Fleet Wide Asset Monitoring:

Sensory Data to Signal Processing to Prognostics

Preston Johnson

National Instruments, Austin, Texas, 78759, USA
preston.johnson@ni.com

ABSTRACT

Next generation fleet wide asset monitoring solutions are incorporating machine failure prediction and prognostics technologies. These technologies build on signal processing of vibration time waveforms, process parameters, and operating conditions of the machine. For prognostics algorithms to work well, the signal processing algorithms need to be applied correctly and the results need to be reliable. This paper provides a survey of signal processing techniques as applied to specific machine component with a focus on the output and use with prognostics technologies. With properly organized outputs, prognostics algorithms transform the fleet condition and health management challenge into a deployable fleet health management solution. To arrive at the deployable fleet management solution, a systematic approach in the design of the prognostics system is preferable. This approach includes data and model driven failure patterns, sensory data connectivity from deployed assets, prognostics analytical applications, and advisory generation outputs which guide the asset owners and maintainers.

1. INTRODUCTION

As costs decline to collect sensory data from industrial assets, it is more practical than before to implement an asset health management system for critical and balance of plant assets. Sensory data is available from supervisory control systems, and from low cost embedded data acquisition systems supporting specialized surveillance such as vibration or electrical power monitoring. To transform this abundance of data into actionable scheduling and maintenance activities, a systematic approach in design and implementation of a prognostics solution is recommended (Lee, 2009).

There are several steps to consider when implementing a Fleet-wide health management system, Figure 1. The first is to identify the assets within the fleet for which a business case exists that justifies the expense of gathering, analyzing, and advising operations and maintenance. There are many sources of business benefit including uptime impacts on revenue, safety of workers, productivity, or even improvements in asset design (Hollingshaus, 2011). In the case of power generation plants, assets selected for advanced monitoring and prognostics include circulator water feed pumps, coal pulverizes, gas turbines, steam turbines, generators, and transformers.

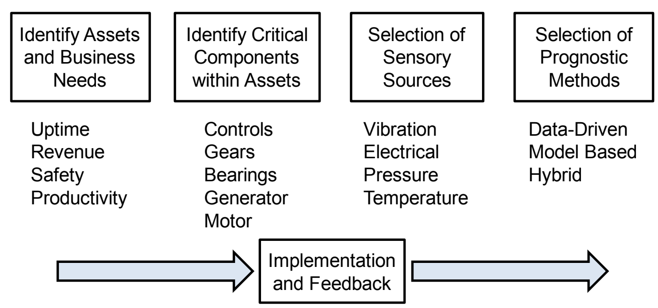


Figure 1. Four steps in design of prognostics systems

A second step in the design and implementation of a fleet-wide health management system is selection of critical components within an asset class that impact the ability of the asset to perform its function to acceptable standards. A typical methodology is the Failure Mode and Effects Analysis (FMEA) and Failure Modes, Effects, and Criticality Analysis (FMECA). In several industries, the process is formalized and includes published standards (Reliability 2004).

For a given asset, there may be several components whose failure will prevent the asset from performing its function.

Further, within these components, some may warrant automated surveillance, while others may warrant periodic replacement. Relating failure modes to business benefit helps to refine the selection of the components for application of a monitoring and prognostic application.

The third step in the implementation process is sensor selection. Sensor selection builds on selected asset component, expected failure and degradation modes, and availability of proven sensory data interpretation algorithms. Selection of sensors and sensory data is impacted by availability of built-in sensor data from existing systems, cost of additional sensors and installation, and impact of data storage requirements. Further, some experimentation may be necessary to fully determine whether specific sensory data and analytics lead to information that is useful in predicting machinery component failure (Lei, 2004).

A fourth step in the implementation process is selection of the prognostic method for the asset class and business environment. Data driven methods require historical operational data to use as comparison using statistics and probability functions to derive estimates and predictions of health and reliability for a given asset. (CALCE, 2012), (NASA, 2012). Even if failure data patterns are not available, data driven methods can be used to compare current machinery surveillance data with historical normal operation. Any deviation from the normal, can be considered an anomaly and worthy of additional study by subject matter experts. Given a degradation is detected, a new pattern can be added to the collection of fault signatures for future use.

Physics driven prognostics often involve a model, or accepted standards for surveillance monitoring outputs. The Physics-of-failure (PoF) approach relies on knowledge of the assets life cycle and the impact of loading, operational conditions, geometry, materials, and failure mechanisims. For example, there are a number of standards for interpretation of vibration signatures including acceptable vibration levels for specific machine components and classes of assets. A bearing vibration analysis incorporates geometries of the bearing, speed of the machine (operational condition), loading, alignment of the shaft, and perhaps the L10 design life of the bearing. And of course, both data drive and physics driven methods can be combined to form a hybrid approach to fleet-wide asset monitoring applications.

Finally, most fleet-wide implementations begin with a selected few assets in the fleet. With an initial deployment step, costs can be contained and the deployment strategy validated. Many questions or challenges are investigated during this pilot phase of implementation. These include the ability to make sensory measurements under consistent conditions, ability to reduce sensory data using embedded computations, and the ability of analytics on collected and historical data to predict patterns and rates of degradation.

This paper expands on each of these steps, and introduces a specific case study in pilot phase implementation.

2. SIX CLASSES OF MACHINES AND ASSETS

There are many parameters to evaluate in determining whether a collection of assets deserve monitoring for degradation and automatic processing of degradation indicators. It is up to the owning organization to determine whether financial, safety, or environmental merits exists to justify an expense of condition monitoring and prognostics. The FMECA methodology mentioned earlier serves as a model for making these evaluations. Given merits for monitoring and prognostics, it is desirable classify the asset and identify critical components within the asset family.

There are many types of machines and assets. Assets can often be grouped into a class of machinery with similar condition monitoring techniques, sensory uses, and recommended condition monitoring practices. In beginning the implementation process, it is useful to categorize the assets into one of the following classes, Figure 2.

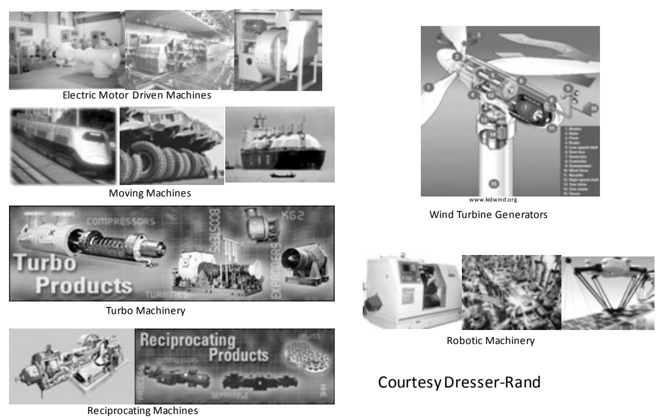


Figure 2. Six common classes of machines

For each class of machine, there are specific commercial and experimental techniques for condition monitoring that offer methods for predicting mechanical and functional degradation. For example, motor driven machines may incorporate electrical power sensors and signature analysis. Moving machines may require special load and speed sensors to organize sensory data into operational cycles. Each class of machine brings with it a traditional approach of condition based maintenance and specific and accepted sensors and signal processing techniques.

Within each asset, there are multiple critical components common to mechanical function of the machine. In rotating machinery for example, several component failure modes are common, Figure 3.

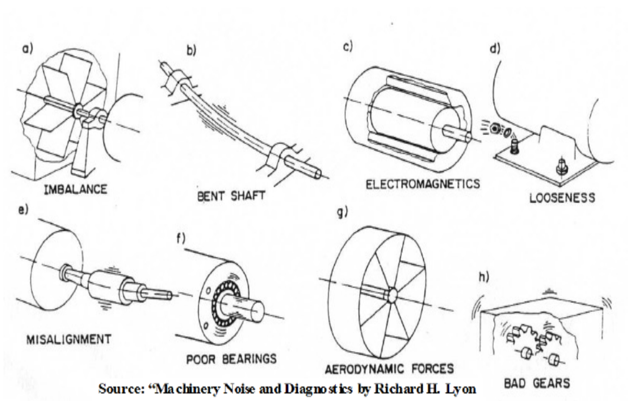


Figure 3. Common mechanical failure sources

With understanding of the asset type within the fleet, it is prudent to identify the key components whose failure directly or significantly impacts the function of the asset. The classes of assets and common mechanical failures are widely used categories for breaking down the asset monitoring and prognostics problem in rotating machinery.

Since most industrial assets have rotating components, it is appropriate to consider common sensors and analytics used to derive parameters that can indicate machinery degradation and failure.

3. SENSOR SELECTION AND ANALYTICS

There are many sensors available for monitoring and control of machinery assets. Many exist in the machine as a control related sensor, while others are added to the industrial asset for performance or mechanical health indicators. Common sensor types are shown in Table 1.

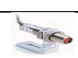
Sensor	Graphic	Use
Temperature		Heat as friction indication
Flow		Flow of fluids or gas
Speed		Rotational speed
Acceleration		Vibration
Displacement		Shaft movement
Pressure		Pressure (cylinder)
Electrical Power		Motor Current / Machine Load

Table 1. Common sensors use for asset monitoring

Other sensory information reported from the control system may include error codes, torque, cycle step, and so on. These control system parameters are often useful in correlating the machine's work and operating condition with measurements from the common sensors in Table 1. It is important to sort measurements into operating modes or regimes to improve correlation of on-line measurements to historical data patterns.

Analysis of sensory data allows the fleet asset monitoring system to transform data into information useful in determining amount and pace of degradation, and therefore in predicting a failure of the asset to perform its intended function. The output of analysis algorithms reduces the raw sensory data into features which describe the original measurement. These features or descriptors are the numeric inputs which prognostic algorithms use to perform association of an asset's current state of health with historical machine health patterns, or models of machinery health. Figure 4 offers several analytic techniques and the feature results these analysis techniques may produce.

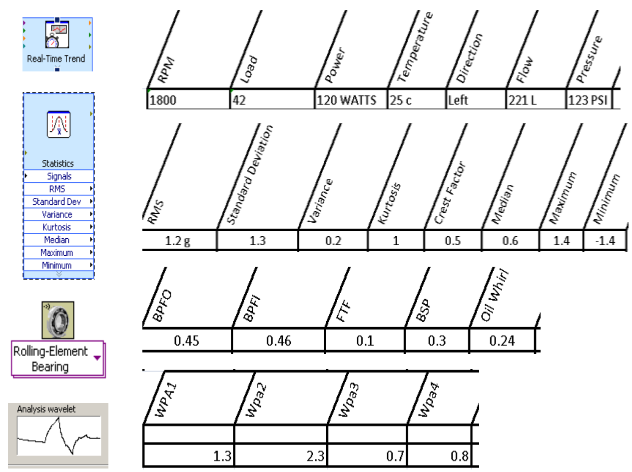


Figure 4. Analysis with feature and numeric results

In Figure 4, the top row lists a series of time series trend analysis that yield averages, rates of change, and current values. The second row lists several statistical measures of a time series vector or trend which indicate shape and distribution of a series of sequential measurements from a single sensor. In the case of a roller bearing, frequency analysis of a high sample rate vibration snapshot can reduce the sensory data to characteristic fault frequency amplitudes indicative of defects in the roller bearing. An advanced analytical technique, wavelet analysis, reduces a high sample rate snapshot from a dynamic sensor to wavelet packet coefficients which indicate presence of transient phenomenon in the measured signals. Transients may be indicative of impacts in the case of a roller bearing, pulsation anomalies in the case of flow or pressure, and so forth.

Knowing that vibration sensors are common sensory measurements used in rotating machinery applications, we may consider taking a closer look at frequency analysis of vibration signatures recorded by accelerometer or displacement probe sensors. Figure 5, depicts the Fast Fourier Transform (FFT) of a vibration sensor signature from the bearing on the input side of a gearbox.

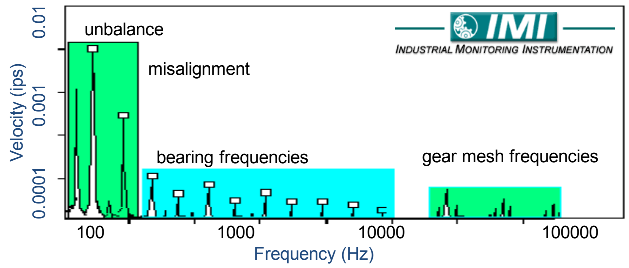


Figure 5. Fault frequencies of machine vibration

In fact, many mechanical faults are detectable using vibration amplitude analysis or extensions to frequency analysis, Table 2 (Jayaswal, 2008).

Item	Fault
Gears	Tooth messing faults misalignment cracked and/or worm teeth eccentric gear
Rotors and shaft	Unbalance Bent shaft Misalignment Eccentric journals Loose components Rubs Critical speed Cracked shaft Blade loss Blade resonance
Rolling element bearings	Pitting of race and ball/roller Spalling Other rolling elements defect
Journal/bearing	Oil whirl Oval or barreled journal Journal/bearing rub
Flexible coupling	Misalignment Unbalance
Electrical machines	Unbalanced magnetic pulls Broken/damaged rotor bars Air gap geometry variations
Structural and foundation faults	Structural resonance Piping resonance Vortex shedding

Table 2. Typical faults detectable with vibration analysis

Using the results of the FFT, analytically it is typical to measure the amplitude shown in Figure 5 as Velocity in inches per second (IPS) and compare the amplitude for specific fault modes to historical norms, or to vibration severity standards such as the ISO 10816. When the amplitudes of specific vibration frequencies exceed historical norms, or a standard recommended warning level, the machine component where the vibration sensor is located is considered degraded to the extent its vibration level has exceeded the historical norm or standard warning level.

However, depending on the indicative features of interest, there are a number of signal processing algorithms used to alternatively or subsequently analyze the time waveform or the results of the FFT. Some of these are listed in Table 3. Advanced analytics build on the FFT creating additional numerical features and augment the degradation status of the machine.

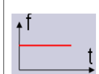
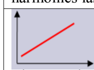
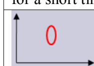
Signal Characteristic	Analysis Methods	Machine Example
 Narrow frequency band lasting for a long time	• Frequency Analysis • Fast Fourier Transform • Power Spectrum	Unbalance in a single speed machine
 Narrow frequency band with harmonics lasting for a long time	• Quefrency • Cepstrum	Damaged bearing in a machine with roller element bearings
 Time varying frequency band	• Time-frequency analysis • Order analysis	Unbalance in a variable speed pump
 Wide frequency band signal lasting for a short time	• Wavelet analysis • AR Modeling	Low speed machine with compressor valve impacts
 Narrow frequency band signal lasting for a short time	• Wavelet Analysis	Electrical motor driven machine with rub and knock noise.

Table 3. Signal processing options for dynamic sensors

Specific use cases of advanced signal processing include time synchronous averaging (TSA) to isolate non-synchronous signals from synchronous signals. Additional advanced techniques include Cepstrum which is a frequency type analysis of the FFT (Zhang, 2008). Wavelets and order analysis are additional examples. Each of these advanced signal processing techniques works to clarify specific features found in the original FFT, by removing or isolating those specific dynamic signal amplitudes that best indicate the asset component's degradation trend or pattern.

4. PROGNOSTIC METHOD SELECTION

There are two general methods of prognostics applications; data driven and model based (Sankavaram, 2009). Data driven methods work best with historical data sets indicating common failure and normal operation of the entire asset as well as its individual components. Model driven methods use mathematical models to describe the relationship between measurements and expected asset behavior.

With data driven methods, historical data is pre-processed to reduce the sensory data to a set of calculated features that describe the normal and various failure conditions. Once this reduction is complete, the data-driven model then relies on one or more health assessment algorithms. These health assessment algorithms work to evaluate the fit of current measurement data to the normal and failure condition feature sets. Example health assessment algorithms include logistic regression, statistical pattern matching, Hidden Markov Models, and Gaussian mixture models.

With model driven methods, a system model is derived from first principle analysis and simulations. Measured data and features, along with system state variables become inputs to the model equation where the outputs map to normal operation or a failure condition. To adapt to specific machinery or operation conditions, often an adaptive learning or model update process is required. The model is derived from system physics and expected behavior. The model then serves as a reference to normal and various failure conditions. Health assessment algorithms then work to fit current measurements to model outputs under similar operating conditions.

As a comparison, data driven methods often require run-to failure data which may be expensive or impractical to obtain. Model driven methods require accurate modeling and the ability to execute and tune the model in real-time leading. Developing models can be expensive from an engineering perspective. Executing models in real-time as measured data arrives may require extensive computational resources.

Often, a combination of approaches is desirable. Test cell data from design verification testing or factory acceptance testing can provide normal behavior data sets. Many mechanical components have accepted limits on calculated features such as vibration severity levels for which a simplified model can be inferred. By combining data driven, and macro model driven approaches, a basic automated degradation detection and trending system becomes possible.

It is not the intent of the author to imply the prognostics process is easy. Identification of critical assets and selection of sensory information to monitor are well established practices. Yet, development of data driven failure signatures and physics of failure modes are much more difficult. Many Small Business Innovation Research (SBIR) grants are made each year to small prognostic domain expert companies to fit a particular prognostic method to a specific class of industrial machines. Much research at the university level and in industry continues in efforts to formalize algorithms and methodologies for prognostics. One may conclude then, that prognostic is not an absolute science, yet one with much interest and activity in both research and industry. Further experimentation and case studies promise to document successful approaches to make the prognostics system design easier for future implementations.

5. Pilot Implementation within a Fleet (Case Study)

Given a solid understanding of the assets in the fleet, availability of sensors and operational data, as well as historical data sets and any models of asset behavior, it is then possible to design a pilot implementation where baselines and preliminary prognostic results can be evaluated.

The Electrical Power Research Institute (EPRI) (Hollingshaus, 2011) continues to sponsor a fleet wide asset monitoring project within a special working group, the Fleet-Wide Monitoring Interest Group (FWMIG). This program aims to articulate a condition based maintenance and prognostics solution for its power generation members. The applications framework leverages data available within power generation plants, a fault signature database, and traditional monitoring and analysis techniques for rotating machinery, (Hussey 2006) Figure 6.

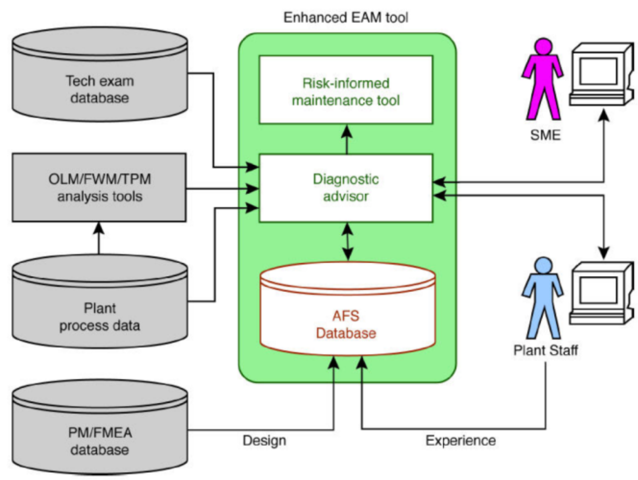


Figure 6. Overview of EPRI FMWIG pilot

Acronyms from Figure 6 are defined here:

- EAM: Enterpise Asset Management System
- AFS: Asset Fault Signature database
- OLM: On-Line Monitoring Systems
- FWM: Fleet Wide Monitoring
- FMEA: Failure Mode and Effects Analysis
- TPM: Thermal Performance Monitoring
- SME: Subject Matter Expert (ex: vibration analyst)
- PM: Preventative Maintenance records

Figure 6, outlines EPRI's vision for Smart Monitoring and Diagnostics. Currently, existing EPRI pilot projects have included anomaly detection systems such as General Electric's SmartSignal, and Instep Software's Prism. These anomaly detection systems operate from plant historian data such as an OSI Soft PI database. These anomaly detection systems are able to develop normal trend patterns and provide notifications when expected operating parameters do not match measured operating parameters. While these trend analyzers provide anomaly detection, it is the technical exam data (vibration, motor current signature, etc) which leads to specific maintenance actions and schedules.

To build on the anomaly detection, EPRI and Progress Energy (now Duke Energy) have embarked on a project to automate the technical exam, especially vibration. By automating the vibration data collection, the current vibration SMEs will move towards 80% of their time reviewing vibration analysis, as compared to 80% of their time collecting data. (Johnson, 2012), (Cook 2012). To make this shift from data collection to data analysis, the cost of installing permanent vibration monitoring systems had to reduce significantly.

By leveraging high volume commercial off the shelf vibration measurement equipment, and competitively priced vibration sensors, Progress Energy is able to afford installation of over 300 vibration monitoring systems using both wired and wireless Ethernet communications technologies. These systems cover the majority of "balance of plant" equipment including circulating water pumps, pulverizes, fans, transformers, and so forth.

To provide for remote vibration diagnostics, Progress Energy and EPRI are working with vibration analytics software providers to develop an on-line and off-line vibration analytics, which meet the de-facto industry standards for vibration analytics. With hardware and software in place, data storage, aggregation, mining, and fault signature association will become future challenges for the EPRI/Progress team.

Both EPRI and Progress Energy have seen millions of lost dollars in loss of power generation capabilities. The belief is that broader coverage of on-line monitoring along with automated analytics for diagnostics and prognostics will predict and prevent future losses.

As the project moves forward, both data-driven and physics of failure prognostics will be employed as part of the EPRI diagnostic advisor to extend its capabilities to include predictive features. However, data mining, fault signature association, and related prognostics algorithms must be validated to become a universal solution for power generation applications.

The EPRI diagnostic advisor will use the asset fault signature database (AFS) along with on-line monitoring (OLM), trend analysis, any technical exam results, and subject matter experts (SME) to advise plant maintainers and operations of any specific next steps.

As the EPRI project moves forward, with additional pilots, the asset fault database (AFS) will grow and the prognostic methods will improve. The on-line monitoring options including sensors and embedded data acquisition devices will also evolve. There is much to learn from this pilot, yet the opportunity in power generation applications is promising.

In EPRI's summary, condition based maintenance, diagnostic advisories, and prognostics using asset fault databases will lead to actionable information in time to economically benefit plant operations (Hollingshaus, 2011). The current pilots are working to validate the prognostics implementation and financial benefits.

6. Conclusion

The implementation of a fleet wide asset monitoring and advisory system combines several disciplines. These range from traditional condition based maintenance practices, to development of fault models, to implementation of hybrid prognostic systems. There are potentially many benefits derived from a systematically developed prognostic system. These benefits may pay well to electrical power generation and other industries that employ many mechanical assets of similar types and function.

Similar pilots are occurring in the Oil and Gas industry for land based drilling and extraction equipment. Other pilots are just beginning in mining industries, centered on haul trucks, swing shovels, and drag lines. These pilots are similarly challenged by the cost of sensors and data acquisition hardware, cost effective analysis, cost effective data storage, and the development of data driven and physics of failure fault signatures.

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BIOGRAPHY

Preston Johnson is the Global Program Manager for Asset Monitoring Systems at National Instruments (NI) in Austin, Texas. NI creates innovative computer-based products that aid engineers in the design, prototyping, and deployment of instrumentation systems for test, control, and embedded applications. He has worked for National Instruments for 25 years in roles of Field Sales, Sales Management, Automation Business Development, Sound and Vibration Segment Manager, and Platform Manager for Condition Monitoring Systems. In his current role as Asset Monitoring Systems Program Manager, his interest lies in embedded signal processing and data acquisition systems and architectures. Preston works with NI OEM and End User customers to deploy fleet-wide asset monitoring systems that lower operation costs, improve machinery reliability, and ultimately increase revenue. He earned his BSEE in Electrical Engineering and Computer Science from Vanderbilt University in 1985 and his MBA in Information Technologies from the University of Texas in 1987.