Proceedings of the IMAC-XXVIII
February 1–4, 2010, Jacksonville, Florida USA
©2010 Society for Experimental Mechanics Inc.

Structural Damage Identification in Wind Turbine Blades Using Piezoelectric Active Sensing

Abraham Light-Marquez[1], Alexandra Sobin[2], Gyuhae Park[3], Kevin Farinholt[3]

[1] Dept. of Mechanical Engineering, New Mexico Institute of Mining and Technology
[2] Dept. of Aeronautic Engineering, Daniel Webster College
[3] The Engineering Institute, Los Alamos National Laboratory, Los Alamos, NM 87545

Abstract

This paper presents a variety of structural health monitoring (SHM) techniques, based on the use of piezoelectric active-sensors, used to determine the structural integrity of wind turbine blades. Lamb wave propagation, frequency response functions, and a time series based method are utilized to analyze the wind turbine blade. For these experiments, a 1m section of a 9m CX100 blade is used. Different types of simulated damage are introduced into this structure and a performance matrix is created to compare the validity and functionality of each technique. Overall, these three methods yielded sufficient damage detection to warrant further investigation into field deployment. Time series analysis shows the most effective and reliable to detect damage while lamb wave testing could locate, as well as detect the onset of damage. This paper summarizes considerations needed to design such SHM systems, experimental procedures and results, and additional issues that can be used as guidelines for future investigations.

Introduction

In past years, wind turbine technology has become a topic of extensive investigation. The DOE projects that 20% of the US electrical supply could be produced via wind power by 2030 [1]. In order to reach this goal, an increase in the efficiency of wind power generation will be required. Therefore, a nondestructive, structural health monitoring (SHM) technique that can be used in real-time during operation could be very useful in the wind turbine industry [2]. These structures are not only immensely difficult to install due to their large size but are normally placed in remote locations. It would be cost-effective to design and implement an SHM system which would enable the operator to monitor these structures from an offsite location, while safely maintaining the system. An important component of the wind turbine system to monitor is the blade because it contributes 15 – 20% to the total cost, is one of the most expensive components to repair, and can create secondary damage to other components due to rotational imbalance [3].

The goal of this study is to assess the advantages and disadvantages of using high-frequency SHM techniques, including lamb wave, frequency response function, and time series based measurements as a way to nondestructively monitor the health of a wind turbine blade with piezoelectric sensors [4-6]. An array of piezoelectric sensors on a 1m section of a 9m CX100 blade are used for the purposes of this research. The assessment will delve into how to provide damage detection effectively with each method. Optimization of issues which arise with items such as testing procedures, data collection and data processing are attempted. Lamb wave propagation uses waves traveling through the thickness of the structure. Similarly, frequency response functions measure the frequency response of the structure given an excitation. On the other hand, time series analysis uses time domain responses from the structure to determine a data-driven model and use that model to determine if the system is damaged. These three techniques measure real-time data at high-frequency ranges (>5 kHz). When a system response is compared against baseline, undamaged, measurements a noticeable variation can imply structural damage.

A performance matrix is then created to look into the three SHM techniques and compares a defined set of damage detection parameters. Damage detection has been defined with three major parameters which will be detailed in the later section: the detection area of an individual sensor, the ability to locate the onset of damage, and the minimum damage size for damage verification. Industry is optimally looking for a technique that can detect the location of minor damage with a small number of sensors within a large area. The wind turbine blade

itself can easily be damaged with no signs due to the delamination occurring within the composite material. Moreover, the turbine blade could catastrophically fail, cause an imbalance, and render the system inoperable.

In addition to these parameters, commercialization and implementation concerns (weight, cost, installation, etc.) are addressed after analyzing the three techniques. For instance, it is crucial for complex SHM systems to self-diagnose and interpret errors within sensors. Sensor fracture is the most common type of failure, which can be attributed to the brittle nature of many piezoelectric devices. Another issue that arises is the bonding condition of the PZT sensors to the structure. During use, the adhesive can easily fail which would result in inaccurate data. If there is no self diagnostic tool within the system, then sensor damage would be interpreted as structural damage and the health monitoring system would be ineffective. These concerns will also be part of the performance matrix in order to accurately assess the commercial feasibility of each technique.

2 Experimental Procedure

The basic experimental setup for the comparison of structural health monitoring systems consisted of a 1m section of a CX100 wind turbine blade instrumented with piezoelectric patches, as shown in Figure 1 below. The patches were connected to a National Instruments PXI data acquisition system, shown in Figure 2 below.

2.1 Lamb Wave Propagation

The lamb wave propagation experiment was performed, which utilizes one of the piezoelectric patches as an actuator and another as a sensor. The user interface for this program can be seen in Figure 2 below.

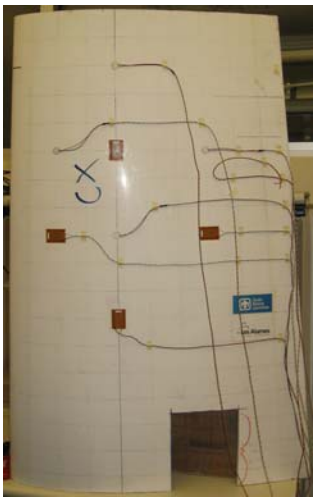

Figure 1: Turbine Blade Section

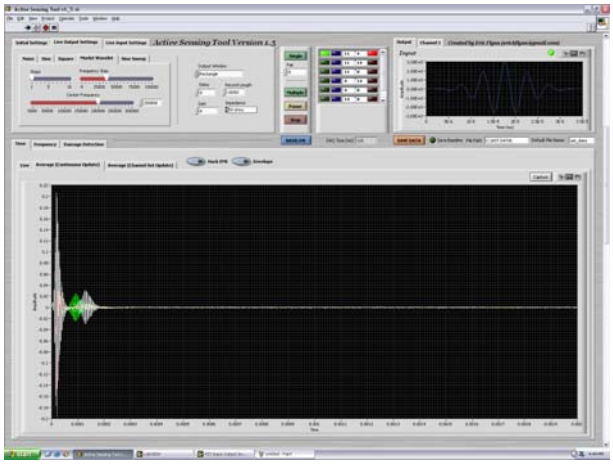

Figure 2: Lamb Wave Testing Interface

The interface allows for the modification of the excitation waveform, both shape and magnitude. For this set of experiments a Morlet Wavelet was selected and the interface provides control over the waveform's center frequency. The tests used four piezoelectric patches which results in six wave propagation paths, as seen in Figure 3 below. The vertical path is located directly on the center support spar of the blade, as seen in the cross section picture in Figure 4.

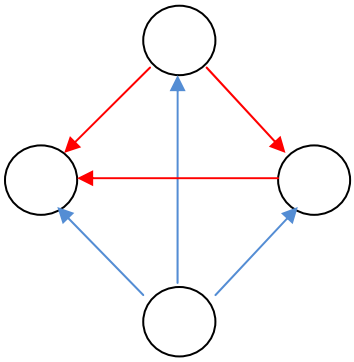

Figure 3: Propagation Directions

Figure 4: Cross Section View of Turbine Blade

2.1.1 Input Waveform Frequency

To maximize the effectiveness of the lamb wave technique the excitation frequency needs to provide a response that is capable of indicating damage. In order for damage detection to be possible the magnitude of the response must be of a sufficient magnitude, and the response must be separated by a sufficient amount from the electromagnetic interference to allow for proper identification of the arrival waveform. Due to the complexity of the blade section, traditional methods of predicting the ideal excitation frequency for homogeneous material are not applicable and the ideal frequency must be determined by experimentation.

The aforementioned setup was used to modify the center frequency of the input waveform and the response was recorded along each of the propagation paths. The response was recorded for a range of frequencies from 15 kHz to 250 kHz. The frequencies which displayed the best response were selected for further testing to identify damage detection capability.

To determine the damage detection capability of each frequency the natural response of the system was used as the baseline. Damage was then simulated by applying a piece of industrial putty to the surface of the turbine blade in the path of propagation of the lamb waves. The putty simulates changes in the damping of the structure in a localized area, similar to the effects of delamination formation. For this set of tests the putty section was approximately a 3.5cm square with 0.5cm thickness. The putty was placed in the path of the propagating waves; this was done for all of the paths. Figure 5 illustrates an example of the putty acting as damage on the structure.

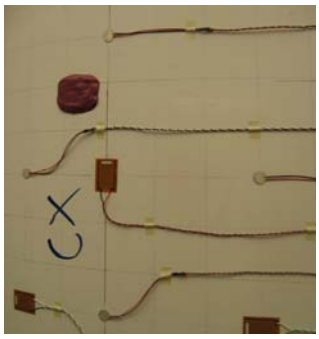

Figure 5: Putty attached to the blade to simulate Damage

2.1.2 Baseline Measurements and Environmental Variations

After the ideal excitation frequency has been determined, multiple baselines for the undamaged structure were recorded. Thus these baselines contain some variations in the boundary conditions to attempt to simulate potential real world variability. Several damaged measurements were also taken during this set of testing to

determine the damage detection capabilities of each technique. Table 1 contains a list of environmental variations and damage locations that were tested.

Table 1: Environmental Variations

Upright on Table	On Pink Foam Upright on Table	On White Foam Upright on Table	On Bubble Wrap Upright on Table
Upside-down on Wood Table	Laying on Back on Table	Upside-down on Table	Upright on Wood Table
Leading Edge on Table	Hammering + Upside-down	Rocking Upright	Rocking on Leading Edge

The tests were conducted along all six paths for the frequency(s) of interest.

2.2 Frequency Response Method

The frequency response method was investigated using a National Instrument data acquisition system. The user interface for this program can be seen in Figure 6 below.

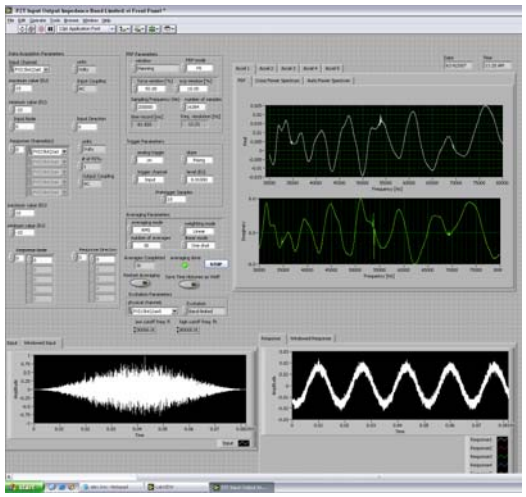

Figure 6: FRF User Interface

The interface uses one of the piezoelectric patches as an actuator and a different one as a sensor. The actuator is connected through an amplifier to the DAQ function generator. The waveform sent to the actuator by the amplifier is recorded by connecting the amp to one of the DAQ's inputs. The sensor is connected directly to one of the DAQ's input channels. The program allows for the manipulation of the excitation waveform, specifically the excitation bandwidth. The program creates the frequency response function (FRF) based on the recorded excitation waveform and sensor output.

Four paths, shown in Figure 7, were experimentally tested and as in the lamb wave propagation method, a variety of boundary conditions was used to determine variations in the baseline data for each path (See Table 1). These data sets were then used to compare with the damaged data, simulated by applying a square piece of industrial putty to the surface of the turbine blade.

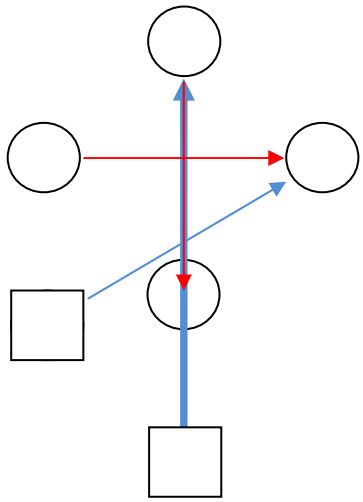

Figure 7: FRF Propagation Directions

2.3 Time Series Analysis

The system used to capture the time domain response of the structure was a Dactron LabVIEW program. The structure was excited with a chirp signal from 5 – 20 kHz over a voltage range of 30 volts. The sampling frequency was 48 kHz, a total of 8192 points data points were recorded. Two paths were analyzed, as seen in Figure 8.

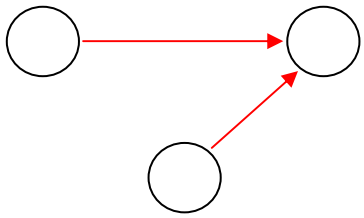

Figure 8: Time Series Propagation Paths

3 Results

The data analysis for this project was conducted using EPDLab, an interactive Python environment.

3.1 Lamb Wave Propagation

Lamb wave testing consisted of two phases. The first was determining the ideal excitation frequency. As previously stated, the ideal excitation frequency could not be determined with traditional methods and had to be determined experimentally with an anisotropic material. The second phase was the collection of multiple baseline cases as well as damage identification testing. The purpose of this peculiarity in the testing was to see if the high frequency source could excite the structure so that even small damage could be detected.

3.1.1 Preliminary Testing Analysis

The preliminary testing consisted of a qualitative analysis on the systems response. The response at a range of frequencies (15-250 kHz) was visually analyzed to determine the frequency which gave the best response for each path (See Figure 3: Propagation Directions). The parameters monitored were the time offset, noise disturbance, and magnitude of the systems response. See Figure 9 for a graphical description of some of these parameters.

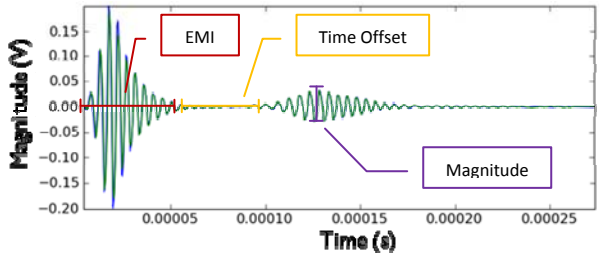

Figure 9: Lamb Wave Response Parameters

Overall, most of the paths showed desirable responses with an input frequency of 25 kHz. Two paths did not follow this trend and gave more advantageous responses with an input frequency of 200 kHz. Therefore, the second phase of lamb wave testing was conducted at both 25 kHz and 200 kHz.

3.1.2 Baseline and Damage Testing Analysis

Once a reasonable frequency for each path was determined from the preliminary qualitative analysis, additional testing was performed on the structure. The testing consisted of collecting baseline and damaged cases. The purpose of this study was to detect damage within the structure. In order to accomplish this task, the data were reduced by transforming time-domain data into the frequency domain, and performed a cross-correlation analysis between a "true" baseline measurement and newly acquired data.

The first step in the process was to reduce the collected data sample. This step was required because the experimental set up yielded an output signal with a large electromagnetic interference (EMI) (as seen in the first portion of Figure 9). Thus the data were truncated to remove this unwanted portion of the data.

Next, the truncated output signal was converted into the frequency domain with a discrete Fourier transform. The system acts like a 'band pass filter', allowing some frequencies to pass more readily than others. The frequency domain allows a graphical representation of the system's frequency response to a given input. To determine an acceptable variation in the signal's frequency response, multiple baseline measurements were taken with changing environmental parameters, as mentioned in the Experimental Procedure section, to produce a bank of responses. This bank of baseline responses provides a foundation to compare with the damaged cases. If damaged is induced, the Fourier transform can potentially depict a distinct change in either the magnitude or the frequency content of the response signal versus the baseline measurements. See Figure 10 to visually describe an example of how the data were processed.

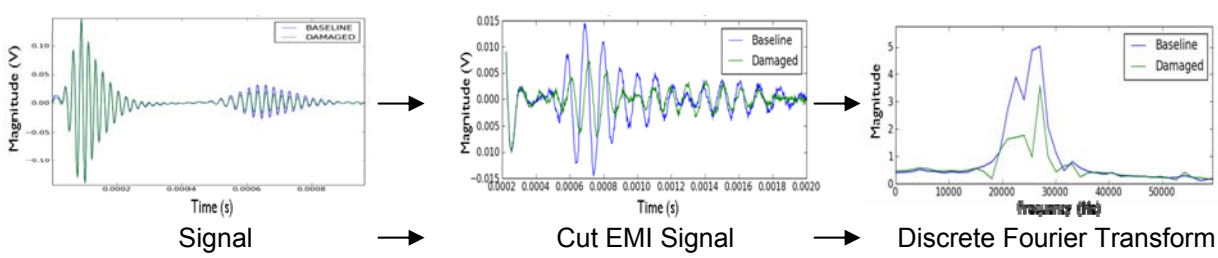

Figure 10: Lamb Wave Data Reduction

Once the data were transformed into the frequency domain, a cross correlation analysis was made between the baseline and damaged frequency domain data. Cross correlation is a measure of linear relationship between two waveforms, while a time-lag function is applied to one of them. One can potentially see a drop in correlation magnitude between the data sets as well as a lag or lead in the position of the largest magnitude correlation. Figure 11 illustrate an example. Each baseline and damaged case is compared to a single 'true' baseline case to determine if a significant difference in correlation is evident. The red dots represent the damaged case while the other nine dots of varying colors represent the baseline cases. One can see a lower correlation of the damaged case with respect to the baseline cases.

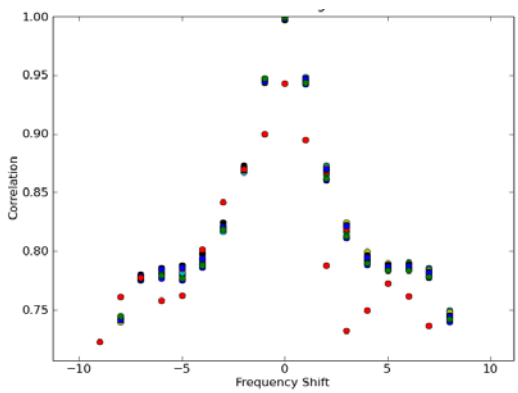

Figure 11: Lamb Wave Cross Correlation Graph

A damage index was created, which uses the maximum value of each cross correlation and subtracts the value from one. In Figure 12, one can clearly observe a large difference in the damage index between the damaged measurement and the other baseline comparisons. The last measurement was taken when the putty was attached in the direct path between the sensor and actuator. The value of the damage index allows for a decision to be made on the structural integrity of the system and if damaged has occurred.

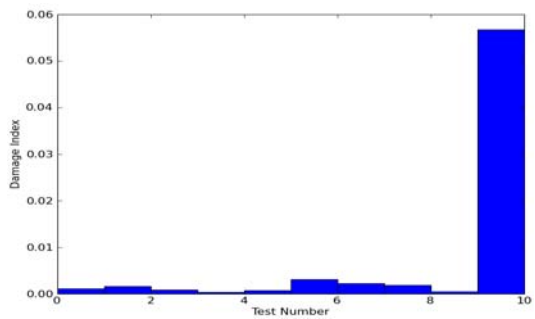

Figure 12: Lamb Wave Damage Index Graph

3.2 Frequency Response Testing Analysis

Initially, the testing was conducted using an input frequency bandwidth of 30-80 kHz on each path, as shown in Figure 7. The data were captured in the time (to perform an auto-regressive time series analysis found in the next section) and frequency domain. For the purposes of frequency responses, only the frequency domain data were used.

3.2.1 Frequency Response Functions (FRF) Analysis

Much like the lamb wave propagation data, a cross correlation was performed to compare a bank of baseline responses (all with different environmental procedures) with damaged responses. See Figure 13 for an example. One can see on Figure 13 lines 1-10 are baseline cases while line D is a damaged case. The same applies for Figure 13 where the red dots show a low cross correlation with respect to the nine baseline cases, which correlate very well.

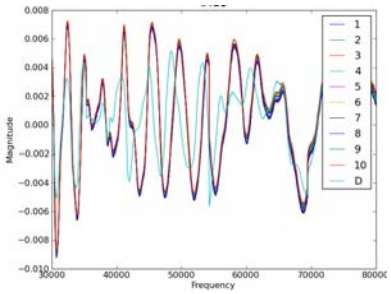

Figure 13: Frequency Response Function

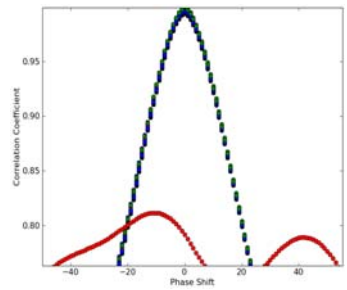

Figure 14: FRF Cross Correlation Graph

Next, a damage index was created from the cross correlation graph to determine a qualitative value between the damaged and undamaged cases as in Figure 15. This once again shows likelihood for damage in the tenth response.

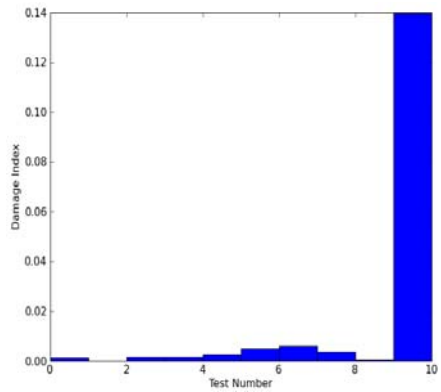

Figure 16: FRF Damage Index Graph

3.3 Time Series Analysis

An auto-regressive with exogenous input (ARX) time series analysis uses the data obtained during the frequency response testing (in the time domain) to calculate a predictive model and apply it to potentially determine damage in the structure. An ARX model is used to predict the output response of the system using data gathered in the time domain from both the output and input sensors. This predicted output response from the ARX model can then be compared to the actual response initially captured during testing to determine if significant error is present. If the model is incapable of predicting the newly measured response, then the system has changed in some way that damage may be present.

3.3.1 Normalizing Data

The time domain data was first cut to include just 60% of the data (from 20% - 80 % of the data set) in order to decrease computational time and ensure the noise seen at the extreme excitation frequencies did not significantly affect the model. This reduced data set was then normalized with respect to the standard deviation so that each set could be compared during the statistical portion to determine damage. See Equation1 for the normalization procedure.

$$X_{normalized} = (X_{original} - X_{mean})/\sigma \qquad (1)$$

Lastly, a high and low pass filter of 5 and 20 kHz, respectively was applied to the resultant data set.

3.3.2 Creating an ARX Model

Using time domain data from a random excitation input signal from one sensor to another, an ARX model can be formulated. Theoretically, the equation can be written as:

$$x(t) = \sum_{j=1}^{k} A_j * x(t-j) + \sum_{i=1}^{k} B_i * y(t-i) + e(t)$$

Initially to create the model, baseline data needs to be taken. The baseline data from the input and output sensors can be placed on both the right and left hand side of the equation in order to solve for the unknown coefficients (A_j and B_i). These coefficients model the system's baseline output response. Applying new data to the ARX model, a predicted output response can be created. If one were to apply a different baseline case to the newly created ARX model, the predicted response would be expected to highly correlate to the actual response of the system. Figure 16 illustrates the predicted and actual baseline response.

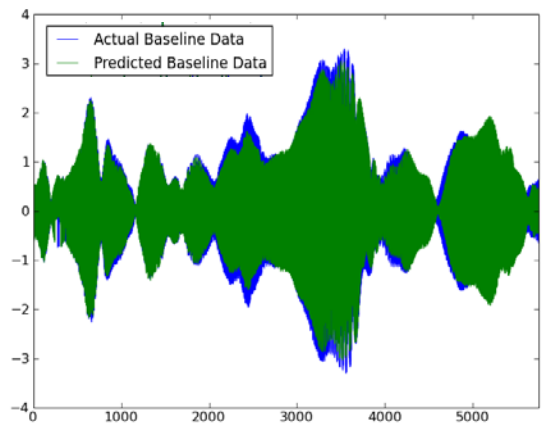

Figure 16: Predicted and Actual Baseline Responses

3.3.3 Determining Order

To perform this time series analysis, one must first determine the optimal order of the model. For the purposes of this project, The Akaike's Information Criterion (AIC) was used with built-in Matlab functions. An order of 218 for the input and 177 for the output was found. However, an order of 218 will be used for both the input and output for this project, since it provides better results.

A normal probability plot of the residual error between the actual and predicted data should show a normal distribution if the model is working accurately. As can be seen in Figure 17, the model order chosen works accurately and provides a normal probability of error.

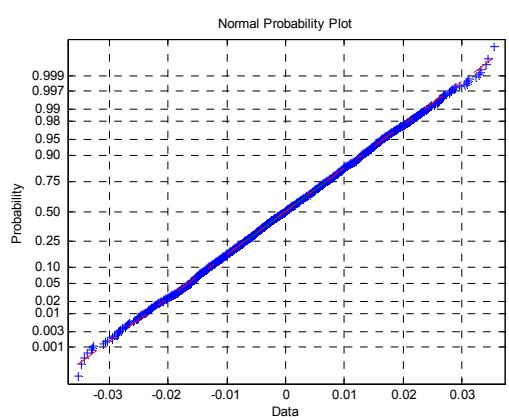

Figure 18: Residual Error Normal Probability Plot

3.3.4 Correlation Technique: Residual Error

The ARX model can be used to make a predicted response as stated before from an actual response of the system. The predicted response can be correlated to the actual response using the residual error between the actual and predicted responses of the system. In practice, the actual and predicted responses from a baseline case should correlate well and have a relatively small residual error value. Using this method, a set of correlated baseline cases can be used to determine a threshold residual error value, much like the lamb wave and frequency response methods. Damaged cases and their corresponding residual error values can be compared to the bank of baseline residual error values to find any significant difference to determine if damage is present. Potentially, the actual and predicted damaged cases should yield a relatively large residual error value.

This trend can successfully be seen in the data, shown in Figure 18. The baseline residual error is significantly smaller on average compared to the damaged residual error for a representative example baseline and damaged case.

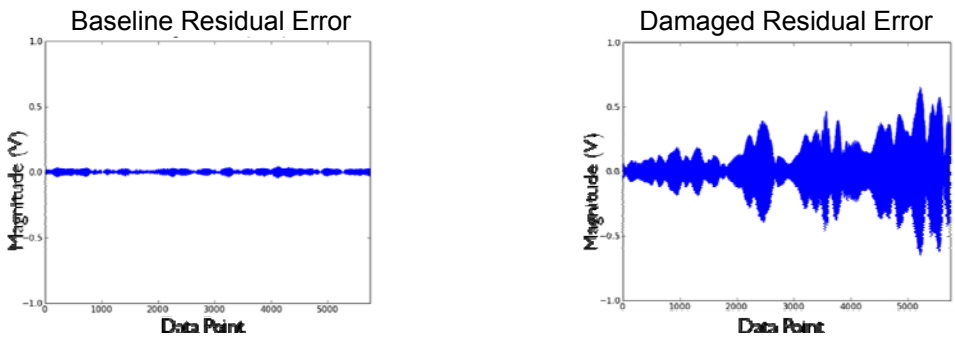

Figure 18: Baseline and Damaged Residual Error Value Comparison

Comparing all the cases, both undamaged and damaged, damaged cases close to the path could be detected, while damaged placed farther away or with little surface area could not. Figure 19 shows the RMSE (root mean square error) values of the undamaged cases in green and damaged cases in red. The blue line was chosen by visual inspection of the chart and determining the threshold residual error value so that no false positives would occur. A value of 0.038 was used for damage detection in this study.

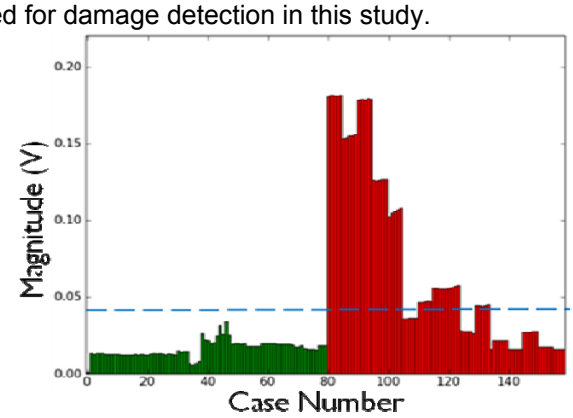

Figure 19: Path 2 Residual Error Plot

As seen in Figure 19, not all damage can be detected since it is distant from the path, although some causes larger variations than undamaged conditions. This results points out the importance of identifying better threshold limits for damage identification. In addition, a further study is needed in order to quantify the sensing range of this method.

4 Conclusions

It can be shown that all three techniques (lamb wave, frequency response, and time series analysis) can detect damage, have localized sensing capability, and are less sensitive to operational variations. Lamb wave testing was capable of detecting damage only when it was close the path of the propagating wave. For this reason lamb waves could be used to determine the location of the damage. The frequency response method showed an intriguing ability to detect damage when it was located anywhere along the spar of the blade section. This is significant because the majority of the delamination in turbine blades occurs when the skin detaches from the spar. The time series analysis is the simplest of the three techniques and thus the memory and power usage of the system is minimal. This is ideal for a SHM system that needs to be self powered when in operation on a real structure. Table 2 depicts the advantages and disadvantages of each technique to give a comparison between the techniques and illustrate which technique is best for a given scenario.

Table 2: Performance Matrix

	Pros		**Cons**			
			Memory	**Power**	**Damage Detection**	**Other**
Lamb Wave	Locate Damage		High Memory Usage	High Power Consumption	Damage Very Close to Path	Multiple Frequencies
Frequency Response	Sensitive to Spar Damage		Moderate Memory Usage	Moderate Power Consumption		
Time Series	Memory Usage	Power Consumption			Damage Close to Path	EMI Effect

In order to determine a viable damage detection package for commercial use, actual system testing within operating wind turbine blades needs to be performed. Also, an investigation into wireless sensing and power harvesting for the sensing network should be looked into. Additionally, a more rigorous statistical analysis to create a threshold value should be determined.

4 References

1. Energy, U.S. Department of. "20% Wind Energy by 2030: Increasing Wind Energy's Contribution to U.S. Electricity Supply." July 2008. Wind & Hydropower Technologies Program. <http://www1.eere.energy.gov/windandhydro/pdfs/41869.pdf>.

2. Rumsey, M.A., Paquette, J.A., “Structural Health Monitoring of Wind Turbine Blades,” *Proceedings of SPIE*, V.6933, 2008.

3. Ciang, Chia Chen, Jung-Ryul Lee, and Hyung-Joon Bang. "Structural health monitoring for a wind turbine system: a review of damage detection methods." Measurement Science and Technology (2008).

4. Park, G., Rutherford, C.A., Wait, J.R., Nadler, B.R., Farrar, C.R., 2005, “The Use of High Frequency Response Functions for Composite Plate Monitoring with Ultrasonic Validation,” *AIAA Journal*, Vol. 43, No. 11, pp. 2431-2437.

5. Raghavan, A., Cesnik, C.E., 2007, “Review of Guided-wave Structural Health Monitoring,” *The Shock and Vibration Digest,* Vol. 39, No. 2, pp. 91-114.

6. Park, G., Sohn, H., Farrar, C.R., Inman, D.J., 2003, “Overview of Piezoelectric Impedance-based Health Monitoring and Path Forward,” *The Shock and Vibration Digest,* Vol. 35, No. 6, pp. 451-463.