psi_j\} \quad (9)$$

$$j = 1, 2, \dots, n \times p$$

where p is the number of measurement sensors, j denotes the j th column of the eigenvectors matrix, and n is the order of identification. The next step is to find the natural frequencies and damping ratios by converting the system eigenvalues from discrete time to continuous time using zero-order-hold [26]:

$$\lambda_i = \frac{\ln(\mu_j)}{T} \quad (10)$$

$$\omega_j = |\lambda_j|$$

$$\zeta_j = -\frac{\text{Re}(\lambda_j)}{|\lambda_j|}$$

where ω_j is the natural frequency in radians, f_j is the natural frequency in Hertz, and ζ_j is the damping ratio. Extracting the features from data corresponding to an undamaged system, some features should be selected manually using engineering intuition or automatically using machine learning algorithms such as Principal Component Analysis (PCA), both of which are carried out herein [9]. The first three natural frequencies, as well as corresponding mode shapes, are selected among all natural frequencies and mode shapes since they are detectable precisely from all the data sets, whereas some natural frequencies cannot be obtained from some measurement individually. Afterward, PCA is used to detect two main principal components which have the most significant variation, from the three natural frequencies and mode shape so that visualizing the results will be possible. Although the PCA algorithms are mainly used for dimensionality reduction, it is also used in 2D and 3D data to embolden variations, which can help better illustrate the damaged measurement in the current study.

2.3. Statistical Modelling For Feature Discrimination

Statistical modeling is used here to classify the current state of the health of the system as healthy or faulty. Such a model will take the features obtained from ARMA and modal methods as inputs and yields a probability associated with the failure. The statistical modeling problem could be formulated as an unsupervised anomaly detection problem or a supervised classification problem. In the former, only deviation from the normal condition (i.e. damage) is detected without any diagnosis whereas, in the latter, the damage classification could be performed providing more information about the nature of failure, its location, etc.

Table 2. Natural frequency results from FEM for undamaged system and different damage scenarios

Condition	1 st Natural Frequency (Hz)	2 nd Natural Frequency (Hz)	3 rd Natural Frequency (Hz)
Healthy	1.7972	3.6828	8.2936
Whole spar damaged	1.6975	3.5041	7.6787
Two-fifths of the spar damaged	1.7660	3.6401	8.0258
One fifth of the spar damaged	1.7769	3.6617	8.1374

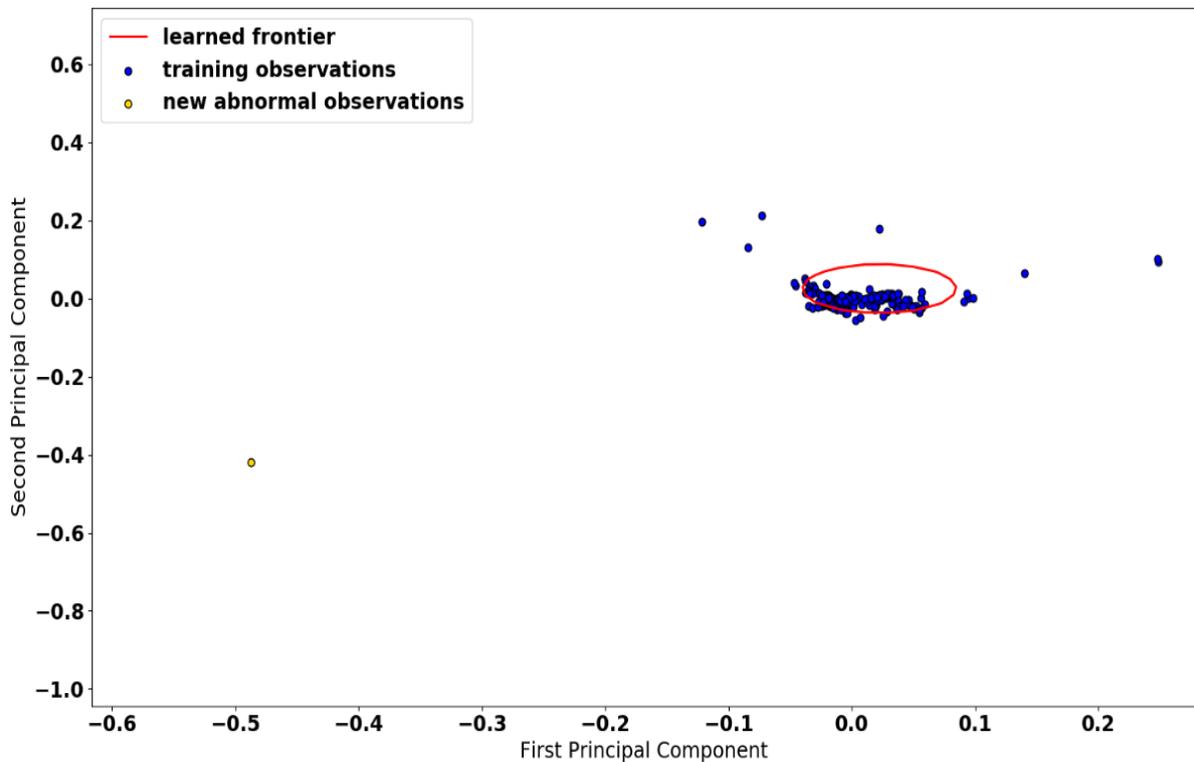


Fig. 3. Detecting damage induced by the first scenario in the whole blade using the natural frequency feature

The algorithm used here is the well-known supervised classification algorithm called Support Vector Machine (SVM) that is modified for nonlinear semi-supervised anomaly detection problem. This algorithm is called one-class kernel SVM that is developed by Schölkopf *et al.* [27]. Getting data sets corresponding to the healthy system, the algorithm creates a frontier to distinguish the class of undamaged data, this is known as the training step. When a new data set is given to the algorithm, it determines whether

the new data fits within the defined frontier or not. Based on the distance from the defined frontier, it can be expressed that with what probability the data belongs to a damaged blade or not. Using this scheme, the existence of damage, as well as its location, can be addressed.

3. RESULTS AND DISCUSSION

An SVM model is trained using the data obtained from the FE simulations on a healthy structure. In the next step,

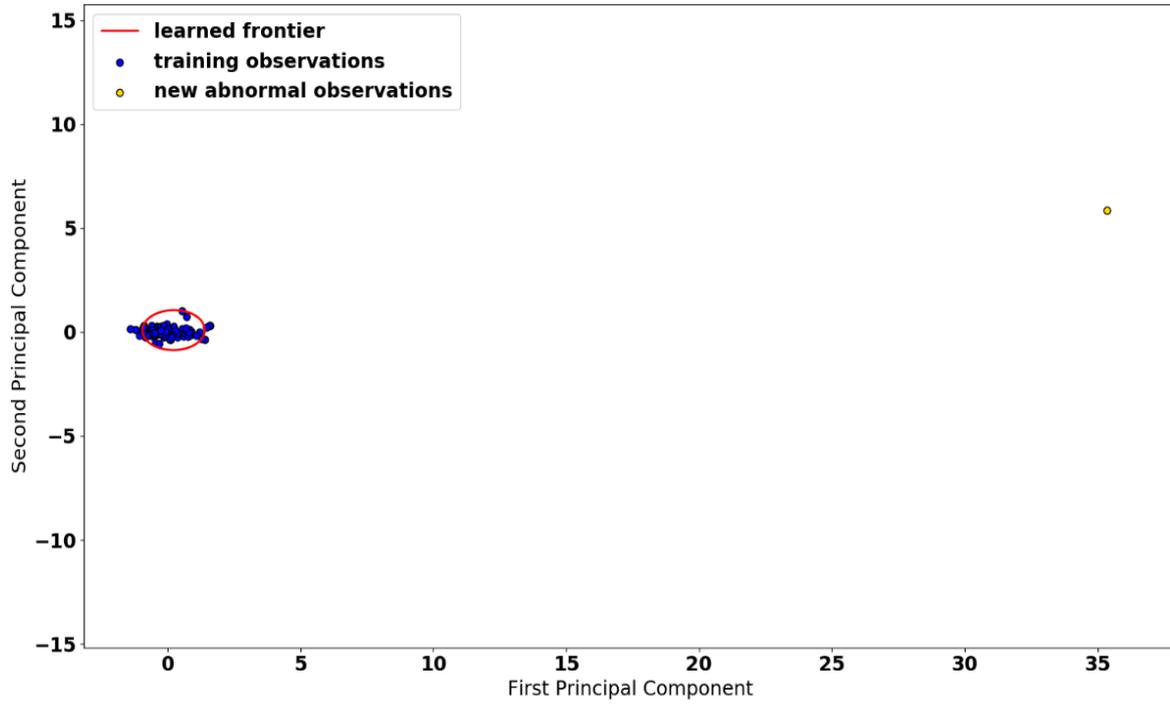


Fig. 4. Detecting damage induced by the first scenario in the whole blade using the mode shape feature

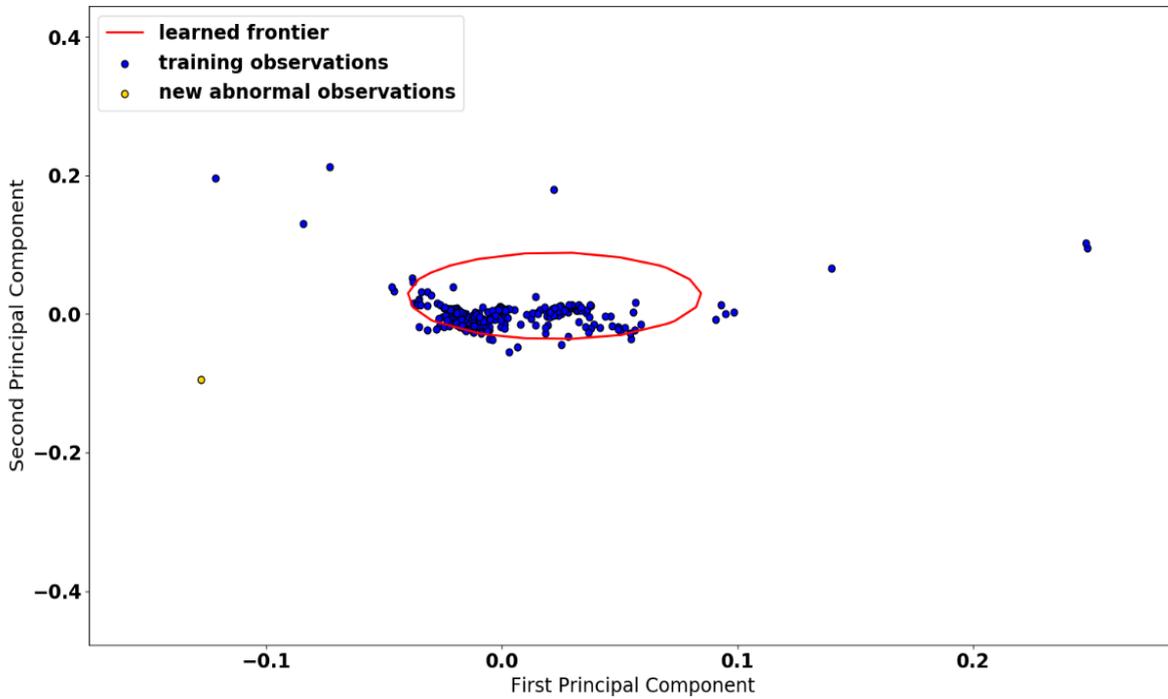


Fig. 5. Detecting damage under second damage scenario using the natural frequency feature

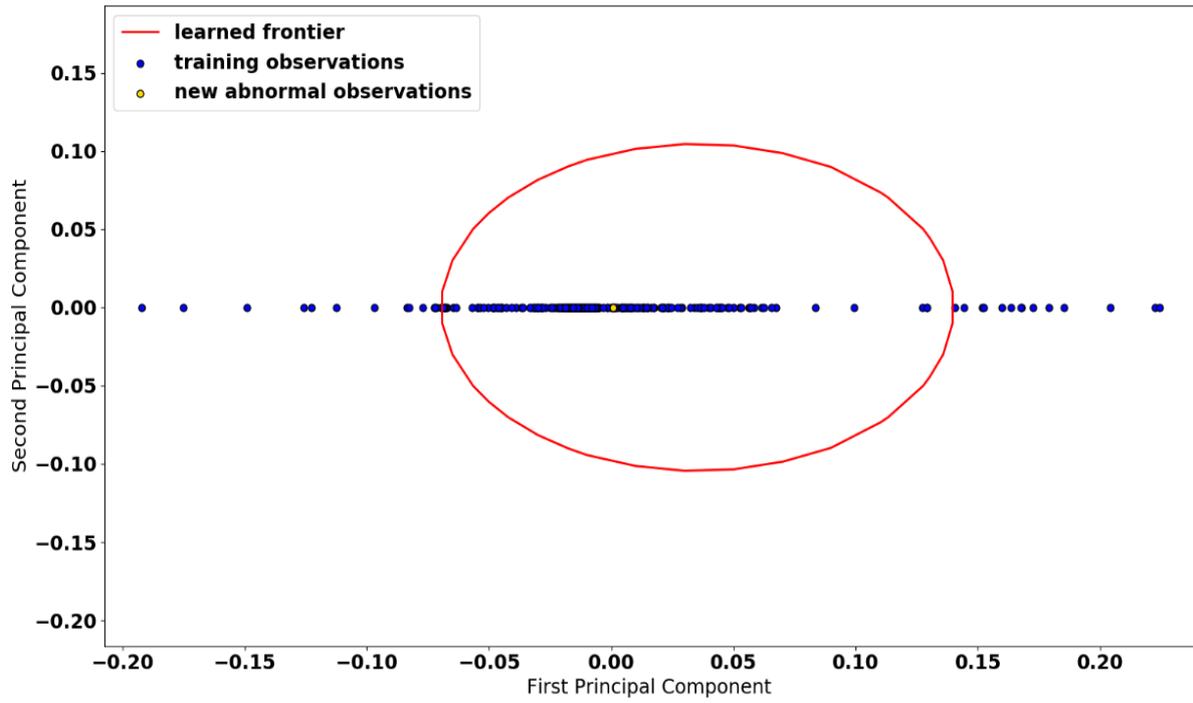


Fig. 6. Indicating the health of the structure under the second damage scenario in the undamaged part using the mode shape feature

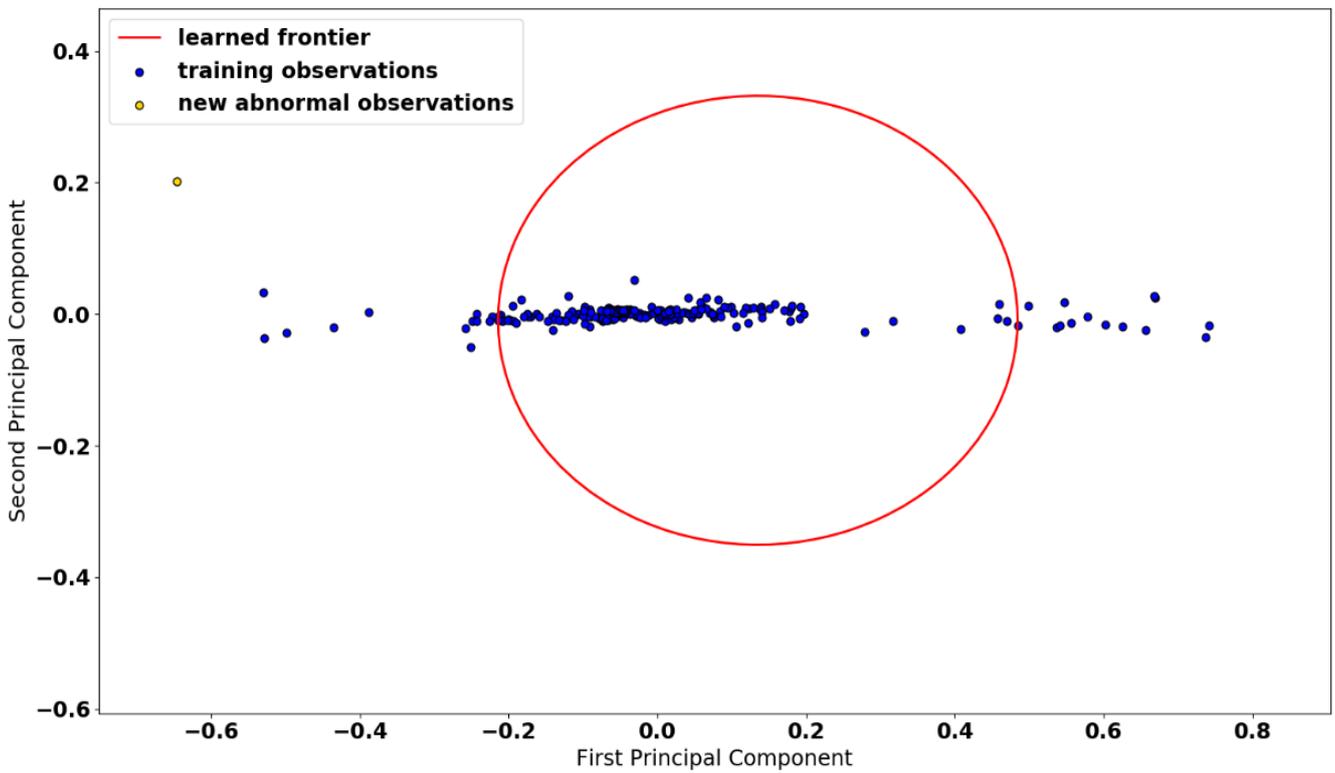


Fig. 7. Indicating the health of the structure under the second damage scenario in the damaged part using the mode shape feature.

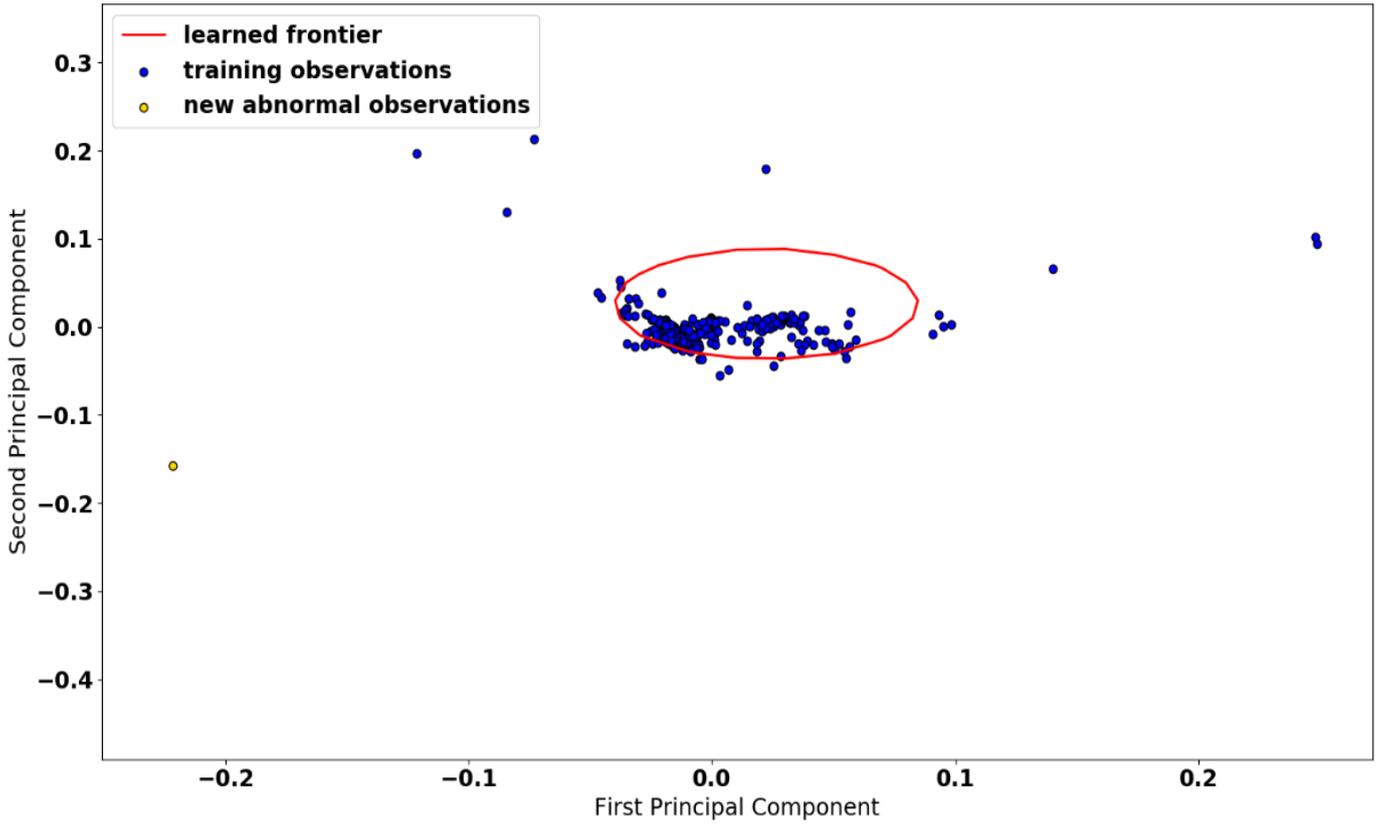


Fig. 8. Detecting damage in two two-fifths of the blade using the natural frequency feature

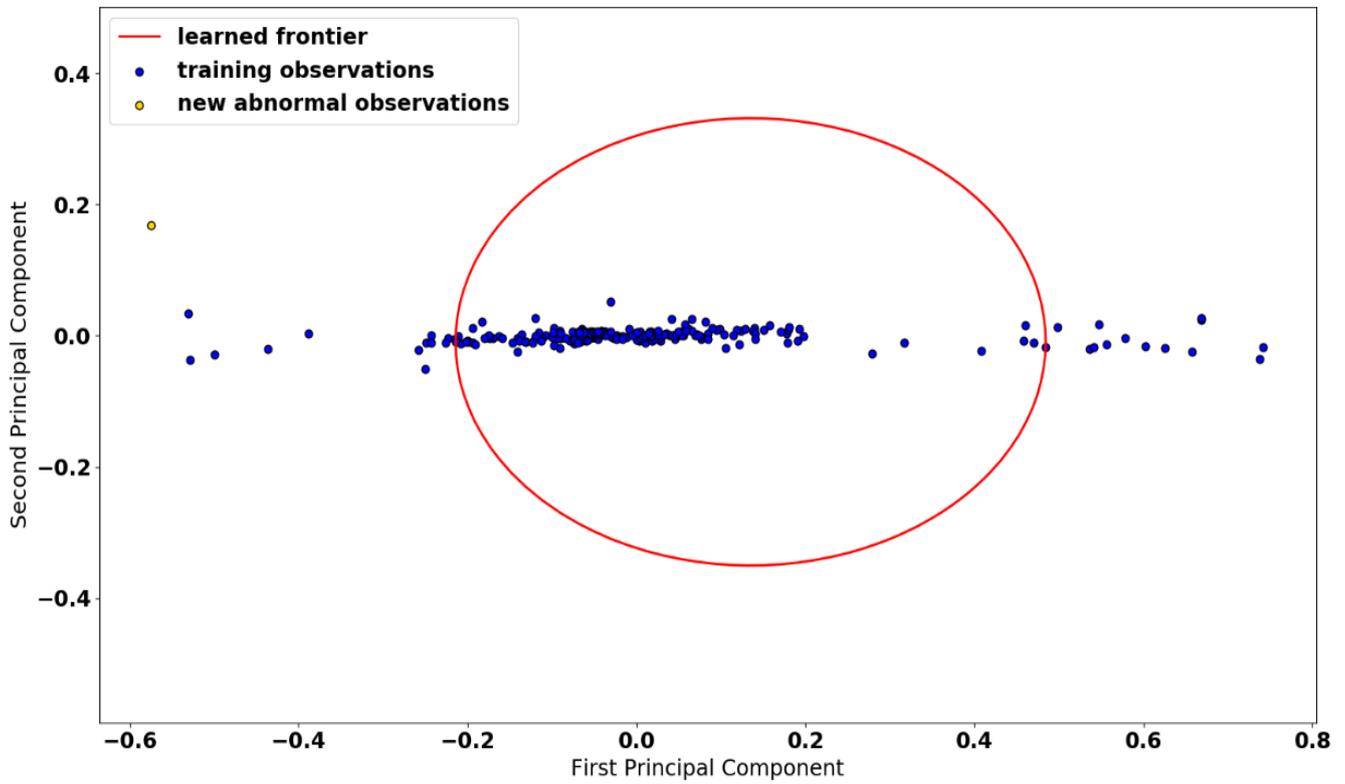


Fig. 9. Detecting damage in two two-fifths of the blade using the second element of the mode shape feature

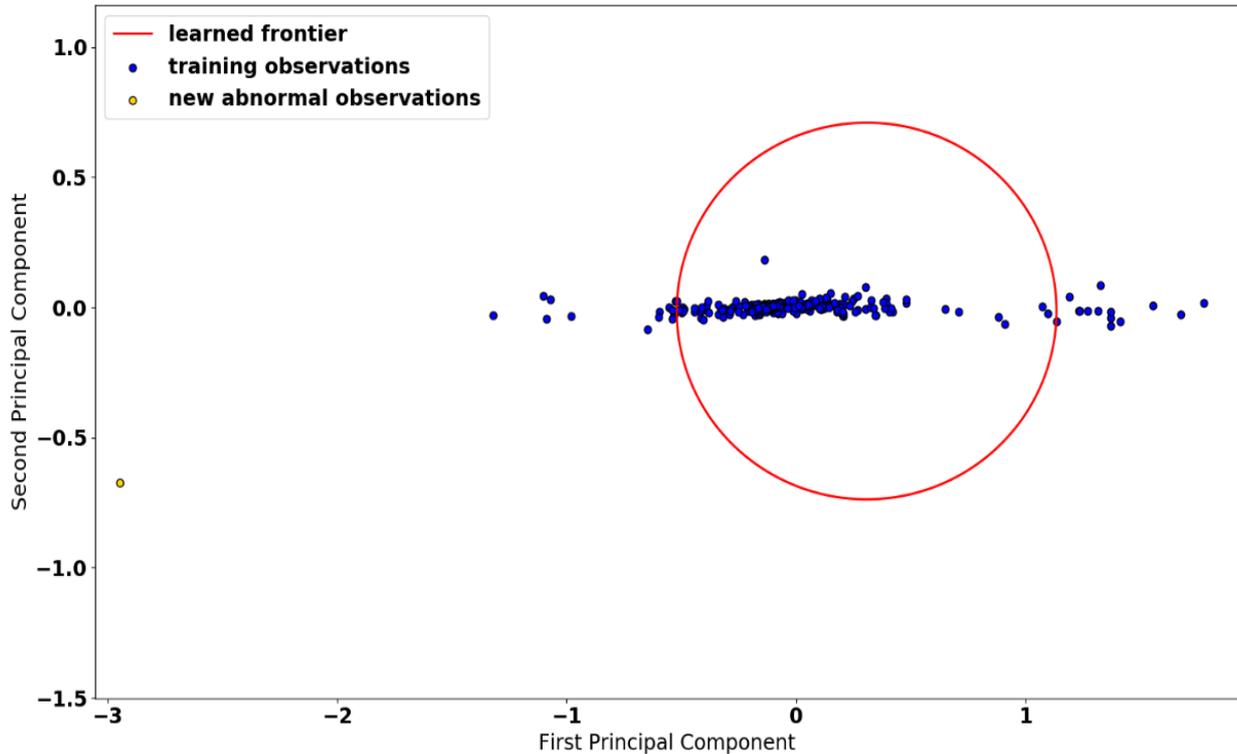


Fig. 10. Detecting damage in two two-fifth of the blade using the third element of the mode shape

the damage is introduced to the FE model of the structure by three distinct scenarios as mentioned before. Thereafter, implementing SVM on the FE simulation outcomes, the existence and location of damage can be successfully determined.

3.1. Modal Parameters From Fe Simulations

The first three natural frequencies results from FE forward solution on health and damaged systems are presented in Error! Reference source not found.. Considering the results in this table, the effect of damage and its different scenarios is obvious on the changes in modal parameters of the system. It should be noted that the damages have been inflicted on the spar, which is a bar in the middle of the blade that boosts the structural rigidity of the blade.

3.2. Damage Detection By Modal Parameters

Implementing the first damage scenario, the existence of damage is detected successfully by introducing the first three natural frequencies and all elements of the first three mode shape features of the blade to SVM, as illustrated in Figs. 3 and 4, respectively. In these figures, each point represents a measurement. The horizontal axis depicts the first principal component and the vertical axis depicts the second principal component. The blue markers represent the training data and the learned frontier, obtained from training data, is drawn in

red. The damaged measurement is represented by the yellow marker. However, the location of the damage could not be detected as expected. In other words, the effect of damage is observed in all the elements of the mode shape vector.

In the second scenario, again the existence of damage is detected by the natural frequency. Moreover, the location of the damage is detected by analyzing the second and third elements of the first mode shape. The result of the natural frequency analysis is depicted in Error! Reference source not found..

The analysis of the mode shapes under the second damage scenario is also illustrated in Error! Reference source not found. for the undamaged part of the blade and in Error! Reference source not found. for the damaged part. As clearly depicted, only the elements corresponding to the damaged part of the spar indicate the existence of the damage.

In the third scenario, the stiffness of two-fifths of the spar was reduced by 50 percent, and the same steps are taken. The natural frequency analysis is illustrated in Fig. 8. Furthermore, the study of mode shapes indicated the existence of damage correctly in the second and third fifths of the spar. These results are illustrated in Figs. 9 and 10, respectively.

4. CONCLUSIONS

The stochastic subspace identification is capable of

identifying the system modal parameters very well, no matter how significant the noise level is, and is a reliable way to extract damage-sensitive features. Modal parameters of the structure seem to be a good indicator of damage, but the extent of the damage must be substantial. The anomaly detection algorithm is capable of finding the damaged data autonomously once trained with a large data set. There is a possibility of false positive alarms, which means the algorithm diagnoses normal data as an anomaly. But it can be overcome by enlarging the training data set so that the trained frontier of one-class kernel SVM will be more precise. For further research, the capability of other features like wavelets and modal curvature could be investigated. The performance of different anomaly detection algorithms could also be compared with the current algorithm.

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