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Vibration Based Structural Health Monitoring for Utility Scale Wind Turbines

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Vibration Based Structural Health Monitoring for Utility Scale Wind Turbines

By

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Declaration of Previous Publication

This thesis includes 2 original papers that have submitted for publication and 1 original manuscript to be submitted for publication in a peer reviewed journal, as follows:

Thesis Chapter	Publication Title/full citation	Publication Status
Chapter 2	Bassett, K., Carriveau, R., Ting, D. S-K., 2009 Vibration Analysis of 2.3 MW Wind Turbine Using Discrete Wavelet Transform. J. of Wind Engineering	Submitted
Chapter 3	Bassett, K., Carriveau, R., Ting, D. S-K., 2010 2.3 MW Wind Turbine Vibration Response to Yaw Motion and Shut Down Events. Wind Energy	To be submitted
Chapter 4	Bassett, K., Carriveau, R., Ting, D. S-K., 2010 Structural Health Monitoring for Utility Scale Wind Turbines using WARD Algorithm and Wind WARDEN Reliability Program. Wind Energy	To be submitted

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Abstract

Structural health monitoring (SHM) is a process of implementing a damage detection strategy for a mechanical system. Wind turbine machinery stands to benefit from SHM significantly as the ability to detect early stages of damage before serious malfunction or collapse reduces the overall operating costs of wind power projects. Vibration analysis of dynamic structural response is an approach to SHM that has been successfully applied to mechanical and civil systems and shows promise for wind turbine application due to availability of instruments, ease of installation, and overall affordability. This study presents the development of vibration based wind turbine structural health monitoring through experimental analysis of an operating wind turbine. A database of acquired vibration response signals detailing over 3 hours of turbine operation was assembled and a Daubachies 6^{th} order wavelet was used to perform a 12 level discrete wavelet decomposition such that general trends and patterns within the signals could be identified. After determining response behavior of a healthy turbine, a novel vibration based SHM scheme is developed based on findings from experimental work. Specific interest has been paid to monitoring yaw and braking systems as they have been identified as problematic. With further development this vibration scheme can be applied by wind farm operators to reduce downtime and failure frequency of utility scale wind turbines.

Dedication

This work is dedicated to the current and future generations of wind turbines. May they stand tall and spin soundly for lifetimes to come.

Acknowledgements

The author wishes to express his appreciation and gratitude to his research supervisors, Dr. R. Carriveau, and Dr. D. S-K. Ting for their time, knowledge, and support throughout this exciting course of study. Also, much thanks to the wind farm operators who have provided access to turbines for study.

Most importantly I would like to thank my father Blair, whose genius inspired my scientific and academic development from its most early stages.

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> My brother, Jeff, for his friendship and comedic relief.
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> My beautiful girlfriend, Jessica, who gave me the confidence to pursue my dreams and has put up with many years of my spontaneous monologues.
>
> And those no longer with us including Frank, Bill, Brad and Barry Jr. who have taught me to value each day

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NOMENCLATURE

AR	Auto regression
a	Scaling factor
b	Translation parameter
C_{AR}	AR coefficient based condition
C_{RMS}	RMS based condition
CWT	Continuous wavelet transform
D_{AR}	Distance in AR values
D_{rms}	Difference in RMS values
db6	Daubachies 6^{th} order wavelet
DWT	Discrete wavelet transform
N_{rms}	RMS of new response signal
H	Height of accelerometer on turbine tower (m)
H_{aveAR}	Average AR coefficients for HSD
H_{averms}	Average RMS value for healthy state database
HSD	Healthy state database
L	Learning curve
P	Length of signal x
t	Time
T_{rms}	RMS damage threshold
U	Average wind speed (m/s)
x	Response signal
Ψ	Wavelet

Chapter 1

Introduction

1.1 Motivation

Wind turbines are an environmentally benign and renewable energy generation alternative [1]. Through the utilization of energy present in moving atmospheric air, an electric generator can be operated to provide electricity for remote application or integration within a utility grid. Such renewable energy can be used on a large scale to reduce the carbon dioxide emissions for a given area where wind turbines are used. Wind turbine technologies have undergone rapid growth throughout the world as social interest in environmental responsibility and renewable energy has increased. This increase in social interest has resulted in economic demand for wind turbines and wind turbine farms. In Canada, an average of over 30% industry growth has been reported over the past five years [2]. Wind farm arrays have been constructed throughout the Canadian provinces with the majority of them within Southern Ontario. On a global scale, rapid industry growth has been met by wind turbine manufacturers who have increased the scale and power capacity of turbines through advances in rotor and tower design. Wind turbines of power capacity greater than 2.0 MW have been extensively used throughout Europe and are now being used in recent wind farm development throughout Canada and the United States.

Despite the rapid advancement in wind turbine design resulting in overall larger turbines, the demand for wind energy continues to increase. The Canadian Wind Energy Association [CanWEA] has outlined a strategy to increase total installed wind energy capacity in Canada to 55,000 MW by 2025 [3]. Considering the current level of wind energy utilization throughout Canada, with 85 wind farms and a generating capacity of 2246 MW, the proposed goal would require notable extensive increases in the number of wind farms and potentially, turbine sizes.

The operators of a recently constructed wind farm in southwestern Ontario have graciously allowed a University of Windsor research team to complete testing on a fully operational 2.3 MW wind turbine. This limited access has allowed researchers to conduct an investigation into the vibration response of the utility scale turbine and more importantly how that response can be used to evaluate the structural and operational conditions of the turbine.

1.2 Scope of Study

The research in this study is presented in a series of three research papers considered for publication in various engineering journals. The first paper, now submitted to the journal of Wind Engineering, discusses results and analysis from turbine that took place on June 11^{th} and August 6^{th} 2009. Vibration response to turbine start up and operation was acquired and processed with discrete wavelet transform.

The second paper, to be submitted to the journal of Wind Energy, studies six full operation response signals obtained on the October 22, 2009 test day and analyzes them with discrete wavelet decomposition and root mean squared amplitude analysis. Detailed study and quantification of forced yaw events and turbine shutdown is performed and trends identified and discussed.

The third paper presents the development and outline of a structural health monitoring (SHM) scheme that can utilize the now obtained and quantified vibration response of the turbine. A novel combination of discrete wavelet decomposition and Auto Regressive (AR) analysis has been utilized to assemble an approach to SHM for application on utility scale wind turbines. The approach has been named the WARD (Wavelet Auto Regressive Diagnosis) algorithm.

Considering the three papers as a series on the subject of structural health monitoring for utility scale wind turbines, the overall objectives have been summarized into the three points below.

- Obtain vibration response of wind turbine through field testing on three dates
- Characterize healthy turbine behavior and response for tests considered through 12 level discrete wavelet analysis of obtained signals
- Propose a novel structural health monitoring scheme using wavelet analysis and auto regressive coefficients devised to utilize characterized response in order to evaluate future structural conditions.

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1) Clean Air Renewable Energy Coalition, Cleaning the Air with Renewable Energy, Briefing Note Fall 2002, 2002

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Chapter 2

Vibration Analysis of 2.3 MW Wind Turbine Operation Using the Discrete Wavelet Transform

2.1 Introduction

Wind turbines are an environmentally benign and renewable energy generation alternative [1]. Through the utilization of energy present in flowing atmospheric air, an electric generator can be operated providing electricity for remote application or integration within a utility grid. Such renewable energy can be used on a large scale to markedly reduce the carbon dioxide emissions for a given area where wind turbines are used. Wind turbine technologies have undergone rapid growth throughout the world as social interest in environmental responsibility and renewable energy has increased. This increase in social interest has manifested itself in economic demand for wind turbines and wind turbine farms. In Canada, an average of over 30% industry growth has been reported over the past five years [2]. Wind farm arrays have been constructed throughout the Canadian provinces with the majority of them within Southern Ontario. On a global scale, rapid industry growth has been met by wind turbine manufacturers who have increased the scale and power capacity of turbines through advances in rotor and tower design. Wind turbines of power capacity greater than 2.0 MW have been extensively used throughout Europe and are now being used in recent wind farm development throughout

Canada and the United States. Turbines of this power capacity typically have towers and rotors that average 80 meters in height and 92 meters in diameter, respectively.

Despite the rapid advancement in wind turbine design resulting in overall larger turbines, the demand for wind energy continues to increase. The Canadian Wind Energy Association [CanWEA] has outlined a strategy to increase total installed wind energy capacity in Canada to 55,000 MW by 2025 [3]. Considering the current level of wind energy utilization throughout Canada, with 85 wind farms and a generating capacity of 2246 MW, the proposed goal would require notable extensive increases in the number of wind farms and potentially, turbine sizes.

Several challenges present themselves when considering the widespread use of large-scale wind turbines. Hahn et al. [4] stated that issues of reliability become a serious concern for turbines of large scale and power capacity as inspection and maintenance are challenging due to turbine size. Also, it has been shown that the natural vibration frequency of the structure decreases with increased cell mass or tower height [5]. This is significant as a lower natural frequency could potentially result in dynamic magnification of vibration energy as the natural frequency approaches the rotational frequency of the rotor. The lifetime of the turbine is critically important in determining the cost effectiveness of a wind farm project. Due to the high demand and relative novelty of commercial wind turbine units, up-front capital costs tend to run very high. If these large scale turbines prove to be less reliable than initially projected, with extensive downtimes or increased maintenance, extensive wind farm operations may prove to be uneconomical considering a wind farm project life. This would stand as a significant roadblock to the proliferation of wind generation's contribution to long-term energy sustainability.

The reliability and lifecycle performance of a wind turbine is strongly dependant on the aerodynamic environment in which the turbine operates. Wind speed has been identified as being of primary influence on turbine reliability by Tavner et al. [6]. Throughout its operation a turbine may experience severe operating environments such as storms which introduce precipitation, temperature extremes and high speed gusts. Studies of the effects of these events have revealed that high speed wind events such as storms and gusts will influence static loading of the turbine, consuming disproportionate amounts of fatigue life for main components [6]. Modeling of gusts has been performed in the determination of the momentary extreme load conditions that turbine components may face [7]. These extreme weather loading conditions are detrimental to the overall lifetime performance of the turbine and fatigue patterns may be altered. The immediate performance of the turbine may appear normal but when larger temporal scales of months, seasons and years are considered, turbine performance could be significantly hindered; with possible catastrophic failure as a worst case scenario.

Given the importance of identifying unsafe operating conditions and detecting damage before accelerated fatigue or catastrophic failure, some research has been focused on analyzing the structural condition of a turbine based on a measureable response. When historic response data is compared against current response data to assess the structural condition of the turbine the process is known as structural health monitoring (SHM). One such measureable response that has been used extensively for SHM is vibration response as acquired through an accelerometer. Vibration based analysis and damage detection began in the late 1970s and early 1980s by researchers in aerospace and offshore oil industries [8]. This seminal research utilized modal parameters to compare the response of damaged and undamaged parts. More recently, SHM has been applied to civil structures such as buildings and bridges. SHM has been performed on span bridges with promising results [9] and extensive bridge monitoring techniques have been developed by Wong [10].

Beyond civil structures, SHM has been applied to rotating machinery. Farrar and Doebling [11] stated that vibration analysis is most successfully employed on rotating machinery due to the presence of operating frequencies within a vibration signal. These detectable frequencies are used to define healthy response of the machinery such that damaged states can be determined. Fault detection and identification using vibration signals for rotating machinery has been considered by Wegerich [12] and it has been argued that the successful application of vibration monitoring depends largely on techniques used in processing vibration signals [13].

A comprehensive review of vibration based condition monitoring by Carden and Fanning [8] has identified several methods for vibration signal analysis including natural frequency based methods, mode shape based methods, operational deflection shape based methods, frequency response function based methods, statistical methods and wavelet analysis based methods. For the present study of SHM applied to wind turbines, the system characteristics must be considered before the most appropriate methods can be identified.

A wind turbine is a dynamic system of complex and non-linear nature. Due to constantly changing environmental conditions, particularly the wind speed, the response of the turbine is in constant state of flux. This intermittency presents specific challenges to wind turbine structural health monitoring as several established techniques such as natural frequency based methods, modal analysis and frequency response function based methods are dependent on certain response characteristics remaining steady. These methods may be appropriate for certain civil applications where dynamics effects are limited, but for complex wind turbine machinery the dynamic effects may be very dominant. In order to limit dynamic behavior of the system a number of structural health monitoring applications for wind turbines have involved the analysis of the turbine in a stationary state [14]. These methods require the turbine be shutdown for the testing period, resulting in lost revenue for the wind farm operator. As wind farm arrays grow larger the costs associated with stationary SHM could become very high. In order to prevent lost revenue and decrease turbine downtime, an optimal SHM scheme ought to analyze vibration response of fully operating turbine taking into account the dynamic aspects of turbine operation. Pitchford *et al*. state that through utilization of piezoceramic patches a wind turbine component could be excited by vibration generated in the patch and the response to this input monitored to determine the structural state [15]. This technique is considered active SHM due to the excitation required. Active SHM is not appropriate in operational analysis where the turbine's operation is the excitation force from which a response is measured. Thus dynamic, passive analysis techniques using piezoelectric accelerometers are more suited.

With the goal of full scale structural health monitoring in mind, the authors first followed the direction of Farrar and Doebling who have suggested that damage detection is a problem of statistical recognition [11]. Statistic based SHM has been outlined by Sohn and Farrar [16] using Auto Regressive (AR) and Auto Regressive with erroneous input (ARX) coefficients. This technique was considered by authors, this study demonstrated the successful damage detection of damage modeled through anomalous mass addition for various steady state wind speeds [17]. Vibration signals were analyzed with AR coefficients and leveraged through the use of a healthy state database.

A healthy state database is an archive of system behaviors obtained during healthy operating conditions. When the real time structural condition of a structure is surveyed, the historic behavior is considered as a standard by which to judge the newly acquired data. For the first SHM study performed by authors the healthy state database was constructed for several periods of steady state wind speed. This form of analysis was effective in identifying anomalies for constant wind speeds. The present method under development seeks the capacity to better process signals from a strongly transient environment.

2.1.1 Wavelet Analysis

In order to account for the environmental variability and the constantly evolving vibration response of the turbine, wavelet analysis has been considered. Wavelet analysis involves the evaluation of a signal with respect to a mother wavelet [18]. The wavelet transform coefficient parameter (WT) can be calculated to measure the frequency content of a signal in a certain frequency band within a certain time interval as calculated by the below equation [19].

$$WT(b,a) = |a|^{\frac{1}{2}} \int_{-\infty}^{\infty} x(t)\overline{\Psi\left(\frac{t-b}{a}\right)}dt \qquad (1)$$

where a is scaling factor which determines frequency content, b is translation parameter, t is time, and $\overline{\Psi}$(t) is the complex conjugate of wavelet Ψ. The process of wavelet analysis allows for the decomposition of a signal into a set of frequency channels [18]. Equation 1 represents the continuous wavelet transform (CWT) which offers the possibility of detailed analysis of vibration transients. Due to the finite length of each wavelet, the wavelet transform allows for the periodicity-based comparison of events with differing durations. A challenge with the CWT is the computation demands of its execution. Since all scales of the mother wavelet are compared to the signal extensive and time consuming calculations are required. One way to address this challenge of computational demand is to utilize the discrete wavelet transform (DWT) as expressed by [19].

$$WT(k2^j, 2^j) = \left|2^j\right|^{\frac{-1}{2}} \int_{-\infty}^{\infty} x(t)\overline{\Psi\left(\frac{t-k2^j}{2^j}\right)}dt \qquad (2)$$

This extracts wavelet scales from the CWT on a two dimensional grid (a, b) with dyadic scales $a=2^j$ and $b=k2^j$. This transform allows for a full range of frequency resolution while limiting the computational load for calculations thus making it well suited for wind turbine application where large amounts of data must be handled. A DWT breaks up a signal into decomposition levels related to wavelet scale. In performing the DWT, wavelet scales between levels are not individually extracted for analysis but frequency content of the signal between levels will be reflected in the decomposition levels of the transform.

Various applications of wavelet based vibration analysis have been performed by many researchers. One promising application has been on a helicopter gearbox by Wang and McFadden [20]. This study analyzed the transient vibration signals for detection of a cracked gear using wavelet scales and it was proven that, unlike time-frequency distributions used for other vibration analysis techniques, wavelet analysis can successfully represent both large and small scale variations in vibration. Wavelet analysis has also been applied to rotating components such as bearings with encouraging results [19]. In these applications of wavelet analysis the general behavior of the vibrating components was understood such that component-specific damage detection could be performed with effective wavelet bandwidths and speed of dilation to ensure that wavelet scales cover the frequency band of specific interest such that redundancy in computation is limited. The mother wavelet selected for the subsequent analysis is the Daubachies 6th order wavelet chosen for its success it with fault detection on rotor applications [21]. For these applications the operational response of the rotor was used to assess its condition and the effectiveness of the Daubachies 6th order wavelet was demonstrated. This wavelet is depicted in Figure 2-1. Wavelet scale, decomposition level and frequency are related by the following equation [22].

$$F_a = \frac{F_c}{a \bullet \Delta} \quad (3)$$

Where a is the scale, Δ is sampling period, F_c is center frequency of wavelet and F_a is the pseudo frequency corresponding to the scale in Hz. A 12 level decompositions method has been chosen for analysis of operations signals allowing for a highly detailed analysis of the low frequency content of the signals. Table 1 displays the level, scale and pseudo frequencies for the following analysis. Pseudo frequency will simply be referred to as frequency for the vibration analysis.

Currently, the vibration behavior of commercial wind turbines is yet to be entirely understood both due to the proprietary nature of commercial turbine design and operation and the novelty of the technology. The authors seek to expand the knowledge base of turbine vibration with the subsequent vibration analysis. In order for optimal structural health monitoring techniques to be developed and tested, the overall behavior of the turbines must be understood. This will be accomplished through the analysis of several sets of vibration signals for a given turbine, identifying key signal traits and patterns. Another unique aspect of the present vibration analysis is the utilization of the wind turbine mast as a conduit for response. The potential to measure nacelle or foundation sourced responses from a limited number of or single turbine-mounted accelerometer would be very desirable in a structural health monitoring context. The effectiveness of this technique will ultimately have to be evaluated based on the quality and clarity of response features within the signal.

Table 2- 1: Level, scale, frequency relationship for decomposition

Level	Scale	Pseudo Frequency [Hz]
1	2	181.8182
2	4	90.9091
3	8	45.4545
4	16	22.7273
5	32	11.3636
6	64	5.6818
7	128	2.840
8	256	1.4205
9	512	0.7102
10	1024	0.3551
11	2048	0.1776
12	4096	0.0888

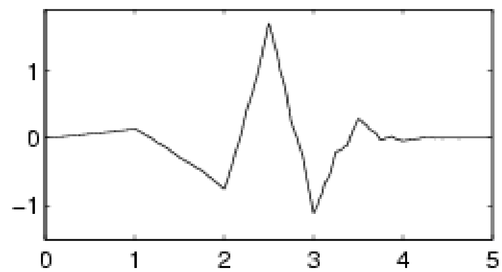

Figure 2-1: Daubachies 6 wavelet. Amplitude vs. Length (dimensionless).

2.2 Vibration Analysis Experiment

Vibration signals were acquired for a 2.3 MW wind turbine operating as part of a wind farm array in Ontario, Canada. Details for the acquired samples and turbine tested are presented in Table 2-2. Turbine specifications were obtained from the manufacturer. Figure 2-2 depicts the test turbine.

Table 2-2: Instrument and Turbine Specifications

Instrument Specifications		**Turbine Specifications**	
Sampling rate	500 Hz	Turbine Rating	2.3 MW
Accelerometer	Piezoelectric	Rotor Diameter	93 m
Accelerometer sensitivity	10.2 mV/g	Tower Height	80 m
Accelerometer location signal 1	50 m	Rotor Speed	6 – 16 rpm
Accelerometer location signal 2	17 m	Generator Speed	1500 rpm

The piezoelectric accelerometer (PCB 352C34) was mounted to the inside surface of the turbine tower at 17 and then 50 meters. The data acquisition system was configured to acquire continuous samples throughout the operation period at the specified sampling rate. The turbine was started by the operator while the vibration rig was left to measure vibration signals conducted through the tower. These initial signals represent a potential "healthy" baseline by which future signals may be evaluated against. The vibration signals available for analysis are shown in Figure 2-3. These plots represent the first 17 minutes of operation of each signal.

Figure 2-2: Turbine test sample.

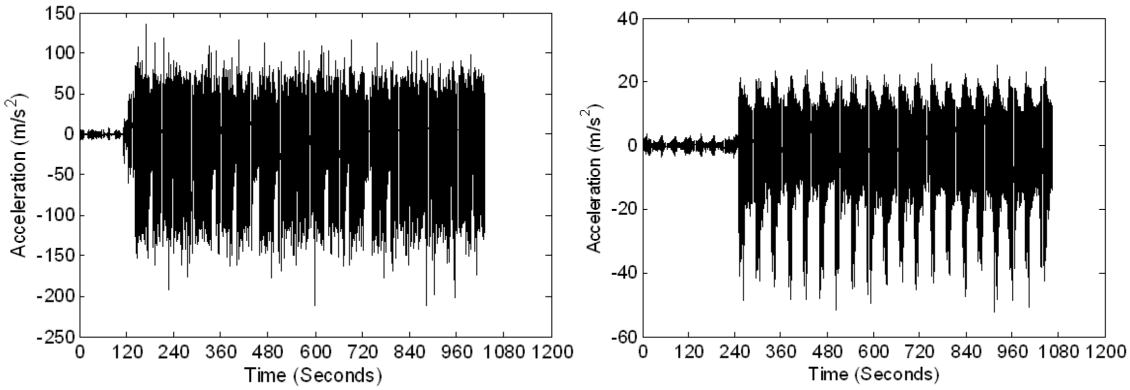

Figure 2-3: Operational raw vibration signal 1 (left frame), operational raw vibration signal 2 (right frame).

Inspection of the signal plots reveal that the vibration signals obtained begin with low amplitude events which correspond with the turbines start-up sequence. The start up of this machine involves the release of the mechanical brake on the main shaft and the pitch control of the blades; which must articulate from the stalled angle of attack. Depending on both the direction of the wind and the orientation of the parked turbine the yaw mechanism may be initiated to rotate the turbine into the wind. Each of the signals displays unique characteristics during this pivotal start-up stage. In order to aid in the analysis of the signal the start up segment of each signal has been extracted for detailed analysis as presented in the following section.

Following the start up sequence the signal notably increases in amplitude indicating the operation of the spinning rotor. This high amplitude vibration is maintained throughout the remainder of the signal until the turbine shut down sequence was initiated by the turbine operator. This segment of operation will be considered steady state operation as a means of distinction from start up or shut down signal segments. Data segments have been taken from the turbine steady state operation for detailed analysis and signal feature extraction. The shut down behavior of the turbine is to be considered in a following study. Before the relative properties of the signals can be assessed it is essential to note the different environments in which these signals were obtained. The test environment specifications are presented in Table 2-3. Environmental data was acquired from a weather station located approximately 32.5 km from the wind farm array. Wind speed data was acquired from a cup anemometer mounted to the nacelle of the turbine.

Table 2-3: Signal environmental specifications

	Signal 1	**Signal 2**
Test Date	June 11, 2009	August 6, 2009
Accelerometer Location	50 m	17 m
Average Wind Speed	8.1 m/s	5.5 m/s
Temperature	16 C	20 C
Relative Humidity	75%	56%
Precipitation	0	light rain

The relative behavior measured during the sampled periods can be investigated with the two obtained signals. The vibration analysis seeks to identify common traits between the two signals. Through the comparison of traits and evident trends the turbine response can be considered relative to environmental conditions and the methodology for obtained signals can be assessed relative to accelerometer positions. Once the nature of response data is understood further, investigation into the correlation between environmental phenomena and turbine response can be made involving high frequency wind velocity data.

2.3 Signal Feature Extraction from Wind Turbine Operation

2.3.1 Start Up Analysis

Start up segments were extracted from the original signal such that a more detailed analysis could be performed. The signals represent 128 seconds of the turbine startup sequence and extend briefly into the early full operation signal. By creating these segments the vibration response of the turbine can be assessed and potential trends identified for quantification. The 12 level DWT was calculated for each signal and is presented in Figure 2-4. For all the following figures, plots pertaining to signal 1 will be in the left column and plots for signal 2 will be in the right column.

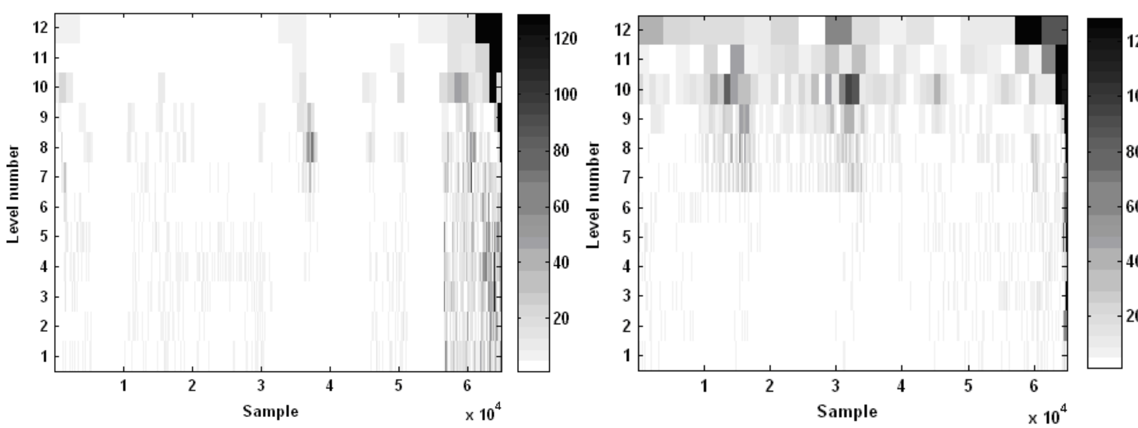

Figure 2-4: DWT of start up signal 1 (left frame). DWT of start up signal 2 (right frame).

For the DWT plots the areas of highest coefficient values are colour mapped in black. These areas indicate large magnitudes of signal energy within the corresponding decomposition level. Both signals contain high signal energies towards the end of the signal at low decomposition levels 10 through 12 as can be seen in the top right corner of each plot. The details of this low frequency activity are assessed by considering the signal decompositions for each given level. Figure 2-5 depicts the original start-up signals along with the level 12 and 11 decompositions, revealing the low frequency trends.

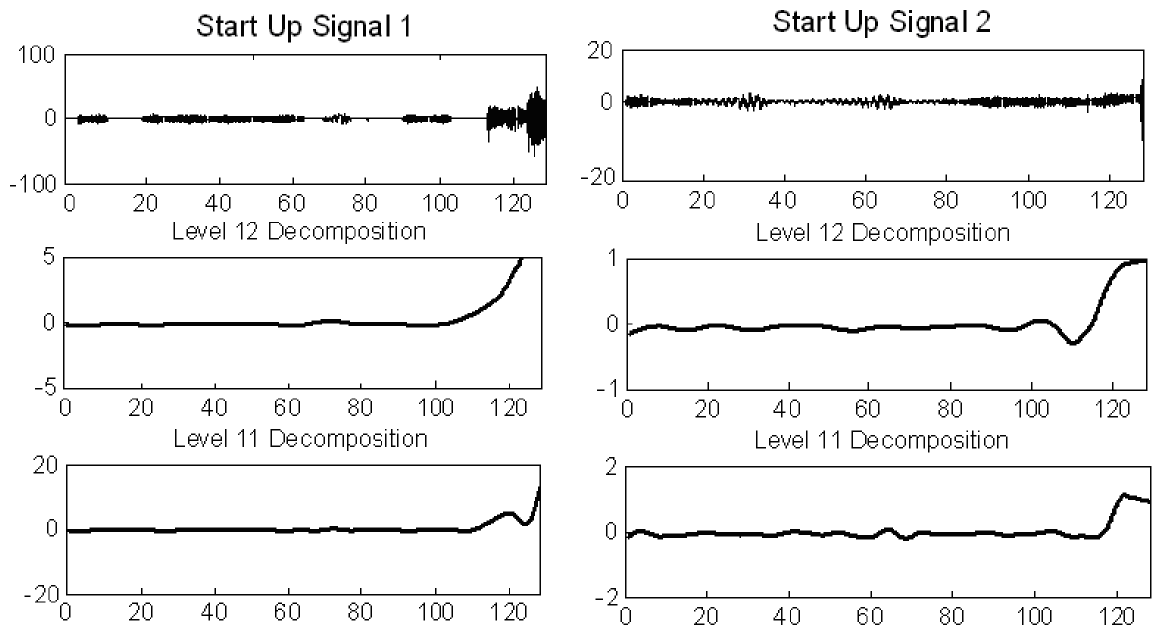

Figure 2-5: Start up raw vibration signals with level 12 and Level 11 decompositions. Signal Amplitude (m/s^2) vs. Time (seconds).

From these figures several characteristics of the turbine's start up behavior can be assessed. The 12th level decomposition of each signal reveals the ramping of signal amplitude corresponding to the start up of the turbine. The turbine manufacturer specifies the operation range of the turbine to be 6-16 revolutions per minute which corresponds to the 0.1-0.267 Hz frequency band. During the start up phase of turbine operation the rotor must begin from rest and accelerate into its outlined operation range. This corresponds to low frequency motion in the range of 0-0.1 Hz. The 12th level decomposition corresponds to the frequency range of 0-0.088 Hz, and inspection of this level reveals a trend that is likely driven by the low frequency spinning of the rotor before full operation speed has been reached.

Beyond the low frequency trends presented above, a more localized analysis was performed on a specific feature that was present in each signal. The DWT of Figure 2-4 was used as a tool to identify sections within the temporal domain of the signal which contain distinct high energy events. The DWT allows localization in both temporal and frequency domains. Thus a feature can be extracted based on both the segment of time that contains the signal feature and also the decomposition level that reveals the feature for a given wavelet scale. These sections could be further identified from DWT plots by the decomposition level which displays the highest wavelet coefficient values. The features extracted with this method can be described as a clear amplified vibration that grows slowly and dissipates quickly after reaching maximum amplitude. For Signal 1, the start up sequence contained one of these features at 64.3 through 78.6 seconds of the start up signal. The feature was present twice in succession in Signal 2 at 17.7 through 74.8 seconds of the start up signal. These features have been extracted and are presented in Figure 2-6 for detailed analysis. The DWT of each signal reveals noteworthy behavior as depicted in Figure 2-7.

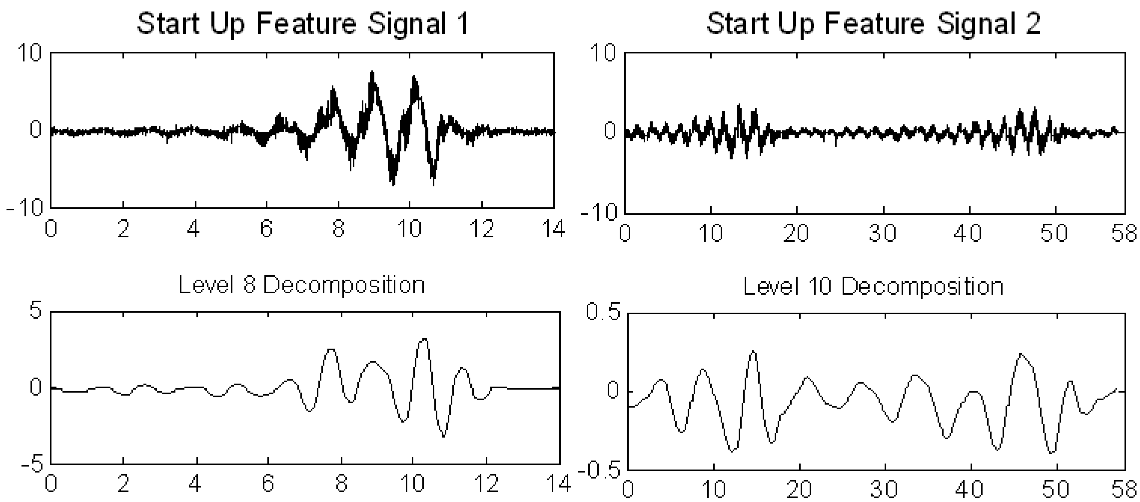

Figure 2-6: Start up features of raw signal with corresponding decomposition level. Signal Amplitude (m/s^2) vs. Time (seconds)

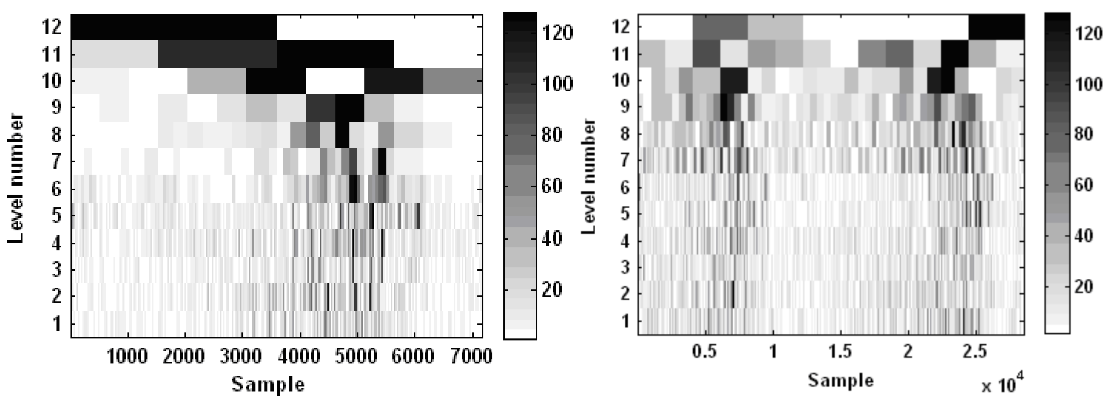

Figure 2-7: DWT of signal 1 start up feature (left frame). DWT of signal 2 start up feature (right frame).

From the above DWT plots the short term evolution of the vibration signal can be seen with respect to the DWT decomposition levels. For the above DWT plots the scale of the coefficients color map has been adjusted such that the colour mapping would reflect the coefficients relative to the feature. The behavior during this segment is complex but features can be extracted for comparison. Each feature takes place late in the start-up stage within a minute of the energy ramp-up as evident from the global start up analysis. Considering the physical phenomenon occurring during this interval the feature may be due to the activation of yaw mechanisms or pitch control motors. Further research is required to correlate and distinguish vibration features with start up phenomena to a higher level of certainty. The presence of these common features is promising, calling for further quantification and study as a more comprehensive dataset becomes available. This start up feature may be defined as distinct turbine behavior which can used for structural health monitoring. It is of interest to note that each feature consists of large low frequency events which introduce energy into channels of higher frequency. This cascade is evident in the shape of the DWTs.

2.3.2 Steady State Analysis

Several performance characteristics for which spectral targeting may prove effective are evident from rotor and generator speeds. These rotational frequencies are present and detectable within vibration response signals and thus will serve as the frequency bands of interest for preliminary analysis. The first frequency considered is the rotor rotational frequency produced by the dynamic motion of the 60 tonne rotor assembly. As noted above, the turbine manufacturer specifies the operating range to be 6-16 rpm. This corresponds to a frequency band of 0.1-0.267 Hz. The second frequency considered is the frequency of the induction generator used to convert rotational energy into electricity. The synchronous speed of the generator is 1500 rpm thus the frequency of interest is in range of 25 Hz. Figure 2-8 depicts typical DWT plots for the steady state signals.

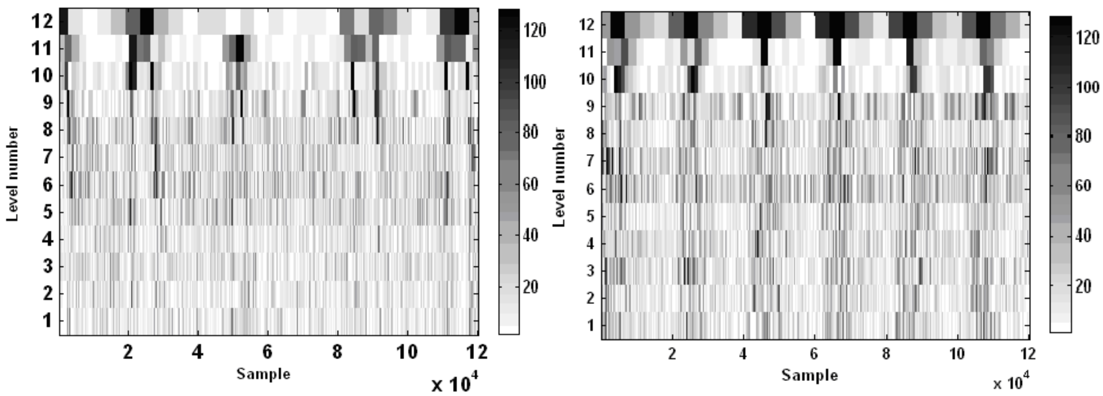

Figure 2-8: DWT steady state signal 1 (left frame). DWT steady state signal 2 (right frame).

From Figure 2-8 several key trends can be identified. The level 11 and 12 decompositions each reveal low frequency periodicity for the operation signals. Signal 1 exhibits higher periodicity in the 11th decomposition level while signal 2 exhibits it in level 12. These decomposition levels are related to the rotational frequency of the turbine rotor and indicate the periodic variation of energy in that frequency range. The period of this variation can be extracted from these plots by measuring the time between peaks.

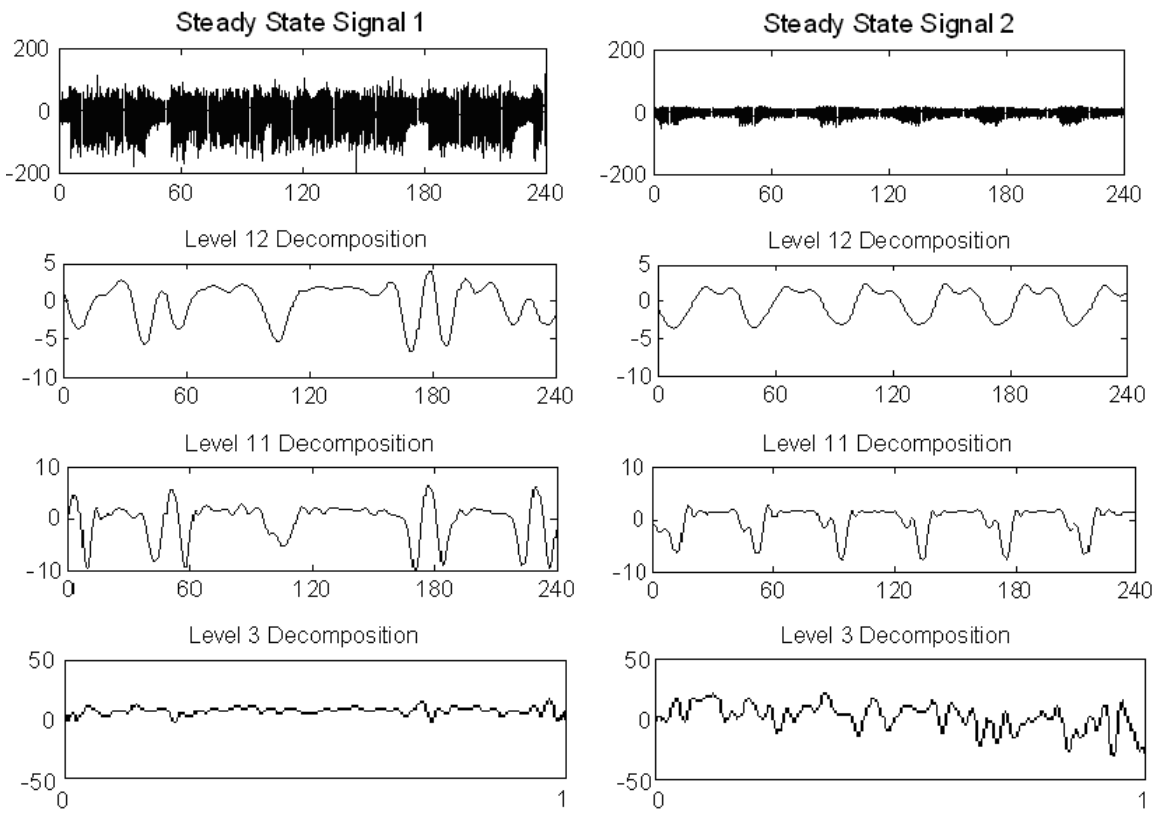

Figure 2-9: Raw vibration signals with Level 12, 11, and 3 decompositions. Signal Amplitude (m/s^2) vs. Time (seconds).

Considering periodicity, the first signal is more intermittent than the second signal with the longest between peaks period of 65.2 seconds. The second signal is much more constant in its periodic trends and the average period between peaks is 41.2 seconds with a max of 44.1 seconds. Of particular interest in Figure 2-9 is the presence of these low frequencies at comparable magnitudes despite the relative difference in overall magnitude for the original raw vibration signal which is significantly influenced by proximity to the nacelle.

In order to zoom-in on behavior on magnitude with the operation of the generator the level 3 decomposition of each signal has been calculated and is illustrated in Figure 2-9. The time scale has been modified such that the waveform can be seen. This decomposition level relates to the frequency band of 22.72-45.45 Hz which includes the 25 Hz synchronous speed of the induction generator. It is important to note that the generator will not exactly operate at 25 Hz and the difference between operating speed and synchronous speed is referred to as slip. The presence of this slip makes spectral targeting of the generator a challenge from this preliminary stand-point when the overall behavior of the generator has yet to be fully understood. Further research including the isolation of vibration sources from turbine nacelle is called for to further understand behavior and response of the generator.

2.4 Conclusions

In summary, vibration signals obtained for a 2.3 MW wind turbine during two operating conditions have been analyzed through wavelet analysis. The two unique signals could be representative of potential baseline for turbine behavior and response; which could be further developed and utilized for structural health monitoring application. The following outcomes were realized.

- Analysis of start up signals revealed the low frequency ramping up of energy on the order of the rotor rotational frequency. Signal 1, obtained higher on the turbine tower, had a higher overall vibration magnitude than signal 2. Although the average wind speed was higher for the first signal, the amplitude of response is significantly greater; verifying the intuitive notion that the nacelle is the significant source of vibration for the system and accelerometers located closer to this source will measure stronger signals. This phenomenon may be utilized to analyze different aspects of turbine response with accelerometers mounted closer to the nacelle capturing high vibration levels from the generator and control mechanisms; while accelerometers mounted further from the nacelle, closer to the foundation would capture global structural movement.

- The time and frequency localization property of the DWT was used to identify high energy events within the turbine start up signal. A localized analysis of these areas revealed distinct vibration features common to each signal. These features correspond to a physical event that is a part of the start up sequence of the turbine such as yaw motion. Further research into the exact correlation between the response and event is called for.

- Steady state operation signals were dominated by low frequency trends which become clear upon consideration of level 11 and level 12 wavelet decomposition plots. These plots reveal that periodic trends are much more consistent for signal 2 obtained lower on the turbine mast. The average period of this motion was 41.2 seconds.

- The presence of distinct trends within steady state operation signals is promising as it confirms that the turbine tower may be utilized as a conduit for turbine response. This is significant as this convenient mounting location reduces the time and effort necessary for installation. Further, and most notably, this opens the possibility of significantly reducing the number of sensors required to purchase, install, and monitor in a comprehensive SHM routine. Subsequently making vibration analysis based SHM an attractive feature for implementation in wind farm maintenance regiments.

- With further development the presented method of vibration analysis can be used as part of a structural health monitoring scheme which may be able to prevent catastrophic turbine failures and reduce both downtime and maintenance of large scale wind turbines. Ideally, this would work to make wind energy more feasible and accessible in the short term and allow for more sustainable growth of the wind energy industry in the long term.

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Chapter 3

2.3 MW Wind Turbine Vibration Response to Yaw Motion and Shut Down Events

3.1 Introduction

In recent years wind energy technology has gained considerable attention from the public and private industry sectors. With this attention has come investment and opportunity for those committed to developing this renewable energy. Many countries including the United States and Canada have outlined goals for drastically increasing wind energy generation in order to reduce the requirement for imported or non-renewable energy such as oil and coal. The United States Department of Energy has outlined a goal of increasing American wind energy penetration to 20% of total usage by the year 2030 [1,2]. This goal calls for a threefold increase in annual installations. The Canadian Wind Energy Association (CANWEA) has too outlined a goal of 20% penetration by the year 2025; requiring an increase of 50,000 MW of wind energy generating capacity [3]. In each case the vast proportion of wind energy capacity will be met through the installation of utility-scale wind turbines rated at greater than 1MW. Turbines of this scale currently consist of towers ranging in hub height from 50 to >100 m. Several challenges must be met to achieve this planned North American growth.

Turbine Reliability

One such issue is the reliability of turbines of this size. A comprehensive survey of failures in wind power systems within Germany, Finland and Sweden for the time period of 1997-2005 revealed that larger turbines have a higher annual failure rate than smaller turbines [4]. The study also revealed that for turbines rated above 1 MW, the failure rate increases each operational year. These points become of greater concern from a social perspective as a country's utility grid becomes more dependent on wind energy for significant proportions of its total power. Wind turbine fleets must prove as reliable as traditional energy sources such that a secure and balanced grid based on significant proportions of renewable energy can be obtained. To address this concern of reliability many researchers have devised condition monitoring techniques often referred to as Structural Health Monitoring (SHM) schemes. A SHM system is a process of implementing a damage detection strategy for a mechanical system [5]. There are currently many approaches to SHM; which vary based on application, equipment required, and algorithm utilized for data processing. One such approach utilizes modal analysis which employs dynamic information from a structure along with varying degrees of statistical processing to assess a structural condition. This method has been utilized successfully for many different mechanical and civil systems including bearings [6], rotors [7], bridges [8] etc. When considering the structural health monitoring of wind power systems the modal approach has many attractive qualities. Vibration sensors typically used for modal analysis are relatively inexpensive and readily available when compared to other techniques requiring acoustic emission, thermal imaging or ultrasonic equipment. The technique is also considered straightforward to implement on a given structure making it suitable for the complex tower structure of a wind turbine. Studies into the reliability of European wind energy systems have determined that reliability data contains periodicity [9] and modal analysis can be utilized to access and quantify these trends. Despite the attractive qualities many researchers have criticized the method based on several criteria including inaccessibility to turbine response datasets [10], inconvenient and extensive sensor arrangement, and unavailability of undamaged turbine structural response data [11].

The present authors have taken several key steps to addressing the above issues such that modal based structural health monitoring can be applied on utility scale wind turbines located throughout Ontario, Canada, and abroad. The first step was to secure a strong relationship with existing wind farm operators and developers such that undamaged turbine structural response datasets could be obtained. This was made possible by a wind energy developer looking to invest in the long-term reliability of their wind turbine fleets. This process of developing a working business/research relationship with a private wind energy developer began in January 2007. Since the commissioning of the wind farm the operator corporation has allowed and facilitated select testing of turbines within their farm. This limited access to an operating wind turbine has opened the doors to novel vibration analysis. Before full scale testing could commence, an initial SHM procedure was developed in the laboratory. The statistics based scheme proved successful in detecting damage sustained by a simplified wind turbine model during wind tunnel testing [12]. Following lab experiments researchers sought more information from the frequency content of turbine vibration signals. Considering the non-stationary nature of wind turbine vibration signals, traditional frequency transforms such as the Fast Fourier Transform were not suited for this use in this structural health monitoring application. This has led researchers to consider wavelet methods in order to better account for the transient nature of operational turbine vibration response.

Wavelet Analysis

Wavelet analysis involves the evaluation of a signal based on a wavelet of discrete length. The length of the wavelet, often referred to as scale, is related to frequency through a defined relationship. A wavelet analysis can be executed in several different ways and the method of particular interest in this study is the discrete wavelet transformation. This technique decomposes a signal into multiple frequency levels and determines correlation coefficient values based on the comparison between the shapes of the signal waveform and the wavelet. Table 3-1 depicts the relevant frequencies and scales utilized for the 12 level discrete wavelet transform for a Daubachies 6^{th} order wavelet. The Daubachies 6^{th} order wavelet has proven successful in damage detection for non-stationary signals emitted from a rotor [7] and thus it has been chosen for this analysis.

A twelve level discrete wavelet transform has been selected for its suitability in the analysis of the low frequency range of the signal. Low frequencies are of particular interest in this analysis of commercial scale wind turbines. Table 3-2 illustrates the relevant operating frequencies for select major turbine components.

Table 3-1: Level, Scale, Frequency Relationship for Decomposition

Level	Scale	Frequency Window [Hz]
12	4096	(0-0.089)
11	2048	(0.089-0.18)
10	1024	(0.18-0.36)
9	512	(0.36-0.71)
8	256	(0.71-2.84)
7	128	(2.84-5.68)
6	64	(5.68-11.36)
5	32	(11.36-22.73)
4	16	(22.73-45.45)
3	8	(45.45-90.91)
2	4	(90.91-181.83)
1	2	(181.83+)

Table 3-2: Operating Frequencies for Select Major Turbine Components.

Component	RPM	Frequency [Hz]	DWT Level
Rotor Rotation	6 – 16	0.1 – 0.267	11 – 10
Low Speed Shaft	6 – 16	0.1 – 0.267	11 – 10
Generator Speed	540 –1500	9 – 25	6 – 4
High Speed Shaft	540 – 1500	9 – 25	6 – 4
Blade Passing	18 – 48	0.3 – 0.8	10 – 8

It should be noted that although the RPM range for rotor rotation begins at 6 RPM and the appropriate shaft speeds are harmonics of this frequency, the turbine primarily operates at its rated speed of 16 RPM. Therefore the DWT level location can be known for cases where a range spans more than a single level. With wavelet-based spectral targeting of turbine components, and access to an operating turbine with which to test this method the authors proceed to demonstrate how a database of quantified turbine undamaged response can be compiled.

Wavelet methods were first utilized to analyze the start up and steady state operation segments of two signals obtained from the wind turbine earlier in the project. The results of this study were presented in a recently submitted manuscript. The proceeding sections present the results of a more in detailed experiment completed on a 2.3 MW wind turbine for a variety of operational events. It is the intention of the authors that the data presented and discussed may be further used by other researchers to aid in the advancement of vibration based SHM techniques for wind turbines. The objectives of this investigation are to obtain vibration response signals from the turbine tower, relate the obtained response signals to environmental, operational and experimental conditions, and identify trends within signals that may characterize healthy turbine response.

3.2 Vibration Testing

Vibration testing of a 2.3 MW commercial wind turbine took place on October 22, 2009. Throughout the day six tests were executed involving the operation of the turbine and the recording of the subsequent vibration response of the structure. The turbine utilized for this investigation (as depicted in Figure 3-1) is typical of utility-scale used throughout the world. There are currently more that 500 of these turbines installed in the United States and many in other countries including Canada (174) and France (30) [13]. The popularity of this turbine serves to further emphasize the value of the present work as a database of its healthy response can be used by researchers and wind farm operators around the world to diagnose, troubleshoot and evaluate the fatigue of their specific turbine. Relevant turbine specifications are defined in Table 3-3.

Figure 3-1: Turbine (foreground) Examined in Study.

Figure 3-2: Researcher Ascending Turbine to Prepare Testing Instrumentation.

Table 3-3: Turbine Specifications

Parameter	Value	Parameter	Value
Hub Height	80 m	Rotor Mass	60 tonne
Rotor Diameter	93 m	Nacelle Mass	82 tonne
Generator Type	Synchronous	Tower Mass	162 tonne
Synchronous Speed	1500 RPM		
Max Rotor Speed	16 RPM		

Response was obtained through a piezoelectric accelerometer (PCB 352C34) mounted on the inside surface of the turbine tower at a specified height. It is to be noted that the present study utilizes standard turbine operation as the excitation from which response is derived. Methods utilizing these innate excitation techniques have considerable advantages over other techniques such as externally delivered forced vibration provided by an impact hammer, electrodynamic shaker, or laser pulse as analysis can be performed under service conditions and require no artificial exciters [14]. Several forms of innate excitation are relevant when applying vibration analysis techniques to a wind turbine including ambient excitation, static yaw motion, start up, operation and shut down. Each of these system excitations provides a unique and potentially valuable structural response as the nature of the response can be considered relative to the turbine components which introduce the mechanical excitation into the turbine system. The executed study has considered and obtained response to the aforementioned natural excitations.

Figure 3-2 illustrates a researcher ascending the turbine during the installation of the accelerometer sensors. The height variable is of particular interest due to the possible localization property it may exhibit. This could be significant for the potential isolation of specific turbine component monitoring such as foundation, tower, yaw bearing, generator and gear train based on sensor location. The three heights of 17m, 50m, and 80m were considered for this study and two operation tests were executed at each height. This method of measuring response from the turbine tower has many advantages when considering modal testing. The turbine tower is a highly accessible and convenient point of measurement that allows for rapid installation and set up as the turbine nacelle need not be entered and no disassembly of turbine components is required. The turbine tower itself is composed of multiple sections with flanged ends that are bolted together during assembly. These bolts must be tightened as part of standard turbine maintenance procedure. Tower mounted accelerometers may provide indications of loose bolt connections between tower sections and this would be very advantageous as preventable fatigue to turbine components may be averted. In previous structural health monitoring approaches vast arrays of sensors are required, the proposed method has the potential to do away with these arrays through the utilization of wavelet decomposition.

Signals from the sensor were transmitted to a pc-based data acquisition system for storage and processing. The acquisition interface was set to record samples at the specified sampling rate of 500 Hz throughout the test duration. This sampling rate was selected because it allows for the timely processing of obtained data. When applying a wavelet transform the computation time is highly dependant on the number of samples recorded for each second of operation. In order for real time structural health monitoring to be realized the transform needs to be completed in a shorter time period than the dataset length. This means that for a thirty second sample the computation must be executed in less than thirty seconds such that the next sample can be evaluated without delay and the system can keep up with acquired data. Also, the major turbine components considered for this study have fundamental harmonic frequencies below 50 Hz and thus the accuracy of data within this range is ensured by sampling at ten times this value. As turbine response becomes better understood (and computer processing speeds increase) higher sampling rates can be used to target smaller components such as individual bearings and gears which operate at higher level harmonics of the fundamental operating frequency.

Several environmental and operational parameters were recorded during the tests in order to aid in the study of the parametric relationships between relevant environment/operation variables and recorded events. The turbine data acquisition system was utilized to obtain this supplementary data. Rotor mean speed, generator mean speed, maximum wind speed and mean wind speed were tracked throughout the test day and are displayed in Figure 3-3. Raw data has been processed into ten minute averages by the wind farm SCADA system.

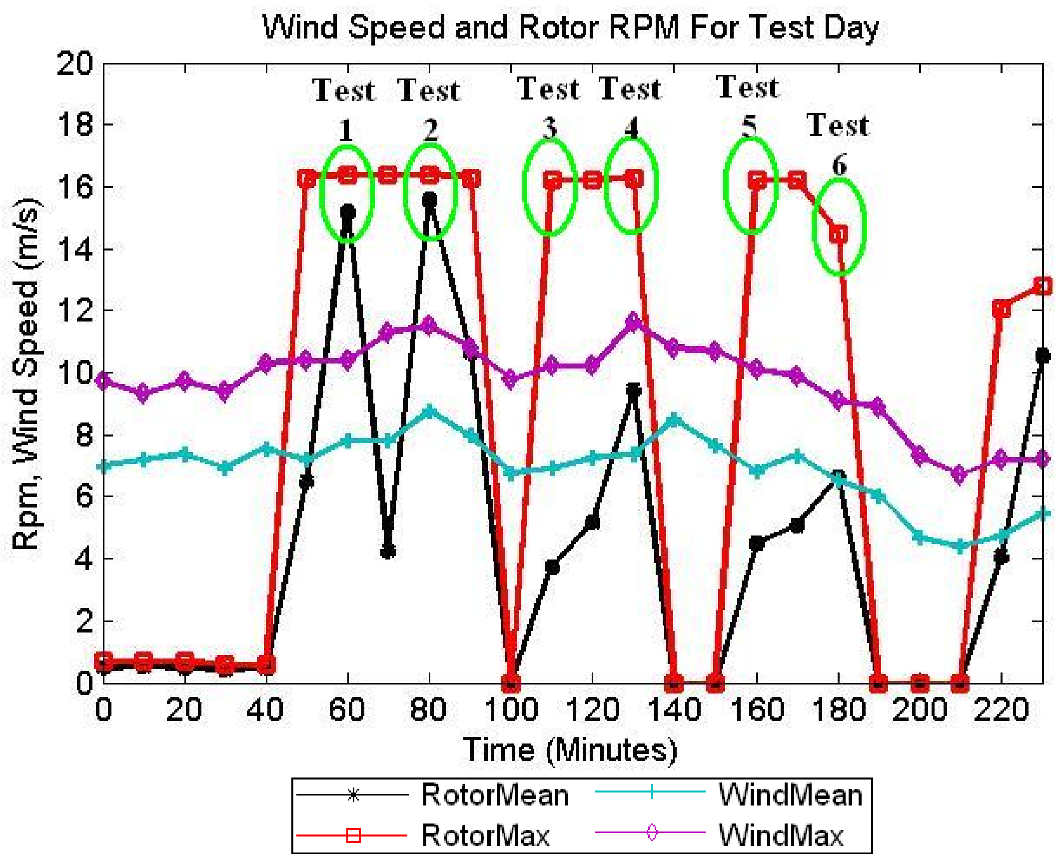

Figure 3-3: Wind Speed and Rotor RPM for Test Day.

Each of the six test periods are identified on the figure and the associated characteristic parameters will be used to understand the vibration response within the context of wind and operating speeds. Time periods where the maximum rotor speed is zero correspond to periods where the turbine was parked while the technician ascended the tower to change the location of the accelerometer sensor.

3.3 Vibration Event Mapping

In order to help facilitate the positive identification of the operation of a variety of turbine sub-components within vibration signals collected only in the turbine tower, control level event maps were recorded to overlay on vibration signals to establish temporal correlation of vibration signals and operation control signals. Some of the specific turbine mechanisms that were tracked from the SCADA interface included forced yaw events, periods of rotor speed acceleration, pitch articulation, start up and shut down. The raw vibration operation figure for Test 2 is typical of other obtained signals and is displayed in Figure 3-4.

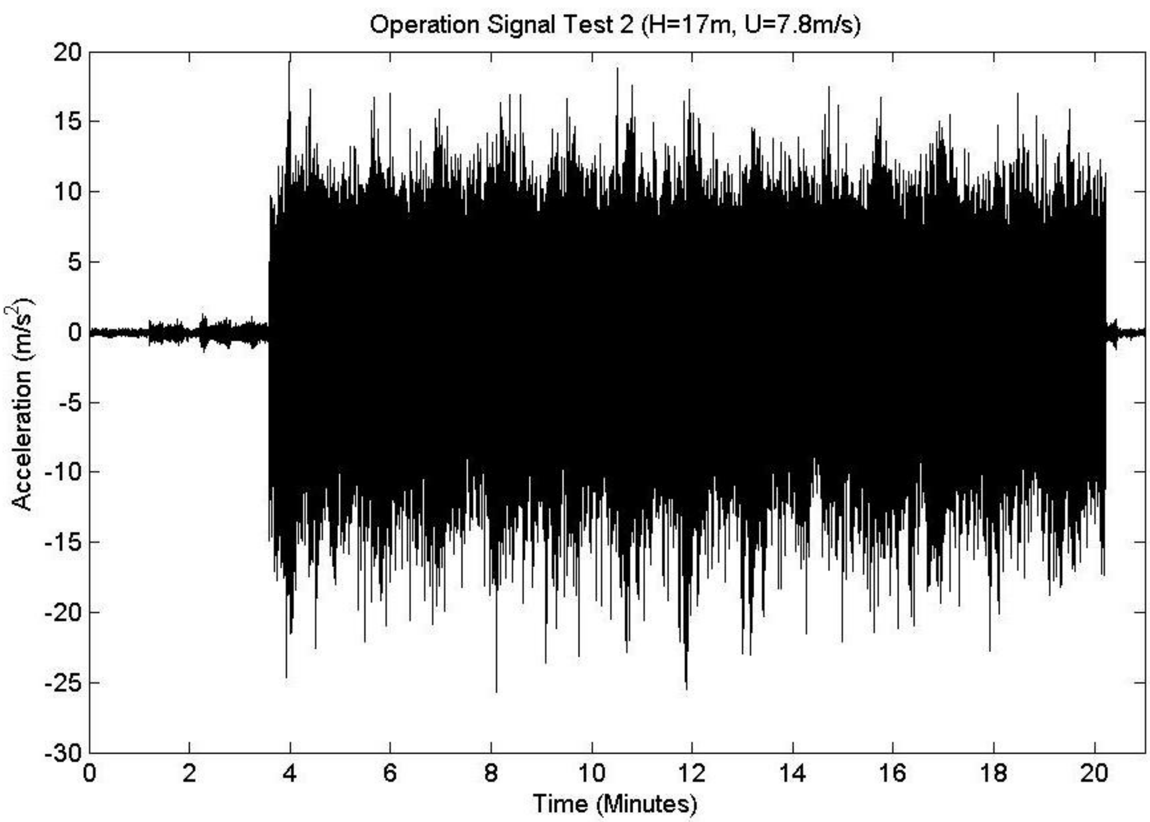

Figure 3-4: Raw Vibration Operation Signal for Test 2

In this figure the start up, operation, and shut down response is displayed and a sense can be developed for the general shape and magnitudes of the response signals. After correlating the time stamp from vibration signals with the time of each event, event maps could be constructed. Timestamp and event data for Test 2 are shown in Table 3-4. Figure 3-5 displays the detailed vibration event map for Test 2 with indicators for the location of the event timestamps.

Table 3-4. Observed Events and Associated Times for Test 2

Event	**Time [s]**	**Event**	**Time [s]**
Yaw initiated	71.3	Yaw stopped	87.3
Turbine start	131.3	Blade pitch	147.3
Breaker Switch	211.1		

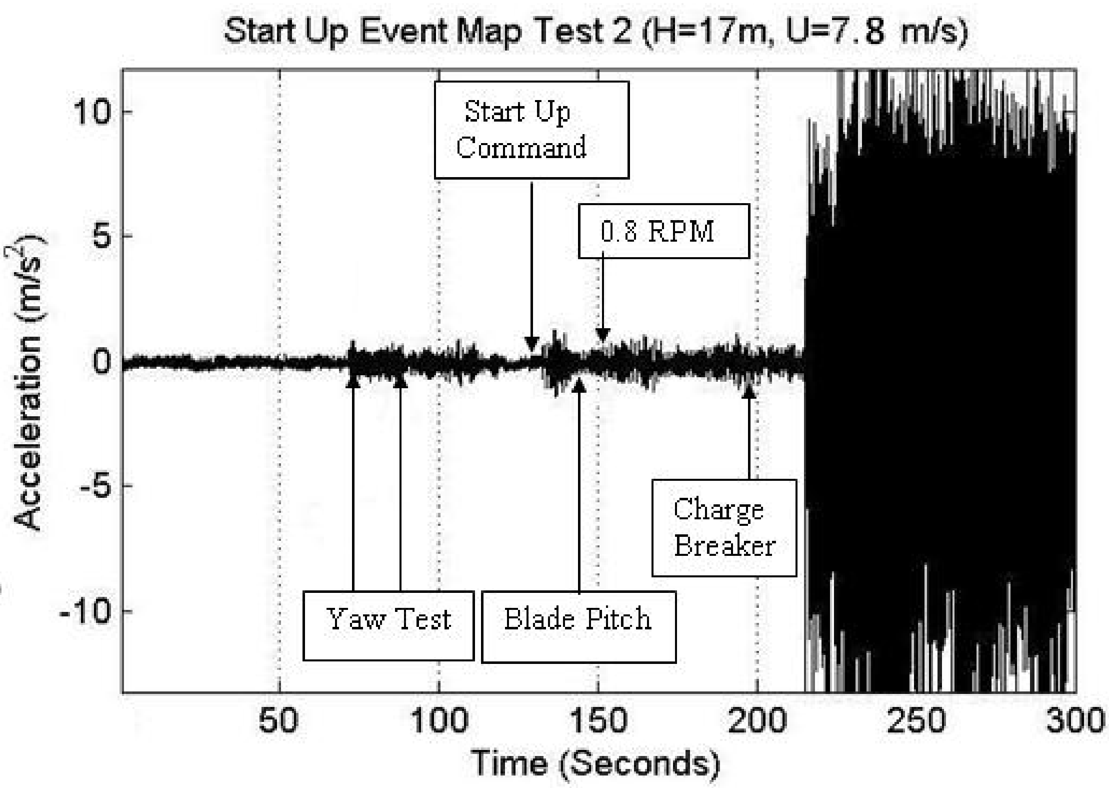

Figure 3-5 Start Up Event Map for Wind Turbine Start Up Test 2.

From Figure 3-5 the various events can be observed and the vibration responses identified. The first aspect of the figure to be considered is the base level vibration before any turbine motion has been initiated. This can be considered ambient signal excitation and can be observed in the first 50 seconds of the above figure before the yaw test occurs. This ambient excitation level is low relative to the magnitudes of full operation but should be considered for lower magnitude excitations such as yaw motion and thus it is further discussed in the yaw analysis presented below.

Following the base excitation level the first event to take place in this operation sequence was a yaw test. This yaw movement was intentionally initiated as part of the yaw motion analysis of the turbine. The vibration response of the turbine to yaw motion begins with a peak in vibration followed by a sustained vibration level and then a second peak. After completing the forced yaw event the turbine was set to complete a standard start up sequence. The initialization of this start up is located on the above plot and is followed by a local peak in vibration. By considering the standard start up sequence for this particular turbine it has been determined that this first peak following initialization of start up is caused by the release of the mechanical brake on the high speed shaft of the rotor. Immediately following the disengagement of the brake is blade pitch articulation as indicated by the turbine controller. During this time the response signal has two periods of gradual amplification followed by rapid dissipation. It was noted during the vibration event mapping procedure that the turbine had not yet reached any significant rotational frequency and the instantaneous rotational frequency is noted as 0.8 RPM. These features have appeared in historic response signals and were the subject of analysis in a previous recently submitted manuscript. Following the pitch articulation the turbine did accelerate into normal rotational operation and a dramatic increase of vibration amplitude occurs at the 220 second mark. During the event mapping procedure it was noted that immediately before the turbine reached full operation a breaker switch had been hit allowing for grid electricity to enter the turbine generator charging the induction rotor and allowing for electricity to be harnessed from the motion of the spinning rotor. This charge applied to the induction rotor corresponds to a drastic increase in vibration amplitude which is sustained until the shut down sequence of the turbine is initiated. This charge point is indicated in the event plot and is in fact a critical point within the response signals. The drastic increase in vibration beyond the charge point is the result of turbine's process of converting kinetic to electrical energy through electrical load applied to the induction generator. The turbine rotor is in fact spinning before the charge is applied and thus it has been observed that simple dynamic motion of the rotor introduces low amounts of vibration when considered relative to levels during the power producing segment of the signal.

This vibration signal as portrayed in Figure 3-5 and Figure 3-6 is significant as it represents what we have defined as the healthy response of the wind turbine and offers insight into the typical dynamics of turbine operation. At this point, the question of "what is healthy?" should be raised. Ideally, we would have had a thoroughly comprehensive inspection of the machine the morning we began the tests to ensure its health. We were satisfied that it met the fully-operational criteria required for it to run that day (i.e. there were no known unhealthy conditions present). The preferable scenario involves monitoring vibration signals from successful commissioning onwards throughout the life of the turbine. In this study; we start at roughly the 2 year old mark and establish these response signals as a healthy baseline. Though, it should be noted that theoretically these signals will inherently contain nearly two years of aging.

The raw signal in its entirety has been stored in a growing database of turbine response signals amassed in this research program such that it may be utilized and leveraged when the most suitable structural health monitoring scheme is developed. Certain events of interest are to be extracted from the full signals for detailed study including static yaw movements and dynamic shut down sequences. The analyses of these events are presented in the proceeding sections.

3.4 Study of Static Turbine Yaw Response

The yaw motion of the turbine under investigation is similar to a variety of utility scale turbines with active yaw systems in that yaw motion is controlled automatically during operation. The system actively works to rotate the turbine rotor into the wind through an elaborate drive mechanism. This mechanism is made up of an externally geared slew ring bearing driven by eight electrical gear motors. The brake for the system is passive and friction based.

The yaw motion of the turbine is of interest, as a 15 year study in Germany has shown that yaw bearings have a high failure rate second only to wind blade tip break [15]. This study also showed that the yaw system accounted for 8% of all unforeseen malfunctions.

Results from a 4 year survey of Swedish wind power plant downtimes and failures showed that failures in the yaw system accounted for 6.7% of total failures and the average downtime per failure was 259.4 hours [4]. Yaw system failures were the second most time consuming component malfunction which speaks to the complexity of yaw system diagnosis utilizing available methods.

By utilizing the constructed event maps seven yaw samples were extracted from the test signals. These yaw events were captured for the stationary turbine rotor and will be used to derive the influence of yaw motion on the structure of the turbine. Figure 3-6 displays the raw vibration signals for the seven yaw samples.

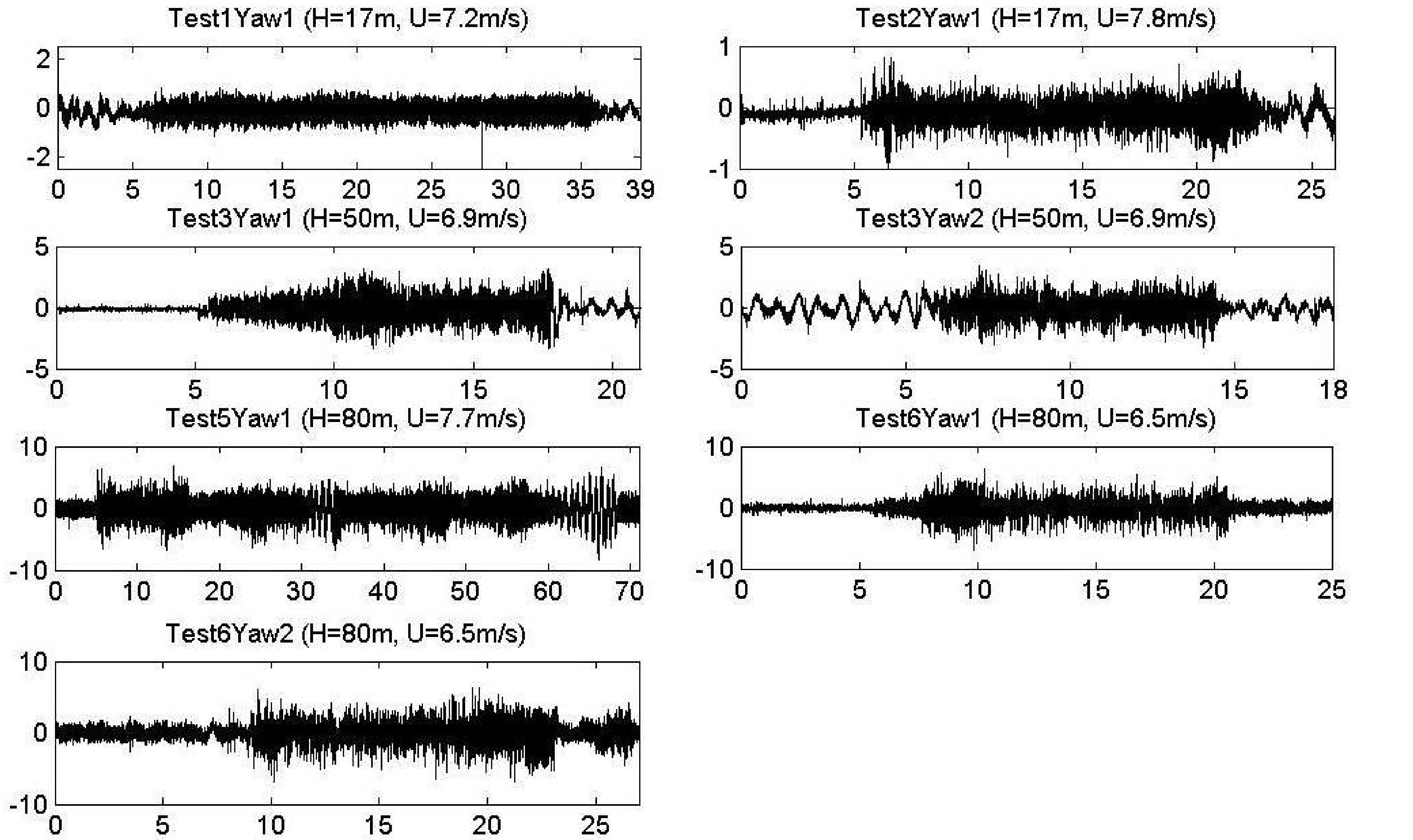

Figure 3-6 Raw Vibration Signals for Seven Yaw Events. Acceleration (m/s^2) vs. Time (seconds).

These samples underwent wavelet decomposition as discussed and presented in the introduction. In an effort to further characterize trends from the vibrations signals the RMS amplitude of vibration has been calculated for each original signal and each subsequent decomposition level. With this technique the amplitude of vibration for the healthy yaw events can be examined with respect to environmental variables and spatial location of the sourced sensor. Table 3-5 displays the RMS values for respective decomposition levels.

Table 3-5. Yaw Signal RMS for Decomposition

Yaw Event	**T1Y1**	**T2Y1**	**T3Y1**	**T3Y2**	**T5Y1**	**T6Y1**	**T6Y2**
Original RMS (m/s^2)	0.267	0.152	0.526	0.607	1.014	0. 615	0.766
1	0.229	0.130	0.397	0.504	0.813	0.474	0.588
2	0.203	0.114	0.319	0.433	0.655	0.343	0.448
3	0.184	0.107	0.255	0.381	0.530	0.246	0.327
4	0.179	0.105	0.235	0.358	0.465	0.198	0.282
5	0.177	0.104	0.217	0.339	0.413	0.150	0.247
6	0.176	0.103	0.198	0.317	0.376	0.111	0.213
7	0.172	0.100	0.174	0.283	0.338	0.099	0.180
8	0.169	0.096	0.115	0.114	0.176	0.080	0.137
9	0.167	0.095	0.110	0.099	0.118	0.069	0.101
10	0.167	0.097	0.110	0.094	0.103	0.067	0.086
11	0.166	0.097	0.113	0.093	0.103	0.065	0.073
12	0.165	0.102	0.114	0.103	0.088	0.063	0.076
Location (m)	17	17	50	50	80	80	80
Mean Wind Speed (m/s)	7.2	7.8	6.9	6.9	7.7	6.5	6.5

When this data is arranged graphically several key trends become evident. Several different plots can be assembled displaying the various relationships in the above dataset.

The first figure to be considered will be stationary in time. Figure 7 displays the direct relationship between RMS and decomposition level in a 3 dimensional representation.

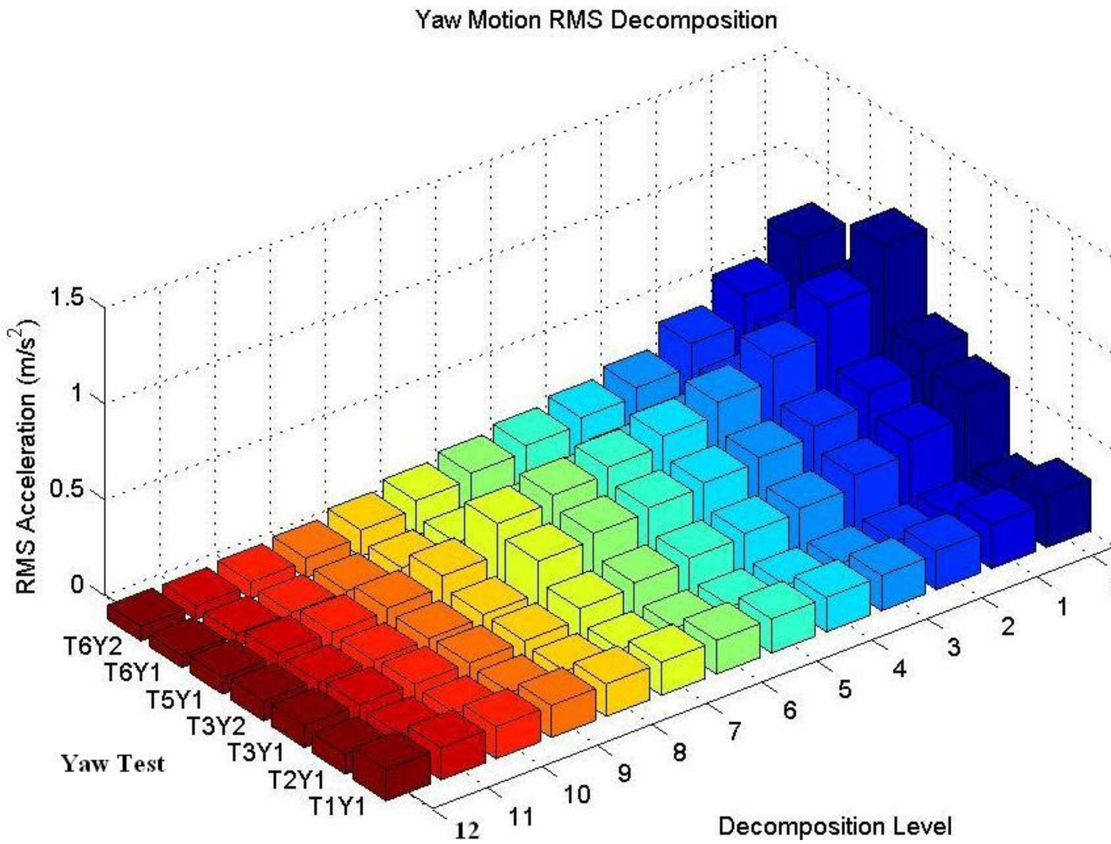

Figure 3-7. Yaw Motion RMS Decomposition. RMS Acceleration (m/s^2) vs. Decomposition Level for Seven Yaw Samples.

From this figure it is clear that there is an inverse relationship between acceleration magnitudes and decomposition level. As suggested by the figure, the degree to which this relationship holds depends on the height from which the signal was acquired. In order to further investigate this trend a 3 axis plot has been constructed and presented in Figure 8. This figure displays the three-dimensional relationship between height within the turbine, decomposition level, and RMS acceleration.

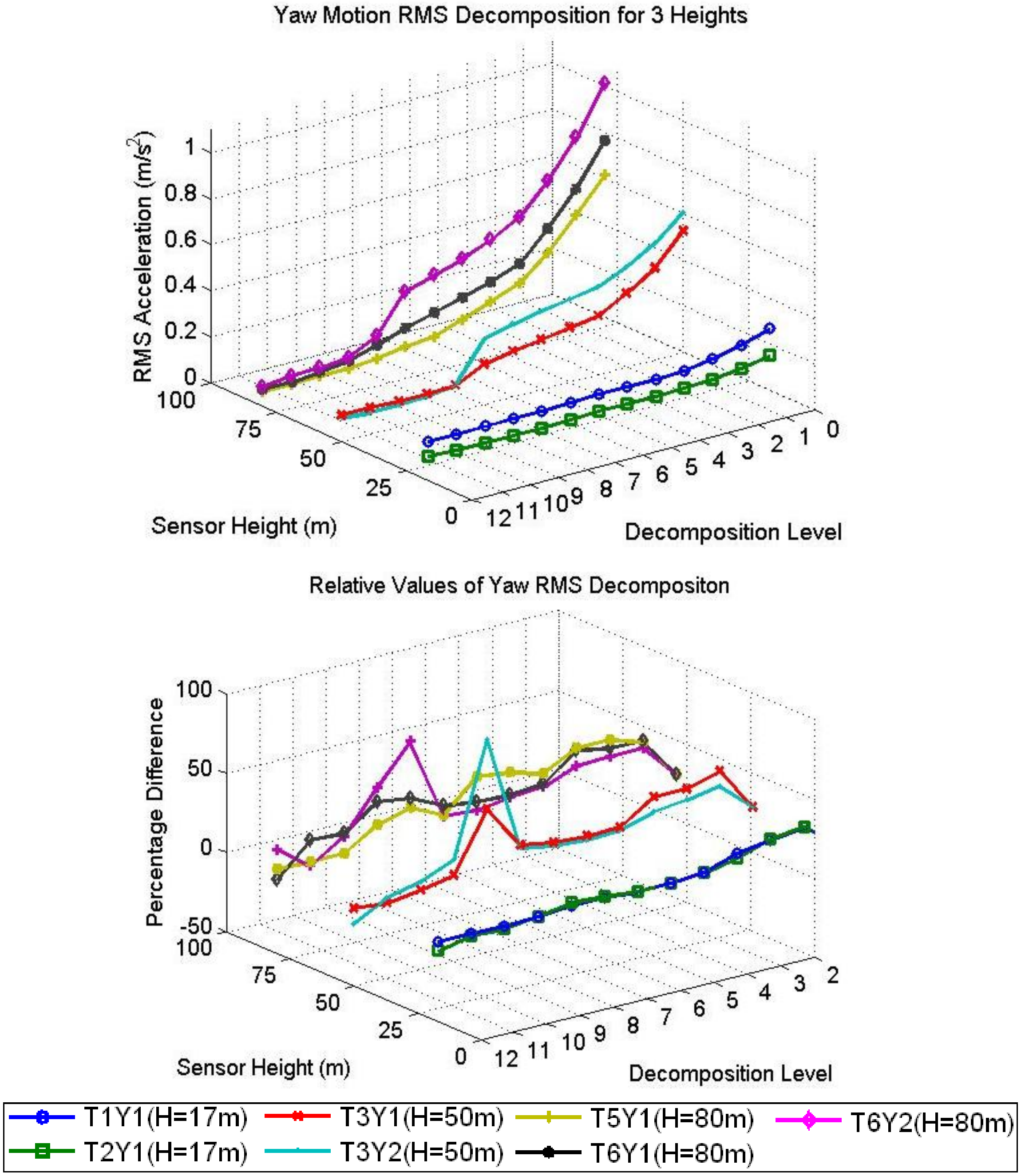

Figure 3-8. Yaw Motion RMS Decomposition for 3 Heights. Height (m), RMS (m/s^2), Absolute and Relative values.

From this figure it can be seen that the relationship between RMS and decomposition level is highly dependant on the location of the sourced signal. When the sensor was low on the turbine mast the relationship was typically constant across the decomposition range. This was indicated by both the absolute and relative values that remain relatively constant throughout the frequency range. When the sensor was higher on the turbine mast the relationship is less linear and more parabolic with greater spread between maximum and minimum values. When considering the percent difference plot a drastic peak in sensitivity is apparent between the 7^{th} and 8^{th} decomposition levels for signals obtained at the 50 and 80 meter locations. This suggests that there may be significant physical phenomena existing in this frequency range that is most easily detected by sensors mounted nearest to the nacelle. Also, zero crossings occur at the high decomposition levels 10-12. This suggests the presence of meaningful data in this frequency range that characterizes healthy turbine response.

Another important parametric relationship that should be considered when analyzing the acquired yaw signals is the aerodynamic environment in which the yaw motions took place. This has been expressed by average wind speeds for each test and the plot for this data is depicted in Figure 3-9. Wind direction was not considered in this study in the quantification of ambient wind excitation.

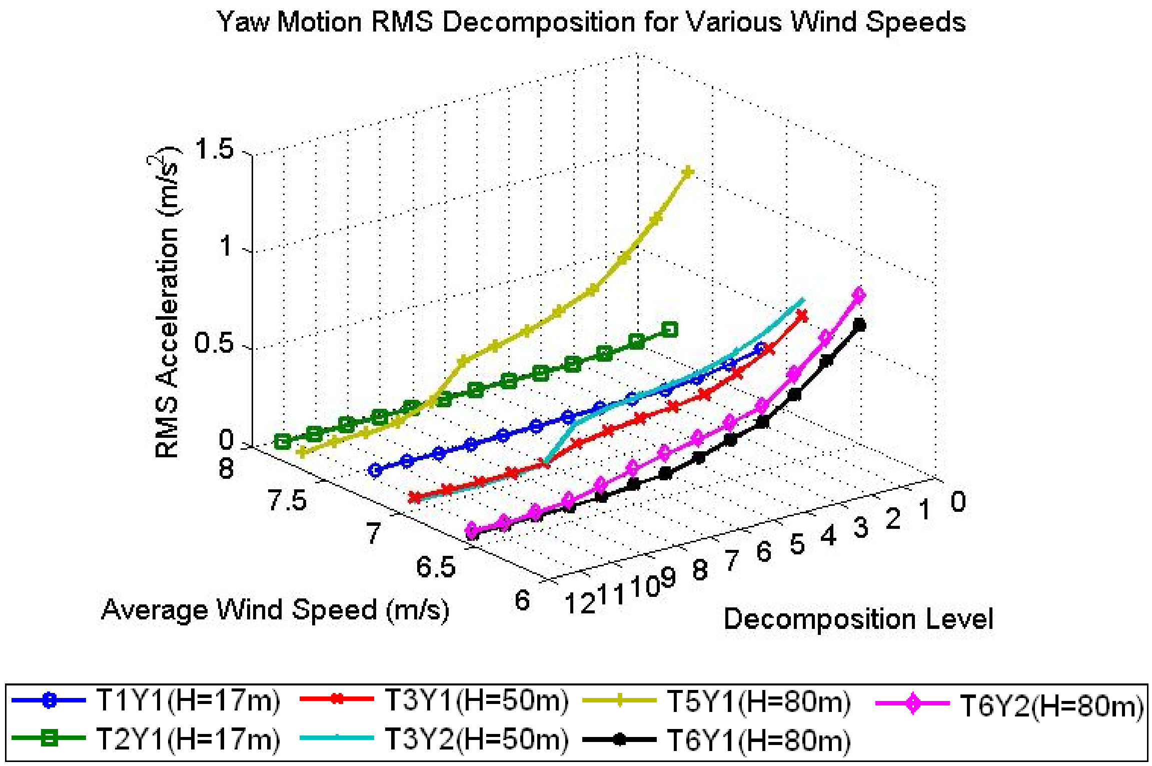

Figure 3-9. Mean Wind Speed (m/s), RMS (m/s^2), Decomposition Level Relationship.

Figure 3-9 works to demonstrate that sensor height is of greater influence on the overall vibration signal than wind speed for the range of wind speeds considered. The signal with the highest average wind speed of 7.8 m/s obtained at 17m had significantly lower vibration levels than a signal with a wind speed of 6.5 m/s obtained at a height of 80m.

Beyond simply considering the RMS values for each decomposition level it is of greater interest to display the evolution of each decomposition level with respect to time. These plots reveal the evolution of the signals' frequency content sub-banded for each of the decomposition levels. In order to determine areas of high energy activity both in frequency and temporal domains, wavelet coefficient plots are considered. Plots for Test1Yaw1 and Test2Yaw1 have been produced below in Figure 3-10.

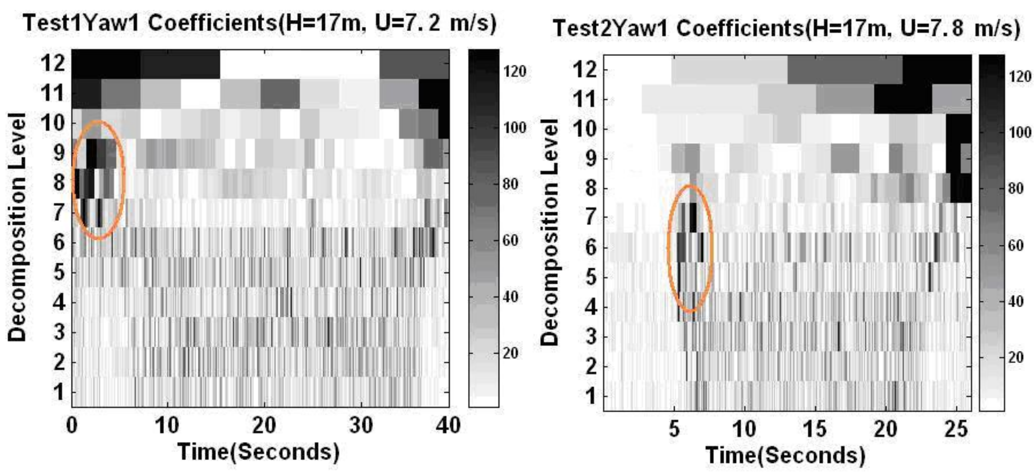

Figure 3-10. Wavelet Coefficient plots for Test1Yaw1 (left frame) and Test2Yaw1 (right frame). Decomposition Level vs. Time (seconds).

Certain features become apparent upon considering these obtained yaw events. One such feature is the relation between the vibration amplitude at the beginning and ends of signals. The coefficient plot for Test1Yaw1 exhibits high energy behavior at the beginning and end of signals at high decomposition levels (as depicted by the darkest shading at the highest decomposition levels). These high decomposition levels correspond to low frequency phenomena. Another feature of note is an intermittent excitation at the 9 through 7 decomposition levels which occurs early in the signals. These features have been circled in Figure 3-10. To demonstrate this feature, decomposition plots have been constructed. Figure 3-11 displays decomposition plots for the yaw signal Test1Yaw 1 and Test1Yaw2. Decomposition levels 9 through 7 have been extracted for Test1Yaw1. Levels 7 through 5 have been extracted for Test2Yaw1.

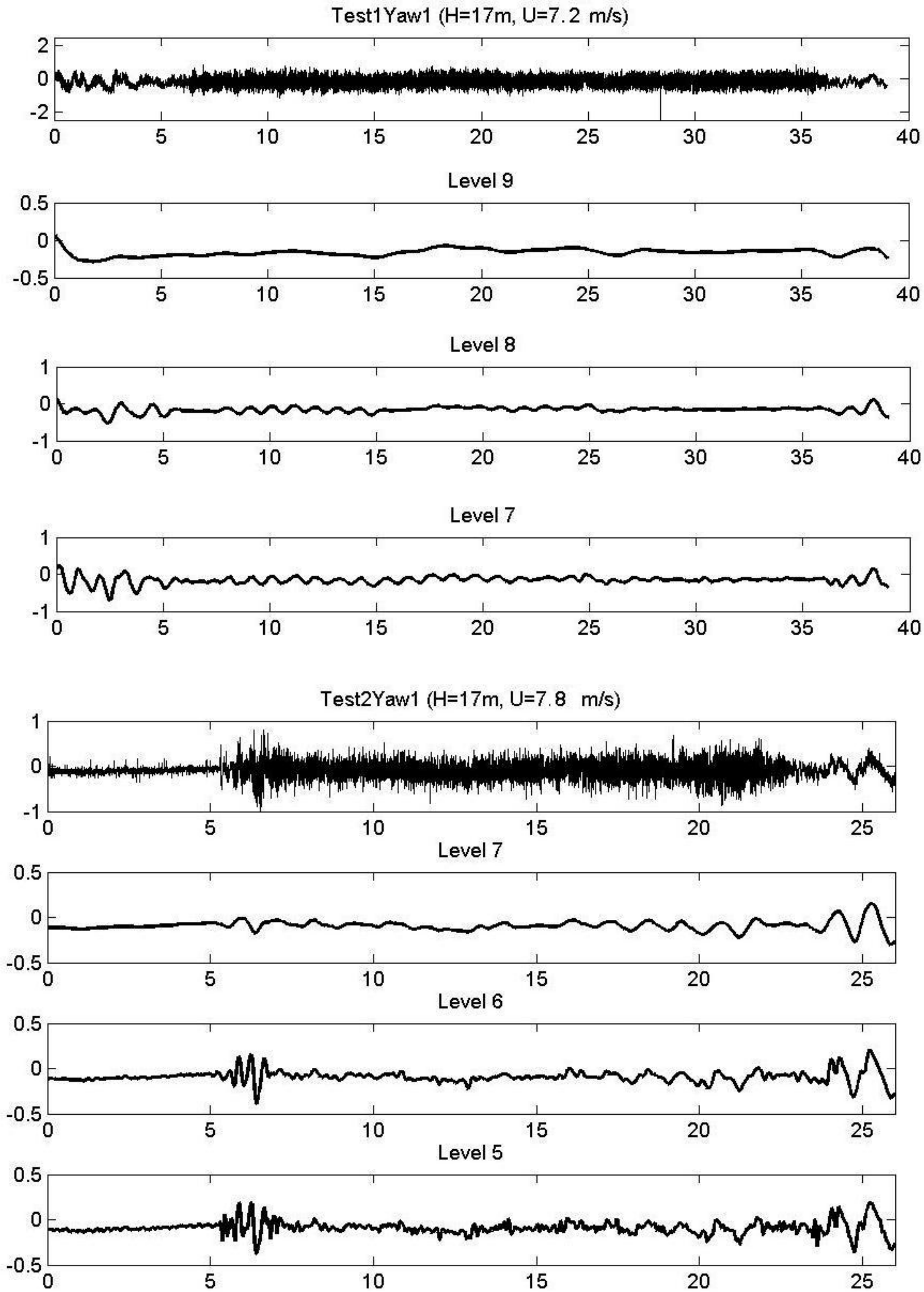

Figure 3-11. Test1Yaw1 (Top 4 frames), Test2Yaw1 (bottom 4 frames) Signals with Decompositions. Acceleration (m/s^2) vs. Time (seconds).

These figures are useful in observing the specific frequencies most excited by the observed yaw motion. For Test1Yaw1 the raw vibration signals displayed significant vibration amplitudes before and after the yaw event occurs. These waveforms are most evident in decomposition level 7. This corresponds with the observed sensitivity of the 7th decomposition level from the relative RMS values. This suggests that the frequency band of this level is especially excited by global turbine sway. It has been determined that vibration levels experienced before the yaw motion was initiated and after the yaw was stopped are the result of the only excitation occurring at these points; ambient excitation. Ambient excitation is caused by the fluid structure interaction between the stationary turbine and the wind and is dependent on the direction of the prevailing wind with respect to rotor position.

For the Test2Yaw1 signal a peak in the original signal at 7 seconds corresponds to excitation at the 6th decomposition level. This early peak was observed for several of the yaw samples. Also, the signal begins with low vibration levels but exhibits large amplitude behavior similar to that experienced by Test1Yaw1 at the end of its time series. This suggests that the elevated vibration amplitudes are the result of ambient excitation that occurs at higher degrees for certain yaw positions relative to prevailing wind direction. For this case the turbine started in a position with low relative ambient vibration and rotated into a position with a higher excitation level. This case of significant ambient excitation was most distinctly evident in signals obtained from the 17 and 50 m sensor positions while yaw motion at sensed from the 80 m position was dominated by higher frequencies

3.5 Study of Dynamic Turbine Shut Down Response

The obtained operation signals contain shut down segments during which the turbine was ordered to stop from the maintenance deck control unit. The turbine shut down sequences used by the wind farm operations can be classified as “soft” or “hard” stops based on the conditions under which they occur.

In ordinary wind levels while all systems are running soundly the aerodynamic braking is applied first. The pitch angles of the blades are articulated such that the blades go into a stalled state and are no longer producing relevant lift forces. As the rotor decelerates and the majority of rotational energy has been dissipated aerodynamically, mechanical braking is applied. The mechanical braking system is hydraulically actuated and consists of a dual caliper disc brake located on the high speed shaft. The braking force is controlled through a diaphragm in the hydraulic system that affords varying degrees of fluid pressure. After aerodynamic braking is applied the braking force is slowly increased as the rotor slows to a stop.

In elevated wind conditions such as storms or gale force winds, a hard stop sequence is issued and blades are immediately articulated into stall while full braking force is applied. This hard stop braking sequence is of interest to wind farm operators because it has been qualitatively observed that these stops result in high levels of deflection and turbine vibration. The effects of these stops on the overall structural health of the turbine are of particular importance in determining the optimal course of action during elevated winds.

The high speed shut down procedures during storms have been problematic within the global wind energy industry as many catastrophic failures have occurred in this way around the world. The Caithness Windfarm Information Forum has reported 70 structural turbine failures around the world that have been confirmed by wind turbine operators between the years 2000 and 2009 [16]. The structural failure data has shown a trend of increased failure frequency with every passing year. For these cases the relevant loading conditions of the turbine are to be considered and it has been identified that critical flap wise and edgewise loads are at a maximum during high speed shut down procedures [17]. An undesirable worst-case scenario for a wind turbine is if a braking mechanism were to fail in a high wind condition.

To understand the conditions of a high speed shut down and the effect it has on turbine structural and mechanical components; the conditions of a standard low speed shut down should first be quantified and understood. To this effect, the shut down response of the turbine was captured during operation testing. Six shut down segments were extracted from full signals such that detailed analysis could be performed. Figure 3-12 displays obtained vibration signals for shut down segments.

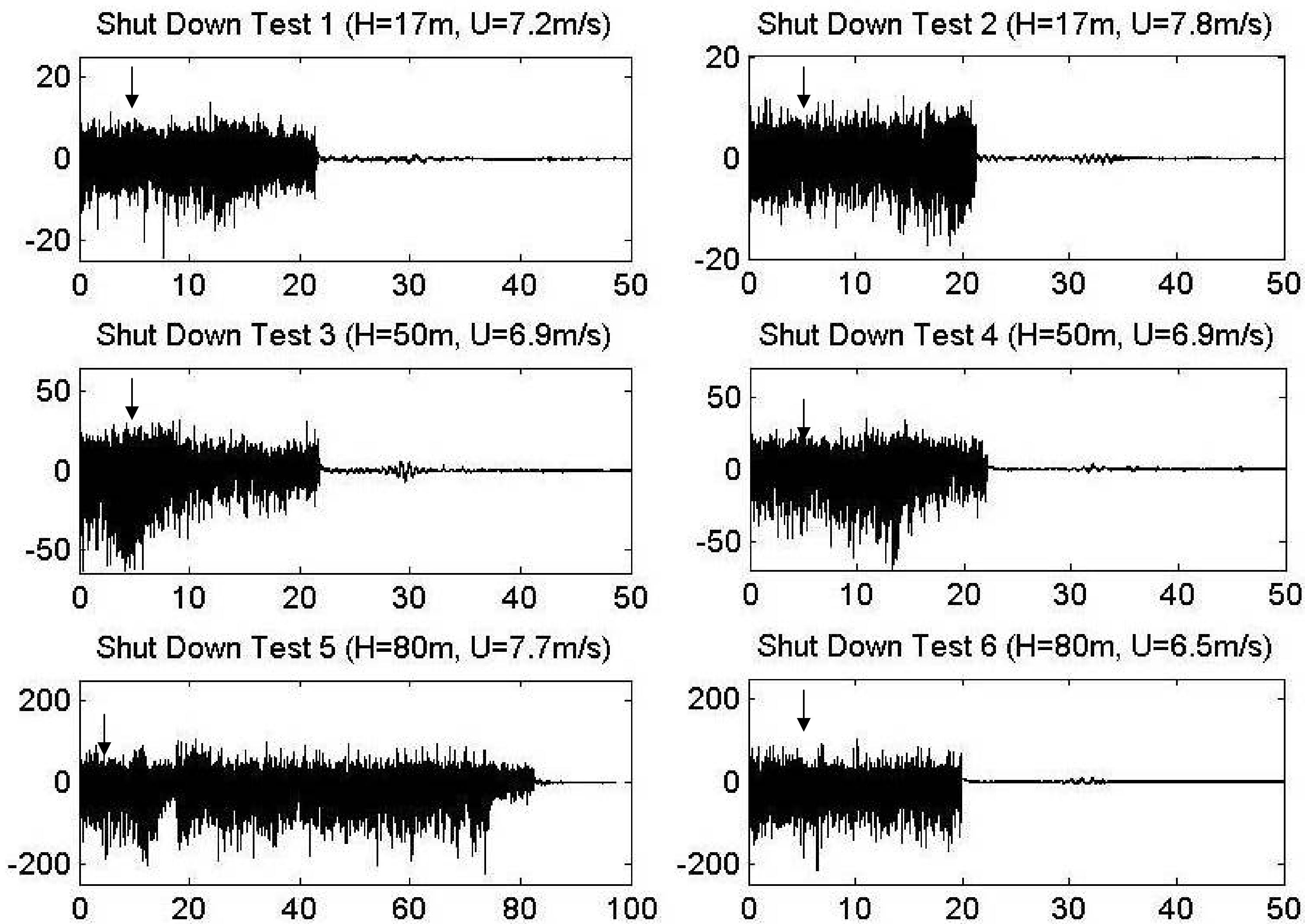

Figure 3-12. Raw Vibration Signals for Six Shut Down Events. Acceleration (m/s^2) vs. Time

The command to shut down the turbine was initiated at the 5 second mark for each of the plots above as indicated by the arrows. It is of interest to note that for five of the six samples the turbine had stopped within 45 seconds of the shut down command (as represented by the end of the displayed signal). It was observed and noted on the test day that Test 5 exhibited a prolonged braking period. This is reflected in the vibration signal which indicates a total of 95 seconds between shut down command and the stationary turbine state. This is of interest as it represents a deviation from the perceived normal shut down behavior. An ideal structural health monitoring scheme would identify stops such as this one and bring it to the wind farm engineer’s attention.

Wavelet decomposition was applied to the shut down signals and the RMS acceleration calculated for each corresponding decomposition level. Table 3-6 displays the data for RMS decomposition. This data can be displayed graphically to aid in interpretation as depicted in Figure 3-13.

Table 3-6: Shut down signal RMS for decomposition

Shut Down Event		Test 1	Test 2	Test 3	Test 4	Test 5	Test 6
Original RMS (m/s^2)	1.332	1.277	3.528	3.446	15.02	9.535	
1	0.953	0.906	2.678	2.578	11.95	7.393	
2	0.702	0.676	2.065	1.973	9.091	5.853	
3	0.497	0.505	1.691	1.498	7.637	4.908	
4	0.388	0.377	1.467	1.198	6.450	4.344	
5	0.330	0.306	1.357	1.021	5.717	4.014	
6	0.286	0.278	1.296	0.914	5.275	3.832	
7	0.258	0.245	1.164	0.839	5.101	3.758	
8	0.221	0.174	0.894	0.703	5.025	3.665	
9	0.155	0.150	0.874	0.550	4.952	3.400	
10	0.148	0.142	0.964	0.541	4.986	3.343	
11	0.147	0.130	0.920	0.471	4.908	3.383	
12	0.120	0.128	0.887	0.352	4.351	3.217	
Location (m)	17	17	50	50	80	80	
Mean Wind Speed (m/s)	7.2	7.8	6.9	6.9	7.7	6.5	

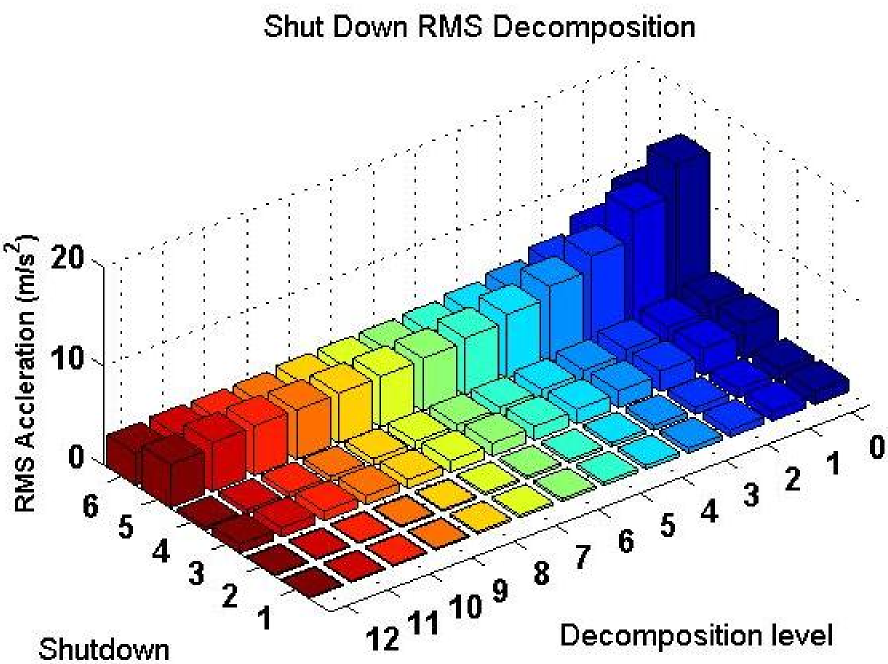

Figure 3-13. RMS Acceleration vs. Decomposition Level for Shut Down Segments.

From this figure several aspects of turbine shut down become apparent which were otherwise undefined by existing literature. The most distinct feature of the shut down signals is the drastic decrease in vibration magnitude that occurs when grid charge is removed from the induction rotor. Another aspect of interest is the overall shutdown RMS which is highly dependent on the total time required for the shutdown. This suggests that longer shut down times impart higher levels of loading and subsequent vibration due to this loading. The exact cause of the extended shutdown is unknown but literature suggests that it may be the result of an extreme gust or significant change in wind direction. Extreme gusts and direction changes have been identified as resulting in large loads and increased levels of turbine fatigue [18] and thus there is value in evaluating turbine response during these conditions. Another possibility is that a brief delay occurred within the electric control unit resulting in a gap between the time the stop command was issued and the time the controller issued signals to pitch the blades and apply mechanical braking. The definitive cause of this extended shut down is of interest to wind farm engineers and operators, as once identified the operators can work to prevent these high loading situations from taking place.

RMS values can be plotted relative to their sensor height such that the relationship between height and vibration level can be examined. Figure 3-14 displays the absolute and relative values for the RMS decomposition of shut down.

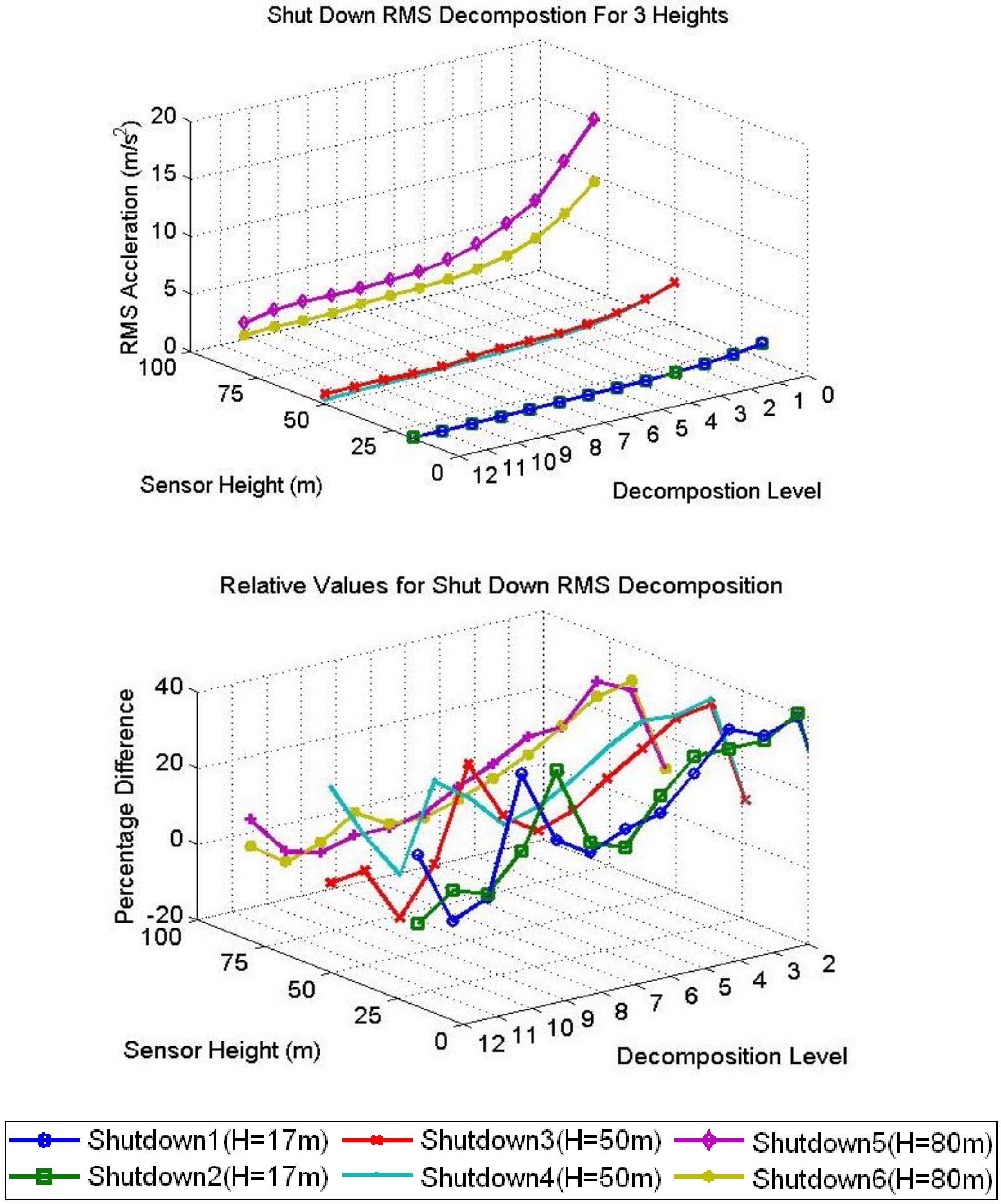

Figure 3-14. Height (m), RMS (m/s^2), Decomposition Level Relationship for Shutdown. Absolute Values (Top frame), Relative Values (bottom frame).

These plots demonstrate the value of the multiple sensor locations used for the analysis. The top frame plot of absolute RMS values depicts the relationship between frequency and RMS for the considered dataset. An inverse relationship between decomposition level and RMS is evident and the signals from the sensor mounted at 80m have the most pronounced inverse correlation. The low RMS trends at high decomposition levels containing low frequency signal content are hard to examine by simply considering absolute values and thus relative values have been calculated as depicted in the bottom frame. This plot displays various peaks in percent difference between RMS values at the seventh and eighth decomposition levels. This drastic change in frequency content between the 0.71-2.84 Hz and 2.84-5.68 Hz frequency windows suggests the presence of unique phenomena occurring at this level. Also, zero crossings occur at high decomposition levels that are not experienced at the lower levels. In order to observe the changes in frequency content within the signal through the shutdown coefficient plots have been produced. Figure 3-15 displays typical coefficient plots for shut down.

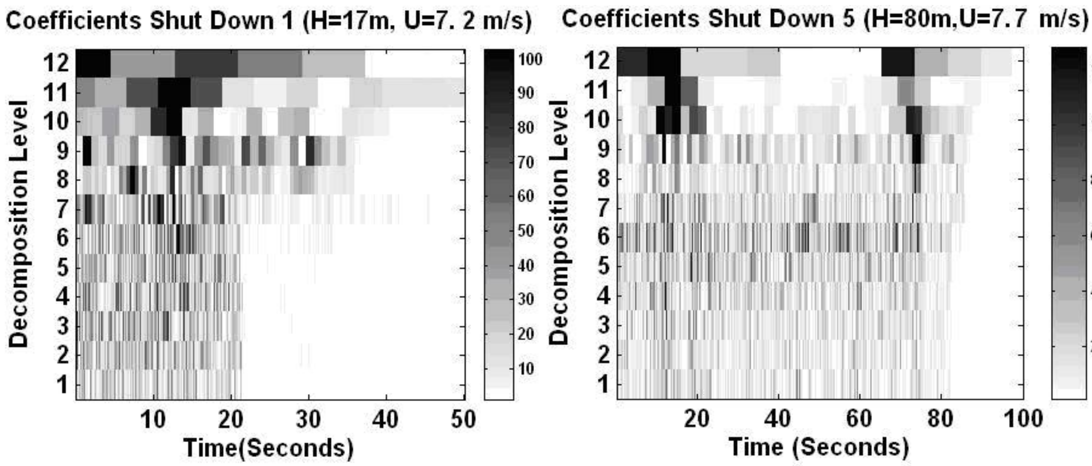

Figure 3-15. Wavelet Coefficient Plots for Shut Down 1 (left frame) and Shut Down 2 (right frame). Decomposition Level vs. Time (seconds).

These plots are of interest as they indicate that high energy activity at low decomposition levels (high frequency) dissipates rapidly at a distinct point in time during the shut down sequence. For Shut Down 1 this occurs at the 23 second mark which corresponds to the time when the charge on the induction rotor has been discontinued as revealed by the drastic change in overall vibration magnitude indicated in Figure 12. This removal of rotor charge corresponds to drastic drop in coefficient values for the first six decomposition levels. A similar point is apparent in the plot for Shut Down 5 at the 83 second mark but with a distinct difference being that all decomposition levels experience the drastic drop in coefficient values. This difference can be associated to the relative sensor height for each signal as the sensor located higher up is more dominated by high frequency excitation that vanishes when grid charge is removed.

3.6 Conclusions

For this study the healthy state response of a 2.3 MW wind turbine has been obtained, analyzed and discussed. Event mapping techniques have been used to correlate response signals with operational events and environmental parameters. Wavelet analysis has been applied to break obtained signals down into frequency components that offer clearer insight into behavior and response. RMS vibration amplitudes were calculated for each frequency level such that the relationship between vibration magnitude, sensor height, and frequency could be examined. The outlined procedure and analysis can be used as a diagnostic tool to provide researchers, wind farm operators and engineers with a unique glimpse into a turbine's dynamic structural response. The following conclusions have been drawn from the work presented in this study. These include:

1. The 2.3 MW wind turbine observed provided unique and distinct response patterns for each of the excitations considered namely ambient excitation, yaw motion, start up, operation, and shut down. An ideal SHM scheme may take advantage of these innate means of excitation.
2. The most significant change in response during turbine operation occurs when charge is applied to the turbine's induction generator. This charge results in a drastic increase in high frequency vibration levels which are sustained until charge is removed during shut down sequence.
3. RMS vibration magnitude of a response signal is a function of both sensor height and wind speed. Sensor height was found to be the variable of greatest influence for the wind velocity range examined.

4. Turbine vibration response to yaw motion has been identified and presented. It was observed to impart high levels of response at the seventh decomposition level which corresponds to a frequency window of (2.84-5.68) Hz. The waveforms depicted may be used by researchers and engineers alike to assess and potentially diagnose the yaw system of another 2.3 MW wind turbine.
5. Ambient excitation was found to be a significant factor that must be considered for yaw analysis. It was observed that ambient excitation could in fact be of greater magnitude than mechanical yaw excitation for certain yaw positions relative to the prevailing wind direction. This point was here depicted for two yaw tests but was observed for the entire yaw dataset.
6. Turbine vibration response to a soft stop sequence has been obtained, presented, and quantified for six shut down samples. The duration of turbine shut down from command to full stop was found vary between 40 and 50 seconds for 5 of the 6 samples considered. An outlying shut down lasted 90 seconds and displayed elevated vibration levels. The quantified response can be used to provide insight into high vibration levels experienced during hard stop shut down sequences.
7. Coefficient plots of shutdown reveal that higher frequency (5.6 Hz+) excitation rapidly dissipates upon removal of charge on the induction rotor for signals obtained at the 17 and 50 meter locations. Low frequency activity (0-5.6Hz) persists beyond this point. Shut down signals obtained at 80 meters did not display this distinct change as clearly.
8. Percentage differences of RMS values within the decomposition range for yaw and shutdown suggest a peak in response sensitivity in the seventh decomposition level.

The degree to which this sensitivity holds depends on the nature of excitation and sensor location. During shut down when mechanical excitation from the nacelle is high this sensitivity was evident in sensors mounted at 17 and 50m. During yaw motion when mechanical excitation from the nacelle was low this sensitivity was most evident in sensors mounted at 50 and 80m. This suggests the value of utilizing multiple sensors.

3.7 Next Steps

Considering the results of this study the authors have determined the next steps necessary to develop the proposed method of SHM for wind turbines such that it may be used to benefit the wind energy industry. Steps are listed as follows:

1. Expand database of response signals through further testing. A system has been assembled for permanent installation on the turbine specimen such that continuous vibration response is obtained for analysis. This will be engaged to more broadly define the general healthy response and evaluate the aging process of the turbine.
2. Integrate analysis techniques into wind farm's SCADA systems such that response can be analyzed by wind farm engineers and operators remotely from wind farm central control center.
3. Investigate the correlation and relationships between signals obtained simultaneously from sensors at various heights. This would provide a measure of turbine structural connectivity that can be potentially used as a damage sensitive feature in a SHM scheme

4. Develop appropriate structural health monitoring scheme to process and leverage response data. The developed method should evaluate response based on wavelet decomposition levels which have been effective in evaluating intermittent and non-stationary nature of wind turbine response.

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Chapter 4

Structural Health Monitoring for Utility Scale Wind Turbines using WARD Algorithm and Wind WARDEN Reliability Program

4.1 Introduction

Structural health monitoring (SHM) is a process of implementing a damage detection strategy for a mechanical system [1]. Wind turbine machinery stands to benefit from SHM significantly as the ability to detect early stages of damage before serious malfunction or collapse occurs would reduce the overall operating costs of wind power projects. Many researchers in the fields of engineering and applied mathematics have taken to developing SHM schemes for wind turbines and these approaches can be categorized by several different characteristics. Despite a wide array of possible methodologies for execution, three general functions for SHM can be defined. These functions are early warning, problem identification, and continuous monitoring [2]. Wind turbine manufacturers, wind farm operators and wind energy developers stand to realize many potential benefits if the appropriate SHM scheme should be developed and become available. Some potential benefits include the avoidance of premature breakdown, reduced maintenance costs, remote diagnosis, and improvement of capacity factor [3]. Also, wind turbine manufacturers could benefit through the use of obtained structural health response to optimize current designs and improve future generations of turbines.

This study presents a novel wind turbine structural health monitoring scheme designed to carry out the all three of the SHM functions in one elegant systematic procedure. The algorithm used to execute the response analysis has been dubbed the wavelet auto regression diagnosis (WARD) algorithm. The scheme has been developed using vibration response signals acquired from a fully commissioned and operational 2.3 MW wind turbine. These response signals have been utilized to develop a system that can be readily applied by wind farms around the world which utilize the same turbine model. There are currently more that 500 of these turbines installed in the United States. Other countries using this turbine include Canada (174), France (30) and Denmark (3) [4]. Assuming an installed cost estimation of 2.0 million dollars per turbine, the proposed SHM scheme can be utilized to protect and monitor more than 1.37 billion dollars worth of installed equipment in North America alone.

The presented research has developed through many stages and several studies have been written documenting the project. Interested parties are directed to refer to these documents for background on the current research. The first study involved wind tunnel testing of a wind turbine model and the subsequent analysis of vibration signals emitted from this aerodynamically excited system [5]. This initial lab study was completed in preparation for full scale testing which occurred on three test dates where turbine access was granted. Figure 4-1 displays the turbine test specimen that was examined for field testing. Figure 4-2 displays a researcher viewing obtained data from the turbine maintenance deck. These field tests resulted in over three hours of valuable response data that has been studied and analyzed using the mathematical processing tool known as the discrete wavelet transform. Essential wavelet analysis theory and details of how it can be used as a tool for vibration analysis have been presented in [5]. Following this study the identification of turbine response to yaw motion and shut down was completed through an event mapping procedure and the analysis of these response signals has been adapted for the article *2.3 MW Wind Turbine Vibration Response to Yaw and Shut Down Events*.

The response signals amassed throughout the project are significant as they represent a baseline for healthy turbine response. The specific turbine used for the analysis has been deemed of sound and healthy structural condition by both wind farm operators, who have been using the turbine continuously since its commissioning date and the turbine manufacturer who validate turbine performance through contractual output guarantee. The manufactures guarantee typically applies for the first three years of turbine operation, during which the manufacturer is responsible for turbine maintenance. The examined turbine specimen was covered by the guarantee at time of testing.

The following sections present and discuss the developed SHM scheme and various aspects of its design. The intention of this article is to present an overview of the developed scheme along with an outline of how data signals are managed and processed as part of the WARD algorithm. Several particulars with regards to optimal algorithm execution are to be the subject of future studies and will depend on the user preferences.

This system layout has been presented for the sake of progressing towards practical and value added structural health monitoring that would be viewed by wind farm owners as a welcome supplement to existing turbine instrumentation and monitoring. The benefits of such a system would extend beyond an individual turbine, array, or wind farm and have positive effects on the energy industry as a whole as it progresses to higher and higher levels of wind energy penetration at which turbine reliability is critical.

Figure 4-1: 2.3 MW wind turbine used for study

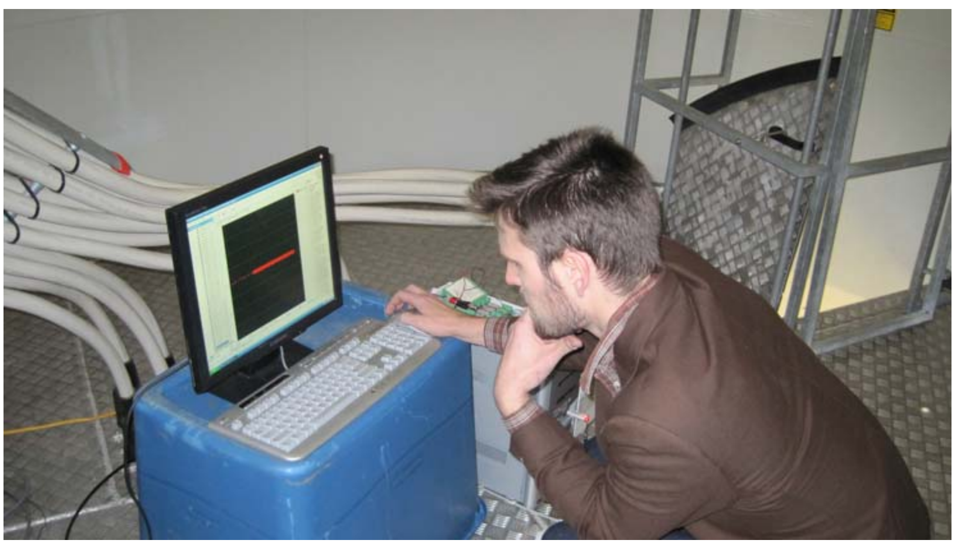

Figure 4-2: Researcher Kyle Bassett viewing obtained data from turbine maintenance deck

4.2 Vibration Response Analysis with WARD Algorithm

4.2.1 – System Overview

The developed SHM scheme utilizes vibration signals as the response phenomena for analysis. Vibration response is obtained through three piezoelectric accelerometers (PCB 352C34) mounted to the turbine tower at specified positions. The signals emitted from the accelerometers are transmitted to a PC-based data acquisition system which obtains samples at the defined sampling rate. The sampling rate has been set to 500 Hz for the present study. This sampling rate has been selected due to its computational efficiency within the SHM scheme. The dominant operating frequencies of interest for major turbine components are below the 50 Hz level and thus accuracy is achieved by sampling at ten times this rate. It should be noted that the proposed scheme is easily adapted to high frequency sampling procedures when higher computation speeds exist and smaller components which operate at high harmonics of the fundamental are to be diagnosed.

After obtaining the raw vibration response the signal proceeds through several stages of analysis and processing. During this processing the signal undergoes a discrete wavelet transformation which breaks it down into several frequency levels. These frequency levels are related to individual turbine components by referring to the relevant operating frequencies for these components and considering the level which contains these frequencies. After wavelet processing, response levels are compared to historic turbine behavior with a healthy state database. A healthy state database is an adaptive database of turbine response signals obtained during a known healthy structural state (such is the condition of turbine response obtained during field testing). It serves as the reference by which future conditions are evaluated. The evolution of typical turbine behavior over time is captured and reflected in healthy state database statistics. A diagram of the overall system process is depicted in Figure 4-3. Each block of the SHM process will be discussed in detail in the following sections.

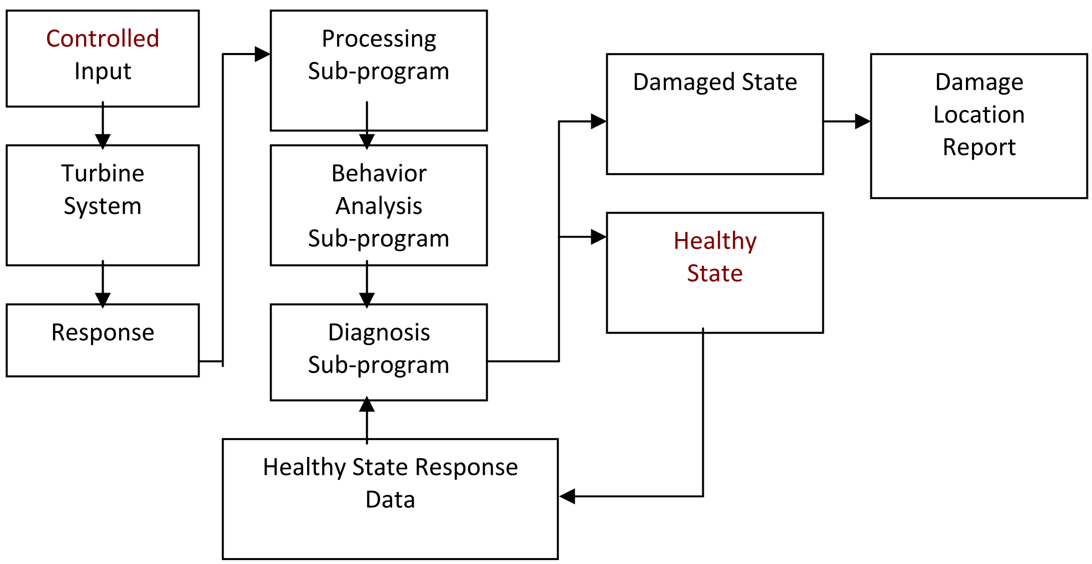

Figure 4-3: Structural health monitoring system overview

4.2.2 – Controlled Input Conditions

Many forms of input excitation conditions have been considered by many researchers with varying results. Traditional methods involve introducing a forced vibration into the structure through a device such as an impact hammer or electrodynamic shaker [6]. These methods have proven effective in determining a structures frequency response function [7] but do not allow for analysis of the structures operational behavior. One investigation into SHM for wind turbine blades utilized a quasi-static load induced by a pulse generator [8]. These input types, categorized as artificial excitations, are non-ideal when considering a wind turbine system as impact, shaker, and quasi static load tests must be executed with a stationary turbine, lending itself to lost revenue due to turbine downtime. Also the equipment costs associated with artificial excitation may be very high and must be considered in addition to costs associated with transporting this equipment to a turbines often remote location.

The developed SHM scheme presents an improvement upon artificial structural excitation as the system is designed to analyze five standard inputs that each demonstrate different aspects of turbine behavior. These inputs are considered natural excitation as they require no additional equipment and utilize standard turbine operation as the system input. These inputs for the proposed SHM scheme include

- Ambient Excitation
- Static Yaw
- Start Up
- Operation

- Shut Down

The first input, ambient excitation, occurs as the parked turbine sways and moves due to the wind passing over it. This is the lowest level of excitation possible and offers a glimpse into the most structurally isolated turbine condition. This response is without influence from operational machinery. An ambient signal of 15 seconds is recorded and used for analysis.

The second standard input, static yaw, involves the rotation of the turbine rotor about its vertical axis while the rotor is in the parked position. The SHM scheme is designed to accept a turbine response signal to a yaw of 15 degrees in the clockwise direction with respect to the prevailing wind direction. This standard input is used to diagnose components of the yaw system such as the slew ring, eight drive motors, and the electronic yaw control program.

The third input, start up, begins when a start up command is issued by the turbine operator. The turbine will then undergo a sequence of events including the release of locks on blade pitch motors, articulation of the blades, release of mechanical lock on rotor shaft, acceleration of the turbine rotor, and activation of grid charge to the generator. The scheme is designed to accept a start up signal beginning with the start up command issued by the operator and ending when grid charge has been applied to the generator. It has been noted in previous turbine vibration studies that the most significant feature of operational turbine response occurs when the grid charge is applied to the generators rotor, resulting in a drastic increase in high frequency vibration. The start up system input provides a unique look into the structural response of the turbine before this high frequency vibration occurs. This input will be used to diagnose the conditions of pitch motors, mechanical brakes, the control software executing the start up and the turbine rotor.

The fourth input, operation, represents the condition most commonly experienced by the turbine throughout its life. During operation the turbine is operating at its rated RPM and producing power. Vibration levels are high and excitation is significant in the high frequency range (+5.6Hz). Operational strain response for a vertical axis wind turbine (VAWT) test bed was obtained and analyzed by James *et al*. [9] who displayed the potential for the technique in determining certain modal features. Operational response from the 2.3 MW wind turbine used for this study was first presented and discussed in the paper *Vibration Analysis of 2.3 MW Wind Turbine using the Discrete Wavelet Transform.* It was noted that operation signals displayed operationally influenced periodicity with an average period of 41 seconds. For this reason the developed scheme will accept 2 minutes of turbine operational response randomly sampled from operation segments. This sampling length may be modified as longer term trends become of interest in the future. Figure 4 depicts a standard operational response signal.

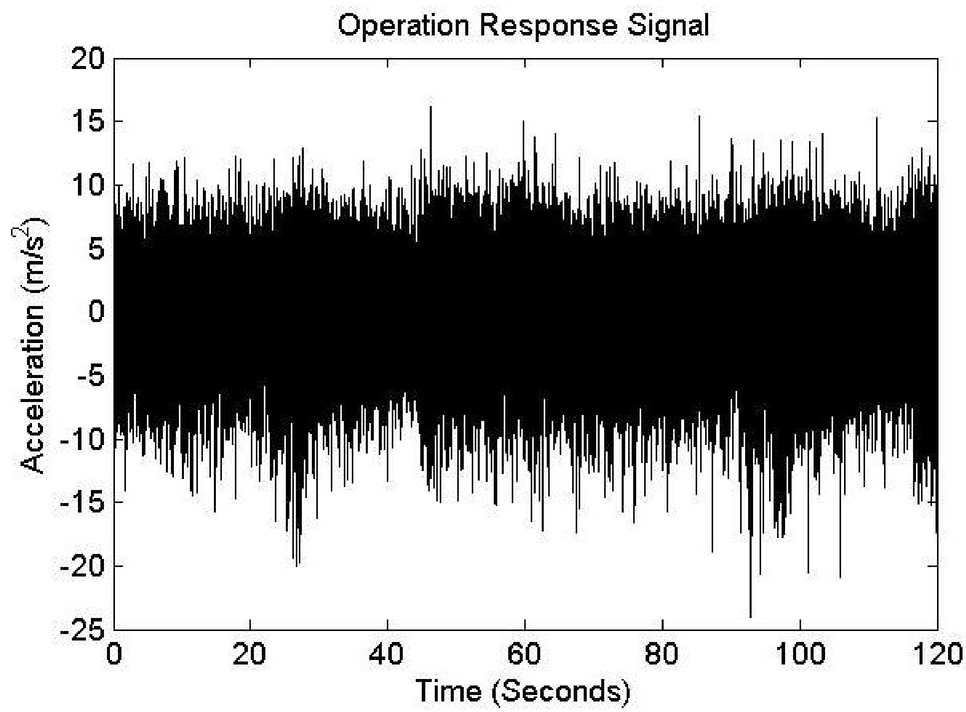

Figure 4-4: Raw vibration response signal obtained for two minutes. Acceleration (m/s^2) vs. Time (seconds).

From Figure 4-4 the low frequency periodicity is once again evident for a response signal obtained on an alternate test date. The developed scheme seeks to summarize this periodic behavior and quantify it such that it can be compared to the response baseline determined by the healthy state database.

The final input, shut down, occurs when a shut down command is issued by the turbine operator and involves the articulation of blades into a stalled angle and the application of a mechanical brake. The standard signal will begin at the point that the shut down command was issued and end when the rotor speed has reached 0 RPM.

4.2.3 – Response

An array of different response signals have been considered by researchers in the search for practical and cost effective SHM routines. Certain schemes have utilized laser vibrometer [6], strain [9], acoustic emission [10] response signals with some positive results. Acoustic emission based methods have shown promise but have considerable challenges due to the cost and complexity associated with each sensor requiring a preamplifier as well as the challenge of converting data to digital form using high sampling rate A/D converters [10]. A recently published condition monitoring scheme for turbine drive trains utilizes generator output signals as an operational response [11].

For the proposed scheme response to the standard inputs is obtained through multiple tower mounted accelerometers. Currently the scheme is based the three sensors mounted on the tower at the heights of 17, 50, and 80m. These heights have proven themselves responsive to the considered inputs and the relationships between signals obtained at various heights has been examined and presented in the previous study. Accelerometers have been selected as the choice response sensor for the scheme upon considering the high availability and low cost of the equipment. Equipment costs for the SHM system are presented in Table 4-1.

Table 4-1: Approximate Equipment Costs for SHM System

Component	Quantity	Per Unit Cost ($)	Total ($)
Accelerometer	3	650	1950
Signal Cable	3	200	600
Data Acquisition System	1	500	500
Processing Computer	1	1000	1000
System Total			**4050**

Table 4-1 demonstrates that the proposed SHM solution can be implemented to an existing wind turbine for less than five thousand dollars. This equipment cost is practically negligible when considering the value of the machine on which it is implemented. Considering a turbine value of 2.0 million dollars the SHM equipment costs account for less than 0.2 % of the initial turbine cost. Traditionally, vibration based SHM techniques have been criticized due primarily to the unavailability of response signals for healthy turbines. Considering the access granted to authors by the wind farm research partner this issue has been addressed and a considerable database has been under construction so that signals may be available to future researchers addressing the wind turbine SHM challenge.

Each accelerometer mounted at its particular height provides unique information of the turbine and its various systems. It has been determined that accelerometers mounted nearest to the turbine nacelle will pick up highest levels of vibration from nacelle vibration sources such as the generator and braking systems. Accelerometers located closer to the turbine foundation have exhibited response to turbine sway which is indicative of tower condition. A typical response signal to yaw input is depicted in Figure 4-5.

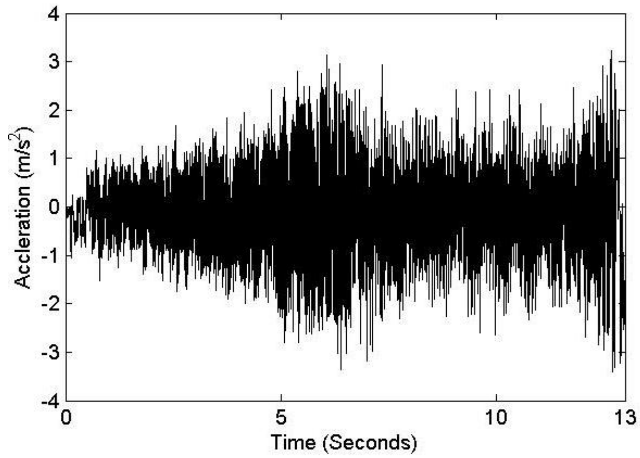

Figure 4-5: Turbine response to yaw motion. Obtained from accelerometer mounted at 50m. Acceleration (m/s^2) vs. Time (seconds).

It should be noted that although the response signals from each tower mounted accelerometer provides valuable information when considered separately the correlation and relationships between these simultaneously obtained signals offer another damage sensitive feature that is to be further investigated in the future.

The standard SCADA (supervisory control and data acquisition) system is to be integrated into the process as it measures many vital operational and environmental parameters including average wind speed, max wind speed, rotor rpm, and generator speed. These systems are standard equipment on the particular turbine of this study and are in fact installed on each and every turbine in the studied wind farm. The use of an alternate ultrasonic anemometer mounted at hub height 2 rotor diameters away from the tower has been integrated as a welcome improvement in wind speed measurement precision. Figure 4-6 depicts the Meteorological tower installed at the appropriate location for the test turbine. The data stream from ultrasonic anemometer is to be integrated into the standard data transmission protocol used for the turbine SCADA.

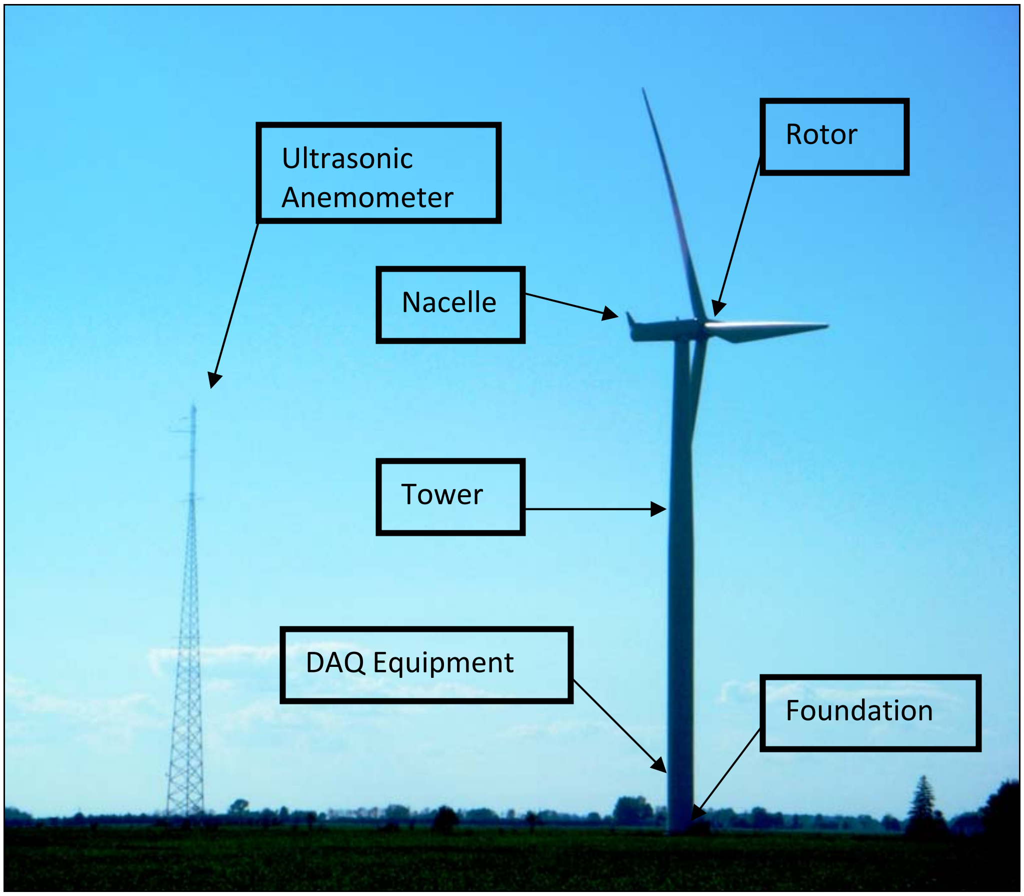

Figure 4-6: 2.3 MW wind turbine with MET tower.

The operational parameters are recorded by the SCADA for each input period and stored in an information matrix that will be paired with its associated response signal. The response signal and information matrix then proceed to the processing sub-program.

4.2.4 – Processing Sub-Program

After response signals have been obtained for an input event of interest the data proceeds to the processing sub-program which transforms data into a more meaningful and useful form. A discrete wavelet transform occurs which breaks a response signal down into various frequency components that display a clear picture of turbine response. A twelve level discrete wavelet transform is executed using a Daubachies 6th order wavelet and select frequency levels are extracted for the structural information they contain. The DWT can be expressed in the form [12]

$$WT(k2^j, 2^j) = \left|2^j\right|^{\frac{-1}{2}} \int_{-\infty}^{\infty} x(t)\overline{\Psi\left(\frac{t-k2^j}{2^j}\right)}dt \qquad (1)$$

where a is scaling factor which determines frequency content, b is translation parameter, t is time, and $\overline{\Psi}$(t) is the complex conjugate of wavelet Ψ. This extracts coefficients on a two dimensional grid for further processing into decomposition levels.

While a SHM scheme could be developed considering the entire decomposition range it is best to eliminate unnecessary calculations for the sake of computational efficiency. The decomposition levels used for this system have been selected based on the mechanical operating frequencies they contain as well as historic sensitivities exhibited in previous studies. Table 4-2 displays the frequencies levels for extraction and the features of each level.

Table 4-2: Extracted decomposition levels, frequencies, selection criteria

Decomposition Level	Frequency Window [Hz]	Selection criteria
12	(0-0.089)	Lowest frequency components of signal
11	(0.089-0.18)	Fundamental rotor rotation for start up
10	(0.18-0.36)	Fundamental harmonic rotor rotation
7	(2.84-5.68)	Displayed high sensitivity to global motion
4	(22.73-45.45)	Fundamental generator harmonic

Root Mean Squared (RMS) vibration magnitude is calculated for the original signal and these select frequency levels. These RMS values serve as an indicator of the overall vibration level characteristic for each signal and corresponding decomposition. For a new response signal x, the RMS is calculated with the following equation.

$$N_{RMS} = \frac{\sqrt{x(t)^2}}{P} \qquad (2)$$

Where x(t) is the response signal, and P is the length of the response signal. After RMS values have been calculated the program proceeds to the behavior analysis stage.

4.2.5 – Behavior Analysis Sub-Program

Analysis of the obtained signals continues beyond magnitude evaluation to consider the time series behavior of the signal. After RMS values have been calculated for each signal and decomposition level an auto regressive (AR) model is calculated for each data series. Signals and levels are first normalized using a standard score expressed by the following equation.

$$z = \frac{x - \mu_x}{\sigma_x} \qquad (3)$$

Where z is the standard score, μ_x is the data series mean, σ_x is the data series standard deviation and x is the data series. The auto regressive model serves to describe the evolution of the response signal with respect to time. An AR model can be expressed in the following equation [13].

$$x(t) = \sum_{j=1}^{p} N_{AR} x(t-j) + e_x(t) \qquad (4)$$

where x(t) is original signal, N_{AR} are the coefficients, e is error and p is the order selected for the model. The order selected for the scheme has been set to 30 based on work by Box *et al.* [13] and the previous study completed in [5]. This auto regressive model is used to summarize time series behavior of the signal with 30 characteristic coefficients which allow for the timely handing and comparison of signals. These coefficients will be stored in a 1 dimensional matrix. At this point a signal will move onto the diagnostic sub program where it is evaluated based on its comparison to historic healthy state response data.

4.2.6 – Diagnosis Sub-Program

The first stage of damage detection and turbine diagnosis is based on results from the processing sub program which returns select wavelet decomposition levels and the associated RMS values for the response signal. The structural condition of the response signal will be evaluated based on the difference between the calculated RMS value and the average of historic RMS values stored in the healthy state database. For diagnosis of the turbines structural state, historic response information must be available and stored in a healthy state database. The multiple alert and warning criteria are based on the difference between characteristic parameters of response for unknown (new) and known (historic) structural conditions. These characteristic parameters for known structural state are stored in the Healthy state database. The following section will address details of this database so for now it is to be taken as granted for sake of understanding the diagnostic procedure. This evaluation is completed for each wavelet level and is executed with the following equation.

$$D_{rms} = N_{rms} - H_{averms} \quad (5)$$

where D_{rms} is the difference, N_{rms} is the RMS value for the response signal under evaluation, and H_{averms} is the average RMS value for all processed signals in the healthy state database. A criterion has been defined such that an alert will be issued when a newly acquired signal exceeds a threshold indicating that a deviation from normal turbine behavior is being experienced. The threshold is a function of healthy state database size, and a program defined learning curve, L.

$$T_{rms} = H_{averms}(L) \quad (6)$$

This parameter L, allows for unsupervised learning of the SHM program. Values for the learning curve are established such that the SHM scheme can increase in damage detection sensitivity as the healthy state response of the turbine becomes better understood from a statistical point of view as the database size increases. Figure 4-7 displays the learning curve for a SHM scheme throughout its first 700 healthy state database samples.

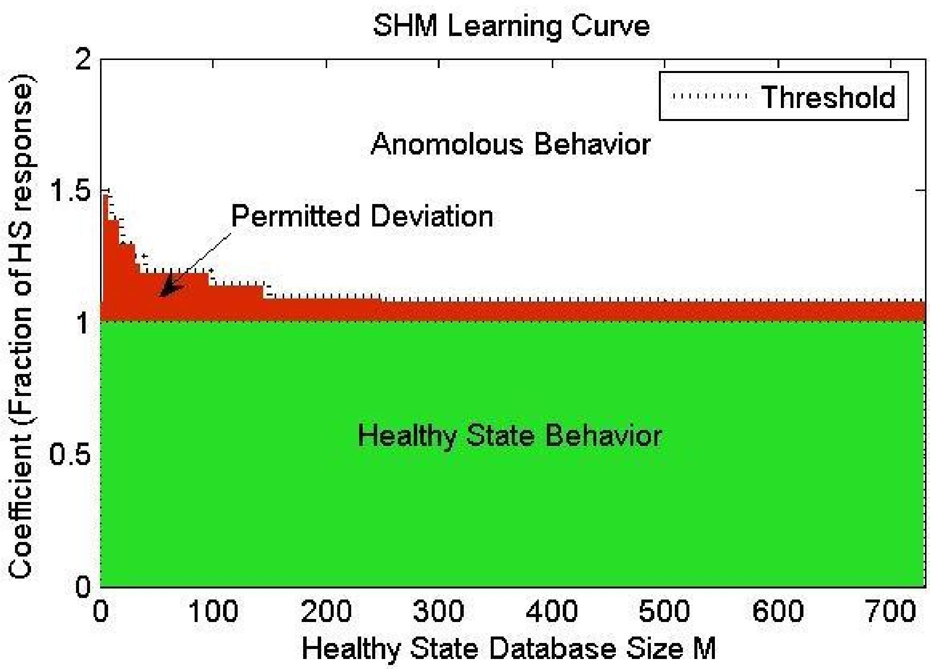

Figure 4-7: Sample learning curve for SHM program. Threshold value vs. Healthy State Database size, M.

This learning variable L defines the maximum deviation allowed expressed as a percentage of the healthy state average accepted without an alert. When the SHM procedure is first implemented on a turbine the threshold variables are necessarily high. This allows for the system to begin learning standard turbine behavior without issuing unnecessary alarms due to limited HSD size. As the HSD grows in size M increases and the program adjusts thresholds to reflect the defined normal behavior. Alerts will be issued depending on the value of a binary condition variable defined as follows

$$C_{rms} = \begin{cases} 1, D < T_{rms} \\ 0, D \geq T_{rms} \end{cases} \quad (7)$$

If the C value is ever found to be 0 for any of the examined wavelet levels a deviation from historic response is being experienced and an alert is issued to wind turbine operators so attention can be paid to the turbine. This alert can take the form of a visual cue on a controller screen, or audible alarm sounded at the wind farm control center. A condition report is printed along with the alarm stating the wavelet levels that exhibited the anomalous response. This serves to satisfy the problem identification feature as the wavelet level is associated to the turbine components that operate within its frequency range. Of course the nature of the inputs themselves provides a degree of damage localization as the components functioning during the input are to be considered. Table 4-3 displays components that function during each input.

Table 4-3: Input conditions with associated active components for damage localization

Input	Active Components
Ambient Excitation	Tower sway, mechanical brake
Yaw Motion	Yaw gear motors, Control programs,
Start Up	Turbine rotor, Pitch motors, control programs
Operation	Induction rotor, Generator, turbine rotor, control programs
Shut Down	Turbine rotor, pitch motors, braking system

Following a condition diagnosis based on RMS values the system proceeds to consider the results from the behavior sub-program for each response signal in order to evaluate turbine condition based on behavior. Euclidean Distance is calculated between the AR coefficients of the new response signal and the healthy state AR model. Figure 4-8 displays calculated AR Coefficient values for seven historic yaw inputs stored in the current healthy state database.

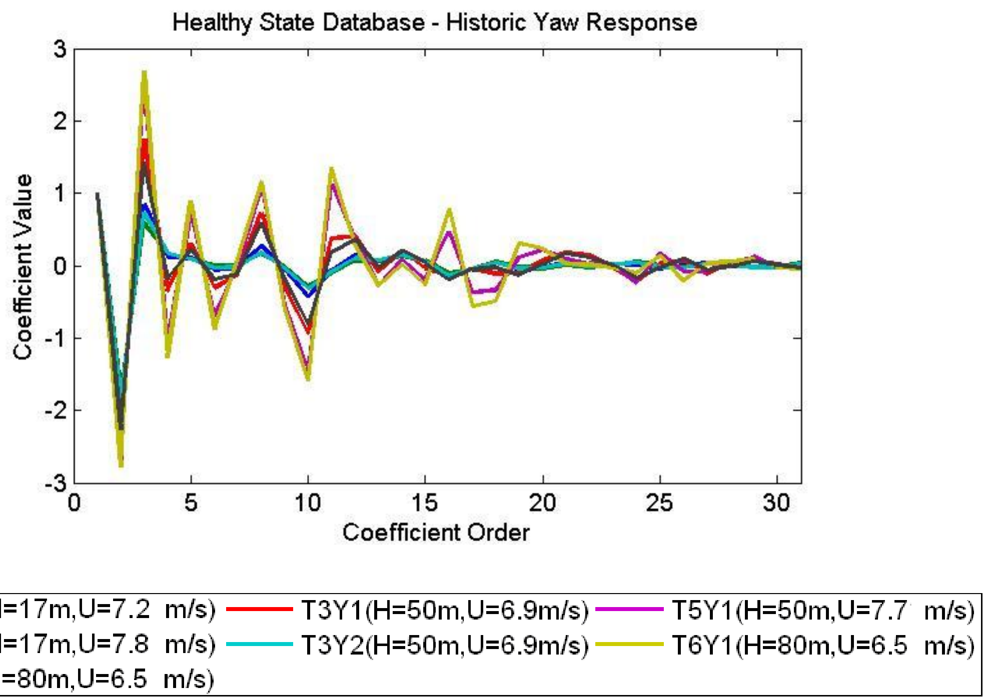

Figure 4-8: Historic response to Yaw input

From this figure the similarity in AR coefficients is evident for several yaw input response signals obtained at various heights and under various wind conditions. It is due to this similarity that effective thresholds can be set and the unsupervised learning occur, converging onto the healthy state behavior of the turbine for a given input.

In order to evaluate response based on time series behavior a distance calculation is executed with the following equation.

$$D_{AR} = \sum_{i=1}^{30} (N_{AR_i} - H_{aveARi})^2 \quad (8)$$

where N_{AR} is an array containing the 30 coefficient values calculated for the new response signal, H_{aveAR} is an array of average coefficient values from the healthy state database (HSD). This distance is evaluated based on a second damage sensitive criteria that calculates the distance between the healthy state average and the historic response model that is closest in wind speed to the obtained response.

$$T_{AR} = D_{ave-ws}(L2) \quad (9)$$

A second condition variable is calculated

$$C_{AR} = \begin{cases} 1, D_{AR} \leq T_{AR} \\ 0, D_{AR} \geq T_{AR} \end{cases} \quad (10)$$

If this behavioral condition variable is found to be 0 an alert is issued which serves as an early warning to behavior that is deviating from historically recorded response. This alert is issued before anomalous loading occurs and thus informs an operator that detrimental operation conditions may exist that will lead to accelerated fatigue of the turbine components. The cause of this strange behavior may be the result of load intensive weather conditions or the early stages of component fatigue or damage. The warning is issued with a printed report of the wavelet levels that violated the diagnosis conditions. Correlations to turbine components in Table 4-3 are once again considered for identification of possible faulting components.

After both condition parameters are calculated and neither are found to be 0 for all of the wavelet levels in the scheme then the response signal will be deemed of healthy nature and is added to the healthy state database along with the appropriate information matrix. For a healthy state database size M, the newly validated response signal is stored as entry M+1. After the response signal has been cycled through the SHM program the functions of damage detection (via RMS) and damage localization (via wavelet decomposition) have been completed. To expand beyond immediate behavior and evaluate the turbines evolution on the scale of seasons, months and years descriptive statistics of the HSD are to be considered. The behavior model serves the function or offering early warning to damaged states that will result in elevated vibration levels.

4.2.7 – Database Adaptation

The healthy state database is a dynamic dataset that will evolve and change as new response signals are obtained and processed as part of the SHM procedure. Currently the HSD contains 3 hours of standard turbine operation. This will expand rapidly as the SHM scheme is permanently implemented on the structure and baseline data is acquired. It is through the healthy state database that long term trends of turbine behavior and evolution are assessed. Mathematically speaking the database will take the form of a M x X matrix with individual healthy samples stored in the columns. For programming sake the first few rows can be considered headers containing environmental parameters including average wind speed and an index parameter. The healthy state database takes the form expressed by the equation below.

$$HSD = \begin{pmatrix} Entry1 & .... & ...... & ...... & EntryM \\ WindSpeed1 & .... & ... & .... & WindSpeedM \\ Index1 & .... & ..... & ..... & IndexM \\ RMSArray1 & .... & .... & .... & RMSArrayM \\ ARArray1 & .... & .... & .... & ARArrayM \end{pmatrix} \quad (11)$$

It should be noted that as the HSD grows to include thousands of data entries it may be beneficial from a computational standpoint to arrange the HSD according to a seasonal or yearly index. This would reduce computational demands during response evaluation. In this case the healthy state response would be recalculated for each season and this would be used as the starting point for the HSD for subsequent operation years. Beyond its use for evaluating a new response signal the HSD has purpose in determining the long-term evolution of the turbine system. As materials age and fatigue occurs the normal turbine response evolves to reflect these changes. The rate at which normal response changes with respect to time can be considered by researchers when predictions of turbine life are to be made. Interested parties may find it beneficial to implement alerts based on the rate of change of healthy state database information.

4.2.8 – Standard Diagnosis Procedure

The SHM scheme based on the WARD algorithm is executed on a turbine of interest in six steps which are to be iterated during each new operation day. When executed in this fashion the system will rapidly adapt to learn healthy response for each of the five designated inputs providing a considerable mass of condition data on which to address future behavior. The procedure is as follows

Step 1- Set initial conditions.

- Turbine is in parked position facing prevailing wind direction

Step 2- Ambient response analysis

- Response to ambient excitation is recorded for 15 seconds.
- Signal processed with WARD algorithm
- WARD will return RMS and AR condition variables. If alerts issued stop procedure and examine turbine referencing the printed diagnosis report

Step 3- Yaw Analysis

- Turbine yaw command issued for 15 degree yaw
- Signal processed with WARD algorithm
- WARD will return RMS and AR conditions. If alerts issued stop procedure and examine turbine referencing the printed diagnosis report

Step 4 – Start up Analysis

- Start up command issued
- Turbine starts and accelerates to operating speed and grid charge is applied
- Signal processed with WARD algorithm
- Start up condition report issued
- If no alerts, turbine continues to operate as normal

Step 5 – Operation Analysis

- Turbine proceeds to operate as normal
- 2 minute response samples extracted from data stream twice an hour
- Turbine conditions returned following each sample. If alerts issued stop procedure and examine turbine referencing the printed diagnosis report.

Step 6 – Shut down Analysis

- When time comes for turbine to be shut down response obtained
- Response signal spans shut down duration from command to instant generator speed is zero
- Signal processed with WARD algorithm
- Condition reports issued. If alerts issued stop procedure and examine turbine referencing the printed diagnosis report.
- Iterate through to Step 1 when turbine is to be start up again

4.3 Scheme Application

As of the date of this publication damage has not been experienced by the turbine under study. This is favorable from the owners and operators standpoint but this may not always be the case as the machine ages. In fact there may be few maintenance issues experienced within Canadian and North American wind farms over the next 3-5 years due primarily to youth of the installed turbines. This does not undermine the importance of gathering baseline structural data. Historic reliability data sourced from the European wind energy industry supports this conclusion. A survey of downtimes and failures within the Danish and German wind power industries suggests of utility scale turbines (>1MW) having an increase in failure frequency each operational year [14]. When considering this failure model with the proposed SHM scheme a proportional relationship exists between damage sensitivity and likelihood of turbine failure. This is a favorable relationship which suggests the value of assembling a database of turbine response beginning early in the turbines life as the assembled database will become of greater value as turbines fatigue.

Although a turbine damage state has not yet been captured, a shut down analysis completed contained an anomalous dataset which has been identified by the WARD algorithm as a deviation from normal behavior. Figure 4-9 displays the anomalous signal.

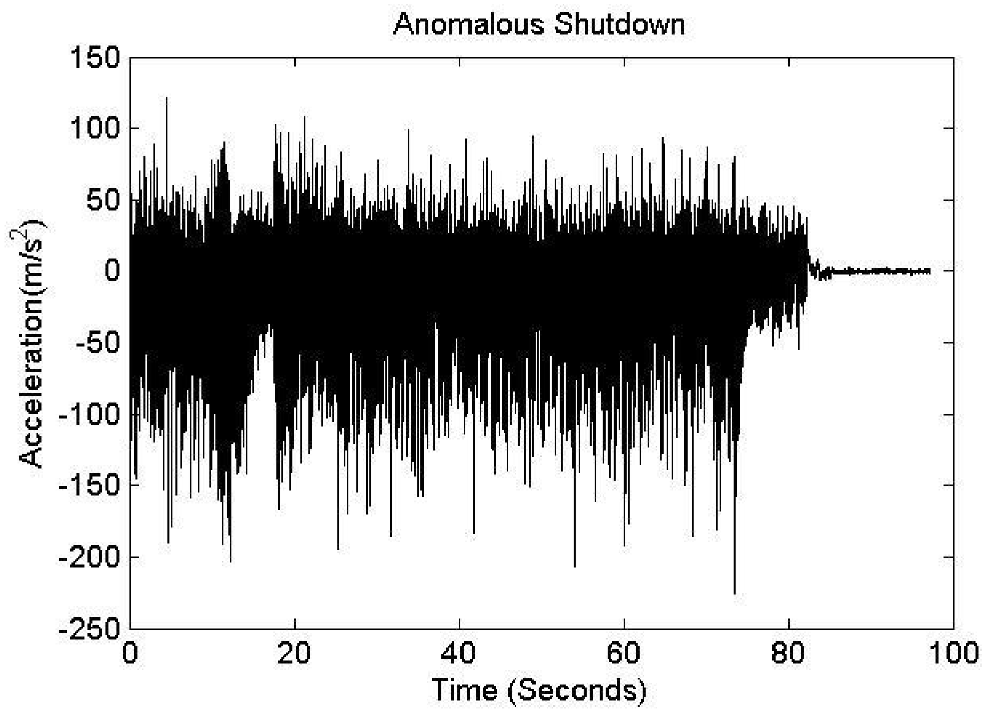

Figure 4-9: Anomalous Shut down signal. Acceleration (m/s^2) vs. Time (seconds).

When considering the time series behavior of the response signal a clear deviation from normal response was found in the 4th decomposition level corresponding to the turbines generator frequency. Figure 4-10 displays the auto regressive coefficient values for this anomaly.

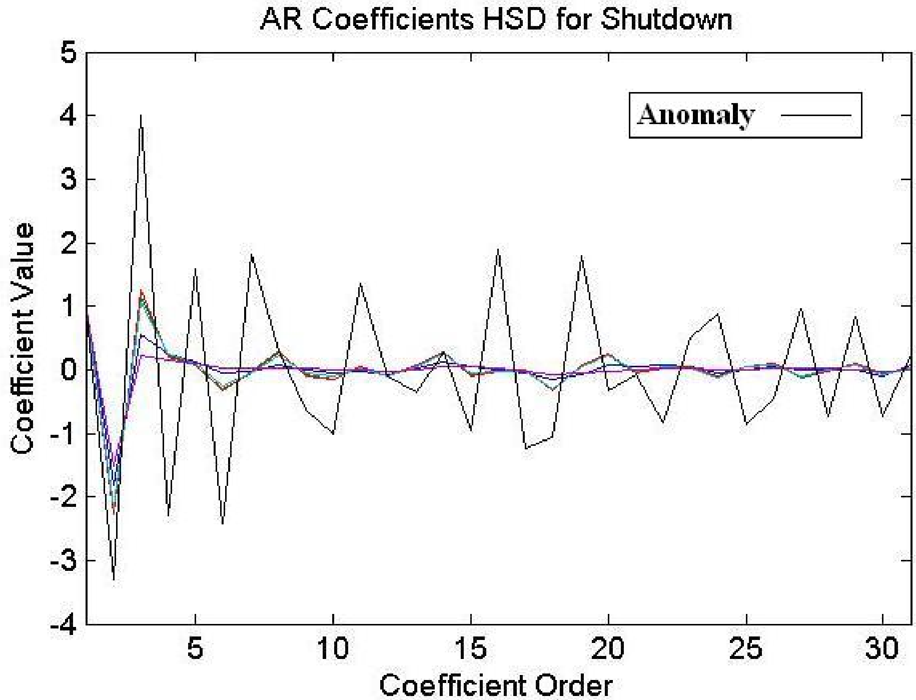

Figure 4-10: Auto Regressive Coefficients for Shut down Anomaly relative to healthy state behavior. Coefficient value vs. Coefficient order.

This figure illustrates the distinct difference in time series behaviors between the healthy state signals and the anomalous response. This deviation resulted in a D_{AR} value that violated the healthy condition criteria set in the WARD algorithm. This anomaly cannot be classified as damage but was found to result in elevated levels of vibration which could in turn result in increased rates of fatigue during this period. Conditions such as these are to be identified to the wind turbine operator so that the cause of these conditions can be investigated and prevented.

This preliminary application has demonstrated the schemes ability to identify situations and operating conditions that may lead to increase turbine fatigue. Despite a limited healthy state dataset the programs value as a diagnostic tool can be realized from the first day of SHM analysis. This value will increase as the turbine ages and problems and maintenance issues are to be dealt with.

From a nation's infrastructure planning point of view the proposed scheme has considerable value as it will aid in determining the condition of turbines as they reach the end of their design life. Important decisions are to be made at the turbine's design life end as the owners must decide if the turbine is of sound condition to continue operation with reasonable levels of maintenance and up keep or if it would be more cost effective to remove and replace the aged turbine.

4.4 Implementation Recommendations

4.4.1 – Wind WARDEN Reliability Assessment Program

It seems logical that the presented WARD algorithm for wind turbine SHM be expanded and applied to multiple turbines such that a wavelet auto regressive diagnostic energy network (WARDEN) is formed. This network would present a means to connect multiple turbines together such that communication and information sharing can occur resulting in a net benefit for the network. With a Wind WARDEN program comparisons can be made between response obtained from turbines located in different turbine arrays, wind farms, and geographical areas. This allows for an individual turbine's operation to be understood in the context of a population of healthy turbines. This will work to improve the WARD algorithm by drastically reducing the learning time required for the system to determine healthy state behavior. This healthy state behavior would be thoroughly understood and available via the WARDEN program when a new turbine is installed and integrated into the North American utility grid. A network such as this one proposed would offer a new level of insight into the life cycle evolution of utility scale wind turbines for wind turbine manufacturers, owners, operators and policy makers.

Much of the infrastructure necessary to construct such a network currently exists in the forms of SCADA protocols and internet connections. It may simply be a matter of transferring healthy state database matrices onto an appropriate server from which it may be extracted and accessed by other wind farm operators. One concern with this approach is the issue of data ownership. This issue may be irrelevant when sharing information at the inter-corporate level but beyond this point the data may be best controlled by a public entity such as a government's Ministry of Natural Resources.

4.5 Conclusions

For this study a potential solution to issues of wind turbine reliability has been proposed in the form of a novel vibration based SHM scheme. The scheme has been developed and preliminarily applied to a fully functioning 2.3 MW wind turbine. The turbine used for testing and development is extensively used throughout the global wind energy industry and due to the flexibility of the processing algorithm the scheme can be adapted to any existing wind turbine model, on which accelerometers may be tower mounted. The

WARD algorithm presented may also be used to evaluate other response phenomena obtained in the form of time series data. Highlights of the proposed scheme include

- Minimal downtime required for installation of response sensors as the nacelle need not be entered nor components disassembled
- Natural excitation techniques eliminate the need for external exciters which increase complexity and cost of system implementation
- System utilizes highly available and cost effective accelerometer sensors that contribute to the practicality and attractiveness of the technique
- Computationally effective transforms allow for real time monitoring of turbine condition as it operates in a transient environment
- Multiple alert criteria allow for identification of damaged states as well as conditions that result in deviation from normal behavior which may lead to damaged states
- Adaptive thresholding based on the amount of healthy response data available allows for unsupervised learning of the turbines normal behavior. This also makes it possible for the system to be implemented on a turbine for which no historic data exists.
- Program may be used to evaluate turbine condition following (and potentially during) earthquakes and extreme weather
- Operation response data is amassed throughout turbine life which aids in decision making at the end of a turbines design life.
- The WARD scheme can be expanded to tie many turbines into a reliability network currently referred to as the Wind WARDEN

- Network integration would allow turbines to be assessed within greater context of turbine response
- Network approach used to extend benefits to entire utility grid such that a net increase in reliability be achieved for the wind farm, company, province, or country that adapts the network

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Chapter 5

Conclusions and Suggestions for Future Work

5.1 Summary

Vibration based structural health monitoring has been examined and developed for a full scale 2.3 MW wind turbine. Vibration testing of the turbine was completed on three test days resulting in a dataset of historic turbine response. These response signals represent healthy turbine behavior and provide a baseline for condition evaluation in a SHM program. In Chapter 2, two of these response signals were processed using the discrete wavelet transform which revealed features and characteristics of the signals. Start up analysis revealed ramping of low frequency energy on scale with the rotor rotational frequency. Steady state analysis uncovered low frequency periodicity. Following this study additional datasets were examined in Chapter 3 and an event mapping procedure completed which allowed for vibration features to be correlated with physical turbine motion such as yaw articulation and shut down. It was found the yaw response was influenced by ambient excitation from wind flows affecting the parked turbine. Shut down analysis was performed to quantify typical shut down behavior and an anomalous dataset was found that exhibited higher loading and extended shut down duration when compared to the other signals. The seventh decomposition level containing the 2.84-5.68 Hz frequency range exhibited high sensitivity to changes in response. Finally, the approach to vibration analysis used for Chapters 2 and 3 was synthesized into a SHM scheme using the WARD algorithm that could be used as a diagnostic tool for wind turbines in Canada and abroad. The algorithm was applied to the obtained datasets and was effective in alerting the user to the anomalous shut down. It has been proposed that the WARD algorithm and SHM scheme be applied to multiple turbines so each turbine could be assessed relative to a population of healthy turbines resulting in a better understanding of dynamic turbine response.

5.2 Recommendations for Future Work

The dynamic structural response of wind turbine machinery is only beginning to be fully understood as researchers are gaining access to utility scale turbines for testing. Further research into the occurrence and cause of damage is called for. These aspects will reveal themselves once a SHM program, such as the one developed and presented in this Thesis, is fully and permanently implemented on an operating wind turbine. Once implemented, the obtained healthy state response data should be analyzed and stored for reference when turbines face maintenance issues.

Efforts may be directed to further understanding the shut down dynamics of the turbine as this aspect of response has been historically problematic. Response to a hard stop sequence is to be obtained and comparisons made between soft and hard stop dynamics. Finite element analysis may be employed by researchers in this area in order to pin point locations where critical loadings occur. Also, the relationship between simultaneously captured response signals should be investigated for its potential as a damage sensitive feature.

Vita Auctoris

Kyle Bassett was born in 1987 in Scarborough, Ontario. He was raised in small town named Ballentre. He completed high school at Cardinal Carter Catholic High School in Aurora. Following that he attended the University of Windsor where he obtained a B.A.Sc in Mechanical Engineering in 2009. During this undergraduate study he began research into renewable energy, wind turbines and structural health monitoring. He is currently a candidate for the Master's degree in Mechanical Engineering at the University of Windsor and hopes to graduate in winter 2010.