LA-UR- 10-00416

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Intended for: ASNT Spring Research Meeting
Williamsburg Va. USA
March 22-25 2010

Los Alamos
NATIONAL LABORATORY
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Structural Damage Identification in Wind Turbine Blades using Piezoelectric Active Sensing with Ultrasonic Validation

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Abstract

This paper gives a brief overview of a new project at LANL in structural damage identification for wind turbines. This project makes use of modeling capabilities and sensing technology to understand realistic blade loading on large turbine blades, with the goal of developing the technology needed to automatically detect early damage. Several structural health monitoring (SHM) techniques using piezoelectric active materials are being investigated for the development of wireless, low power sensors that interrogate sections of the wind turbine blade using Lamb wave propagation data, frequency response functions (FRFs), and time-series analysis methods. The modeling and sensor research will be compared with extensive experimental testing, including wind tunnel experiments, load and fatigue tests, and ultrasonic scans – on small- to mid-scale turbine blades. Furthermore, this study will investigate the effect of local damage on the global response of the blade by monitoring low-frequency response changes.

Introduction

Global climate change has sparked renewed interest in domestic and renewable energy sources in the United States for both economic and environmental reasons. In 2008, the U.S. wind energy industry brought online over 8,500 megawatts (MW) of new wind power capacity, increasing the nation's cumulative total to over 23,000 MW – accounting for 1.5% of the total energy produced - and pushing the U.S. above Germany as the country with the largest amount of installed wind power capacity[1]. Currently, the U.S. has approximately 15,000 - 20,000 wind turbines in operation across 34 states. The largest wind plant in the U.S. is located in Taylor, Texas, where 421 wind turbines produce 735 MW of electric capacity. On average, wind plants cost $1 million per megawatt of installed capacity, and the annual maintenance cost for each wind turbine is approximately 1.5% - 2% of the original cost [2,3]. With the DOE proposing to expand wind energy to account for 20% of the total energy output by 2030 [1], the ability to transition from time-based maintenance to condition-based maintenance could potentially cut maintenance costs by 50%, resulting in a cost savings of approximately $2 - 3 billion dollars annually.

At present, the turbine/wind interactions that are driving turbine failures are not well understood. In addition, wind turbine blade lengths continue to grow (>50m) in an effort to capture more of the inbound wind energy. As such, unforeseen structural failures due to the complex loading along the length of the blade plague the industry. Also, in order to reduce the weight while still maintaining the necessary strength and stiffness characteristics, manufacturers use composite materials (e.g. fiberglass or carbon-fiber) to construct the blades. However, significant drawbacks exist from the manufacturing process as blades may possess material flaws such as voids in the epoxy, delamination, and surface wrinkles. Under sufficient loading these flaws can grow and in some cases endanger the structural integrity of the blade and by extension the entire turbine. A recent study conducted by Sandia National Laboratory (SNL) shows that structural health monitoring of wind turbines is still in its infancy [2].

Currently, advanced NDT techniques are not often used in maintenance checks in the field. Inspectors working for Vestas, the leading producer of wind turbines in North America, rely primarily on visual inspection and tap tests to identify lightning damage, delamination, cracks, and other serious external flaws. Vestas has indicated that they would like to have imaging tools to locate wrinkles and delaminations under the surface of the blade.

Wind turbine research at LANL is focused on developing modeling capabilities to assess and control the effect of aerodynamic and structural conditions on power output and turbine health, as well as sensing technologies to measure blade response on multiple time- and length-scales for state awareness, damage detection, and control. The core of this project involves controlled laboratory and field experiments on small- and mid-scale wind turbines, ranging in diameter from 2.1m to 19.2m. This paper provides a brief overview of the modeling scope, a preliminary multi-scale sensing platform, and SHM results using Lamb wave, frequency response, and time-series techniques.

Predictive Modeling and Simulation

LANL has developed a modeling approach that will enable the analysis of wind turbines in the presence of realistic wind loads. This capability has been developed by coupling HIGRAD/FIRETEC, an atmospheric hydrodynamics model, with LANL's new wind turbine/wind interaction modeling technique WindBlade. The WindBlade code addresses interactions between rotating wind turbines and complex 3D wind fields. The combination of WindBlade with a structural finite element (FE) code will enable one to identify the nature and source of blade and hub loading. These models assess the local (blade section) and global (turbine and plant) effects of fatigue damage in the presence of pre-existing manufacturing defects, such as a) wrinkles in composite section laminate, b) voids in epoxy used to bond the central shear spar to the outer skins, and c) delamination and fatigue induced laminate level cracks. The local effects will be investigated using detailed FE models of blade sub-regions with explicit geometric representation of manufacturing defects and fatigue cracks. The results will be employed within WindBlade to examine global effects.

Multi-Scale Sensing

The strategy for implementing a damage detection and prognostic sensing system can be divided into four major components: a) local and active sensing to monitor initial and propagating damage, b) global sensing to assess future loading conditions and provide data for model validation/updating, c) optimal sensing to maximize observability for expected failure modes and degradation mechanisms, and d) implementation of new algorithms for efficient and timely application of control algorithms. A successful multi-scale monitoring system will predict the behavior of damaged components in a wind turbine and the implication of that damage on system performance.

In this project, piezoelectric materials (PZT) are used as both sensors and actuators to provide 'active' local sensing. PZTs produce an electrical charge when deformed, and conversely they deform under the application of an external electric field, enabling them to both measure and cause strain. These materials can impose a predefined excitation force on a structure easing signal processing for damage detection and prognosis. Examples of documented successes in the areas of active local sensing for damage detection using PZT transducers are the impedance-based method [3], high-frequency response function techniques [4], and the Lamb wave propagation method [5-6]. This project will integrate several active-sensing SHM techniques using the same PZT patches to improve the damage detection capability. Once structural damage has initiated and is detected, physics-based models will examine the influence of damage on system-level performance, requiring measurement of the system level response. PZT accelerometers and strain gauges will be used to assess the global response of the blade to aerodynamic loading, which is then used to assess the influence of local damage on overall structural response. With the appropriate model it is possible to identify key locations along the blade for sensor placement to predict load evolution and transmission.

One of the central components in the sensing effort is the development of a hardware system to manage the embedded instrumentation devices. For wind turbine applications, conventional approaches using wired networks would pose serious limitations due to lightning and other issues. The sensing hardware must be non-intrusive, provide distributed sensing capabilities, and perform these operations on a fixed energy budget. Because most of these sensing systems will be deployed on the blades themselves, a key task will also be development of energy harvesting devices from such sources as solar, centripetal forces and mechanical vibrations inherent in the blades during operation.

To account for this, a wireless network of energy independent sensor nodes is being developed to telemeter data to a central processing unit which will integrate the data into the turbine's SCADA system. Wireless impedance devices (WIDs) will integrate several components, including a microcontroller, telemetry, multiplexers for up to seven PZT sensors, energy harvesting with onboard storage, and a wireless triggering circuit. The WID is designed as part of a modular hardware platform (Figure 1) that incorporates other sensing capabilities on separate boards, such as low-frequency vibration / time history measurements. By combining modules the capabilities of each module can be shared, resulting in a highly functional sensor node with multiple SHM and state-awareness techniques for the rapid condition assessment of wind turbine applications.

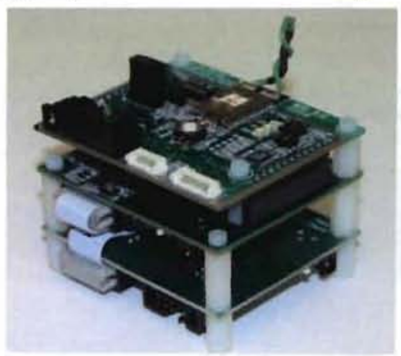

Figure 1. WID/WiDAQ provides high-frequency SHM and low-frequency passive sensing.

SHM Study on a CX-100 blade section

A feasibility study was recently performed at LANL using a 1m section of the CX-100 wind turbine blade developed by Sandia National Laboratory. The blade section (Figure 2) was instrumented with a series of macro-fiber composite (MFC) transducers and ½" diameter piezoceramic transducers from APC International, Inc. Sensors were bonded to the low pressure skin of the blade section using a cyanoacrylate adhesive and were connected to a National Instruments PXI data acquisition system. Four of the eight sensors were mounted along the outer skin above the shear spar that provides structural support along the length of the blade. The remaining sensors were mounted on either side of the shear spar so that they generate an excitation that is orthogonal to the spar. With this arrangement of transducers, SHM studies were conducted using Lamb wave propagation, frequency response, and time-series analysis techniques.

Lamb Wave Propagation - Lamb waves were used to excite the blade surface using one of the piezoelectric patches as an actuator and another as a sensor. A Morlet wavelet was selected for the shape of excitation and was generated along the direction of the shear spar. Due to the anisotropic nature of the blade skin, the center frequency and magnitude of the Morlet wavelet was selected experimentally to provide sufficient separation between the received EMI signal and the Lamb wave (Figure 3). Two center frequencies were identified in this study: 25 kHz (perpendicular to shear spar) and 200 kHz (parallel to spar). Once the excitation was defined, a series of measurements were taken for undamaged and damaged states of the blade. Damage was introduced as an additional mass positioned near the transmission path.

Figure 2: Instrumented CX-100 blade section.

After data was collected, the EMI signal was extracted and the truncated output signal was converted to the frequency domain through a discrete Fourier transform. The blade itself acts like a band-pass filter, allowing some frequencies to transmit more readily than others. Multiple baseline responses were collected with varying environmental parameters. As damage is induced, the Fourier transform could potentially depict a distinct change in either the magnitude or frequency content of the response signal versus the baseline measurement. A cross-correlation analysis can be used to more readily quantify this variation between the baseline measurements and the damaged state in the frequency domain. Based on this approach, a damage index is created using the maximum value for each cross-correlation and subtracting the values from unity (Figure 4). From this analysis it is evident that there is a large distinction in the damage index for normal operation and the presence of damage.

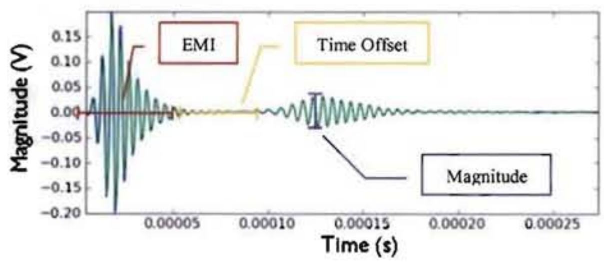

Figure 3: Lamb Wave Response Parameters

Frequency Response Analysis – While the Lamb wave approach utilized a prescribed wavelet excitation, the frequency response analysis used a broadband excitation from 30-80 kHz. As before, data was collected at different environmental conditions to construct a series of baseline measurements before damage was introduced in the form of an applied mass near the transmission path between transducers. A cross-correlation analysis was again used to compare baseline and damaged state measurements, as well as define the damage index shown in Figure 5. As in the previous case, the damage index provides distinct separation between normal and damaged states.

Time Series Analysis – In the time domain approach, the blade section was excited with a chirp signal from 5-

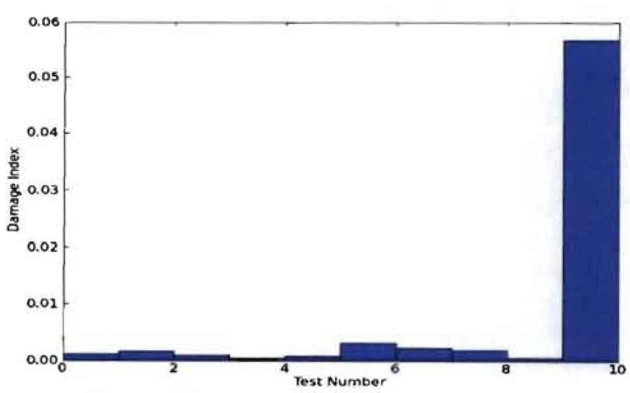

Figure 4: Lamb Wave Damage Index Graph

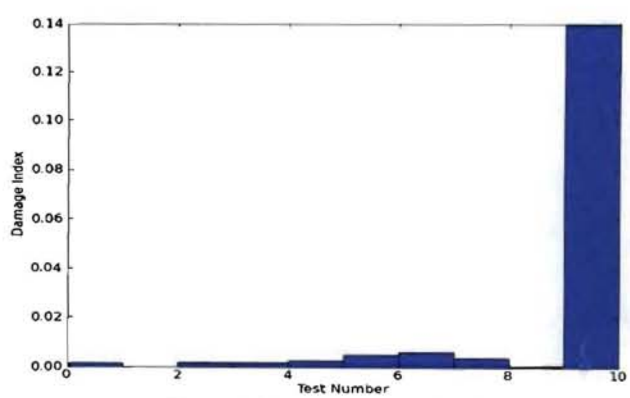

Figure 5: FRF Damage Index Graph

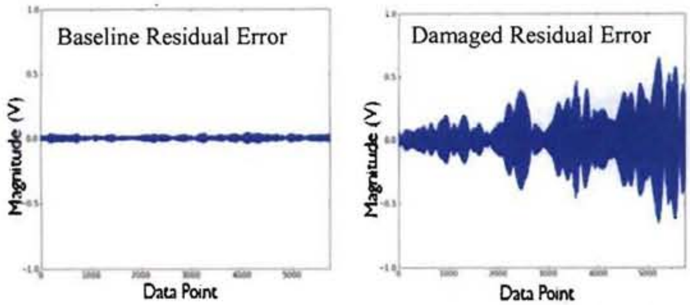

Figure 6: Baseline and Damaged Residual Error Value Comparison

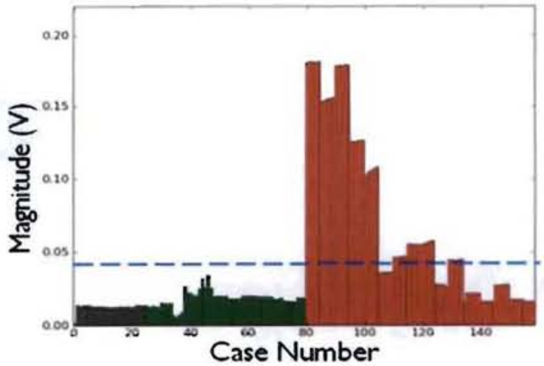

Figure 7: Path 2 Residual Error Plot

20 kHz over a voltage range of 30V. The sampling frequency was 48kHz, and a total of 8192 points were recorded for each measurement. An auto-regressive with exogenous input (ARX) model was developed to provide a polynomial estimation of the time series data based upon both sensor (output) and actuator (input) measurements. Once the ARX model is developed for the baseline condition, it is used to predict the output response of the system using data gathered in the time domain. This predicted output response can then be compared to the actual response measured during testing to determine if there is significant variation between the expected and measured responses. If the model is incapable of predicting the newly measured response, then the system is assumed to have changed in such a way that damage may be present.

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:

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

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. 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 a built-in Matlab functions, and an order of 218 (input) and 177 (output) was found.

With this order of coefficients, an ARX model was constructed from the baseline measurements collected from the CX-100 blade section. The predicted response was then correlated with the measured response using the residual error between the actual and predicted responses of the system. In practice, the actual and predicted responses from the baseline case will correlate well and have relatively small residual error. This trend is seen in the data shown in Figure 6. The baseline residual error is significantly lower on average when compared to the damaged residual error.

Comparing all the cases, both undamaged and damaged, damage close to the path could be detected, while damage placed farther away or with little surface area could not. Figure 7 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 threshold value of 0.038 was used for damage detection in this study. As seen in Figure 7, not all damage could be detected; especially in cases were the added mass was placed far from the path. This result points to the importance of identifying better threshold limits for damage identification. In addition, further studies are needed to quantify the sensing range of this method.

Comparison – The pros and cons of implementing each SHM technique are compared in Table 1. While each of the SHM methods were successful in identifying the presence of damage, the implementation of each technique must be weighed

Table 1: Performance matrix for different SHM techniques

	Pros	Cons			
		Memory	Power	Damage	Other
Lamb Wave	Locate Damage	High Memory Usage	High Power Req.	Damage Close to Path	Mult Freq.
Frequency Response	Sensitive to Spar Damage	Moderate Memory Usage	Moderate Power Req.		
Time Series	Memory Usage Power Req.			Damage Close to Path	EMI Effect

based on power requirements, computational requirements, and the overall observability of the detection method. Additionally, further work must be conducted to characterize each method's sensitivity to damage size and orientation for the anisotropic materials generally used in the fabrication of wind turbine blades.

Conclusions

LANL has recently begun a research program on wind energy to understand the influences of blade damage and loading on the performance of individual wind turbines and extending these results to assess performance of the overall wind plant. This research builds upon LANL's capabilities in sensing, structural health monitoring, non-destructive evaluation, and predictive modeling. Currently, researchers are investigating the feasibility of using Lamb wave, frequency response, and time response methods to detect damage on blade sections. Over the next year these studies will be extended to 9m full length blades, and will be implemented on operating, albeit small-scale wind turbines operating in the field. Over the next three years these studies will be extended to test performance on an operating 19.2m diameter wind turbine. The results of this testing will be used to validate SHM detection techniques, as well as provide data for validation of the physics-based predictive models. A wind turbine blade-specific scanning configuration will also be designed to provide unique experimental data and improve industry maintenance methods.

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