Distributed Real Time Compressor Blade Health Monitoring System

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ABSTRACT

Compressor blades of a heavy duty industrial gas turbine need to sustain long period mechanical stress and vibration induced by high speed rotation and high pressure mass flow. High stress coupled with erosion and corrosion damage during operation is the main driver for blade cracking. Material separation of cracked rotating blade is a serious safety and reliability concern, which not only affects compressor health, but may also cause costly secondary damage at downstream. Early detection of blade anomaly and incipient crack is critical to ensure blade and compressor health and minimize service disruption. In this paper we will introduce a blade health monitoring (BHM) system developed by GE Power. BHM adopts distributed system architecture and operates continuously 24x7 to provide real time rotor blade health assessment. BHM sensors and data acquisition (DAQ) system are installed on the gas turbine to capture blade passing signals (BPS) and assess time of arrival (TOA) for each blade. Advanced signal processing algorithms process the signals locally to calculate key features that associated with blade health. Then finally, a central anomaly detection module, which is fully integrated with GE Power monitoring system, is developed to assess blade health condition and generate anomaly alarms to alert diagnostic engineer.

1. INTRODUCTION

Heavy duty industrial gas turbines are widely used in power generation plants worldwide. Axial flow compressor is a key subsystem of the gas turbine. Due to inlet air flow aero dynamic load and rotor rotation, various mode displacement and vibration on the compressor blades are excited. Excessive vibration may accumulate high cycle fatigue and thermal mechanical stress on a rotor blade, and cracks may initiate and propagate over time. To detect and monitor blade cracks and provide early warning before material liberation is the main focus for any blade health monitoring system.

Blade tip sensing based approaches have been the primary method widely adopted for rotor blade vibration analysis and crack detection (Heath, 1998 and Von Flotow et al. 2000). In this approach, one or multiple non-contacting blade tip sensors are inserted through drilled holes in compressor casing at an axial location directly above the trajectory of blade tips. The sensor can sense the approaching or departure of rotating blades and produce a pulse voltage when the blade passes the sensor midpoint. Two families of blade tip sensors are typically used, eddy current sensors (ECS) and variable reluctance magnetic sensors (VRS). Both sensor types operate based on the principal of perturbed magnetic field caused by blade passing. ECS sensor uses special circuit to produce an active magnetic field, while the VRS sensor uses permanent magnet to produce a static magnetic field. In comparison, the latter one is less expensive since no complex circuit and signal conditioning is required to maintain the active field. On the other hand, ECS sensor can operate for blades of different conductive materials, whereas VRS only works with ferrous materials. Other sensing system such as acoustic pressure sensor and bearing vibration sensor have also been studied (Kestner et al., 2014).

One central based blade health monitoring system (BHM) was developed by Bhattacharya et al (2011) at GE in recent years. BHM uses two VRS sensors for each compressor rotor stage to capture blade passing signal. The BHM system offers configurable 1-3 or 1-6 stages 24x7 continuous monitoring to GE F fleet units. The sensor probe installation for a 3 stage monitoring unit is shown as an example in Figure 1. Both the BPS data from the VRS probe and once-per-rev signal from Keyphasor are captured in

DAQ for TOA calculation. The once-per-rev signal is also used as reference point to mark the blade number. The system architecture is shown in Figure 2. In this system, two data sources are utilized in blade health calculation: a local DAQ is installed to collect TOA data, and turbine operation data from turbine control system is logged in an on-site-monitor (OSM) computer. Both data streams are transferred as data files to a central calculation server for feature extraction and anomaly detection. The data transfer is time based and run once a day for each unit. In the central calculation server, BHM feature calculation is performed. Depending on the operating mode based on turbine speed, TOA data is classified into two categories: steady state or transient state, and corresponding features will be extracted. For transient mode, blade resonance frequency and magnitude will be calculated, and for steady state static deflection will be calculated. An anomaly detection or alarming module is also hosted in the central calculation server, which will generate alarms if resonance detuning during start up or shut down, or shift in static deflection in steady state is detected. And finally, a user GUI screen hosted by a web server is provided to the end user for alarm daily monitoring, dispatching alarms, and feature data trend study or root cause analysis.

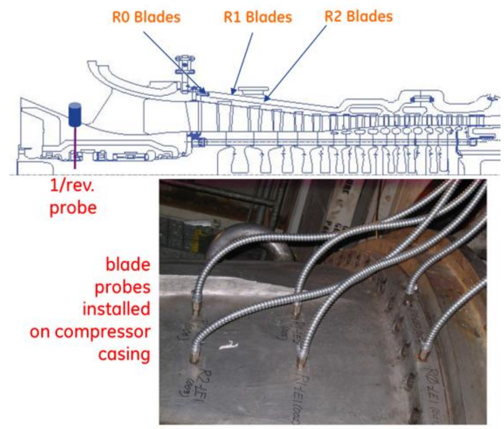

Figure 1. GE BHM System Probe Installation on Compressor Casing

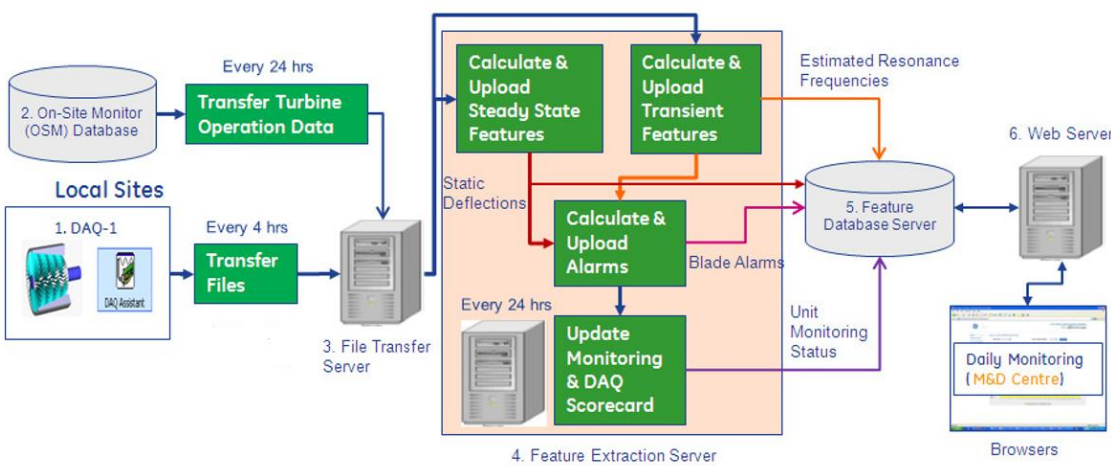

Figure 2. Central Processing BHM Architecture – Previous System

Even though the above described system is fully functional, there are some noticeable drawbacks. The main issue is scalability. Transferring high resolution TOA data files to a central server and running feature calculation takes significant bandwidth and computing power, which cannot be easily sustained for a large fleet. Another issue is time delay. Given the resource and bandwidth constraint, data transfer and calculation runs once a day, meaning typical 24-hour delay from anomaly occurring to alarm being created. It may not be a significant issue for slow developing anomalies, but for time critical failures such as foreign object damage (FOD) caused blade damage or material loss, the alarm delay may cause miss opportunity to detect and prevent costly serious damage.

In this paper, we will introduce an enhanced system with a distributed architecture. It enables near real time BHM feature calculation, and achieves improvement in system scalability. In addition, it provides seamless integration to the existing state-of-the-art GE Power remote RM&D infrastructure; therefore reduce the system redevelopment cost through utilizing existing modules and protocols. Also, other than resonance and static deflection, blade tip clearance feature is added in the feature set for anomaly detection. In the next section, we will first introduce the enhanced distributed real time BHM system architecture, followed by BHM feature calculation – both existing and new feature will be included for completeness. Then the anomaly detection and an example case will be discussed.

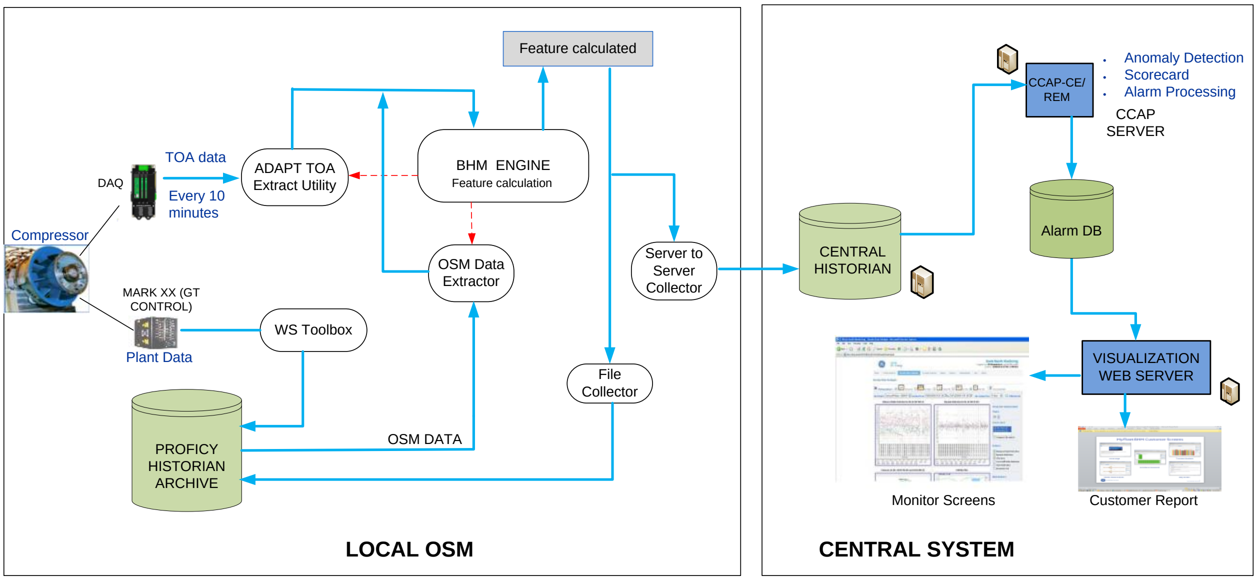

Figure 3. Distributed Real Time BHM Architecture – Current System

2. DISTRIBUTED BHM SYSTEM ARCHITECTURE

The architecture of the enhanced BHM system is shown in Figure 3. There are two main subsystems: a local feature calculation module, and a central anomaly detection and visualization module. The local module is stored at local site on OSM, a windows server computer that provides turbine and plant data archive and running local analytics. The central module is hosted in GE Power central infrastructure at Atlanta, where RM&D team is located and it provides 24x7 monitoring and customer support for all fleet issues.

Local BHM Module

A GE MCS 3701 DAQ is used to capture the blade passing signal and calculate TOA. A junction box is used to connect the sensor wires coming off the compressor casing to the DAQ input channels. There are two channels per stage for each of the two leading edge sensors. Keyphasor signal is also input to the DAQ as reference signal. Figure 4 shows the Keyphasor and BPS signal. The adopted blade numbering convention is that the first blade passing the first BHM sensor after once-per-rev signal arrives is blade 1. The TOA for each blade is calculated as the relative time between once-per-rev and BPS peak signal for that blade at each turbine revolution.

At the core of the local BHM system is a deployed Matlab runtime application for BHM feature calculation, which is referred here as BHM engine. The BHM engine operates continuously to retrieve and process TOA data from DAQ storage. It does so through a utility software - ADAPT TOA extractor, which converts DAQ recorded binary TOA data to CSV format for the calculation engine. Other than TOA data, the BHM engine also gets turbine operation data through an OSM Data Extractor. The operation data provides turbine running mode status, also load information, which is required for steady state feature calculation.

Every a few minutes (configurable) the BHM engine wakes up from sleep and initiates a data request. TOA data is only available when the turbine is in transient (startup or shutdown) or steady state (99%~ 101% full speed). Based on the available TOA data in each operation mode, the BHM engine will trigger either transient or steady state algorithm, which converts raw TOA data into BHM feature data. More detailed feature algorithm will be described later in section 3.

The feature output from BHM engine is loaded into local historian using Proficy™ historian file collector, a service software executing on local OSM that inserts time series data to Historian database. The BHM feature data together with other OSM local data is then synched up with central Historian through server-to-server collector through high speed network. Note that only one set of steady state feature is produced every 3 minutes, and one set of transient feature being produced at every startup or shutdown event. In contrast to the high density TOA data, which is recorded every revolution when the unit is in transient state, and 80-revolution every 3 minutes when unit is in steady state, the feature calculation module essentially converts the high density TOA data to low fidelity feature data. By moving this module from central calculation to local OSM, it reduces the network bandwidth usage significantly avoiding need to transfer high fidelity data, and spreads the computation intensive feature calculation load to a network of OSMs.

Central BHM Module

Once the BHM features are transferred to the central historian, various anomaly detection modules will be triggered to process the feature data, and evaluate health condition of compressor blades. Depending on the operating status, transient anomaly detection module or the steady state module may be triggered. Transient module monitors resonance frequency detuning, whereas steady state module monitors shift in static deflection and clearance feature. Alarm can be raised automatically once anomaly is detected. More details for the anomaly detection module will be provided later in section 4. Sensor or DAQ failure is also monitored to ensure system integrity.

Visualization tool is also part of the central system to provide long term or short term configurable feature trend plot to support alarm analysis. It also supports data comparison and fleet-wide statistical analysis. Web portal data visualization provides access to both GE internal users and external customers to examine BHM dataset. In addition, a monthly reporting service is also provided by the central BHM system. The report includes feature trend plots, summary of observation and data analysis to alert customer on resolved or on-going issues.

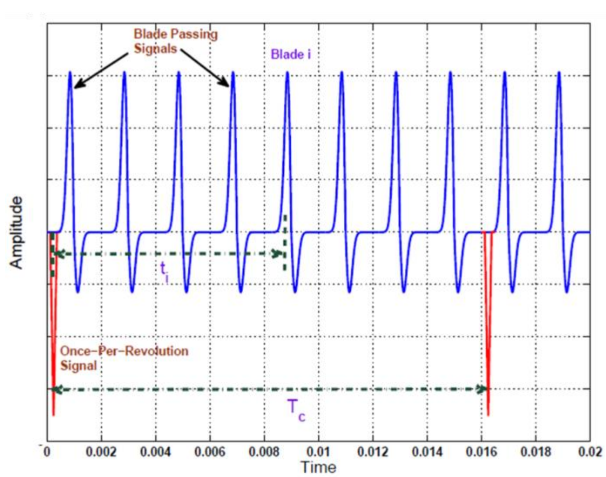

Figure 4. Blade Passing Signal and Once-Per-Rev

3. LOCAL FEATURE EXTRACTION ALGORITHM

TOA data captured by the DAQ cannot be directly used to monitor blade health. In BHM system, three different types of features are extracted from TOA. Resonance and static deflection features have been introduced by Bhattacharya et al. (2011). A brief introduction of these two features will be provided below for completeness. In addition, a tip clearance feature will also be introduced, which has been added to the blade health monitoring feature set.

Resonance

Mercadal et al. (2011) has studied blade resonance changes related to blade damage. Figure 5 shows the wheel spin testing result where blade resonance frequency shifts lower for cracked blade as compared to an un-notched blade. Based on Campbell diagram and rotor design information, a set of resonance modes is selected for resonance monitoring. Finite element model is also performed to assess sensitivity of mode detuning to crack length and crack location. Then during turbine start up or shut down, blade resonance is estimated using single degree of freedom fit (SDOF) algorithm. Along with resonance frequency, resonance magnitude and phase angle are also calculated using SDOF algorithm.

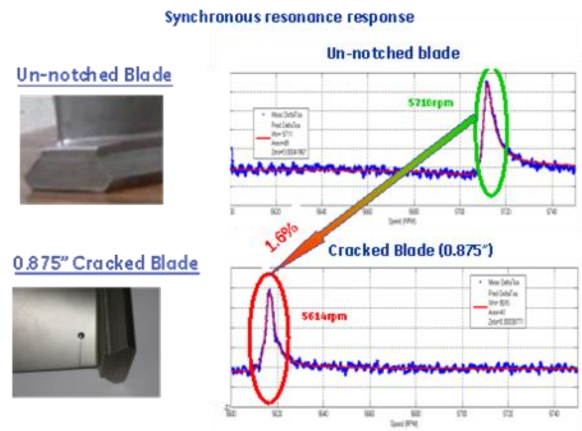

Figure 5. Synchronous Resonance Response of an Un-notched and Cracked Blade

Static Deflection

Static deflection measures the blade displacement from its expected location. It is a function of turbine speed, load, and blade material and physical properties. Crack initiation and propagation may alter blade stiffness, thus cause shift in blade static deflection. Figure 6 shows the correlation of static deflection versus crack size of a leading edge root crack predicted by a finite element simulation model.

The major challenge in monitoring static deflection feature is to separate out variation caused by common factors and special factors. Common factors refer those factors that affect all blades similarly, such as turbine rotating speed and load variation, which will cause blade deflection shift, but not indicative of blade health condition. Special factors refer to crack initiation or crack propagation that affects the defective blades only. Minimizing variation from common factors allows the static deflection feature to be directly monitored using threshold. The signal processing method introduced by Rajagopalan et al. (2012) is applied to extract static deflection during steady state operation. In addition, advanced signal processing algorithm is also applied to further enhance the removal of common effect to reduce static deflection variation and improve signal to noise ratio in blade event detection.

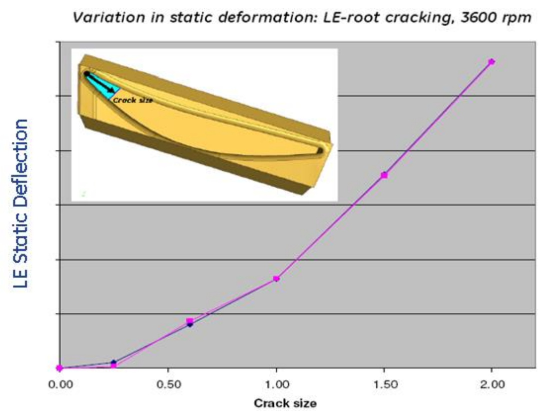

Figure 6. FEA Prediction of Static Deflection vs. Crack Length

Tip Clearance

Another steady state feature is blade clearance signal, which is measured by the voltage of each blade passing signal. The voltage is a function of the setback clearance from blade tip to the BHM probe. Similar to static deflection, clearance is also affected by common factors like turbine speed and load.

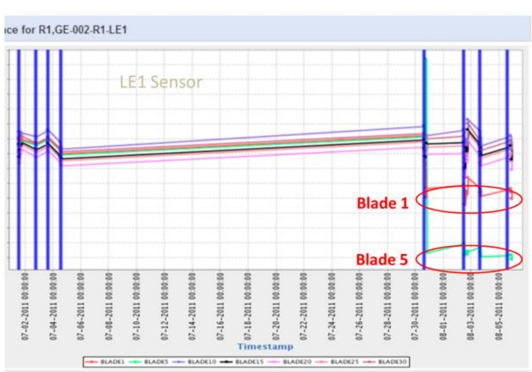

Figure 7. Compressor with Broken Tip Causing Clearance Shift

It is a good indicator for monitoring broken blade tip caused by FOD event. When leading edge blade tip is damaged, it will cause clearance shift or missing BPS for damaged blade. See Figure 7 for an example of clearance shift in blade 1 and 5 when broken tip occurs in a 7F compressor. Blade 28 in the same compressor is also damaged significantly during this event, which resulted in completely missing BPS signal for that blade.

4. CENTRAL ANOMALY DETECTION ALGORITHM

The main objective to have anomaly detection modules on and above BHM features is to reduce the monitoring time per unit and alert the monitoring team only about heightened probability of impending failures in compressor blades rather than asking them to monitor whole fleet continuously. Currently, central BHM module alarms are based on three features - static deflection divergence, frequency detuning and blade clearance as described in previous section. Figure 8 shows various blade failure modes and the corresponding alarming modules that provide coverage.

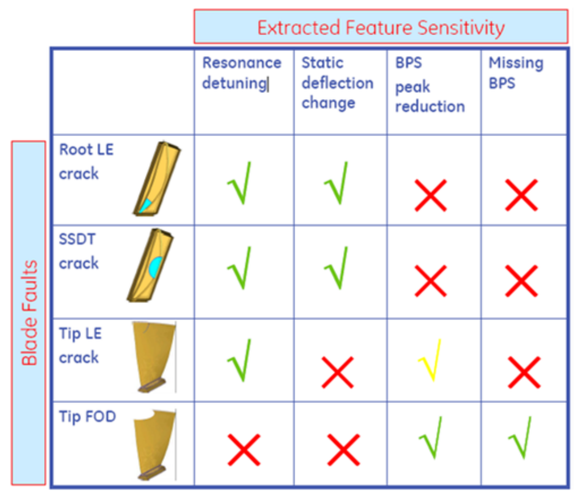

Figure 8. Blade Failure Coverage using BHM Features

Static Deflection Alarms

Static deflection alarm for each blade is generated based on the static deflection trends estimated from the TOA data collected by all the sensors in each stage. It is assumed that static deflection obtained just after installation of BHM system on the compressor reflects the behavior of healthy blades without cracks. The static deflection baselines for each blade in a unit are established by using the data collected in the first two weeks after BHM system installation. The baseline behavior of each blade is established by averaging the static deflection of the blade estimated during base load operation of the turbine.

Thresholds for static deflection alarms have been formulated by developing cracks of different sizes and studying the Finite Element Models of the blade behavior like Figure 6. The alarms for each blade based on static deflection trending are generated if the shift of the static deflection crosses the thresholds persistently. Multiple sensors measure the static deflection of each blade. The alarms from each of these sensors are then fused to conclude final alarm of the blade.

Frequency Detuning Alarms

During startup and shutdown (transient events), blades of different stages in a compressor are excited by various excitation forces from factors like impingent air coming in through the inlet guide vanes at R0 stage. These forces decide the order of vibration that the blade is subjected to. The blade is also subjected to centrifugal force arising out of the rotational speed. As the compressor gains its speed to a steady state value, the blades pass through many modes of vibration. Some of these modes are sensitive to detuning because of cracks at the leading edge root, leading edge tip, and suction side dovetail.

Among all the vibration modes of compressor rotor, a few will be selected as primary and secondary modes for detuning monitoring. The main criteria for determining which modes to monitor are based on the Signal to Noise Ratio (SNR) in field data and mode sensitivity to crack size. Mode having the best SNR and most sensitive to frequency detuning is selected as primary monitoring mode. Baseline resonance for each monitored modes and each blade are then established based on field data during initial health period. The thresholds for the frequency detuning alarms are based on severity level and number of starts the compressor has gone through. The baselines along with the different level of margins are then used to trigger the frequency detuning alarms for subsequent starts going forward.

Clearance Alarms

Another steady state feature is blade clearance signal, which is measured by the voltage of each blade passing signal (BPS). Clearance is useful for monitoring broken BHM sensor or broken blade tip caused by FOD event. When the BHM sensor fails, all BPS measurements will be flat-line signals, causing low voltage in clearance for all blades. When leading edge blade tip is damaged, it will cause clearance shift or missing BPS for damaged blade. Clearance alarm is triggered for the example shown in Figure 7 where clearance shifts in blade 1 and 5 when broken tip occurs in a 7F compressor. The Clearance module will do data quality check to eliminate flat line data and operational data during transient event (i.e. startup and shutdown) and will alarm based on the change in the clearance values of each blade.

All these alarms are then combined first by sensors and then by blades for each stage before being triggered to M&D center so that the team can look at which blade of which stage of the alarming unit has compressor blade health issue.

5. RESULT AND CONCLUSIONS

This paper has introduced a distributed real-time remote monitoring system for compressor blade health. BHM system not only monitors rotor blade health, but also able to monitor its local and central system health. It can alert on faulty BHM sensor, DAQ issue, data transfer or data delay issue, etc.

The robustness and scalability of BHM enables rapid fleet growth - from merely 20 initial pilot units 5 years ago to a fleet of more than 100 units as of today, at scattered locations across the globe. From local to central automated alarm monitoring, to 24x7 expert engineering analysis support, the overall product allows quick problem identification and resolution. Although blade tip timing has been widely used in offline testing facility by various companies, GE BHM is the first commercial system provides on line blade health monitoring, also it is adopted by the largest fleet.

Multiple field blade even has have been detected by BHM since its release. Figure 9 shows an example field event detected by BHM. The unit was operating at steady state, while BHM alarm was trigged for a 50 mil static deflection increase in compressor rotor stage R0 blade 1. Also clearance signal of the same blade decreased by approximately 0.3 volt, independently triggered clearance alarm. Late inspection confirmed FOD event occurred, chipping off portion of the blade tip at the leading edge.

As future work, expansion and enhancement in BHM feature extraction can further enhance the detection capability. Also, alternative sensing technology is being investigated to monitor blades of non-ferrous material.

NOMENCLATURE

BHM	Blade Health Management
BPS	Blade Passing Signal
DAQ	Data Acquisition System
ECS	Eddy Current Sensor
FOD	Foreign Object Damage
NPI	New product Introduction
OSM	On-Site Monitor
RM&D	Remote Monitoring and Diagnostics
SDOF	Single Degree of Freedom
TOA	Time of Arrival
VRS	Variable Reluctance Magnetic Sensor

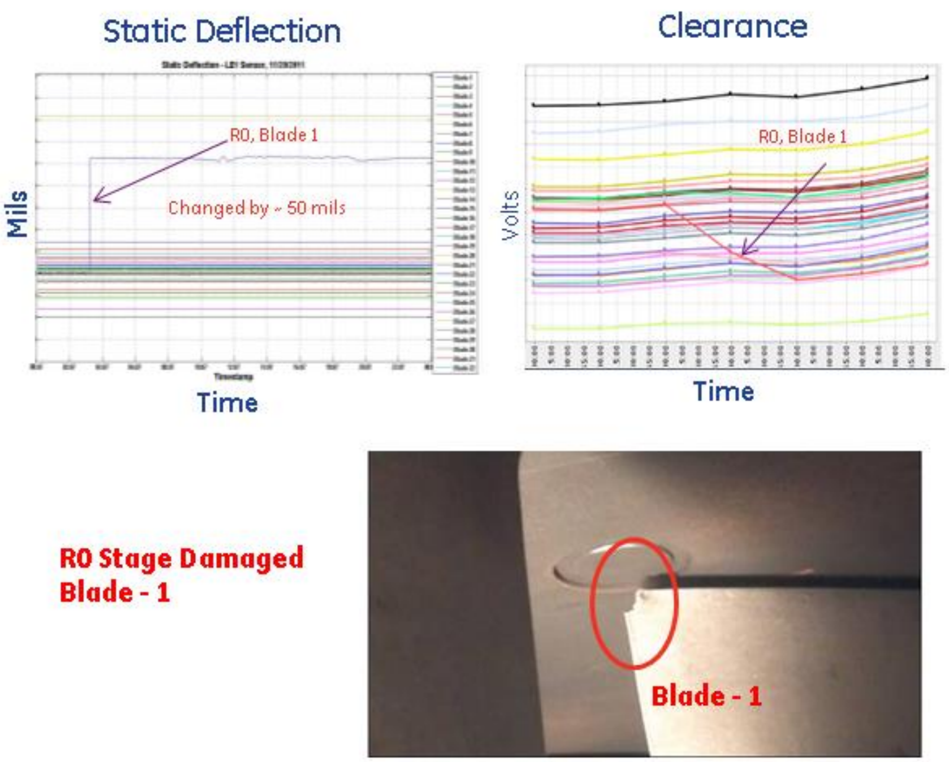

Figure 9. Field Detected Blade Tip Loss Event

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BIOGRAPHIES

Lijie Yu, PhD, has joined GE since 2011. She started her career at the GE Global Research Center at Niskayuna, NY as a research scientist. During that time, she developed advanced algorithms for intelligent systems across multiple GE businesses. She is specialized in signal processing, machine learning, information fusion, and equipment health management. Currently she is a senior analytics staff engineer at GE Power Services, supporting power generation equipment remote monitoring and fleet management. She is holder of 7 awarded patents and authored 15 publications. She is also a certified Black Belt.

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