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Title: Application of a Wireless Sensor Node to Health Monitoring of Operational Wind Turbine Blades

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ABSTRACT

Structural health monitoring (SHM) is a developing field of research with a variety of applications including civil structures, industrial equipment, and energy infrastructure. An SHM system requires an integrated process of sensing, data interrogation and statistical assessment. The first and most important stage of any SHM system is the sensing system, which is traditionally composed of transducers and data acquisition hardware. However, such hardware is often heavy, bulky, and difficult to install *in situ*. Furthermore, physical access to the structure being monitored may be limited or restricted, as is the case for rotating wind turbine blades or unmanned aerial vehicles, requiring wireless transmission of sensor readings. This study applies a previously developed compact wireless sensor node to structural health monitoring of rotating small-scale wind turbine blades. The compact sensor node collects low-frequency structural vibration measurements to estimate natural frequencies and operational deflection shapes. The sensor node also has the capability to perform high-frequency impedance measurements to detect changes in local material properties or other physical characteristics. Operational measurements were collected using the wireless sensing system for both healthy and damaged blade conditions. Damage sensitive features were extracted from the collected data, and those features were used to classify the structural condition as healthy or damaged.

Application of a Wireless Sensor Node to Health Monitoring of Operational Wind Turbine Blades

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NOMENCLATURE

$x(n)$	*discrete time signal*	$\bar{x}$	*feature vector*
a_i	i^{th} *AR coefficient*	$\hat{\mu}$	*sample mean*
ϵ_n	*error signal*	$\{S\}$	*sample covariance matrix*
d	*Mahalanobis distance*		

ABSTRACT

Structural health monitoring (SHM) is a developing field of research with a variety of applications including civil structures, industrial equipment, and energy infrastructure. An SHM system requires an integrated process of sensing, data interrogation and statistical assessment. The first and most important stage of any SHM system is the sensing system, which is traditionally composed of transducers and data acquisition hardware. However, such hardware is often heavy, bulky, and difficult to install *in situ*. Furthermore, physical access to the structure being monitored may be limited or restricted, as is the case for rotating wind turbine blades or unmanned aerial vehicles, requiring wireless transmission of sensor readings. This study applies a previously developed compact wireless sensor node to structural health monitoring of rotating small-scale wind turbine blades. The compact sensor node collects low-frequency structural vibration measurements to estimate natural frequencies and operational deflection shapes. The sensor node also has the capability to perform high-frequency impedance measurements to detect changes in local material properties or other physical characteristics. Operational measurements were collected using the wireless sensing system for both healthy and damaged blade conditions. Damage sensitive features were extracted from the collected data, and those features were used to classify the structural condition as healthy or damaged.

INTRODUCTION

Structural health monitoring (SHM) is the process of detecting damage in structures. The goal of SHM is to improve the safety and reliability of aerospace, civil, and mechanical infrastructure by detecting damage before it reaches a critical state. To achieve this goal, technology is being developed to replace qualitative visual inspection and time-based maintenance procedures with more quantifiable and automated damage assessment processes. These processes are implemented using both hardware and software with the intent of achieving more cost-effective condition-based maintenance. A more detailed general discussion of SHM can be found in (1).

Wind turbines represent a significant investment in the energy production infrastructure of the United States and countries around the world. In the U.S., a recent Department of Energy report examined the issues surrounding the production of 20% of the nation's electricity from wind energy by the year 2030(2). In order to maintain the sheer number of operating wind turbines required to meet that goal, automated and continuous structural health monitoring systems must become a reality. A typical horizontal-axis wind turbine sits atop a tower and has three rotor blades connected to a hub, which drives a low-speed shaft connected to a gearbox. The output of the gearbox drives a generator, which produces the desired electricity. Gearboxes in installed wind turbines seem to have unreasonably high failure rates (3) and are particularly expensive to repair, both in terms of incidental cost and lost productivity.

Although blade replacement is less common and less expensive than gearbox repair (3), it must be the case that the loads causing gearbox failures are transmitted from the wind first through the blades. It may be the case that sophisticated monitoring of the blades' loading and structural condition could prevent all manner of woes for wind turbine maintenance. This study applies a compact wireless data acquisition system to health monitoring of wind turbine blades, with the ultimate goal of improving the overall ability to assess wind turbine health. Although large-scale wind turbines are actually equipped with slip rings, providing power and communications from the tower into the hub, wireless communication systems provide notable advantages. These advantages include fewer additional complications to the blade manufacturing process, no additional maintenance issues caused by failed wires and cabling, and preserving the insulation of the turbine hub from lightning strikes at the blade tip. This study takes a significant step toward understanding overall wind turbine health by monitoring the start of the load path and vehicle for introduction of debilitating damage: the blade.

METHODOLOGY

Any damage detection or classification scheme requires an integrated process of sensing, data interrogation and statistical assessment. Inherent in the statistical assessment process is some comparison to a baseline condition; in order to determine that a given structure or system is damaged, there must be some knowledge concerning its behavior when operating in a healthy condition. This study presents experimental data from wind turbine blades tested in both healthy and damaged conditions. Features were extracted from these collected data, and those features were classified to determine both the condition of the turbine blade.

Two methods of feature extraction were implemented in this study. The first was based on conventional spectral estimation, whereby the power spectral density (PSD) of the measured acceleration data was estimated, and the location of the first resonance was identified using a simple peak-picking algorithm. The state of the wind turbine blade was classified using scalar thresholding on the location of the first resonance. The threshold value was determined, depending on the test, using either visual inspection or a decision rule based on separating two normally distributed random variables. A more detailed explanation of separating random variables can be found in (4).

The second method was based on fitting an auto-regressive (AR) model to the measured acceleration data. An AR model determines the coefficients a_i such that, for a signal $x(n)$,

$$x(n+1) = \sum_{i=n-p}^{n} a_i x(i) + \epsilon_n, \tag{1}$$

where ϵ_n is a Gaussian distributed random variable for a well-fit model. The vector of AR parameters was then used to compute the square Mahalanobis distance (5) from the mean of the set of healthy training data. The square Mahalanobis distance is given by

$$d^2 = [\bar{x} - \hat{\mu}]^T \{S\}^{-1} [\bar{x} - \hat{\mu}], \tag{2}$$

where $\bar{x}$ is the feature vector of interest, $\hat{\mu}$ is the sample mean of the training set, and $\{S\}$ is the sample covariance matrix of the training set. Using the Mahalanobis distance requires an assumption that the underlying data are Gaussian, which may be reasonable if the data are collected without deterministic changes in the experimental apparatus.

The state of the wind turbine blade was then classified by using a one-dimensional clustering algorithm using the square Mahalanobis distance as a scalar feature. The clustering method attempted to minimize the sum of the variances of each cluster group. Given n cluster groups, and denoting as C_j the set of points belonging to the j^{th} cluster, the objective function to be minimized is

$$f(C) = \sum_{j=1}^{n} \sum_{i \in C_j} \left\| \bar{x}_i - \hat{\mu}_j \right\|^2, \tag{3}$$

where C defines all cluster sets, x_i is a cluster member, and $\hat{\mu}_j$ is a cluster mean. A more detailed treatment of cluster analysis can be found in (6).

EXPERIMENTAL SETUP

Acquisition Hardware

Time domain data were collected from the rotating blade using the WiDAQ, or wireless data acquisition system, which was developed previously by the authors (7). The WiDAQ was designed as an expansion to the wireless impedance device (WID3), intended to extend its capabilities beyond high-frequency impedance measurements to collect low-frequency data, such as structural vibration data from accelerometers. The WiDAQ and its major components are shown in Figure 1. The WiDAQ is controlled by an ATmega1281v µCu, but it lacks its own radio. The WiDAQ can function as a stand-alone device using wired communication, but it is primarily intended to be used in combination with the WID3, which provides the wireless communication capability. The WID3 and the WiDAQ have the ability to share resources, such as processing power, data storage, and access to peripheral devices.

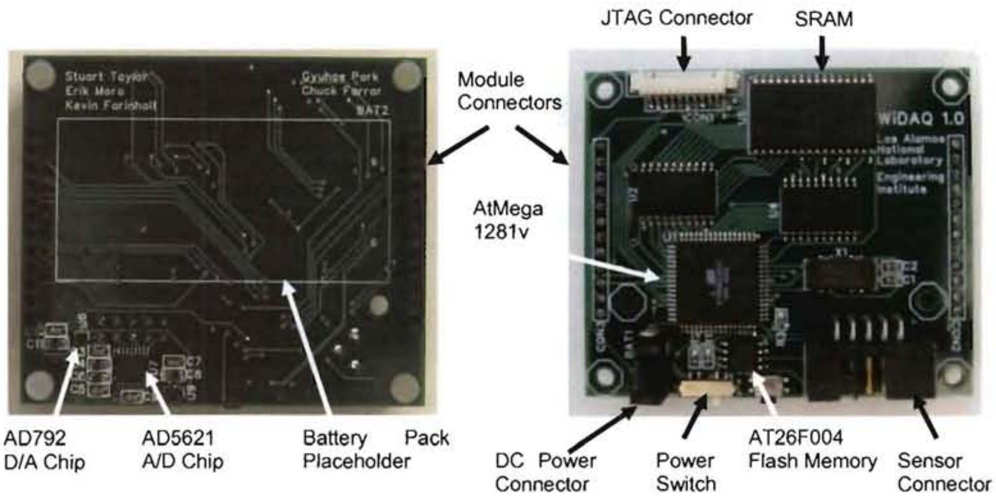

Figure 1. Major components of the WiDAQ

The primary functions of the WiDAQ are data acquisition and signal generation, the key components for which are the Analog Devices AD7924 analog-to-digital (A/D) and AD5621 digital-to-analog (D/A) converters. By excluding sensor-specific conditioning circuitry from the WiDAQ, sensor data can be acquired from any transducer that provides a voltage output; sensor-specific conditioning, such as that required for Integrated Circuit Piezoelectric (ICP) accelerometers, must be included on a third module. The four-channel AD7924 has a 12-bit resolution over a range from 0 to 2.5 V, and it would consume a maximum of 6 mW while sampling at one million times per second. However, the combined system with the ATmega1281v has a maximum useful sampling frequency of 40 kHz. After each measurement sequence, the recorded data can be stored in on-board flash memory for later retrieval. With these capabilities, a network of sensor nodes could wake on schedule, acquire data, and return to sleep. At a later time, a data mule, such as an unmanned aerial vehicle (8), could approach the sensor network and request it to transmit the recorded data.

The sensors used in this study were PCB Piezotronics model 352A24 ICP accelerometers with a nominal sensitivity of 100 mV/g. A separate module, the WiDAQ ICP, provided the excitation power required for the ICP accelerometers, low-pass filtered the signals to prevent aliasing during A/D conversion, and adjusted the output voltage to lie within the 0 to 2.5 V input range of the AD7924. In order to maintain low power consumption, no additional amplification was implemented prior to A/D conversion; however, this lack of amplification resulted in underuse of the A/D converter's dynamic range for low-excitation test conditions. The WiDAQ ICP and the three modules assembled together are shown in Figure 2.

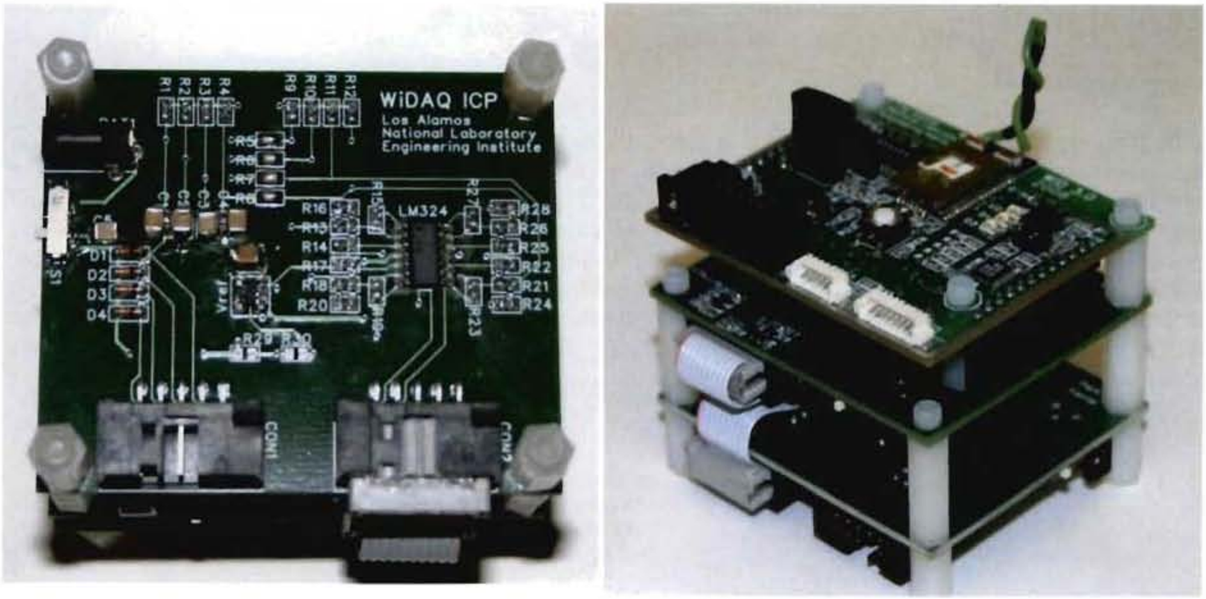

Figure 2. WiDAQ ICP (left) and assembled modules for vibration data acquisition (right)

Test Article and Instrumentation

The test article for this paper was the Whisper 100, manufactured by Southwest Windpower (9), which has a tip-to-tip diameter of 2.1 m and a rated power output of 900 W under 12.5 m/s (28 mph) sustained winds. Four wind turbine blades were instrumented in turn with three accelerometers each, located at 69, 38, and 1 cm from the blade tip. The test setup is shown in Figure 3. Three blades were tested in an undamaged condition, and the fourth was subjected to two successive levels of damage. For each test condition, five replicates were collected using a sampling rate of 504 Hz, and each record contained 2048 points. Each of the three undamaged blades was tested at both 20 and 26 °C, for a total of 30 replicates in the baseline condition.

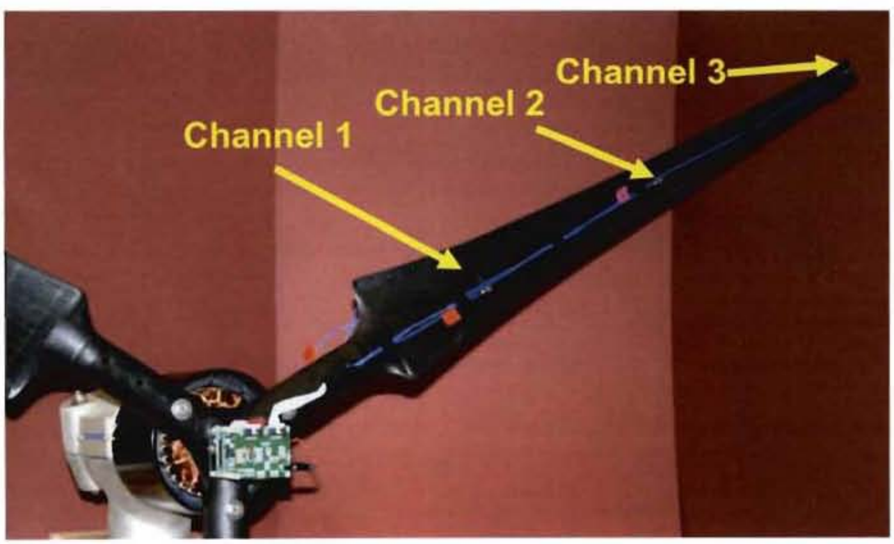

Figure 3. Whisper 100 instrumentation and test setup

Damage

Damage was inflicted by progressively cutting the wind turbine blade perpendicular to its longitudinal direction at a location 70 cm from the blade tip. Two damage cases were tested: in the first damage case, the cut extended 40% of the width of the blade; in the second case, the cut extended 60% of the width of the blade. A photograph of the blade in the second damage condition is shown in Figure 4.

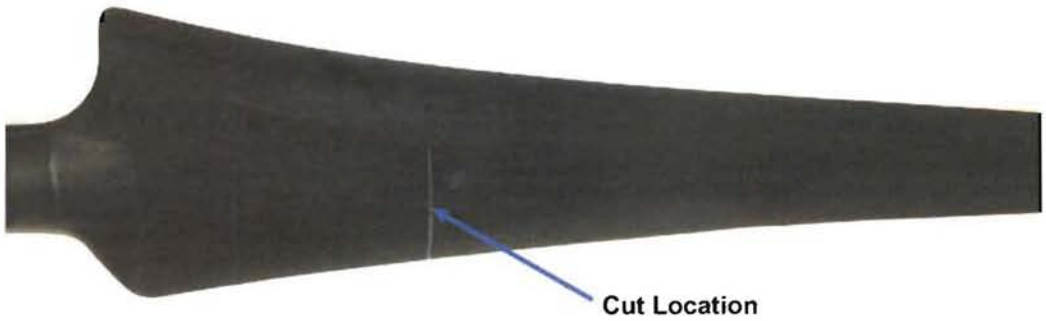

Figure 4. Blade damage case 2

DAMAGE DETECTION METHODOLOGY

Resonant Peaks

All tests in this study were conducted in an output only sense; there was no measurement of input force or initial conditions. Two types of tests were conducted: a free vibration, or "pluck" test, and an ambient excitation, or "free-spin" test. Of the two, only the ambient excitation test would have useful applicability to an operating wind turbine, but the results of the pluck test are informative. To perform the pluck test, the blade was given an initial displacement and subsequently released. This type of test provided a much higher signal-to-noise ratio (SNR) than the ambient excitation test. Results of a typical pluck test are shown in Figure 5. The time histories are shown for each sensor in the left plot of Figure 5, and the PSD estimates are shown on the right. Note that the SNR for sensor 1 is quite low; its response for the first resonance is about 50 dB lower than that for sensor 3, and very little of the A/D converter's 0 to 2.5 V dynamic range was able to be utilized.

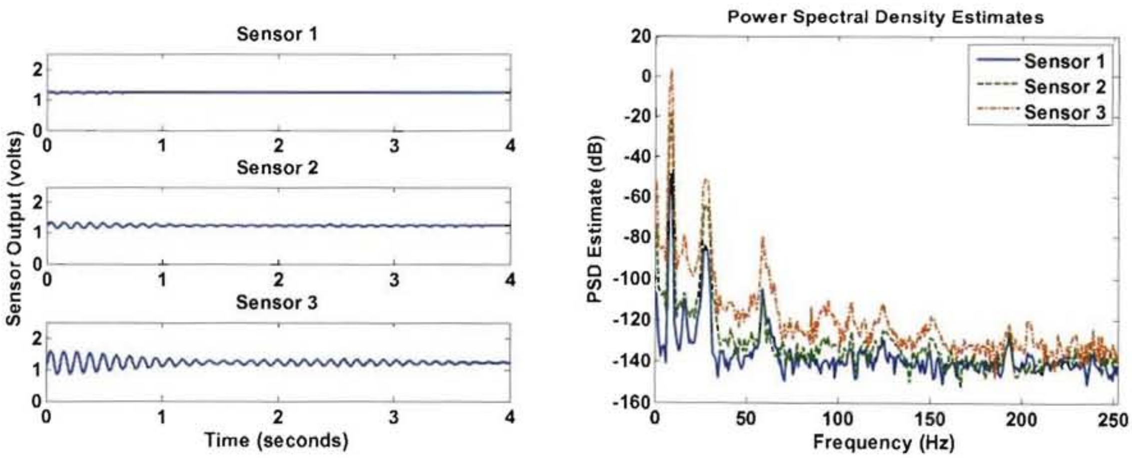

Figure 5. Time histories (left) and power spectral density estimates (right) for a pluck test

To perform the ambient excitation test, the wind turbine was spun by hand and allowed to free-spin while the data were collected. This excitation is similar to the type of excitation the wind turbine would undergo during normal operating conditions. Results of a typical ambient excitation test are shown in Figure 6. The time histories are shown for each sensor in the left plot of Figure 6, and the PSD estimates are shown on the right. Note that only a small portion of the 0 to 2.5 V dynamic range could be utilized by any sensor; the resulting power of the first resonance, visible in Figure 6 (right) is 40 dB lower than that for the corresponding sensor in the pluck test, shown in Figure 5 (right). The low frequency oscillation visible in Figure 6 (left) is likely a low-frequency structural mode related to the turbine's rotation.

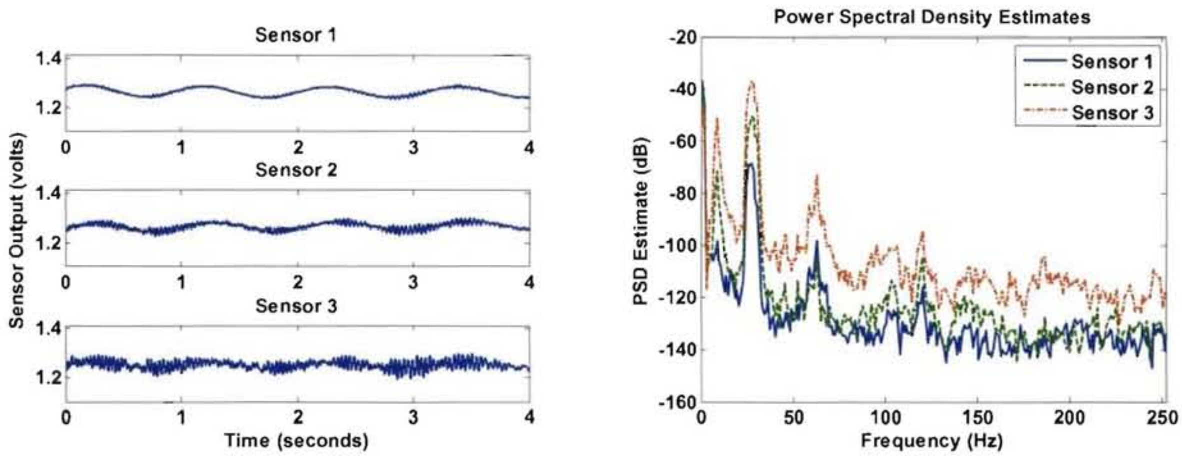

Figure 6. Time histories (left) and power spectral density estimates (right) for a free-spin test

Feature Extraction

The most basic method of structural health monitoring might be observing shifts in structural resonances. Using the pluck test data, shifts in the first resonant peak can be visibly identified for each damage case. A plot of the first resonant peak for the three healthy blades and the two damage cases is shown in Figure 7. As expected for a decrease in structural stiffness, the first structural resonance decreases for each successive damage case. Under theses excitation conditions, the damage can be detected quite easily. However, for the test data obtained under ambient excitation conditions, the same damage is much more difficult to detect. For 30 healthy cases and 10 damaged cases, the first resonant peaks are shown in Figure 7 (right). Although there is a generally visible trend for the damaged cases to show a decrease in the frequency of the first resonance, the low SNR for the free-spin test introduces much greater variability than was apparent in the pluck test.

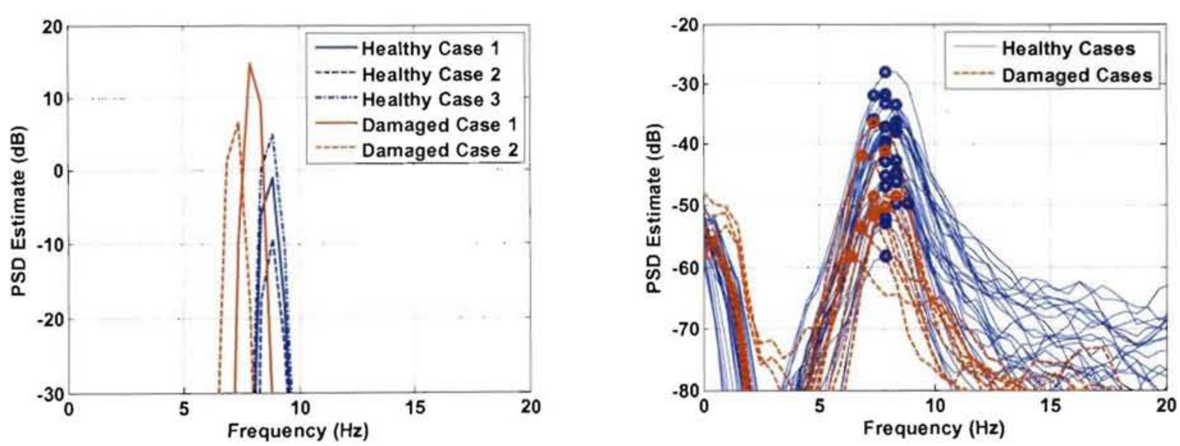

Figure 7. First resonant peaks for the healthy and damaged cases: pluck test (left) and run test (right)

Damage Classification

In the case of the pluck test, the peaks in Figure 7 (left) are coincident for the three healthy cases, and they decrease for the two successive levels of damage. However, for the free-spin test, the peaks shown in Figure 7 (right) are not in easily separable clusters. If one were to assume that the data for both the healthy and damaged conditions were normally distributed, and that training data in both the healthy and the damaged configuration were available, the structural condition could be classified by setting a threshold at the intersection of the probability density functions describing the damaged and healthy data, respectively (4). This method carries the significant disadvantage that training data from the damaged structure must be available in order to classify future measurements. This method also requires that the expected damage be of a predictable and consistent form, rather than simply being a measureable deviation from healthy behavior. Figure 8 shows the results of such a classification scheme. Using this method, two healthy cases would be incorrectly identified as damaged, while three damaged cases would have been missed, having been misclassified as healthy.

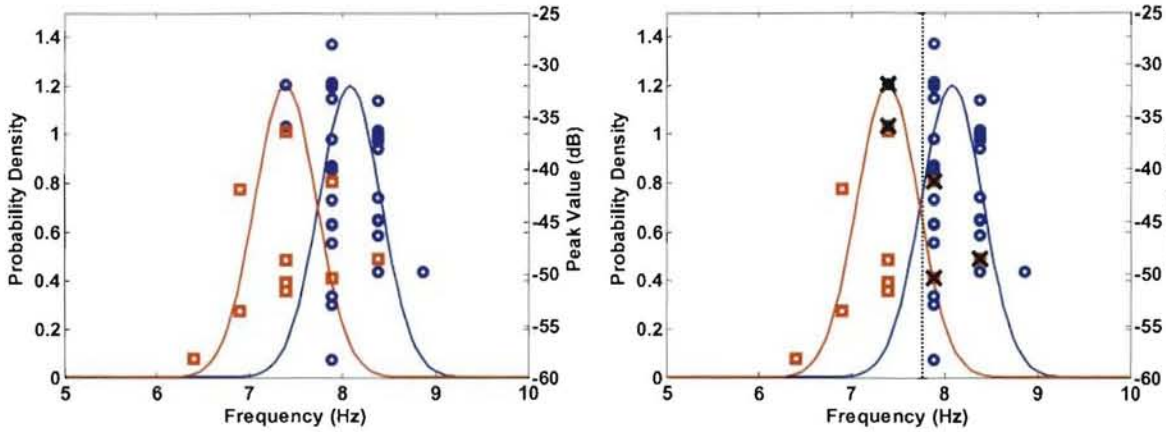

Figure 8. Classification of structural condition using known damaged test cases as training data

Autoregressive Model

Feature Extraction

As an alternative to conventional spectral analysis of structural vibration data, a linear auto-regressive (AR) model of order 14 was determined for each of the 30 healthy test cases and the 10 damaged test cases. Of the 30 healthy test cases, 25 were chosen to train the damage detection algorithm, with the first of each set of five replicate tests was in a control group. Supposing that each of the 14-element vectors in the healthy training set were sampled from the same multidimensional Gaussian distribution, the sample covariance matrix was estimated for the 25 training samples. Using that covariance matrix, the Mahalanobis distance from the mean of the training set was computed for each of the 30 healthy cases and the 10 damaged cases. The Mahalanobis distance was chosen as a damage indicating feature, or damage index, and it is shown plotted versus test number in Figure 9. Visually, the control cases appear to be correctly identified as belonging to the healthy test group, with the exception of test 16. Furthermore, the damaged test cases appear easily distinguishable from the healthy ones, and the two distinct levels of damage are distinct from one another.

Damage Classification

The state of the wind turbine blade was classified using a simple clustering algorithm, which minimized the sum of the variances of each cluster. The algorithm does it require training data taken from the structure in a damaged condition, but only that the features extracted from each structural condition be separable. Partitioning the damage indices into three groups, the clustering algorithm separated the two levels of damage from one another as well as from the baseline data. The clusters separating the two damage levels are indicated in Figure 9; the expected false indication of damage occurred at test number 16.

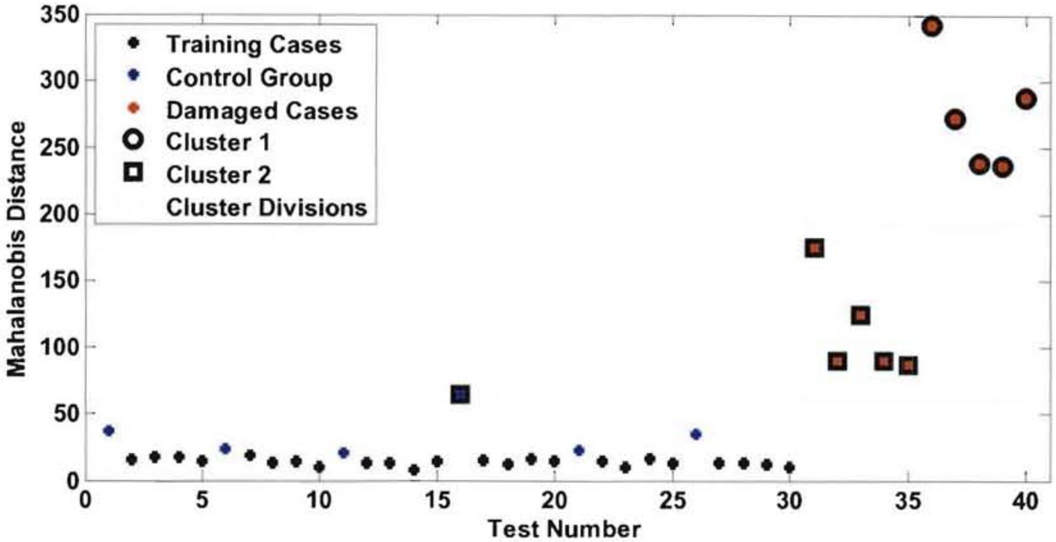

Figure 9. Mahalanobis distance as a damage classifier

SUMMARY OF RESULTS

Structural vibration data were collected from a wind turbine under simulated operational conditions using blades in both healthy and damaged states. Using conventional spectral analysis and resonant peak tracking, the blade damage could be identified using forced excitation, but in the case of ambient excitation, the damage was much more difficult to discern without utilizing training data from the damaged condition. Using an auto-regressive model, the Mahalanobis distance of each AR parameter vector from the mean of the training set proved effective not only to identify damage, but also to indicate relative extent.

FUTURE WORK

This study will be combined with other work utilizing active sensing methods, whereby the wind turbine blade will be actively excited and interrogated using a wireless low-power platform similar to that used for the current study. Using this two-pronged sensing approach, the application will be extended to larger wind turbine blades with composite construction. In addition to varying the temperature, other operational and environmental variabilities will be introduced. Furthermore, having established the ability to detect damage in this case, more realistic damage conditions such as fatigue cracking or delamination will be considered.

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