Commercialization of Prognostics Systems Leveraging Commercial Off-The-Shelf Instrumentation, Analysis, and Data Base Technologies

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Abstract

There are many facets of a prognostics and health management system. Facets include data collection systems that monitor machine parameters; signal processing facilities that sort, analyze and extract features from collected data; pattern matching algorithms that work to identify machine degradation modes; database systems that organize, trend, compare and report information; communications that synchronize prognostic system information with business functions including plant operations; and finally visualization features that allow interested personnel the ability to view data, reports, and information from within the intranet or across the internet.

A prognostic system includes all of these facets, with details of each varying to match specific needs of specific machinery. To profitably commercialize a prognostic system, a generic yet flexible framework is adopted which allows customization of individual facets. Customization of one facet does not materially impact another.

This paper describes the framework, and provides case studies of successful implementation.

1. Introduction

The objective of a prognostic system is to predict the need for maintenance before serious equipment breakdown occurs and to predict the remaining useful life of the equipment components. A prognostics system should operate where possible on its own, to lessen the need for human involvement. This is a tall order for the prognostics systems developer. To ease the required efforts, commercial off the shelf (COTS) components can be used to allow more focus on prognostics algorithms and recommendation reporting.

Prognostics Systems have several components, commonly grouped into data acquisition, signal processing and analysis, and decision making, Figure 1. Figure 1 can be expanded to include communications, visualization, and database components.

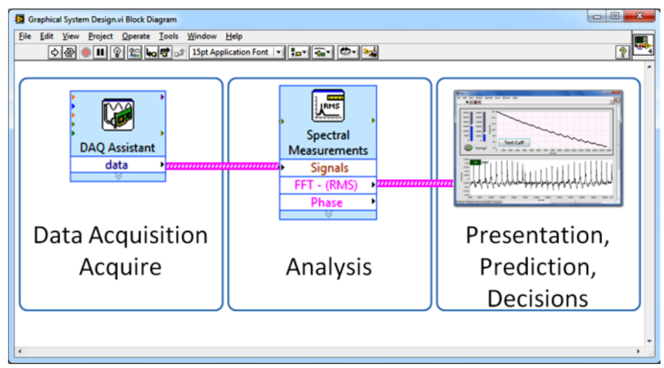


Figure 1: Basic components of prognostic system

To allow flexibility for analysis types, and machinery types, each component needs to be modular to the extent components can be easily interchanged. This interchangeability extends to hardware as well as software. The system needs to scale from small machines up to large machines, and from test cell applications down to portable systems and into on-line embedded systems. Finally, the on-line embedded system components need to be priced competitive to existing data collecting systems. In other words, constraints exist in hardware, software, and development tools in order to maximize modularity, cost and ease of customization. A framework of hardware and software components makes this commercialization possible, Figure 2.

From a cost perspective, it quickly becomes apparent that commercial off-the shelf (COTS) components provide the best cost model for the framework. With COTS, the prognostics systems designer minimizes electronic design as well as software design efforts. Instead, the designer is able to leverage development work already in play within the

COTS suppliers' organization. Further, COTS systems typically provide a faster validation cycle as much of the hardware and software components have validation certificates.

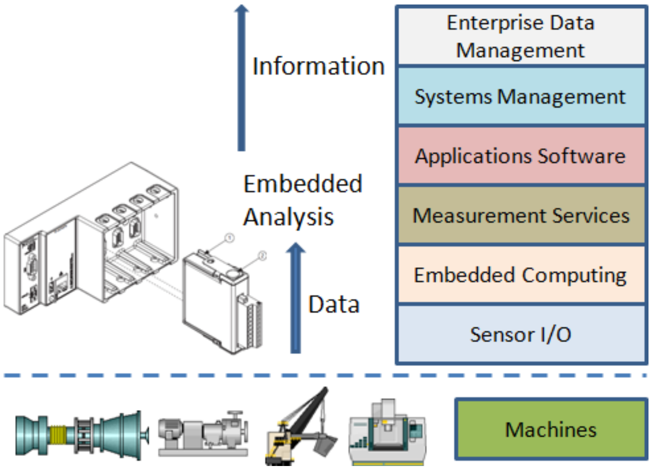


Figure 2: Modular prognostics architecture

This paper examines the prognostics architecture framework and its core components including COTS component options.

2. Modular Architectures

There are several publications promoting a modular architecture for condition monitoring and prognostics systems. One such standard is the ISO 13374 standard, Figure 3, ISO (2003).

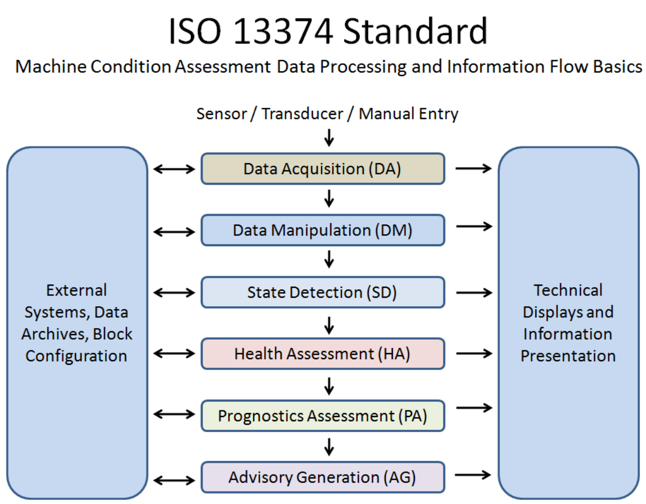


Figure 3: ISO 13374 condition monitoring standard

The ISO 13374 standard divides the condition monitoring and prognostics system into eight subsystems. These include data acquisition (DA) and data manipulation (DM) or data acquisition and signal processing. The ISO 13374 standard also calls out state detection (SD). State detection is often defined as the determination of deviation from normal or healthy operation. It can also be defined as determining the operational state of the machine, for example high speed operation and low speed operation.

Three prognostic functions in the ISO 13374 standard include Health Assessment (HA), Prognostic Assessment (PA) and Advisory Generation (AG). These three blocks perform the hard work of diagnostics, prediction, and information delivery. The outer two blocks on the left and right of the six middle blocks further define data base storage and retrieval, as well as visualization including technical displays and reporting. When following this model, the prognostics developer can save costs by foregoing the need to design these architectures. Further, when following a defined standard, it is possible to mix and match components from multiple commercial suppliers, each of which may specialize in a specific component area.

The University of Cincinnati Intelligent Maintenance Center (IMS Center), for example, takes a unique approach in adapting the ISO 13374 model by adding data filtering and sorting during the data acquisition (DA) step in the process, Figure 4, Lee (2009). The University recommends sorting data into operating regimes.

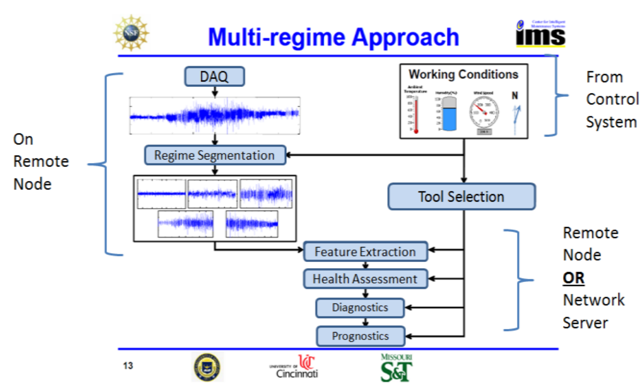


Figure 4: IMS Center multi-regime approach

Operating regimes are distinguished by speeds, loads, and even mechanical failure modes. These regimes are identified during the data collection process. Data is labeled with the regime name, for example speed and load. Downstream, categorization of information is made easy with regime tags made at the data collection point.

In either case, adaption of the ISO 13374 model to specific implementation provides modularity, flexibility, and promises to lower costs.

3. DATA ACQUISITION COMPONENT OF PROGNOSTICS

The data acquisition component (Figure 3) of the prognostic system has the important role of correctly recording sensory information from the machine for downstream analysis and decision making. Data acquisition typically consists of sensors, signal conditioning, and an analog to digital converter. Sensors may include digital sensors as well as analog sensors. Analog sensors commonly used in mechanical system prognostics include temperature, electrical power, strain, speed, and vibration. Often, electrical power, strain, speed, and vibration sensors need fast and high resolution analog to digital converters to transform the analog output of the sensor into a digital format the embedded data acquisition can process, store, and report.

To obtain the best sensory information, many dynamic signals including vibration, need a wide dynamic range data acquisition device. Dynamic range is a measure of the data acquisition's systems ability to detect both strong and weak signals at the same time. In the case of vibration, it is important as many vibration sensors measure vibration from multiple machine components at the same time. In other words, high-amplitude low frequency vibration from unbalance is measured along with low-amplitude high frequency vibration from roller bearing and gears. A wide dynamic range data acquisition system, such as a 24 bit delta sigma analog to digital converter is beneficial in prognostic applications. The difference in amplitudes at various frequencies can be seen in the Figure 5.

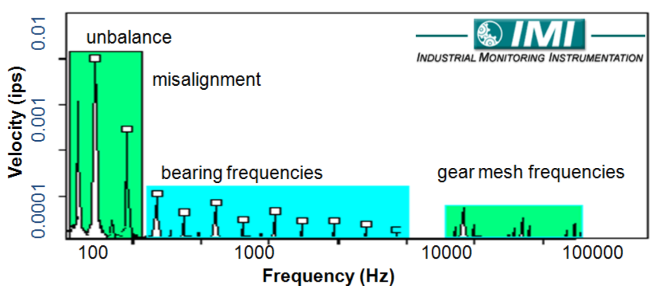


Figure 5: Vibration frequency and amplitude spectrum

A high dynamic range then allows the single sensor to correctly digitize unbalance vibration, mechanical looseness vibration, bearing fault vibration, and even gear mesh vibration.

In addition to dynamic range, there are several other factors for consideration in the data acquisition component. These include anti-aliasing filters, amplification, and sensor power. Typical 24 bit data acquisition hardware includes anti-aliasing filters that remove high frequency noise from the measured signal. While pre-amplification of signals is not often needed with 24 bit hardware, attenuation may be desirable to provide for dynamic displacement or proximity probe sensors. The latest 24 bit data acquisition hardware offers a +/- 30V input range at bandwidths of 40kHz, creating a universal input for accelerometers, proximity probes, voltage inputs, and tachometer signals. Finally, most 24 bit vibration acquisition hardware devices provide configurable IEPE 24V power to power accelerometers, laser tachometers, dynamic pressure, acoustic emission and microphone sensors.

To provide a data acquisition component of the prognostic system, there exist three core choices. First, it is possible to design the data acquisition system from the ground up, selecting analog to digital and signal conditioning semiconductor components, board manufacturers, embedded processors, programming languages, and so on. While this approach can lead to the lowest manufacturing cost for higher volumes, the electronic design domain expertise and time to market costs become prohibitive.

A second choice is to purchase a series of board level products following any number of standards such as PC-104. This choice offers the prognostics developer a range of suppliers to choose from and a range of generic processor and analog to digital boards that can work together. In most cases however, the processor and analog boards have limited software facilities for analysis, data storage, and downstream diagnostics or prognostics. In other words, they provide a fundamental capability, primarily designed for control applications with limited dynamic range, and have limited software support. These products typically are designed to compete on price, with limited advanced features often needed for embedded or downstream analysis. The prognostics developer then must create AND validate signal processing, filtering and other related algorithms in addition to data storage and communications. This effort can become a significant software development effort.

A third choice is to build the prognostics system on a modular system designed for high fidelity sensor measurements with wide dynamic range, with a wide range of hardware certifications, and with a full featured signal processing library for downstream or embedded prognostic analysis.

The second and third options are differentiated by software development tools including mathematics as well as system certification activities. Figure 6 shows a comparison of complete custom (option 1) and modular system (option 3). There is considerable reduction in development effort required when using a instrumentation class modular system as the basis of a prognostics system. A COTS system providing modular instrumentation class data acquisition then allows the prognostic systems developer to focus attention on health assessment and prognostics.

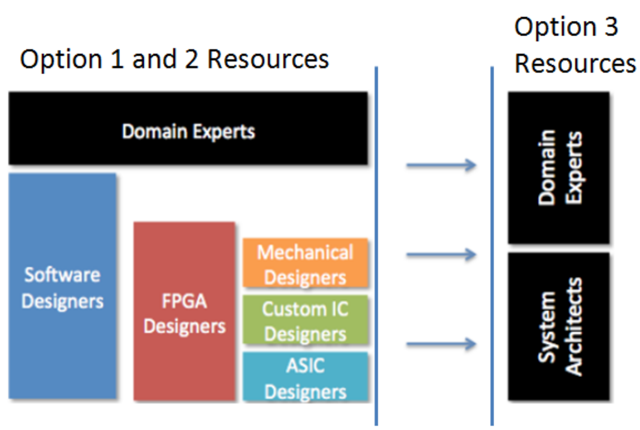


Figure 6: Modular system development effort reduction

Given, there is a data acquisition modular hardware platform in place, it is possible to adjust the sensory input capabilities of the system using modular hardware I/O to best match the machine for which the prognostic system will be used. A modular system allows analog input modules for a variety of sensor types to be selected based on the needs of the system. For example, vibration, temperature, speed, and process variable modules can be added (or removed) based on the measurements that best serve the prognostic system.

Finally, hardware should be industrial grade, meeting high standards for rugged environments. Key measures of rugged reliability include temperature, shock, and vibration. The prognostic systems designer should also consider supplier quality systems and hardware warranty. Table 1 provides common rugged specifications.

Table 1. Common rugged specifications for hardware

Item	Standard	Measure
Operating temperature	IEC 60068-2-1, IEC 60068-2-2	–40 to 70 °C
Storage temperature	IEC 60068-2-1, IEC 60068-2-2	–40 to 85 °C
Operating vibration random	IEC 60068-2-64	5 grms, 10 to 500 Hz
Operating vibration sinusoidal	IEC 60068-2-6	5 g, 10 to 500 Hz
Operating shock	IEC 60068-2-27	30 g, 11 ms half sine, 50 g, 3 ms half sine, 18 shocks at 6 orientations

A number of COTS suppliers provide modular industrial grade data acquisition hardware. Example suppliers include National Instruments, Spectris, Advantech, and Measurement Computing Corporation.

With a solid hardware framework, the prognostics developer is able to focus on the systems architecture, prognostics algorithms, and information delivery aspects of the system.

3.1 Data recording filters

Once the data acquisition system is chosen, it is prudent to determine what signal processing and data storage strategies should be embedded into the data acquisition system component of the prognostic system. On one end of the scale, all time series data from all sensors is continuously recorded. While this strategy insures no loss of data from the machine, it burdens communications and downstream signal processing. For example, simply recording four channels of vibration data at 51,400 samples per second continuously for a week yields 605 Giga-Bytes of data. That is a lot of work for communications, off-line processing, and human interpretation. Much of the data is repetitive.

An alternative is to filter data to limit on board recording to just data that contains new information. This filtering is typically done by onboard analysis.

By analyzing data, it is possible to determine whether the data has changed. On board analysis is performed on monitored sensory data such as speed, temperature, vibration, strain, and electrical power. Examples of onboard analysis include statistical analysis and spectral analysis, The prognostics system should be configurable to allow for deviation limits of sensory information to be used as data storage triggers. With this implementation in place, sensory data is recorded only when it has changed, on a periodic basis, or when an operator request has occurred. Further, the recording includes the condition which caused the data to be recorded. By recording a range of sensory metrics or features along with the recorded data, it is possible to sort the data downstream in the prognostic process. These sensory metrics, then allow the downstream prognostics functions to categorize operational and failure patterns of the same machine and similar machines.

When reviewing the capabilities of COTS technologies for a prognostic system, it is prudent to consider software templates, routines, facilities, etc. that allow for data filtering and data sorting, Figure 7. With the ability of the data acquisition system to filter and sort data, downstream prognostic consumers of the data are more focused and productive.

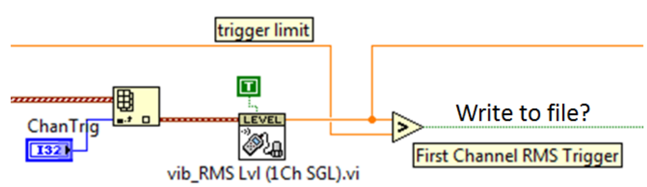


Figure 7: In line analysis drives data recording

Figure 7 shows a simple data recording trigger of vibration RMS level. This block can be replaced and enhanced with a wide range of embedded signal processing including order analysis, envelope analysis, statistics, etc. The ability to customize storage triggering with embedded analysis is an important modularity feature of several COTS hardware data acquisition platforms.

3.2 Data storage format considerations

When considering data storage formats, it is best to leverage a technology or format that works well for the embedded data acquisition system, and provides rich descriptive capabilities for downstream prognostics analysis. One common "schema" for data recording is the Common Relational Information Schema, or CRIS, as defined by the Machinery Information Management Open Systems Alliance (MIMOSA) organization, MIMOSA (2002). This schema defines data types including time waveform data, spectral data, alarm status, process data, and a range of sensory source information including machine asset and sensor asset information. An illustration of the MIMOSA schema is given in Figure 8.

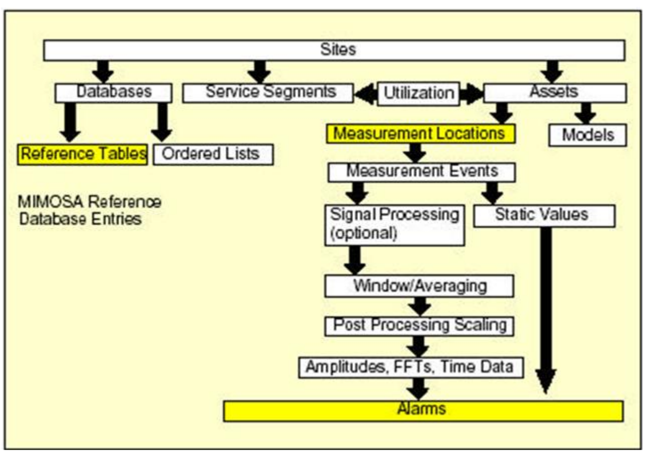


Figure 8: MIMOSA CRIS schema

The MIMOSA CRIS data schema describes a rich data architecture allowing for a combination of time waveforms, spectrum, scalar values, images, and related data types to be stored in a unified data base. When the data sets are organized by sensor, mechanical component, etc, a view of related data sets is easily obtained. For example, opening a sectional view under a roller bearing, one would see time series vibration data, temperature trends, vibration spectra, oil particulate count trends, etc. All of the information is organized as sensory information related to the bearing.

There are several ways to implement an embedded data storage capability which supports this rich data structure. These include common relational database structures and data structures specifically designed for embedded monitoring applications. An example of a embedded data structure format is shown in Figure 9.

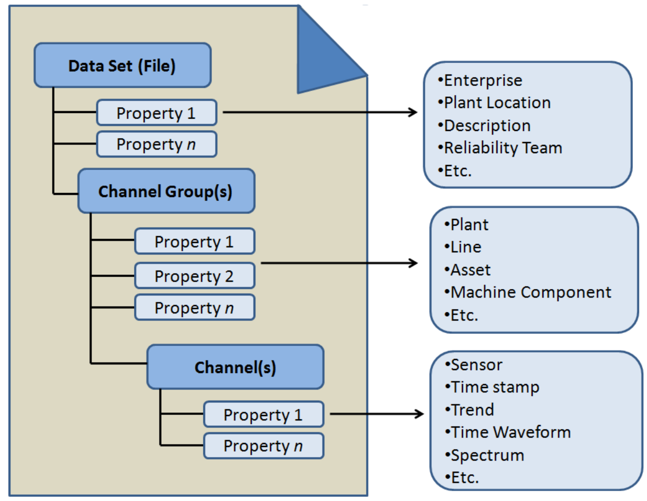


Figure 9: Example embedded data recording structure

Figure 9 illustrates a data structure that is efficient in recording with high speed streaming capabilities. It is rich in data descriptors with the use of data property strings for each data element or channel stored in the data file. In other words, information about the sensor, location, scaling factors, filtering, and mechanical component beneath the sensor, can be stored as labels that describe the time waveform recording. In addition, properties in the data file describe the conditions that caused the data file to be recorded, whether it be an analysis result threshold limit, a time limit, speed change, or operator request.

A second feature of this data structure is the ability to add information along the prognostic system analysis chain. In other words, as the data file record is moved from the data acquisition device downstream to an engineering workstation, additional analysis can be performed on both time series data and extracted features which are stored alongside the original sensory data record, Figure 10.

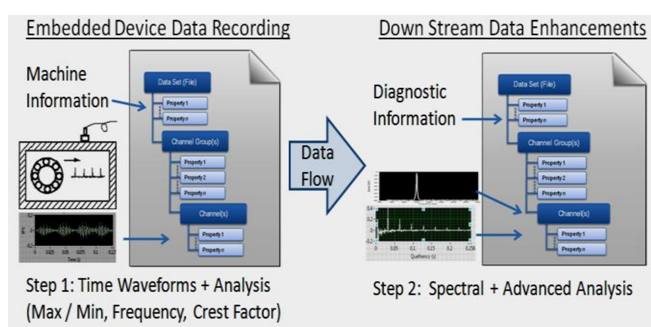


Figure 10: Progression of data structure

The task of analyzing and categorizing data is rarely complete. With a flexible data store, additional analysis results, methods, comparisons, labeling, etc can be added to the data set at any time in the progression of the prognostics process. Going further, if specific empirical patterns emerge, the data files become new models or fault mode references. A flexible and modular COTS data acquisition system provides a core framework for the important task of digitizing and storing necessary sensory data.

3.3 Data acquisition system communications

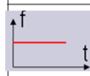
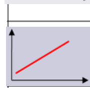
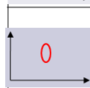
A third important element of the data acquisition system is communications capabilities. While TCP/IP communications is a common monitoring systems requirement, there are situations where alternative methods are beneficial. These communications protocols can include Controller Area Network (CAN) based protocols including DeviceNet, CanOpen, Modbus, etc. (National Instruments 2010). Further, TCP/IP communications may vary in physical form including copper, fiber optic, cellular, and 900 MHz communications. The data acquisition platform framework should be able to easily accommodate many of these communications variants, allowing adaptation of the prognostics systems to oil and gas machinery, to mining equipment, to wind turbines, to remote equipment and many others. With a flexible architecture, the data acquisition system abstracts the communications to a higher level, where specific communications protocols can plug in easily.

By leveraging flexible communications architectures, the embedded component of the prognostics system is able to easily adapt to the needs of the industry and its machines. In addition, with the embedded data recording structure described above, data can be stored locally, and forwarded to the engineering team at the pace of the communications system and when the communications network is available. This "store and forward" capability is valuable for remote machinery locations with sporadic and slower communications.

4. SIGNAL PROCESSING AND VISUALIZATION

Signal processing functions operate on sensory data to extract features or measurements from data acquired from sensors placed strategically on the machine. Signal processing can occur in the data acquisition system, downstream on a engineering or database computer, or even across the internet leveraging emerging cloud computing technologies. Signal processing plays a part in state detection, health assessment, and prognostic assessment steps in the complete prognostic system. Table 2 and Figure 11 illustrate several signal and data processing functions that can play a part in the commercial prognostic system, Zhang (2008).

Table2: Signal processing options for feature extraction

Graphic	Signal Characteristic	Analysis Methods	Machine Example
	Narrow frequency band lasting for a long time	Frequency Analysis 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.

As Table 2 indicates, there are a wide range of signal processing options for condition monitoring and prognostics applications. The choice of signal processing function is made on feature extraction needs, mechanical phenomenon indication desired, and domain expertise and preference of the prognostic system designer. It is important that the software development tools used to implement the prognostic system, offer a wide range of signal processing capabilities.

The IMS Center at the University of Cincinnati has added performance prediction, assessment, and diagnostic pattern matching as a supplement to advanced signal processing, Intelligent Maintenance Systems (2007). These capabilities operate downstream from embedded data acquisition by categorizing extracted features into operating modes and failure modes.

Underlying signal processing and prognostics algorithms is a wide range of mathematics. It is important then that the underlying math meets applicable standards and quality metrics. One such reference is the Numerical Mathematics Consortium, (NMC 2009). In the case of sound and vibration numerical functions, there exist several standards including ANSI, ISO, and IEC. When using signal processing algorithms that meet existing standards, the prognostics system developer is able leverage the certification and validation work of the algorithm supplier.

Health or performance assessment and prediction or prognostics assessment build on signal processing used in the data acquisition, data filtering and sorting, and feature extraction steps of the upstream prognostic components. These additional steps, including logic regression, self organizing maps (SOM), and even the field of statistical pattern recognition; provide tools for matching current measurements with data driven models of system health and failure modes. In other words, the discovery of impacting and out of balance features in vibration data can match patterns of induced stress on roller bearings and help predict a specific bearing failure.

The leverage of signal processing for feature extraction and health indication measurements, leads to visualization of data and signal processing results that the human uses to understand a problem or degradation in the machine. Figure 11 offers one example of visualization graphics.

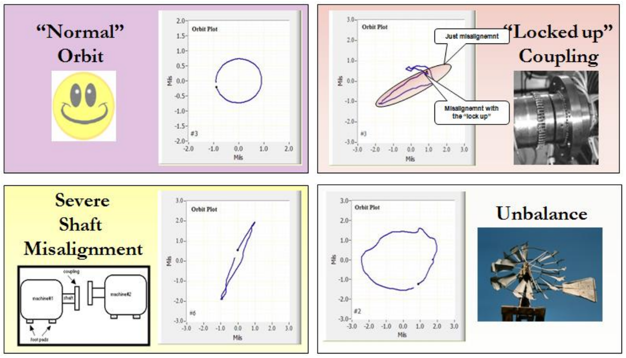


Figure 11: Orbit plot visualization of shaft vibrations

Orbit plots are a common diagnostic and health indicator graphic used in turbine driven machinery applications. These plots indicate the severity of out-of-balance, alignment, and coupling machined degradation issues. The shape and size of the orbit plot indicates the progression of specific shaft vibration problems in the machine. The shape and size of the orbit plat can be analyzed by human domain experts as well as analytically with mathematical algorithms.

Additional visualization tools exist in prognostics software development libraries to summarize multiple machine or system components. These summary plots provide a high level of machine health and allow for selection of suspect machines for further study. The University of Cincinnati's Intelligent Maintenance Systems Center offers several visualization tools for information delivery, Lee (2009), Figure 12.

These graphics provide visual display of health information. The Confidence Value trend chart shows the mechanical health of a specific machine component using a measure of 1 (very healthy) to 0 (badly damaged). The confidence value is commonly calculated using statistical pattern matching described earlier. The Health Radar Chart shows the confidence value of multiple components on a single chart. The Health Map combines machine operational states with machine failure modes. The Risk Radar Chart combines machine state and health indicators along with safety and financial parameters to indicate an element of risk.

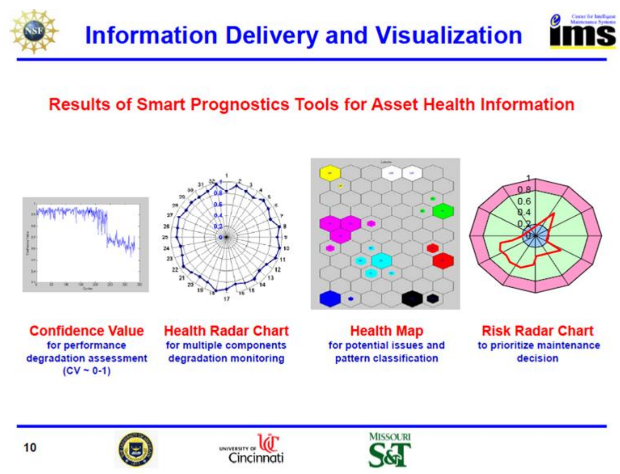


Figure 12: Visualization of machine health and prognostics

Armed with these reports, operations and maintenance teams are best prepared to make operational and maintenance decisions. Of course these end reports build on solid data collection and signal processing techniques described earlier.

The signal processing and visualization components of the prognostic system can be utilized in the embedded data acquisition portion of the system, at the local engineering workstation computer, and over the network and remote engineering centers or data centers. The flexibility of location of mathematical analysis offers the prognostic systems designer options to choose the best place for advanced prognostics in the data acquisition, filtering, storage, and post processing components of the prognostic system.

5. CASE STUDIES

There are several case studies worth review where a modular system framework is in use for condition monitoring and prognostics applications. While several are relatively new to the market, each leverages a common modular hardware data acquisition platform, with modular software architecture allowing for the placement of signal processing and prognostic functions to be placed anywhere along the data acquisition, off-line data manipulation, and visualization sequence of prognostic system activities.

In power generation applications, wind energy continues to lead renewable energies as next generation sources of power. However, these machines are complex and operate in a variety of speed, load, and environmental conditions. These energy generating machines historically have shown to have reliability problems in the drive train. Much interest in research and industry is focused on improved monitoring, diagnostics, and prognostics systems to support wind energy applications. One such example is illustrated in Figure 13.

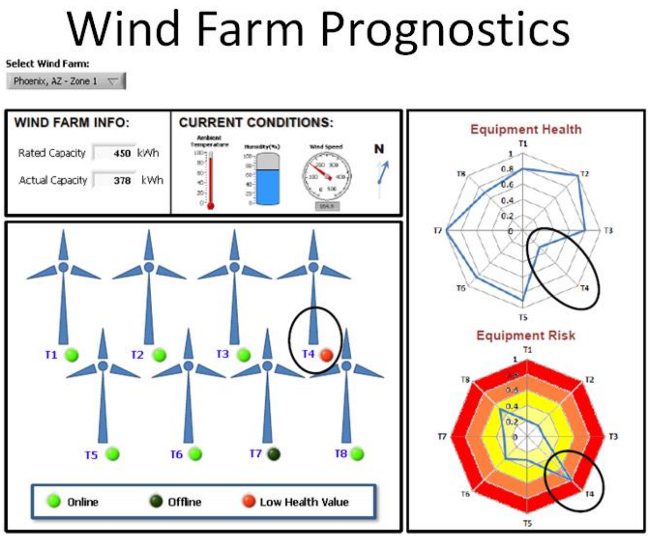


Figure 13: IMS Center view of wind farm prognostics

The IMS Center continues work to adapt state of the art prognostics systems technologies to wind energy applications. In partnership with National Instruments, the IMS center leverages rugged COTS embedded data acquisition technologies, signal processing algorithms, and local and web based visualization tools to implement a wind farm prognostics framework. This framework is used to further research in wind turbine prognostics and to develop an advanced commercial condition monitoring and prognostics system for the wind energy industry.

Another example in wind energy applications is the use of the modular COTS hardware and software prognostics development platform by bearing supplier, FAG, Figure 14.

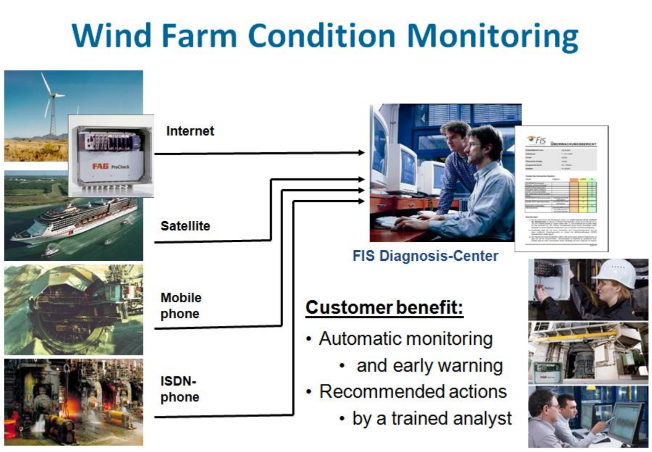


Figure 14: FIS condition monitoring system

FAG Industrial Services, the service division of FAG industrial bearings, has developed an advanced condition monitoring system based on modular COTS embedded data acquisition and signal processing platforms. The monitoring systems are used both by wind farm operators and maintenance service teams, as well as FAG's bearing service and support center. Embedded intelligence in the monitoring system, specifically envelope analysis, reduces sensory data at the data acquisition source to information that is more actionable when it reaches operations and maintenance personnel. The information is transmitted over existing controls networks or wirelessly leveraging cellular and RF technologies, Langer (2006).

Another case study, explores distributed condition monitoring and prognostics in nuclear power, Shumaker (2010), Figure 15.

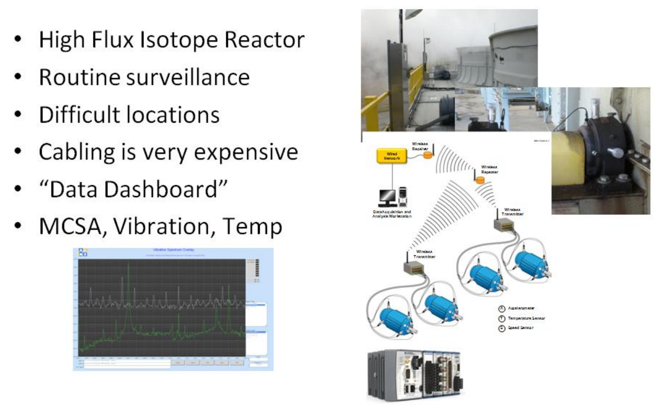


Figure 15: AMS-Corp nuclear pump monitoring systems

Analysis and Measurement Services Corporation (AMS) specializes in testing of process instrumentation and development of specialized test equipment and software products for power and process industries. This project proposes a comprehensive effort to expand and commercialize previous research projects to provide passive, in-containment use of wireless technology at nuclear power plants. Specifically, the effort of the subsequent phases of the project will focus on assembling a complete, commercial, wireless on-line data monitoring and analysis system that can be adapted for use in any pressurized water reactor containment. The system would be used for condition monitoring during plant operation and/or outage time to provide additional measurements that may be needed by the maintenance crews, operations or plant management. Because of the nature and purpose of nuclear plant containment, the introduction of a wireless network/communication system inside the confined area is challenging and, yet, very advantageous. The immediate benefit to the nuclear plant is the reduced cost for monitoring equipment and/or processes within containment and to provide additional data as needed for maintenance work during refueling outages and normal operation.

This particular example, leverages COTS technology including rugged embedded data acquisition and signal processing to gather and digitize sensory information, to store and forward the sensory data over wireless TCP/IP and to format the data in a flexible data schema for off-line analysis and reporting.

Finally, in the mining and materials industry, a wide range of conveying and grinding machinery is used. Crushers are important assets in material processing plants. O'mos developed a condition monitoring solution using a modular architecture to monitor the health of cone crushing equipment, Epie (2011).

The modular conical mill condition monitoring system uses accelerometers, temperature sensors, and pressure switches. O'mos is a service company, providing maintenance services for its customers. With remote monitoring and in-line signal processing, O'mos is able to improve its service offerings to its material processing customers. The ability to leverage COTS embedded data acquisition and analysis components frees O'mos to focus their expertise on off-line analysis, prediction, and reporting. O'mos lowers their cost of service thru data acquisition automation while working to improve reporting and recommendation results leveraging specific conical mill domain expertise.

Several other prognostics suppliers are working to adapt COTS technologies as the foundation for their prognostic offerings. Example prognostics offerings are IMS Center Watchdog™ Agent, Global Technologies Corporation's PEDs hms™, and Impact Technologies ReasonPro™.

6. Conclusion

By leveraging commercial off the shelf (COTS) technologies and a flexible modular architecture or framework, it is possible to develop and bring to market a prognostic system that adapts to a wide range of machines, industries, and applications. The prognostics system developer is able to get to market rapidly and at less cost, than the alternative of developing components that are otherwise commercially available. This benefit is specifically realized, when the COTS components are flexible in data storage, and signal processing capabilities making it possible to adapt the COTS components for specific prognostic algorithms and methods.

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