RESPONSE TO MOWER 14-10 PROGRESS REPORT REVIEW COMMENTS

We have responded to the review comments in the order they were presented. Our responses are presented after each comment.

1) Would you please confirm that you and your CPIs have conducted a thorough literature review and that the work you are proposing has not already been conducted. I see that Wang is conducting some work that is close to dovetailing with your team's approach. http://proceedings.ewea.org/annual2012/allfiles2/1140_EWEA2012presentation.pdf Have you contacted Wang for points of collaboration or difference and possible future coordination?

Response:

We conducted an extensive literature review which revealed the current trends in condition monitoring systems and confirmed that we were on the right track in our approach to the proposed Intelligent Health Monitoring Software System Development. One of the papers we reviewed was "Condition Monitoring of Wind Turbines: A Review" by Sachin Sharma and Dalgobind Mahto published in the International Journal of Scientific & Engineering Research in 2013. It reviewed 85 related papers in the area of condition monitoring. One of the papers reviewed was "SCADA Data Based Nonlinear State Estimation Technique for Wind Turbine Gearbox Condition Monitoring" by Yue Wang and David G. Infield which was presented at the European Wind Energy Association 2012, Bella, Copenhagen, Denmark, April 16-19, 2012. This paper after a detailed review was published as "Supervisory Control and Data Acquisition-Based Non-Linear State Estimation Technique for Wind Turbine Gearbox Condition Monitoring" in the Institution of Engineering and Technology Renewable Power Generation in July 2013. Both the Conference and Journal versions of the Wang's paper use a Nonlinear State Estimation Technique (NSET) to model a healthy wind turbine gearbox using stored historical data. A model is constructed which have interrelationship between model input and output parameters and covers as much turbine operational range as possible and the model is applied to access the operational data. Welch's test together with suitable time series filtering is used in the algorithm so that faults can be detected before they develop into catastrophic failure. In the Journal version, the NSET method is compared to an artificial neural network (NN) model. In addition, Wang and Infield also published a paper "Neural Network Modelling with Autoregressive Inputs for Wind Turbine Condition Monitoring" in the International Conference on Sustainable Power Generation and Supply (SUPERGEN 2012), September 8-9, 2012. Our review shows that Artificial Neural Network modelling (NN) and Nonlinear State Estimation Technique (NSET) modelling have their advantages and disadvantages and as we proceed with the work we will employ modelling methods that produce optimal results. The work we are proposing "has not already been conducted". Most of the works reviewed was on the gearbox of the wind turbine. The three measurable wind turbine performance characteristics are vibration signals, oil debris and temperature. Wang and Infield used temperature in their work. We are using vibration analysis in our work. Moreover, our proposed health monitoring system is based on monitoring other vital components like the blades in addition to the turbine and is directed at offshore wind farms. We believe that this health monitoring software when fully developed will be a big boost to Maryland's desire to develop a cost effective wind farm.

In answer to your question we have not contacted Wang. We may reach out to her and David Infield in the near future when the need arises.

2) Would you please provide a summary for the meaning of FFT and DCT

Response:

A summary of the meaning of the terms are:

FFT is short for **Fast Fourier Transform**. It is an algorithm for quickly computing the discrete Fourier transform (DFT) and it's inverse. The FFT converts signals from the time domain to the frequency domain, and displays the complex frequency components in a signal.

DFT stands for **Discrete Fourier Transform**. It converts a finite list of equally spaced samples of a signal into frequency components.

DCT, **Discrete Cosine Transform**, is similar to DFT but only uses half of the sample size for the signal. It produces nearly the same frequency components as the DFT and only involves real coefficients of the frequency component.

3) From this report, I conclude the remaining focus of the work will be developing a Health Monitoring Software Systems with the 5 phases listed in section 12. Is this correct? If so, would you please provide a brief description of how the focus differs from other approaches that have been investigated - it would be helpful to understand the uniqueness of your investigation.

Response:

The remaining focus of this work will be on developing the proposed Health Monitoring Software System. In our work we are using a two-stage classification system of diagnosis and prognosis. We are proposing a two-stage fault identification mechanism as follows: (a). General fault detection using goodness of fit (GOF) models applied on time domain signals, and (b). Fault classification models applied on frequency-domain signals. All the works we reviewed use one-stage classification. We believe our approach will be more efficient by reducing heavy processing applied on signal characterization and classification by pre-processing the time domain signal first to detect and localize a potential fault. See Figure 1 for the two approaches.

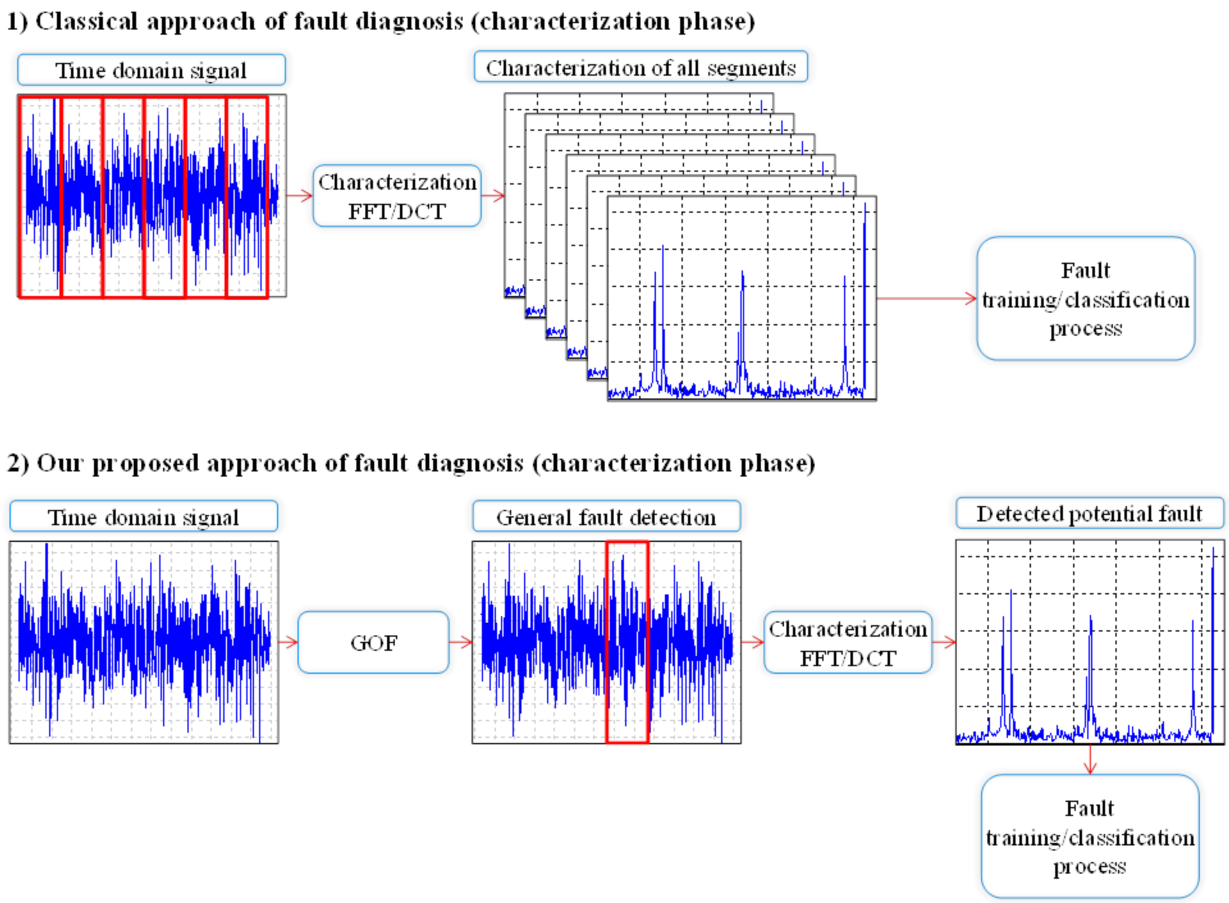

Figure 1 Classical versus Proposed Fault Diagnosis

4) Also, is it correct to assume this project's focus is likely to be more 'general' in nature but has possible application in the 'warranty period' of the components but which will not be included within the remaining year of funding?

Response:

The techniques developed may be considered general only in the sense that we do not currently have access to real-world data nor actual systems to monitor. The techniques have only been applied on the experimental lab data we have collected and will be collecting in the future. However, the techniques are believed to be applicable to the target systems with needed fine tuning and possible retraining if necessary. As we have already indicated, data collected during the "warranty period" will be further used to train the system for normal and abnormal signal signatures to be used for system health monitoring in the post-warranty period.

5) During our May 15 meeting, I had the understanding that you were exploring ways to include UMCP and IBM into the last 12 months of this project hence my suggestion for delaying submission of this report until after the meetings. However, am I correct in understanding that both UMCP and IBM could be potential contributors for 'extended'

research beyond the MOWER II funding but neither would directly contribute to the Health Monitoring Software System?

Response:

It is unfortunate that you misunderstood our presentation to you on May 15, 2015 on our collaboration and partnership efforts with UMCP and IBM IOC. Definitely, if we find out areas they could contribute to our efforts in the next 12 months of the project we will certainly vigorously pursue them. However, our main aim of reaching out to them and others is to leverage the MOWER II grant to extend and sustain our research efforts beyond the MOWER grant. Therefore you are correct "in understanding that both UMCP and IBM could be potential contributors for 'extended' research beyond the MOWER II funding but neither would directly contribute to the Health Monitoring Software System".

6. Last point: I would find it helpful if you could briefly describe the steps your team will undertake to complete phases 3, 4, and 5 of the proposed Health Monitoring Software System and identify the goals you hope to achieve and how this could be applied to lower the total cost of Maryland OSW facility

Response:

Owing to the lack of access to real sensor data on components of an offshore wind farm, we are therefore working with the NREL wind turbine test data to train and test the proposed model. We are currently working on Phase 3 as shown below. The steps we are taking to complete Phases 3, 4 & 5 are shown below:

Phase 3 **<u>System Simulation</u>**

Virtual scenarios of normal and abnormal/anomalous structural states will be simulated and fed into the system to investigate the system capability of recognizing and reporting properly the registered events. The success and satisfactory result of this stage will give us a confidence to move forward with small-scale real world system deployment. Our current stage of the model development in this phase include the following components:

- **Signal normalization**: it is an important step where all signal vectors need to be amplitude normalized by transforming them linearly to the scale of [0, 1] so in the training phase the classifier can be trained with a consistent data set.
- **Signal segmentation**: signals are recorded in real time and can be very lengthy which is inappropriate for signal processing techniques therefore, a systematic time-window is used to crop the signals into uniform size to be processed into feature vectors in the next stage.
- **Feature extraction**: the segmented signals are processed by two techniques: FFT and DCT to characterize their features and represent them in a vector form.
- **Vector space formation**: the input set of vector are organized into two vector spaces: training set which usually 75% of the original set and testing set which is typically 25% of the original set. Both sets are used to train/test an intelligent agent (Neural network, fuzzy logic, etc.).

Phase 4. Small-Scale Real World System Deployment

In this phase we aim to develop IHMSS that is suited for a single wind turbine system. Due to the lack of real data, we propose to accomplish this phase through the following stages:

1. We will utilize NREL data sets and other possible sources as our baseline for training and testing the proposed model.
2. Since characterization phase has been accomplished, we will proceed to study potential intelligent classifiers such as Neural Networks, Fuzzy Logic, Clustering techniques etc. and select one to be used as our classifier to classify the detected fault.
3. Completing the IHMSS model as proposed and implementing our unique event-based characterization vs. traditional characterization methods and comparing the two approaches for potential efficiency gains.
4. Testing the completed IHMSS model on data sets collected from different sources to validate its effectiveness and efficiency.

Phase 5. Large-Scale Real World System Deployment

The goal of this phase is to scale-up the previous phase to a wind farm consisting of possibly of fifty turbines rather than considering a single turbine. We propose to accomplish this phase through following stages:

1. Establishing a real data set for one turbine to be ran for certain period of time which is expected to be within 10 minutes. This data set will have healthy data and data of faulty components (gears, bearings, etc.).
2. The data established in stage 1 above will be modified by adding, removing, amplifying, attenuating, etc. the existing failure events to simulate 50 turbines with different failures.
3. Scenarios will be designed and ran on this simulated wind farm and one agent of IHMSS will be monitoring a single turbine.
4. One central database/server will be simulated to collect, maintain and manage all the events detected by the individual IHSS systems.
5. A communication protocol will be developed to manage the communication between the individual IHSS systems and the server.
6. A user interface will be developed to facilitate the user interaction/queries with the server to generate reports about the health states of the simulated wind farm
7. Testing of the developed wind farm health monitoring system will be conducted using the simulated turbines to verify its operational effectiveness and efficiency.

The research investigation of MOWER 14-10 is mainly focused on developing and implementing a comprehensive Intelligent Health Monitoring Software System (IHMSS) that will be used as a training and information gathering tool. The Software will provide a comprehensive status of the components of the offshore wind farm. During a fault condition, it is possible to know where the fault occurs and in many cases, ascertain the severity of the fault. An engineer/operator in the control room can make an educated decision whether to continue running the farm at a reduced capacity until repairs can be scheduled, or shut it down to prevent further damage to components. Our approach maximizes the economic utility of the offshore wind farm. The aim of developing the IHMSS is to use its early fault detection capability to raise alarms that will enable preemptive actions to be taken to reduce the cost of maintenance and operation of the proposed Maryland Offshore Wind Power generation project.