TITLE: Intelligent Sensor Modes Enable a New Generation of Machinery Diagnostics and Prognostics

INTELLIGENT SENSOR NODES ENABLE A NEW GENERATION OF MACHINERY DIAGNOSTICS AND PROGNOSTICS

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Abstract: Compelling economic, competitive, and technological factors are changing the way many companies view machinery maintenance, repair, and overhaul (MRO) activities. This shift toward a new Maintenance Management Paradigm has implications in many areas of the business including manufacturing scheduling, control, finance, inventory, quality, and asset management. Implementation of the new Maintenance Management Paradigm will require three fundamental building blocks. First, is a framework that enables the efficient re-use of best-in-class diagnostic and prognostic software, hardware, and sensor modules. An open-system architecture will be fundamental to meeting this objective. Second, is the ability to rapidly deploy needed hardware and software elements in a reliable and cost-effective manner across distributed system components. Wireless, intelligent sensor nodes will play an important role in the deployment of future systems. And third, is the infrastructure and that will permit system level integration of an ensemble of distributed intelligent system elements to develop actionable diagnostic and prognostic information. Higher-level diagnostic and prognostic information will drive critical decision making to insure maximum system reliability, lowest operating cost, maximum revenue generation or mission success for example. This paper provides specific examples of elements in the areas of Framework, Distributed Intelligent Modules, and Infrastructure for system-level integration.

Key Words: Agent; diagnostics; distributed intelligence; failure prediction; intelligent sensors; maintenance management paradigm; open systems architecture for condition based maintenance (OSA/CBM); prognostics

I. Introduction: Machinery health assessment is becoming critically important across a broad spectrum of shipboard, industrial, and commercial applications. The operational demands and high procurement costs of today's systems in these applications requires a high degree of uptime and high reliability. Unexpected failures are costly to correct at best, at worst; such failures will be catastrophic.

At a recent workshop on Intelligent Devices various industry representatives consistently said that their top priorities were 1. machinery prognostics and 2. overall process or system-level health [1]. Similar priorities also emerged following a two-day NIST workshop on Condition-Based Maintenance on November 17-18, 1998. The barriers or technology requirements identified at this workshop were 1. continuous monitoring, 2. accurate prediction of remaining useful life, and 3. generate adaptable and actionable recommendations.

The benefits available through effective diagnostic/prognostic system are now becoming a business necessity for many organizations. Labor, material, and energy costs have already been minimized for many plant operations. Maintenance expenses and the operational impact of unexpected failures represent the largest remaining controllable expenditure. In some cases, maintenance expenses may exceed the profit from a plant. For other organizations, industry-leading machinery reliability and maximum uptime are absolutely essential to suceed at various contemporary business strategies such as JIT, TQM, supply-chain management, and OEM service outsourcing among others.

New developments in algorithms, industry standards, communications, and software architectures promise to accelerate the deployment effective diagnostic and prognostic systems. These developments will enable new technologies to be readily integrated with existing systems for near-term, observable business impact.

II. Background: The diagnostic and prognostic needs expressed by a broad range of organizations may be met in a cost-effective manner and with minimal risk by leveraging specific developments occurring in three critical areas. First is a framework that provides the ability to efficiently integrate re-usable algorithms. Second are developments in communications and in particular wireless technologies. Third is the development of an infrastructure for the system-level integration of distributed intelligent system elements. System-level integration provides the foundation for robust systems which are capable of generating actionable diagnostics and prognostic plans., hardware platforms, sensor modules, database information, and intelligent devices in an automation system.

The integration of these three factors together with advanced prognostic algorithms will form the cornerstone of a new Machinery Maintenance Paradigm. This paradigm employs targeted, task-specific sensors and algorithms integrated in a framework that is readily expanded and adapted to changing operational needs. Open, industry-standard systems and interfaces are fundamental to this framework. Such systems will then be readily integrated throughout the plant equipment and coupled with various IT, operational planning, finance, and control systems.

III. Framework: Various components and functional capabilities of diagnostic and prognostic systems may be organized as a framework of system components or building blocks. Such a framework provides a scheme for identifying and organizing essential information about a system and also provides an structure for defining standard interfaces between system elements and functional requirements for important system elements. The requirements for capturing machinery health information, interpreting the data, and acting on the results of the analysis may be arranged in a hierarchy (Table I). This hierarchy ranges from simply capturing data from a particular process or machine to interpreting sampled data to detecting a fault has occurred or what fault or faults will occur. Higher levels of the hierarchy provide a range of capabilities for automatically reacting to novel faults or reacting in advance of an anticipated failure. Higher levels of this hierarchy beginning with diagnosis and prognosis will typically require the integration of multiple data sources as well a knowledge of the process equipment and operating state or context.

Table I
HIERARCHY OF INTELLIGENT MACHINES
1. Data Acquisition
2. Monitor
3. Detect
4. Diagnose
5. Prognosis
6. Prognostics & Control
7. System-Level Prognosis & Control
8. Dynamic optimization / multi-objective control
9. Adaptive / Reconfigurable
Order of increasing complexity / cost / economic benefit

There is clearly a move to intelligent devices and distributed intelligence. Intelligent components may occur at the structural level (e.g. smart materials), at the sensor level, or at the device level (e.g. embedded intelligence). One effort to establish a standard transducer (sensor / actuator) interface is the IEEE 1451 standards effort. This standard seeks to move data acquisition, distributed sensing, and control to more of an open system by establishing a framework and data elements for "smart" tranducers. Included in this standard is a specification to facilitate sensor identification, calibration, documentation, sensor replacement, and network integration among other features [2]. Research in self-validating sensors (SEVA) at the University of Oxford over the last 12 years have been directed at defining intelligent sensors which dynamically sense their own condition and provide information regarding the quality or validity of the sensor value returned [3]. This is an important, emerging area currently being proposed at a draft standard by BSI for Data Quality Metrics [4]. Information on data quality becomes critically important as we move to higher levels of the hierarchy of intelligent machines shown above toward automatic control, decision-making, and autonomous machines.

Data critical to establishing the health of equipment may be captured and stored in an application-specific manner to accommodate essential memory or timing constraints. Preferably, machinery data should be organized in an open, industry standard format such as defined by MIMOSA (Manufacturers Information Management Open Systems Alliance). The data format and definitions established by MIMOSA are the result of many years work by an international team of MIMOSA sponsors and members. This standard is open and accessible to the public [5].

More recently, a group of industry and academic partners have teamed together to develop an Open Systems Architecture for Condition Based Maintenance (OSA/CBM). This program is part of the Dual Use Science & Technology program (DU&ST) program with joint industry-government funding (BAA 98-023). This effort, leveraging off the work of MIMOSA, has resulted in an operational framework for machinery diagnostics in an open-system, layered framework as shown in Fig. 1 [6].

This open system architecture implements a middleware interface to support a broad range of operational models including COM/DCOM, CORBA, and XML/HTTP client-server architecture. This model was demonstrated on a laboratory pumping system in December 2000 and will be demonstrated on aircraft, off-road vehicle, and shipboard applications during the next year.

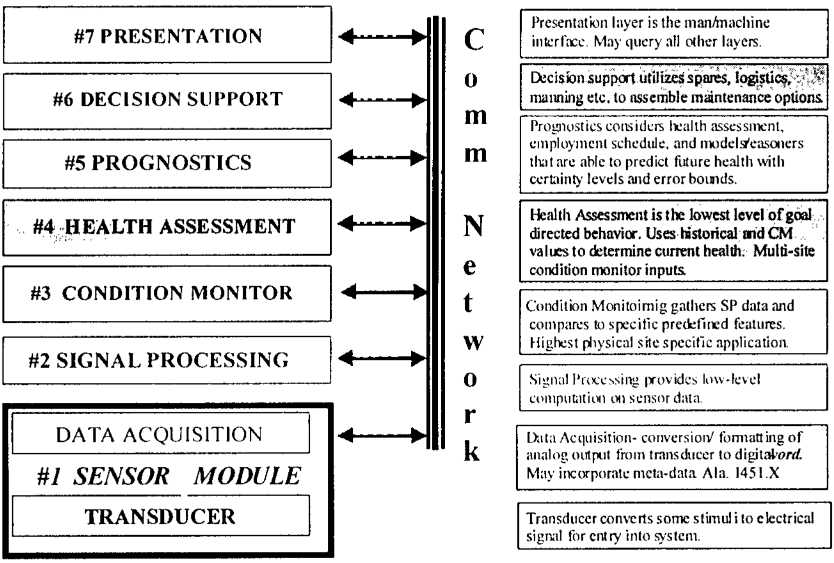

Figure 1
Open Systems Architecture for Condition-Based Maintenance (OSA/CBM)

The integration of intelligent sensors and self-validating sensors in an open, operational framework as specified by MIMOSA - OSA/CBM promotes the development and deployment of distributed intelligent sensors across a broad range of applications.

IV. Distributed Intelligent Sensors

We continue to see a rapid pace of development in intelligent sensors and open systems. These developments are leveraging off developments in software architectures, sensor technologies, and networks which are moving toward open, public standards. The wide-scale deployment of intelligent devices in manufacturing and commercial operations remains limited due to the high cost of installation and the cost and complexity associated the processing and analysis of the massive amount of real-time data received from the hundreds or thousands of sensors. Typically only data is received from remote sensors, as opposed to information (e.g. actionable information or health information).

Developments are occurring in wired networks and wireless networks that promise to reduce or virtually eliminate the wiring costs for distributed sensors. Bit-oriented networks such as DeviceNet are effective for local-scale integration of plant sensors. For higher bandwidth and extended networking TCP/IP becomes more attractive particularly when the higher cost of network access and transport may be justified by many remote intelligent nodes.

Wiring costs are often significant a cost component in the installation of many manufacturing and commercial systems. These costs may be eliminated with the use of wireless communications technology although at the expense of needed radio links. A variety of radio links exist and are selected based on needs for various bandwidth, reliability, distance, interoperability, and network architecture. Various government funded programs from the Department of Energy, Department of Commerce and DARPA seek to support the development of wireless technology for smart devices [7].

Recently there has been significant interest in low-cost wireless networks. Much of this interest is driven by the significant commercial potential for wireless consumer products. The development of the Bluetooth communications standard driven by the huge commercial potential may provide very low cost, 2.4 Ghz wireless data links for local sensor networks and data acquisition [8].

Wireless sensor networks promise to enable numerous applications for sensing and control including machinery monitoring for intelligent maintenance management. Rockwell Science Center has created a development environment for testing wireless sensing applications [9]. The Wireless Integrated Networked Sensing (WINS) platform includes

- bi-directional RF communications hardware and sophisticated networking protocols,
- processing and memory with a multi-tasking, real-time operating system for sensor data acquisition, signal conditioning and algorithmic processing of the data, and
- support for multiple sensor inputs including wide bandwidth accelerometers for vibration monitoring.

The integration of these technologies allows the easy installation of remote access sensors that can be configured in a variety of ways. The individual units, or nodes on the network, receive sensor data from attached sensors, process the sensor data and send back messages to the end-user, informing him/her about the condition of the equipment or process that is being monitored. Implicit in this architecture is a degree of distributed processing that can range from individual WINS nodes processing the data from their sensors and interpreting that data, to higher level algorithms that perform system-wide diagnostics using pre-processed sensor data from other WINS nodes [10].

The current WINS communications network operates in the 900 MHz RF band that is regulated for unlicensed use in the United States for transmission powers under 1 watt (spread spectrum) or 1 mwatt (single frequency). Because of the limited transmit power required for operation at these frequencies, the range of each unit is nominally 100 meters. Added to this the possibility of other path losses from absorbers or reflectors between the WINS nodes and the end-user gateway node, and the possibility that these may be dynamic, the need for a robust network system is apparent.

Rockwell Science Center has launched a commercial product, HiDRA (Highly Deployable Remote Access), that is based on the WINS technology [Fig. 2]. Included in this product is a network protocol that supports broadcast and uni-cast, multi-hop communication links. The multi-hop protocols allow routing of messages from nodes that are out of the RF communications range of the end-user gateway node through intermediate nodes that are within RF range of each other. The system is self-configurable, so that the user does not have to spend time setting up the network, it is done automatically at startup. It is also dynamic, so that if conditions change in the RF environment of the HiDRA node, the routing table for relaying a message through several nodes to arrive at the desired destination will also change.

Figure 2
Rockwell Science Center
Hidra node

The WINS system has been deployed for over a year monitoring the bearing health in the HVAC facility that serves the two plants at Rockwell Science Center in Thousand Oaks. The 10 WINS nodes are mounted on 50-75 hp motors, housed in the cooling fluid pump room, that drive pumps supplying the cooling fluids for the buildings at Rockwell Science Center. Accelerometers are mounted to the motor casing over the bearing locations of the motors and measure the vibration at these locations. A temperature sensor monitors the temperature of the motor case close to the position of the accelerometer. Each WINS node does a spectral analysis of the vibration signals that it receives and computes bearing health status indicators that it transmits through RF link to a base-station WINS node connected to an internet server.

V. Infrastructure for Intelligent Systems

Distributed intelligent sensor nodes capable of processing data from multiple sensors provide unique opportunities for data fusion and for cooperative processing. Our objective is to put as much information into each node and leverage the capabilities for processing complex algorithms in parallel and in collaboration with other sensor nodes. This permits establishing accurate, dynamic, and robust models for diagnostics and prognostics. The following outlines recent developments in model-based and non-linear analysis methods. These new diagnostic / prognostic and modeling tools are considered foundational and provides a basis for future self-organizing sensor networks and dynamically reconfigurable systems.

There are a variety of approaches for the development of fault detection, diagnosis and prognosis algorithms with each having unique advantages and limitations when implemented as distributed processing nodes.

Model-based approaches combine physical modeling of the system with experimental data to determine a mathematical relationship between the occurrence of a fault and the characteristics of a measured quantity in the system. Extended model-based techniques may employ a family of models that relate each of the individual faults and their severity. The residuals from each of the model-based observers are combined and then integrated with other information available from casual modeling, signal processing, expert systems, etc. to arrive at a decision regarding the current operating status of the system. A diagram of the fault detection and diagnosis system implemented for rotating machinery is shown in Figure 3. The core of this technology is an array of nonlinear filter/model-based observer blocks that combine the output from a suite of observers. For details of this structure and operation refer to [11][12].

An important aspect of the system shown in Figure 3 is the ability to integrate information from a variety of different sources such as multiple sensor nodes, into a comprehensive fault detection and diagnosis decision. We have also implemented novel algorithms for the detection and diagnosis of faults in rolling element bearing. These algorithms are particularly well-suited for implementation on distributed sensor nodes. Bearing fault detection has been demonstrated using model-based techniques with a fault-detection filter. The ability to isolate the specific fault (e.g. ball, inner and outer race defects) a time-frequency analysis method was developed. This was demonstrated using experimental data collected from an induction motor system, refer to [13]. Also, for a novel approach that integrates sliding mode observers and fault detection filters for the detection and isolation of faults in rolling element bearings, refer to [12].

A new method has been developed for the detection and diagnosis of defects in ball bearings using the wavelet transform [14]. The signature produced by damage on the DB2 wavelet is used for the wavelet decomposition of the preprocessed vibration signals. A set of feature vectors are then defined based on the wavelet decompositions.

Finally, we present a method for the detection and diagnosis of mechanical faults in rolling element bearings using vibration data and knowledge of the bearing defect frequencies. For a particular bearing geometry, inner raceway, outer raceway and rolling element faults generate vibration spectra with unique frequency components. The bearing defect frequencies are linear functions of the rotating speed of the shaft. Outer race and inner race frequencies are also linear functions of the number of balls in the bearing. The operating speed changes with load and is often unknown and/or unmeasurable. In addition, even if the type of bearing in the machine is known, the number of balls in the bearing may be unknown. Thus, estimating the running speed and the number of balls in the bearing are required for failure detection and diagnosis methods that rely on knowledge of the defect frequencies of the bearing. We have developed and implemented separate algorithms for estimating the rotational speed and the number of balls in a bearing from vibration data.

Spectral information obtained from the Fast Fourier Transform (FFT) of the vibration data is used to obtain these estimates and this information is used to calculate the bearing defect frequencies. The estimation algorithms have been tested using experimental data that consisted of vibration signals gathered from a transducer mounted on the drive-end bearing of an induction motor. The induction motor was operated under four different load conditions (four different running speeds), and three different types of single point defects (inner race, outer race and ball) were introduced into the drive-end bearing. The test results proved the algorithms to be very reliable and when integrated with an envelope detection algorithm reliable fault detection and diagnosis were obtained. Refer to [15] for more details. These core capabilities are well suited to be implements in a distributed agent-based architecture.

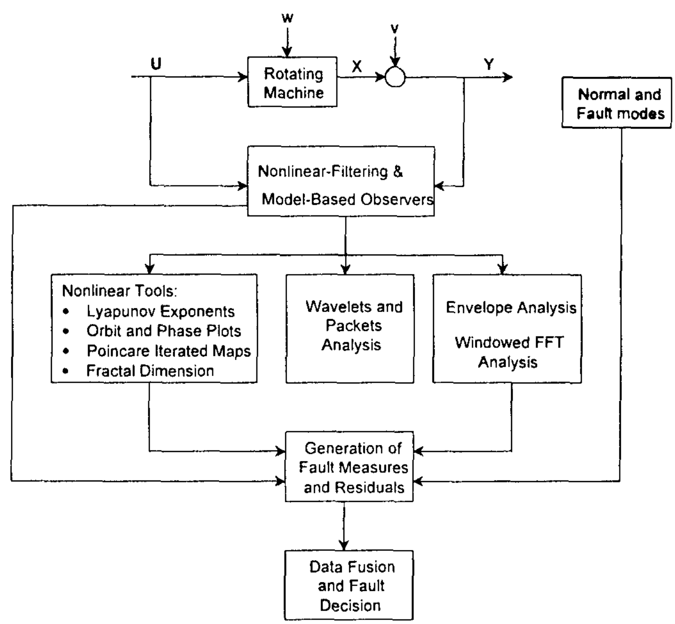

Figure 3
Fault Detection and Diagnosis System for Rotating Machinery

Agent technology expands the notion of distributed computing which may partition a problem to distribute the computation load to one in which the solution method is both localized (autonomous) and also collaborative and adaptive (cooperative/goal oriented). Within the collection of software agents each will have a local goal or agenda. In this sense, each module is autonomous. In addition, there is an overarching goal or system objective that each individual module must accommodate and through the collective efforts of the multiple agents. The collection of such agents is termed a Holonic System. This is a concatenation of the term *Holos*, meaning total or whole, and *on*, as in a neutron or elemental body [16][17].

The multi-agent approach provides an extremely powerful framework for integrating partial solutions into more complex and more sophisticated diagnostic, decision making and control structures [18][19]. This concept is particularly beneficial to machinery diagnostics and prognostics. For example, remote intelligent sensor nodes may efficiently monitor critical system components such as bearings. In the event an excessive vibration level or temperature level is observed, information regarding the degraded operation and reduced component lifetime may be relayed back to a central information system. In addition, specific data on abnormal operation may also be exchanged with neighboring smart sensor nodes. This will permit the nodes to collaborate and each to exchange data and analysis to jointly establish a more accurate, complete hypothesis of the root cause of the fault, such as a bent shaft. This will also permit maintaining a more robust and accurate system model essential for accurately predicting the future operating state of the machinery and estimated time until failure. Wireless technologies will permit the widescale deployment of smart sensor nodes across many system components. This will lead to more accurate system models and prognostic estimates at a much lower cost. It will also enable very flexible and easily reconfigured monitoring and diagnostic system.

The availability of complete and accurate process information and superior failure prediction accuracy directly addresses the key concerns expressed by a broad range of major manufacturers to know 1) overall process health and 2) accurate prognostic information. The integration of this new, accurate information into existing control, information systems, plant monitoring, scheduling, and maintenance system will provide unprecedented levels of plant performance and economic value from installed equipment.

V. SUMMARY

The developments described above provide new and important capabilities for reusable software and hardware modules. International efforts toward standards and open system specifications will provide new opportunities for intelligent sensors and distributed smart adaptable sensor nodes. In this infrastructure, model-based and observer-techniques implemented on smart sensor nodes may be readily integrated into a broad range of critical manufacturing processes. We anticipate future low-cost wireless solutions to further propel the deployment of distributed sensor nodes. With an infrastructure to effectively integrate the massive, parallel, distributed computing power there will be a new era of monitoring and managing even the most complex systems. These new, more powerful tools will form the cornerstone of the new Maintenance Management Paradigm.

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