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Title:

Structural Health Monitoring of Wind Turbine Blades

SE 265 Final Project

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Introduction

ACME Wind Turbine Corporation has contacted our dynamic analysis firm regarding structural health monitoring of their wind turbine blades. ACME has had several failures in previous years. Examples are shown in Figure 1. These failures have resulted in economic loss for the company due to down time of the turbines (lost revenue) and repair costs.

Blade failures can occur in several modes, which may depend on the type of construction and load history. Cracking and delamination are some typical modes of blade failure. ACME warranties its turbines and wishes to decrease the number of blade failures they have to repair and replace. The company wishes to implement a real time structural health monitoring system in order to better understand when blade replacement is necessary.

Because of warranty costs incurred to date, ACME is interested in either changing the warranty period for the blades in question or predicting imminent failure before it occurs. ACME's current practice is to increase the number of physical inspections when blades are approaching the end of their fatigue lives. Implementation of an *in situ* monitoring system would eliminate or greatly reduce the need for such physical inspections. Another benefit of such a monitoring system is that the life of any given component could be extended since real conditions would be monitored.

The SHM system designed for ACME must be able to operate while the wind turbine is in service. This means that wireless communication options will likely be implemented. Because blade failures occur due to cyclic stresses in the blade material, the sensing system will focus on monitoring strain at various points.

Figure 1: Blade failure by delamination (left) and cracking (right).

Section 1: Operational Evaluation

ACME Wind Turbine Corporation is investing in a structural health monitoring system for wind turbine blades. Before such a system is implemented, the economic justification for implementation of such a monitoring system must be established, damage must be defined, normal operating environments must be identified and any limitations on data acquisition should be noted.

A three blade horizontal axis wind turbine will be considered (schematic shown in Figure 1.1). The three blade horizontal design constitutes all “utility-scale” turbines produced by ACME (indeed, all utility scale turbines on the global market use this design). Wind turbines work by converting wind energy into electrical or mechanical energy. The wind spins the blades of the turbine which turns a drive-train that turns a generator. Utility lines collect the electricity generated and then distribute it to consumers. Wind turbine profitability depends on the amount of electricity produced, which in turn depends on both the size of the turbine and the wind speed. Utility scale rotor sizes range from 50 to 90 meters. A typical turbine can produce between 700 kW to 2.5 MW of electricity [1].

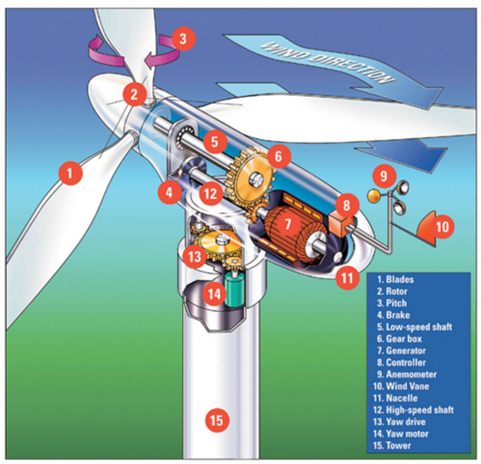

Figure 1.1 Schematic of a wind turbine generator
www.powerhousetv.com/.../ phtv_eb_re_000315.hcsp

Because turbines are typically located in remote areas, away from people, there are no life-safety justifications for implementing an SHM system; motivation for structural health monitoring is purely economic. The Danish Wind Industry Association [2] breaks down wind turbine economics into the categories of initial investment, installation cost, income from electricity sales, and operation and maintenance (O&M) costs. Current annual O&M costs are assumed to be about 3% of the original investment price for older turbines and about 1.5-2% for newer turbines. If we assume an initial investment of about $500K/turbine, then annual O&M costs using the 2% figure are $10K/year/turbine. ACME provides turbines for wind farms that produce approximately 50 MW of power with 50 1 MW turbines. If a turbine is nearing the end of its design life (20 years for the turbines that ACME produces) the wind farm owners may choose to perform a major overhaul on the turbine (payable by ACME if inspection reveals a failure), which might cost 15-20% of the initial investment (in our example, up to $100K every 20 years).

ACME would like to invest in an online SHM system that would alert wind farm owners as to when a major overhaul might be required. Currently the company pays technicians to inspect turbines nearing the end of their life time (a cost reflected in the O&M figure, absorbed by the wind farm owner). Implementation of an SHM system would have an initial cost, but would then save the wind farm O&M costs by reducing the number of technician inspections required, making ACME's turbines more desirable products. Implementation of a truly robust SHM system could also have the potential alerting the wind farm owners as to when major overhauls are truly required. Some unusual loading conditions have caused some turbine blades to fail long before their 20 year expected life time. When blades fail, repair to other part of the turbine system are generally required and in severe cases, sometimes the blade failure causes failure of the entire turbine. A real time SHM system would increase the reliability of ACME's wind turbines making them more marketable than their competitors. More reliable wind turbines will also lead to larger profit margins for ACME as well. In order to justify the purchase of an SHM system, it must at least save ACME its initial startup cost over the life of a turbine. Figure 1.2 shows a conceptualization of the economic goals of a turbine SHM system.

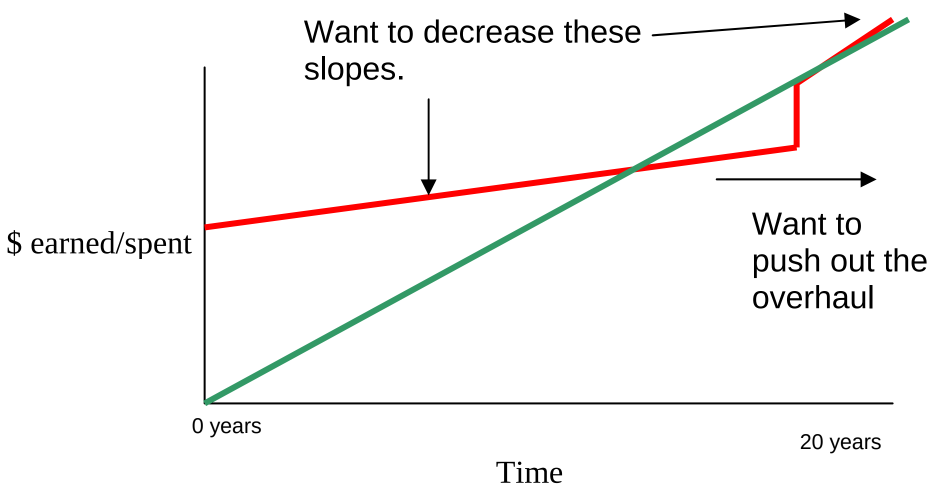

Figure 1.2 Conceptualization of economic goals SHM system must achieve.

Damage in a turbine blade is typically caused by fatigue cycling resulting in some type of cracking or delamination of the blade or loosening of torque in the blade root. Researchers at Montana State University have studied the modes of composite blade failure extensively [3]. They studied manufacturing flaws and structural details (such as skin-stiffener intersections, waviness, holes), both of which can lead to areas of stress concentrations and likely regions of failure. Delamination was studied extensively. The researchers found that, for a directional weave (as opposed to an anisotropic weave, like fiberglass), resistance to delamination is a trade off with tensile fatigue resistance. The research in [3] seems to indicate that a critical crack length of 0.2 mm with a crack length to extension ratio >20 should be the initial flaw size that our SHM system is able to detect. Researchers at Sandia National Laboratory have also investigated loosening bolts near the blade root (these bolts typically are tightened to 200 ft-lbs of torque) [4,5]. Because loss of torque can lead to rattle and rapid fatigue failure at the root of the blade, experiments would have to be conducted to determine where the failure “cliff” is. The SHM system should detect loss of torque well before this failure torque. The SHM system implemented on ACME wind turbines should monitor for both failure modes of composite turbine blades.

Environmental operating conditions for wind turbines can be quite severe, depending on their location. Not only do these turbines have to withstand vibration due to the wind and the resulting fatigue stress, but also diurnal changes in temperature, precipitation, and lightning. One company that has already implemented a monitoring system on their fiberglass wind turbines has even installed a lightning alert system [6]. The SHM system implemented will have to be able to monitor strains and vibrations induced by fatigue loading, while not being influenced by temperature swings, precipitation and potentially even lightning.

Other sensing challenges relate to the operating condition of the turbine itself (operational variability). The blades vibrate at some low frequency in the wind. Because the turbine rotates, communication between sensors and the data collection point could be a challenge. Additionally, the turbines generate an electromagnetic field that could interfere with measurements and transmission (noted by [6,7]). Sensors that have been proposed commercially and in the literature include fiber optic strain sensors, accelerometers [6,7], and full field techniques like laser Doppler vibration monitoring [5]. Power requirements may not be an issue, as it may be possible to convert electricity from the windmill itself into a usable form for the SHM system. Power harvesting (from fatigue vibrations or solar cells) or batteries may also be an option. Finally data will have to be sent back to a central monitoring station via some type of telemetry. The biggest savings would be achieved through having individual turbines telemeter back to a single monitoring station.

Section 2: Hardware Requirements

This section describes the hardware that will be specified by SHM Solutions for ACME to extract, process and interpret data on their wind turbine blades. This data will allow the company to predict conditions that lead to impending failure and to take preventative countermeasures in anticipation of catastrophic blade failure events.

The catastrophic blade failures experienced by ACME have occurred during extreme weather conditions such as gusty winds, high winds, cold temperatures and lightning. Axial and shear stresses that occur during these extreme conditions cause the failure modes of blade cracking and delamination. Transverse loading causes a bending moment in the blade with the largest amplitude near the root. This type of loading also causes a shear stress perpendicular to the load in the axial direction with its maximum value at the neutral axis of the blade.

Figure 2.1: Typical Wind Turbine

Because data will be collected and analyzed in-situ, the SHM system will need the ability to withstand the operating conditions of the environment. Consequently, hardware mounted on the blades will experience centrifugal acceleration and cyclic loading. Hardware mounted on the housing will be subjected to temperature modulation, vibration, electro-magnetic fields from the generator and voltage spikes from lightning. Figure 2.1 shows a typical three-blade wind turbine with a large housing that encloses the gearbox and generator. As shown, lightning rods are mounted to the top of the housing.

The proposed system architecture proposed is shown schematically in Figure 2.2.

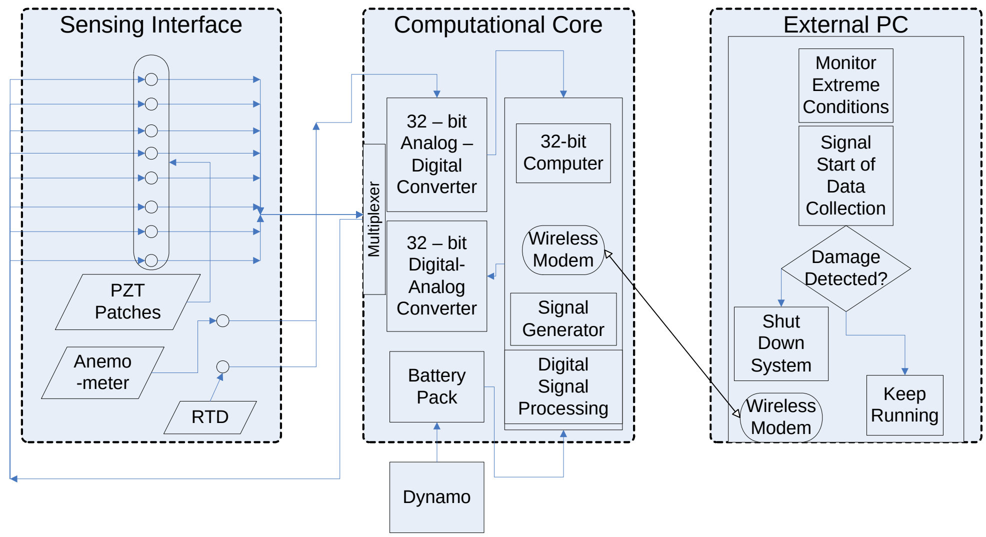

Figure 2.2: System Architecture

Sensing Interface

After careful consideration, equally spaced piezoelectric patches (see Figure 2.3) will be selected as the sensors of choice. Piezoelectric patches can be used to determine the characteristic impedance signatures of the blade by inducing strain in one of the patches with an electric (ac) signal. This actuates the blade with a high frequency vibration that the other patches can sense. By establishing a characteristic vibration baseline, damage can be detected by taking data after an extreme weather event and comparing it to the baseline. Small cracks in the blade will shift the modal peaks of the frequency response [1].

The piezoelectric patches are epoxied onto the upstream face of the blades because the maximum stress in tension occurs on this face. A crack is more likely to occur on this face due to the wind loading and less likely on the downstream face of the blade, which will be in compression. The effect of the presence of the patches on the fluid flow will depend on the thickness of the boundary layer. Boundary layer thickness depends on the flow regime, surface conditions and turbulence of the incoming wind.

Mounting hardware on a blade will induce a mass imbalance vibration in the system. The mass imbalance is equal to the weight times the radial distance from the axis of rotation. Either all three blades can be instrumented with piezoelectric patches placed at the same radial distances or a compensating weight can be added to the blades that are without patches according to the following:

$$W = \frac{\Sigma(w_j r_j)}{r_w} \tag{2.1}$$

where W is the compensating weight, w_j is the weight of each individual piezoelectric patch, r_j is the radial distance to each individual piezoelectric patch from axis of rotation and r_w is the radial distance from axis of rotation to compensating weight.

Two copper conducting wires for each patch are also epoxied onto the blade and are routed toward the hub. These wires attach to a slip ring (Figure 2.4), a device that consists of a rotating bushing around a stationary sleeve enabling the transition of electrical current to and from the piezoelectric patches.

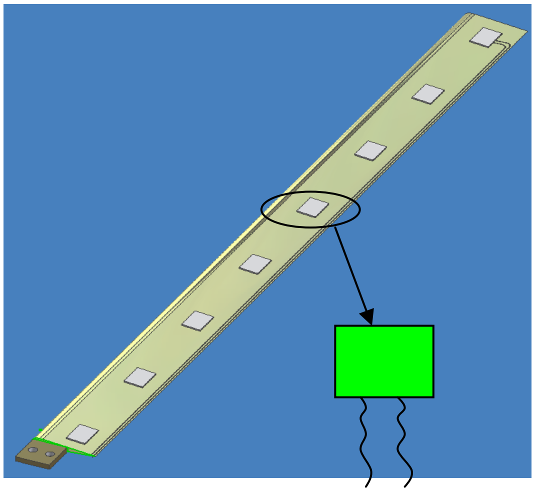

Figure 2.3: Mock Blade with PZT's

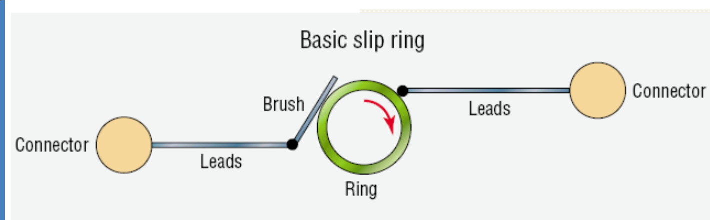

Figure 2.4 Schematic of a slip ring

The Sensing Interface also consists of an anemometer and a Resistance Temperature Detector (RTD). The anemometer is used to detect wind speed and gusts. It is a rotating device that delivers a pulse output once per revolution. The pulses are counted and a multiplier converts the counts per time to wind speed. The RTD is used to detect temperature. This sensor requires a current input and produces a diminished current output. The diminished current is converted into temperature. In a situation where a large group of wind turbines are present, a single anemometer and RTD will be centrally located and read by the base station.

Computational Core

The slip ring described in the previous section is the interface between the rotating and stationary components. It connects the piezoelectric patches to the multiplexer (Figure 2.5); a device containing a set of dual acting switches. Depending on the positions of the switches, the PZT patches can act as actuators or sensors. These switch positions will be programmed by the node computer.

The multiplexer is connected to the node computer (Figure 2.6) via the AD and DA converters (Figure 2.7). As shown in Figure 2.7, the DA and AD converters are available in the form of I/O cards that are inserted into slots on the node computer motherboard. Also, the wireless communication depicted in Figure 2.2 between the node computer and base station is accomplished using a PCI card and wireless modem.

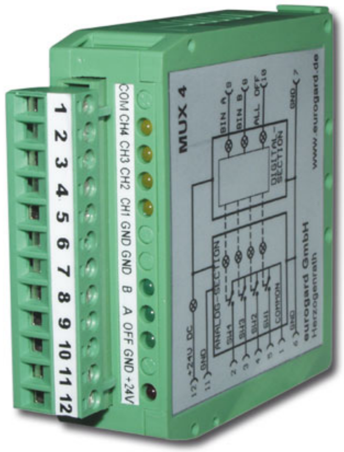

Figure 2.5: Multiplexer

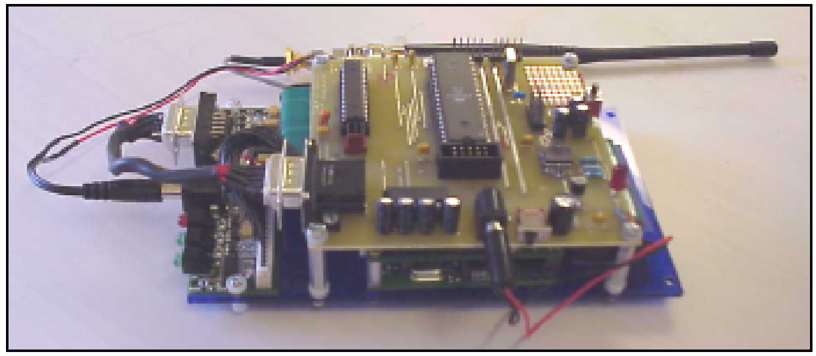

Figure 2.6: Node Computer

Figure 2.7: DA Converter

Due to the volume of data and signal processing requirements, the detection system would not be operated continuously but only after abnormal conditions were present. The anemometer and RTD will be used to detect abnormal operating conditions. The data processed from these sensors is sent via wireless telemetry to the base station computer. Limits developed for these parameters will then trigger the SHM hardware to collect data on the wind turbine blades. Located at the top of the tower is the generator housing, which will be used to mount the anemometer and temperature sensor. There will be some wind speed interference in this location due to the rotating blades upstream, however, having the anemometer at the same height as the rotor will produce much more accurate data for wind speeds and gusts than a ground mounted unit.

Figure 2.8: Dynamo for Bicycle (6V, 3W)

To power the node computer, a dynamo (Figure 2.8) will be adapted to the wind turbine. This device generates a low power output through the rotation of an internal solenoid. The dynamo will continuously supply electrical current to a battery pack that stores power for the node computer. Although the wind turbine is producing electrical power, it was deemed impractical to adapt the wind turbine's power to the SHM system because the voltage would need to be stepped down with a transformer for it to be useful.

The node computer will be enclosed and mounted to the wind turbine housing. This unit will have DA, AD converters, I/O cards, PCI card, CPU, hard drive, motherboard and sufficient memory to process the data specified by SHM Solutions. It will be programmed to generate actuation signals and to extract and process data for the piezoelectric patches. These signals will be processed using Matlab signal-processing algorithms and compared to the baseline data. When damage is detected, a signal will be sent to the base station computer, via a RF signal.

External PC

The external PC or base station will serve several functions. It will monitor data from the anemometer and RTD, judge whether extreme conditions are occurring and instruct the nodes to begin monitoring. It will receive data back from the nodes indicating whether or not damage has occurred and instruct the wind turbine to shut down when an incipient damage indication has been transmitted. The shut down sequence consists of a motor that rotates the direction of the turbine blades into a coaxial direction relative to the wind direction.

Challenges

1. The dynamo will need adapting to the wind turbine. Also, the battery pack will need sufficient storage to supply enough power to the node computer while it is processing and transmitting data.
2. The slip ring will introduce noise into the actuation and sensing signal. It is likely to be low frequency that can be handled by using a high-pass or band pass filter.
3. Electro-magnetic noise will be created by the generator and will influence the node computer and associated hardware. It is expected that this noise will be filtered out. The computer and associated hardware will also be packaged in an enclosure that dampens the electro-magnetic interference. Techniques for noise elimination in the connecting conductors will be employed such as using twisted pairs and shielding.
4. The node computer and hardware will be exposed to vibrations caused from the rotation of the wind turbine, gearbox chatter and generator operation. The components will need to be selected based on vibration tolerance and robustness.
5. The piezoelectric patches will be exposed to environmental conditions including temperature modulation, moisture, radiation, vibration and thermal expansion. The mean time between failures will need quantification so that the PZT's can be replaced prior to failure.

Section 3: Feature Extraction

During normal operating conditions, wind turbines are subjected to a variety of factors that induce vibrations such as the generator, bearings and wind. An excitation frequency for testing should be chosen such that the results are distinguishable from the response of the structure under normal operating conditions. For this reason, the piezoelectric actuators will emit frequencies in the kHz range. There are many different features that can be extracted from the excitations at frequencies in the kHz range. Impedance and Lamb wave methods can both be used. This section includes information about six different methods of feature extraction.

The first possible method for feature extraction is to calculate the frequency response function (FRF) using the Fast Fourier Transform (FFT). Damage in the form of cracks or delaminations will cause a reduction in the stiffness of the material, and thus a shift in the peaks that are associated with the resonant frequencies in the FRF. The advantage of this method is that it only requires an actuator and a sensor, which means that the instrumentation will be significantly less expensive than the methods that require an array of sensors. The calculation of the FRF using a FFT is quick and simple. However, there are several disadvantages to this method. The first is that it often requires a significant reduction in the stiffness for there to be a noticeable shift in the FRF, which means that the system may have a higher level of damage than desired before it can be detected. As mentioned in the previous paragraph, the system will be affected by ambient excitations, and this method will make it difficult to filter out those ambient excitations. Also, this method requires that the operator look at two FRF and make a comparison, which requires substantial training of the operators. This method also requires user input before the system can be shut down.

A second possible feature extraction technique is to use time reversal acoustics (TRA). TRA involves reconstructing the original input signal at the original actuator by propagating the time reversed response from the original sensor. If the structure is linear, the signal can be perfectly reconstructed [4]. However, if there are any nonlinearities in the system, the reconstructed signal will differ from the original one [4]. An advantage to this method is that no baseline data is necessary to be able to detect damage, only a baseline assumption. In TRA, the baseline assumption is that the structure behaves in a linear manner before damage occurs. This method requires fewer sensors than the impedance methods, making it cheaper to instrument, but it requires more than two sensors, making it more expensive to instrument than the FRF method. There are some disadvantages to this method. First, if the system is not linear to begin with, the TRA method cannot be used because the signal will not be able to be reconstructed, resulting in a false positive indication of damage. Second, if the damage does not cause the structure to exhibit a non-linear response, then the method will not indicate damage, which is a false negative. Either situation is undesirable.

A third possible method for feature extraction is an impedance-based method. Damage in the turbine blade will cause a change in its mechanical impedance, which then causes a change in the electrical impedance of the PZT sensor mounted to the structure. An impedance response plot can provide a qualitative approach for damage identification [1].

A quantitative assessment is made by the use of a scalar damage metric, which is calculated as the root-mean-square-deviation:

$$M = \sum_{i=1}^{n} \sqrt{\frac{[\mathrm{Re}(Z_{i,1}) - \mathrm{Re}(Z_{i,2}\ )]^2}{[\mathrm{Re}(Z_{i,1})]^2}} \tag{1}$$

Where M is the damage metric, $Z_{i,1}$ is the impedance of the PZT measured at healthy conditions, and $Z_{i,2}$ is the impedance to be compared [1]. As the value of the damage metric increases, so does the amount of change in the impedance. An advantage of this method is that it results in a damage metric. A threshold value can be established and incorporated into the operating program for the turbine so that the turbine can be shut down and the operator informed that one of the turbine blades is damaged. The threshold for damage and the correction factor for temperature can both be determined experimentally. One disadvantage of this method is that it is highly sensitive to temperature changes. Also, the instrumentation of this method is more costly than the previous two, because an array of sensors is required to get impedance readings for the whole blade. Also, traditional impedance analyzers tend to be bulky and expensive. However, the use of impedance measurement chips can significantly reduce the cost of implementing the impedance method, because they eliminate the need for the impedance analyzer. Impedance measurement chips are capable of excitations up to 100 kHz. They also have an on-board analog to digital converter that samples the voltage and current and calculates the impedance. An on-board DSP engine processes a discrete Fourier transform and returns the magnitude and phase of the impedance measurement [5]. Impedance chips are a solution to making the impedance-based methods more economically feasible.

Another impedance-based method that will yield a damage metric is the impedance moment method. The first moment of the impedance about the lower frequency of the frequency band of interest is the energy contained in the system [2]. It can be calculated as:

$$M = \int_{-w^{low}}^{w^{high}} w^i f(w)^2 \, dw \tag{2}$$

Where M is the moment of the signal, w is frequency and f(w) is the electrical impedance of the PZT patch [2]. The impedance moment method gives a clear indication of damage as well as the location of the damage. The impedance moment method has the same advantages and disadvantages of the previous method.

The fifth possible SHM technique uses the attenuation of Lamb waves. As Lamb waves propagate through a structure, the mechanical energy is dissipated, causing a decrease in the magnitude of the wave [3]. The amount of attenuation between two points on a structure changes when damage is located in the path between them. The S_0 mode of the Lamb wave is used for damage detection because it is non-dispersive and it is the fastest wave, so it will be the least susceptible to the interference with reflected waves from the edges of the turbine [3]. To achieve a reasonably accurate attenuation comparison, the signals for the baseline and tests will be transformed using a wavelet that has the same basis function as the input. The comparison between the test and a baseline is made by using the ratio of the kinetic energy of the test signal to that of the baseline signal, calculated as follows:

$$DI = \left| \frac{\int_{u0}^{u1} Wf_t(u, s_0)du - \int_{u0}^{u1} Wf_b(u, s_0)du}{\int_{u0}^{u1} Wf_b(u, s_0)du} \right| \qquad (3)$$

Where DI is the damage index, and $Wf(u,s_0)du$ is the wavelet transform function [4]. This method is cheaper to implement than the impedance method because fewer sensors are required. Another advantage is that this method is less susceptible to temperature changes than the impedance methods. Temperature affects the speed of the waveform, which will have a minimal effect on the damage index because it is calculated base on the attenuation of the waveform, not the speed. One disadvantage to this method is that the wavelet analysis is computation intensive.

The sixth possible technique for feature extraction employs the cross-correlation of the power spectral density functions between the baseline and test case signals. In this method a sine sweep signal is used for actuation. The power spectral densities of the baseline and test signals are determined and the cross-correlation coefficient is calculated for the range of the driving frequency as described in [4]. The threshold value for damage can be determined from experimental data. One disadvantage to this method is that it is possible to get interference in the signal from reflections that go through the damaged area, giving a false indication for the location of the damage.

The impedance methods and the Lamb-wave-based methods can provide a single damage index, which can be used to automatically shut down the system and alert the operator that there is a problem. A single value method is desirable because it requires a minimal amount of training for the operators and can be easily incorporated into an automated system for shut down and notification. The Lamb-wave- and impedance-based methods are more sensitive to damage than the FRF method, so damage can be detected sooner and action can be taken before the damage leads to catastrophic failure. Lamb wave propagation techniques would be cheaper to implement than impedance methods because fewer sensors are required for a full analysis of the turbine blade.

Section 4: Data Normalization

Data normalization will be an important part of performing damage identification on ACME's wind turbines. Operating conditions and environmental variability must be assessed and the effect each has on damage indicator features determined (if possible). The variability introduced by both the known operating conditions and the unknown environmental variability can be reduced by appropriately processing collected data. The wind turbines are subjected to three main sources of operational/environmental variability:

1) Variability that affects material properties of the blades
2) Load variability
3) Variability affecting the measurement system

For the purposes of this study, only turbines located on land are considered. Blades are assumed to be of composite construction. Turbines operate outdoors and, hence, are subject to seasonal and diurnal temperature and humidity/precipitation changes. Changes in temperature and humidity will cause changes in the material properties of the blades. Exposure to UV may also degrade material properties [1]. Changes in blade material properties caused by environmental exposure may be planned for in the design. These changes may not necessarily cause failure of the blade but they will cause variation in the damage indicator features extracted from the data that does not necessarily mean that damage has occurred.

Variability may also come from the loading on the turbine blades. Blades are subjected to ambient vibration caused by the wind aerodynamically loading the blade. Wind loading could be thought of as causing nonstationary, low-frequency vibration of the turbine blades (statistical estimates of these vibrations are used in design of turbine blades for fatigue criteria). For low frequency damage identification methods, this type of loading might be an appropriate source of ambient excitation. However for the high-frequency methods proposed in the previous section, wind loading is a source of environmental variability that may just be filtered out.

Finally the measurements taken are subjected to the variability introduced by the measurement system itself. For the turbine monitoring problem, the sensor system, if improperly shielded, may be significantly affected by the EMI from the electric generator powered by the turbine blades. EMI might cause noise to appear in the signal, presumably at a frequency related to the speed of the turbine blades. As noted in Section 2, noise from the slip ring brush configuration may also be significant (because wires will be in moving contact). Presumably, this type of noise would be low amplitude (thus not significantly affecting the signal to noise ratio) and easily filtered.

The authors of [2] state that data normalization for any given structural health monitoring problem is performed either with or without *a priori* knowledge of variability introduced by environmental and operating conditions. The wind turbines can be monitored in a healthy condition over "long" periods of time, information on the above three sources of operational/environmental variability can be collected, and a reference database formed.

The choice of how finely to discretize the reference database would depend directly on how sensitive the damage indicators were to environmental variability. For example, it would be most convenient and efficient to be able to have one or two "averaged" reference states with variability bounds. However, if the bounds are large enough to mask the damage introduced in the structure, more reference states would be required (eg for day and night, dry and rainy weather = 4). The implication of having this knowledge is that a lookup table could be formulated or the damage state could be parameterized as shown in equation 4.1

$$D(t, h, p, f_{1...n}) = K_1 t + K_2 h + K_3 p + K_4 f_1 + ...HOT \tag{4.1}$$

Where D is a damage state that is a function of the temperature, humidity, precipitation, and some number of extracted features and the K's are constants (HOT=higher order terms).

All of the damage indicator features discussed in the previous section are single number features and normalization of material property variability due to environmental factors (source 1 above) may be approached using the following simple formula:

$$\frac{x - \mu}{\sigma} \tag{4.2}$$

Where x is the current observation and mu (mean) and sigma (standard deviation) are derived from the reference state. Other methods for normalization exist for comparison of multiple point time histories and frequency bands. This might involve calculation of an average data vector for the reference state, against which further comparison could be made.

The features discussed in the previous section are extracted from high frequency wave propagation time series and impedance measurements extracted from sensors on the turbine blade (time reversal acoustics and the lamb wave damage indicator). For these methods, excitation is not ambient and is introduced by piezoelectric actuators. Low-frequency vibrations caused by wind loading can be separated out by using high pass filtering in the signal processing algorithms. These methods could also use the reference database to normalize changes due to environmental variability.

Once data normalization has been performed the damage indicator feature must then be compared to a threshold to determine whether or not damage has occurred. Formulation of thresholds will require statistical analysis of the reference state database. This topic is discussed in the next section.

Section 5: Statistical Methods

This section defines statistical tools and methods to be used by ACME to discriminate damage to the turbine blades. Through piezoelectric sensor signal processing, impedance-based and lamb wave methods produce a damage index that can be used to measure crack resolutions down to the 2 mm requirement.

Damage Index probability distributions will be recorded for each of the piezoelectric transducers (PZT) used in sensor mode at a predetermined range of temperatures and humidity. These environmental effects cause changes in the mechanical impedance of the blade structure (F/υ) and electrical impedance of the PZT actuator/sensors (V/I). This data set will be normalized to establish the baseline thresholds that will be used to evaluate for damage [1].

SHM Solutions will propose methods to detect damage without *a priori* knowledge of damage in the wind turbine blades. This method is known as "unsupervised" learning and will dictate the statistical tools used to detect damage.

The first statistical tool used by SHM Solutions is the two-class hypothesis test. The null hypothesis H_0, is the undamaged case. The hypothesis H_1, is the damaged case. There are two types of errors: Type 1 – False Positive *and* Type 2 – False Negative (see Figure 5.1).

	Accept H_o	Reject H_o
H_o is true	Correct Decision	Type I error (α)
H_1 is true	Type II error (β)	Correct Decision

[2]

Figure 5.1: Hypothesis Testing Chart

There are three goals with hypothesis testing that cannot be met simultaneously: 1) minimize probability of type 1 and 2 errors, 2) minimize the sample size before the correct decision is made and 3) terminate the testing with the acceptance or rejection of the null hypothesis. Some experimentation will be performed to establish the sample size for the hypothesis testing. A confidence interval of 3σ (99%) will be established to interrogate the data for damage. This value is selected to minimize the number of points lying outside of the distribution and thus, to minimize false positive indications of damage.

A simple test can be constructed: if the damage index of the test data lies outside of the 99% confidence interval of the distribution, damage is present (H_1), otherwise, damage is absent (H_0). However, this test can produce false-positive and false-negative indications of damage because the tails of the damage index distributions are poorly defined with small data sets. Therefore, Extreme Value Statistics (EVS) [3,4], a form of curve fitting, will be used to establish the threshold and minimize false positives and negatives by defining the tail region with more accuracy (Figure 2.2).

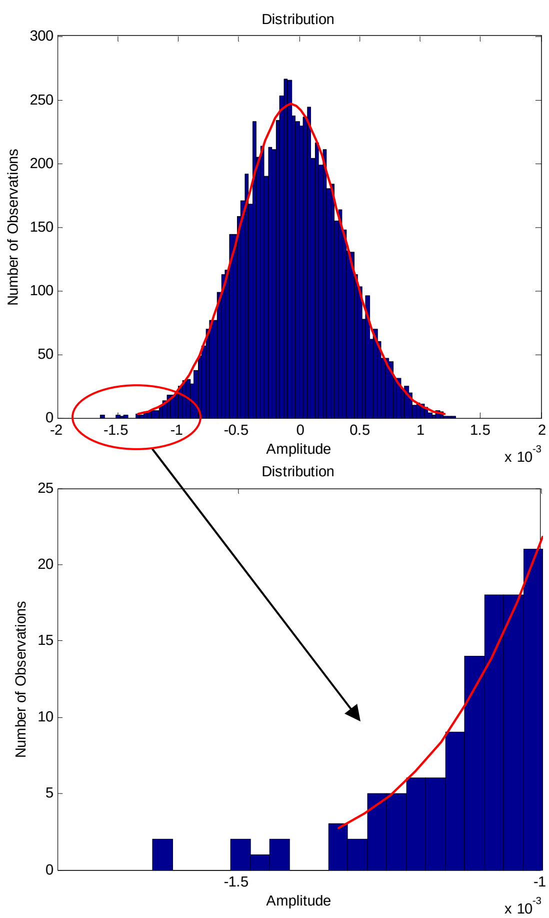

Figure 5.2: Sample Distribution and Scale-Up of Minimum Tail

EVS is independent of the type of data distribution. This fact is an advantage when the type of distribution for the data is unknown.

In the EVS method, the following steps are taken to select the proper curve fit:

1. The data set is broken up into equally numbered data subsets.
2. The maximum damage index value is then extracted from each of these subsets and a distribution of the number of points versus maximum damage index is plotted.
3. From the plot, estimates can be made for the model parameters to fit the curve of the model equation (there are three models to choose from: Gumbel, Weibull and Frechet).
4. By selecting a 99% confidence interval, the model equation produces the threshold value that is used to determine whether the data indicates a damaged or undamaged situation.

Reference [3] describes the curve fitting and parameter determination in great detail.

$$\text{FRECHET}: \quad \underline{F}(x) = \begin{cases} 1 - \exp\left[-\left(\dfrac{\delta}{\lambda - x}\right)^{\beta}\right] & \text{if } x \le \lambda \\ 1 & \text{otherwise} \end{cases}$$

$$\text{WEIBULL}: \quad \underline{F}(x) = \begin{cases} 0 & x \le \lambda \\ 1 - \exp\left[-\left(\dfrac{x - \lambda}{\delta}\right)^{\beta}\right] & x > \lambda \end{cases}$$

$$\text{GUMBEL}: \quad \underline{F}(x) = 1 - \exp\left[-\exp\left(\dfrac{x - \lambda}{\delta}\right)\right] \qquad -\infty < x < \infty \text{ and } \delta > 0$$

Figure 5.3: EVS Curve Fit Equations

Section 6: Implementation Challenges

There are many issues and challenges associated with designing a SHM system. Some of these include economic pressures, effects of false indications of damage, hardware/software integration, system verification, and liability.

Economic pressures

There are various economic pressures associated with wind turbines that can influence the design of the SHM system. One area of economic concern is the maintenance of the SHM system. It would be beneficial to train and certify the turbine maintenance crews to also maintain the SHM system. Having an on-site maintenance crew reduces the travel incurred by bringing in someone from offsite. Piezoelectric patches are inexpensive if purchased in bulk, and can be replaced by a certified technician, eliminating the need for the SHM system manufacturer to visit the site to perform the maintenance. The SHM system will have on board sensor diagnostics that will alert the technician that a sensor needs to be replaced. When there are issues with the telemetry equipment, it may be necessary for the SHM system manufacturer to visit the wind farm to inspect and repair the system.

Downtime of the turbines and the cost of repairs and replacements will cost the turbine owners money. As such, the SHM system should seek to minimize the downtime and maximize the time between repair and replacement of the turbine blades. Time that the turbine is not operational costs the power companies money. Currently, service and inspections are performed every six months, during which time the turbine is taken offline [1]. It is estimated that currently, wind turbines are not in use for 2% of the year due to maintenance or failure of the blades [1]. A SHM system that allows for service-on-demand rather than time based service is appealing to the owners of the wind turbines, because they can reduce the amount of time their turbines are offline, which increases profits. Use of such a system would also result in lower maintenance costs because they will have to send the maintenance crew out less frequently. Another economic consideration concerns the amount of damage in the system. The blades are the most expensive component of the wind turbine system [2]. Repairs and replacement of the blades can be costly. As the amount of damage in the turbine blades goes up, the cost of repairs also goes up [2]. It is cheaper to repair a blade with minor damage than it is to replace a blade that has failed catastrophically [2]. Therefore, ACME would like to be able to detect the damage in the blades during its early stages.

Effects of false indication of damage

An important consideration in the design and implementation of a SHM system is the influence of false-positive and false-negative results. Wind farms are located in sparsely populated areas, so life-safety is not a large factor to be considered for the tradeoff between false-positive and false-negative results. Economics, however, is the main factor to be considered when a decision is made about the tradeoff between false-positives and false-negative identifications. False-positive results can remove turbines from productivity and send maintenance crews out unnecessarily. Removing a turbine from productivity reduces the amount of profit that the wind farm owner makes. Sending a maintenance crew out to the turbine site unnecessarily causes a gratuitous expense. False-negative indications of damage can lead to extensive damage or even catastrophic failure, which leads to costly repairs and replacements of the blades. A rigorous statistical analysis will be performed on the system before and in the early stages of implementation to determine the confidence levels of the system. When determining the thresholds for damage, the economic tradeoff between sending maintenance crews to a site when the turbine is not damaged and having a failure of the blade has to be considered. The minimization of false-positives or false-negatives will be decided based on which option has a greater economic benefit.

Hardware/software integration

In order to implement a SHM system, software must be chosen. Matlab can meet the data acquisition needs and is a powerful tool for signal processing and analysis. Matlab can also be used with most commercial hardware. The PZT patches on the blade will be connected to a minicomputer in the housing of the turbine via wires. There are issues and challenges associated with implementing a system that includes rotating wires. Therefore, as wireless sensors become available, they should be considered. The information from the sensors will be collected and processed in by the computer in the housing, using Matlab. The processed data will be sent wirelessly to a central monitoring facility. Any upgrades in the software or signal processing algorithms can easily be introduced into the SHM system through Matlab. Hardware upgrades, such as wireless sensors, can be implemented by either replacing the individual components or replacing the entire SHM system.

Verifying damage detection capability

Before the SHM system is deployed in the field, its damage detection capability must be verified. There are a few ways in which the damage detection capability could be tested. The first would be to perform an experiment with the proposed SHM system. The experiment should include both undamaged and damaged turbines at various temperatures. The experiment will verify that the system is not only capable of detecting damage, but that it is robust enough to differentiate damage from temperature changes and other environmental operating conditions. Another method for verifying the damage detection capability of the SHM system would be to build a validated finite element model (FEM), and demonstrate the damage detection capability on the model. This method would also require testing to validate the FEM. The experiments would be similar to those for validating the SHM system experimentally.

Liability

Products liability is defined by the authors of [3] as: "the liability of any or all parties along the chain of the manufacture of any product for damage caused by that product." There are three types of defects that incur liability: design defects, manufacturing defects, and defects in marketing [3]. All of these defects must be minimized by the SHM Solutions and their constituents to avoid a law suit should the system fail. SHM Solutions should carefully design and verify that the system works to minimize design defects that could cause damage. The company that installs the SHM system should ensure that their technicians are properly trained and certified to install the system. They should also test the system once it is in place to make sure that all of the components are working properly. These precautions will help to minimize the manufacturing defects of the system as a whole and to detect manufacturing defects of the individual components. The owner of the system also needs to ensure that their technicians are properly trained and certified to perform maintenance on the SHM system, so that they are not held liable for damage due to failure of the SHM system.

Conclusions

The use of an SHM system on ACME wind turbine blades has the potential to improve the company's profit margin by lowering annual operation and maintenance costs. Monitoring turbine blades may also delay major overhaul and replacements in the life of the turbine through early warning of impending signs of failure. The final decision to install a monitoring system would hinge on whether it was able to save ACME at least its own cost over the life of the turbine blade. The system that SHM Solutions has designed places emphasis on the following features:

1. Ability to detect 0.2 mm cracks and incipient loss of root torque.
2. Minimization of false negatives to reduce missed blade failures via robust statistical thresholding algorithms.
3. Detailed characterization of operational and environmental variability for data normalization purposes.
4. Self powered on board, nodal computing.
5. Capability to calculate a variety of damage sensitive features using piezoelectric sensors and high frequency measurements that are easily separated from low frequency noise.

References

Section 1

[1] Wind Web Tutorial: http://www.awea.org/faq/tutorial/wwt_basics.html

[2] Danish Wind Industry Association: http://www.windpower.org/en/tour/

[3] Mandel, J., et al. "Fatigue of Composite Materials and Structures for Wind Turbine Blades." SAND2002-0771.

[4] Gross, E. *et al.* "Application of Damage Detection Techniques using Wind Turbine Modal Data." AIAA99-0047.

[5] Rumsey, M. *et al.* "In-Field Use of Laser Dopper Vibrometer on a Wind Turbine Blade." AIAA 98-0048.

[6] Mortensen, I., LM Glasfiber Presentation "Blade Monitoring System." 2004

[7] Rademakkers, L.W.M.M., *et al.* ECN Report "Fiber Optic Blade Monitoring." 2004

Section 2

[1] Winston, HA, Sun, F, Annigeri, BS, *Structural Health Monitoring with Piezoelectric Active Sensors*, Journal of Engineering for Gas turbines and Power, 2001, ASME

Section 3

[1] Park, G., Sohn, H., Farrar, C.R., Inman, D.J., "Overview of Piezoelectric Impedance-based Health Monitoring and Path Forward," *The Shock and Vibration Digest*, Vol. 35, No.6, 2003.

[2] Rutherford, A.C., Park, G., Sohn, H., Farrar, C.R., "The Use of Electrical Impedance Moments for Structural Health Monitoring," Proceedings of the 22nd IMAC, Dearborn, MI, 2004.

[3] Sohn, H., Park, G., Wait, J.R., Limback, N.P., Farrar, C.R. 2004. "Wavelet-based Signal Processing for Detecting Delamination in Composite Plates," *Smart Materials and Structures*, Vol. 13, No. 1, pp. 153-160.

[4] Swartz, R.A., Flynn, E., Backman, D., Hundhausen, R.J., Park, G., "Active Piezoelectric Sensing for Damage Identification in Honeycomb Aluminum Panels," Proceedings of the 24th IMAC, St. Louis, MO, 2006.

[5] 1 MSPS, 12-Bit Impedance Converter, Network Analyzer Specification Sheet: http://www.analog.com/UploadedFiles/Data_Sheets/423236275AD5933_0.pdf

Section 4

[1] Barbero, E.J., Introduction to Composite Materials Design, 1998.

[2] Farrar, C.R., H. Sohn, K. Worden, "Data Normalization: A Key for Structural Health Monitoring." 2001. LA-UR 01-4212.

Section 5

[1] Park, G., Kabeya, K., Cudney, H.H., Inman, D.J., *Removing Effects of Temperature Changes from Piezoelectric Impedance-Based Qualitative Health Monitoring,* SPIE, March, 1998

[2] Farrar, C.R., *SE265 Structural Health Monitoring: Lecture 15*, Feb, 2006

[3] Sohn, H., Park, H.W., Law, K.H., Farrar, C.R. *Minimizing Misclassification of Damage using Extreme Value Statistics*
[4] Castillo, E., *Extreme Value Theory in Engineering*, Academic Press Series in Statistical Modeling and Decision Science, San Diego, CA 1998

Section 6

[1] Danish Wind Industry Association: http://www.windpower.org/en/tour
[2] Mortensen, I., LM Glasfiber Presentation "Blade Monitoring System." 2004
[3] Products Liability: http://www.law.cornell.edu/wex/index.php/Products_liability