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1. Introduction

1.1 The Evolution of Maintenance Practices

The traditional approach for maintaining the industrial machines and processes has been one that is purely reactive. Mitigating procedures are performed to the equipment once it breaks down. This, as most companies have found out, is a maintenance paradigm with many disadvantages. When a machine is run to failure, i.e. until one of its parts fail making it inoperable, produced parts may not meet quality standards, or the degradation of the other components might have just been accelerated unknowingly, or worse, the cost of restoring the machine to an acceptable and sustained operational state might be more expensive than purchasing a replacement unit. There is also a requirement to store numerous spare parts. Finally, since a machine can break down at any time, maintenance and production operations are not scheduled efficiently, thus a huge maintenance crew is needed to achieve high production throughput rates.

An improved strategy that companies employ is preventive maintenance (PM). Many of the machine manufacturers and suppliers provide component lifetime and maintenance guidelines to their customers. With this method, maintenance activities can be performed so as not to interfere with production schedule. There is no need to store a large inventory of spare parts because they can be ordered at regular intervals just before the parts need to be replaced. The primary advantage of using preventive maintenance is a high overall equipment efficiency (OEE) score, but, it does so at a very high cost. To be able to capture the majority of impending component failures, maintenance personnel must replace or condition the parts at closer time intervals, which mean that spare parts must be purchased more frequently.

Nowadays, many manufacturing companies are adopting condition-based maintenance or CBM. Predictive Maintenance (PdM) is a right-on-time maintenance strategy. It is based on the failure limit policy in which maintenance is performed only when the failure rate, or other reliability indices of a unit reaches a predetermined level. This maintenance strategy has been implemented as Condition Based Maintenance (CBM) in most production systems, where certain performance indices are periodically (Barbera et al. 1996; Chen et al. 2002) or continuously monitored (Marseguerra et al. 2002). Whenever an index value crosses its predefined threshold, maintenance actions are performed to restore the machine to its original state, or to a state where the changed value is at a satisfactory level in comparison to the threshold.

Predictive maintenance (PdM) can be best described as a process that requires both technology and human skills, while using a combination of all available diagnostic and performance data, maintenance history, operator logs and design data to make timely decisions about maintenance requirements of major/critical equipment. It is this integration of various data, information and processes that leads to the success of a PdM program. It analyzes the trend of measured physical parameters against known engineering limits for the purpose of detecting, analyzing and correcting a problem before a failure occurs. A maintenance plan is made based on the prediction results derived from condition-based monitoring. This method can cost more up front than PM because of the additional monitoring hardware and software investment, cost of manning, tooling, and education that is required to establish a PdM program. However, it provides a basis for failure diagnostics and maintenance operations, and offers increased equipment reliability and a
sufficient advance in information to improve planning, thus reducing unexpected downtime and operating costs. This approach takes into account the current state or condition of the component, thereby reducing the number of unscheduled breakdowns by monitoring the equipment condition to predict failures so that remedial fixes can be performed. Using built-in or add-on sensors, signal measurements are extracted to describe the components current performance. Then, this information is compared with previously collected performance history to determine whether a deviation has occurred to suggest that the equipment is at fault or showing symptoms that can lead to an impending failure. The apparent shortcoming of CBM is that it simply detects whether the equipment is at fault or nearing a fault condition. It does not elaborate on the type of failure the equipment has experienced and it does not identify what component is faulty. The information from a CBM system does not provide much insight to the maintenance personnel on what to fix in that machine. Predictive maintenance has been developed as an improvement to CBM so as to infer within a maintenance horizon time when the equipment will fail. Nonetheless, it inherited the same problems as the CBM method in pinpointing the type of fault and the critical component at fault.

1.2 Unmet Needs in Current Maintenance Service Practices

After reviewing the evolution of the different maintenance paradigms, there exist key issues that need to be addressed in order to achieve the maximum availability and efficiency from important company assets. These unmet needs are summarized in Figure 1.1 and are explained in detail in the succeeding sections.

![Figure 1.1: Unmet Needs in Maintenance Service](image)

1.2.1 Equipment Intelligence

There is indeed a need to migrate towards another maintenance paradigm intelligent prognostics. It transcends being merely a predictive maintenance system by exactly identifying which component of a machine is likely to fail, and then highlighting the event to trigger maintenance service and order spare parts. A key principle in intelligent maintenance is the assessment and prediction of the performance degradation
of a process, machine or service. By extracting critical features from signal measurements, performance degradation can be used to predict unacceptable equipment performance before it occurs.

By utilizing sensors and embedded systems, the intelligent prognostics approach will allow the critical asset to be able to

§ automatically trigger itself to acquire appropriate health indicators from its critical machine parts when needed,

§ assess the features from the temporal health data,

§ diagnose itself to determine its current state of machine performance,

§ infer whether significant performance degradation has been detected,

§ identify the imminent fault it is going to experience and predict when failure is going to occur, and

§ automatically call for maintenance crew for conditioning.

These capabilities just mentioned are essential to the future of maintenance service where machines are capable of self-assessment or self-diagnostics and ultimately, self-maintenance and even self-healing. Self-healing can be achieved when the machine is supplied with appropriate control logic to follow whenever its components have reached specific degradation levels such as shutting down secondary subsystems that are not critical to its basic functionalities to reduce load and system power consumption.

1.2.2 Synchronization Intelligence

Currently most of the machine data, if available, is either hidden or kept in the machine. Thus, assets in a manufacturing plant become islands of health indicators that are not being accessed and analyzed for health information. Even if the data undergoes a certain degree of processing, the information that is extracted unfortunately remains trapped in the machine. There is a recognized barrier between the production floor and the management level that inhibits critical machine and process health information to be transmitted so that the latter can make more informed and timely decisions on the machines. What is needed is an infrastructure that enables the health information to be seamlessly transmitted to a higher manufacturing level for decision making, or to other similar machines for peer-to-peer equipment performance comparison.

When machine performance information is sent up the production business unit, comprehensive and real-time decisions can be made on the manufacturing assets such as production scheduling (assigning appropriate order sizes to high performing machines), maintenance scheduling (with a sufficient horizon time, conditioning or mitigating procedures can be performed while not interfering with production runs) and even machine-part matching (assigning the best machine that will meet quality requirements of a particular produced part).

1.2.3 Operations Intelligence

Once the company assets become capable of self-diagnostics and self-maintenance, and the health information (both machine and process) can be shared very easily, especially to the different business functions, then there lies an opportunity to achieve intelligent operations in the manufacturing facility.

Through the use of machine health information, one is enabled to predict and prioritize maintenance activities, and when coupled with the process health information, production can be optimized either to
achieve desired volume orders and/or part quality requirements. Thus, the company achieves intelligent operations in the process because they are now capable of producing quality parts while running at near-zero unexpected downtime.

The missing component to achieving such a goal is an optimized decision making logic modeled on plant operations that integrates production and maintenance activities without interfering with each other.

1.3 The Future of Maintenance Service

In summary, the key issues of the current manufacturing maintenance practices have been defined: (1) equipment intelligence through self-maintenance to be able to extract machine and process health and eventually predict machine performance degradation; (2) synchronization intelligence refers to the seamless communication between the production floor and management unit so that timely and informed decisions can be made based on machine and process health information; and (3) operations intelligence which is the ability to leverage on self-maintenance and intelligent synchronization to efficiently schedule production and maintenance to achieve a near-zero downtime for manufacturing operations. The Center for Intelligent Maintenance Systems (IMS) has been in pursuit to address these key issues by performing relevant research in order to develop the enabling technologies for the different aspects of self-maintenance, intelligent synchronization and intelligent operations. Figure 1.2 summarizes the vision of the IMS Center while providing a directed plan on how to solve these maintenance opportunities.

![Figure 1.2: Intelligent Maintenance: The Future of Maintenance Service Systems](image)
The IMS envisions that degradation information from the critical assets can be used to predict their performance to enable near-zero downtime performance. The asset degradation data can also be fed back to the design stage of the equipment for assessing its reusability and predicting its useful life after disassembly and reuse.

To address the key issues mentioned earlier, the IMS Center has recognized that the following technologies need to be developed:

§ Processing system that extracts machine data, and convert this voluminous data space into a simple but comprehensive health information.

§ Communication infrastructure that can automatically relay health information to appropriate business functions within the company.

§ Decision-making system that uses the health information to make informed business decisions on the company assets.
2. The IMS Center: Systematic Methodology, Tools and Technologies

2.1 Introduction

In 2001, the National Science Foundation created the Industry/University Research Cooperative Center (I/UCRC) for Intelligent Maintenance Systems (IMS) as a center of excellence in research of intelligent e-maintenance systems designed to ultimately impact next-generation product, manufacturing and service systems. The vision of IMS Center is to serve as a catalyst as well as enabler to assist company members to transform their operation strategies from todays Fail-to-Fix (FAF) to Predict-and-Prevent (PAP) performance as can be seen in Figure 2.1. The IMS Center brings value to its members by validating high-impact emerging technologies as well as by harnessing business alliances through collaborative test-beds.

Through this end, the IMS Center enables products and systems to achieve and sustain near-zero breakdown performance, and ultimately transform maintenance data to useful information for improved closed-loop product life cycle design and asset management. The IMS Center is focused on frontier technologies in embedded and remote monitoring, prognostics technologies, and intelligent decision support tools and has coined the trademarked Watchdog Agent prognostics tools and Device-to-Business (D2B) Infotronics platform for e-maintenance systems.
2.2 IMS Systematic Methodology: 5S Approach

Addressing future maintenance services necessitates a systematic 5S approach (see Figure 2.2).

![Figure 2.2: IMS 5S Approach](image)

This approach was devised by IMS Center in order to develop and research all aspects of future maintenance infrastructures. This systematic approach consists of five key elements:

§ **Streamline**: this encompasses techniques for sorting, prioritizing, and classifying data into more feature-based health clusters. This may also include reducing large data sets (from both maintenance history and on-line data DAQ) to smaller dimensions, leading to correlation of the relevant data to feature maps for better data representation.

§ **Smart Process**: using the right Watchdog Agent tool for the right application. This requires techniques for selecting appropriate prognostics tools based on application conditions, criticality of each conditions for machine health, and system requirements.

§ **Synchronize**: converting component data to component degradation information at the local level and further predicting trends of health using a visualized radar chart for decision-ready information. Maintenance data is transformed to health information and to an automated action (i.e. order parts, schedule maintenance based on criticality of component or machine). This process ensures a key characteristic of Only Handle Information Once (OHIO).

§ **Standardize**: creation of a standardized information structure for equipment condition data and health information so that it is compatible with higher-level business systems and enables the information to be embedded in business ERP and asset management systems. The goal here is to keep the process as a standard approach for day-to-day practices.
§ Sustain: utilizing the transformed data for information-level decision making. System information is then shared amongst all stages of product and business life cycle systems: product design, manufacturing, maintenance, service logistics, and others in order to realize a closed-loop product life-cycle design and continuous improvement of product-level quality and business-level performance.

2.3 IMS Tools: Watchdog Agent®

For more than a decade now, the IMS Center has been spearheading the development of a processing system called the Watchdog Agent® in a bid to address the first issue. Simply put, the Watchdog Agent® is an enabling technology that shall allow for a successful implementation of intelligent maintenance. The toolbox is a collection of algorithms that can be used to assess and predict the performance of a process or equipment based on input from sensors, historical data and operating conditions. Referring to Figure 2.3, the algorithms can be classified into four major categories: signal processing and feature extraction, quantitative health assessment, performance prediction and condition health diagnosis. Performance-related information can be further extracted via multiple sensor inputs through signal processing, feature extraction and sensor fusion techniques. The historical behavior of process signatures can be utilized to predict future behavior and thus enable forecasting of the process or machines performance. Proactive maintenance can therefore be facilitated through the prediction of potential failures before they occur. In addition, various visualization tools are also generated as illustrated in Figure 2.4. Different personnel within a company require different health information. A confidence value chart is a good tool to quickly determine presence of degradation trends or performance drift. For multiple component monitoring, a health radar chart is an indispensable tool to pinpoint the "least" healthy component that the maintenance crew can prioritize for repair. A health map, on the other hand, can also help the repair crew to troubleshoot the possible failure mode of the critical component. Finally, if cost models associated with repairing components, then a risk radar chart can be generated.

By leveraging on current technologies, the Watchdog Agent® can either exist in Matlab or LabVIEW™ platform. Development is also underway to port the Watchdog Agent® in PLC controllers and C-based platforms. This has been done to address the diversity of platforms that are currently being used in most manufacturing facilities.
<table>
<thead>
<tr>
<th>Signal Processing &amp; Feature Extraction</th>
<th>Health Assessment</th>
</tr>
</thead>
<tbody>
<tr>
<td>Time Domain Analysis</td>
<td>Logistic Regression</td>
</tr>
<tr>
<td>Frequency Domain Analysis</td>
<td>Statistical Pattern Recognition</td>
</tr>
<tr>
<td>Time-frequency Analysis</td>
<td>Feature Map Pattern Matching (Self-organizing Maps)</td>
</tr>
<tr>
<td>Wavelet/wavelet Packet Analysis</td>
<td>Neural Network</td>
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<tr>
<td>Principle Component Analysis (PCA)</td>
<td>Gaussian Mixture Model (GMM)</td>
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<tr>
<th>Performance Prediction</th>
<th>Health Diagnosis</th>
</tr>
</thead>
<tbody>
<tr>
<td>Autoregressive Moving Average (ARMA)</td>
<td>Support Vector Machine (SVM)</td>
</tr>
<tr>
<td>Elman Recurrent Neural Network</td>
<td>Feature Map Pattern Matching (Self-organizing Maps)</td>
</tr>
<tr>
<td>Fuzzy Logic</td>
<td>Bayesian Belief Network (BBN)</td>
</tr>
<tr>
<td>Match Matrix</td>
<td>Hidden Markov Model (HMM)</td>
</tr>
</tbody>
</table>

**Figure 2.3**: The Watchdog Agent® Toolbox

**Figure 2.4**: Visualization Tools

- **Confidence Value**: for performance degradation assessment (CV ~ 0-1)
- **Health Radar Chart**: for multiple components degradation monitoring
- **Health Map**: for potential issues and pattern classification
- **Risk Radar Chart**: to prioritize maintenance decision
3. IMS Project Portfolio

3.1 Introduction

This section briefly summarizes several projects and test-beds where the Watchdog Agent® has been used. The general methodology of IMS intelligent prognostics is still being applied; only the algorithms are selected and reconfigured depending on the monitoring task being implemented.

The Center for Intelligent Maintenance Systems (IMS) is working with its research partners to file joint patents and technology transfer for industrial applications. Examples of such efforts are IMS activities with Parker-Hannifin, TechSolve, and Siemens. A snapshot of select projects conducted by the IMS is shown in Table 3.1.

Table 3.1: Snapshot of IMS Project Portfolio

<table>
<thead>
<tr>
<th>INDUSTRY</th>
<th>COMPANY</th>
<th>PROJECT</th>
</tr>
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<tbody>
<tr>
<td>Automotive</td>
<td>Toyota</td>
<td>Surge Map Modeling for Air Compressors</td>
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<td></td>
<td>General Motors</td>
<td>Prognostics of Vehicle Components</td>
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<tr>
<td></td>
<td>Harley Davidson</td>
<td>Spindle Bearing Monitoring</td>
</tr>
<tr>
<td>Heavy Machinery</td>
<td>Komatsu</td>
<td>Diagnostics and Prognostics of Truck Diesel Engines</td>
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<td></td>
<td>Caterpillar</td>
<td>Machine Tool Health Monitoring</td>
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<td></td>
<td>Omron</td>
<td>Precision Energy Management Systems</td>
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<tr>
<td></td>
<td>General Electric</td>
<td>Intelligent Prognostics for Machine Health Monitoring</td>
</tr>
<tr>
<td></td>
<td>Hong Kong EMSD</td>
<td>Health Monitoring of Airport Chiller</td>
</tr>
<tr>
<td>Consulting</td>
<td>TechSolve</td>
<td>Smart Machine Platform Initiative (SMPI)</td>
</tr>
</tbody>
</table>
3.2 Industrial Projects

3.2.1 Toyota: Surge Map Modeling for Air Compressors

General Background

This project is conducted between the Center for IMS and Toyota Motors Manufacturing, Kentucky, Inc. (TMMK), the objective of which is to improve the accuracy and efficiency of surge avoidance control for centrifugal air compressors. The main goals of the project work were to use data-driven tools to model an improved surge map, and provide positive feedback control of inlet guide vane (IGV) to reduce the rate of surge events in the manufacturing facility of TMMK.

Project Duration

February 2005 - December 2007

Project Objectives

The objective of this research was to develop a data-driven modeling based approach for obtaining surge maps for air compressors under variable operating conditions so as to achieve surge prevention with high efficiency.

Summary of Technical Approach

Surge refers to a phenomenon of large oscillating reverse flow when compressor is operated under low flow rate and high pressure. Surge leads to costly damage of the compressor and downtime of the system powered by the compressor. To prevent the damage, a surge map is widely used where a surge line is defined to separate surge and not-surge operation (Figure 3.1).

![Figure 3.1: Compressor Surge Map](image)

However, the exact location of the surge line cannot be accurately located due to the fact that large number of variables related to compressor operation, including ambient air conditions can affect the occurrence of surge. Hence the operators would have to operate the compressor far from the surge line to avoid the possibility of experiencing surge, which would decrease compressor efficiency. In order to operate the compressor at optimal efficiency while preventing surge, a data-driven method is used to develop an improved surge map model for actual operation in the specific environment. Figure 3.2 shows the application of the IMS systematic methodology in the data-driven surge map modeling.
Multivariate measurements are synchronously sampled under known surge or not-surge conditions. Variables include pressure readings, flow rate of airflow, electric current, IGV feedback, IGV command, humidity, temperature readings etc.

Principal Component Analysis (PCA) is employed to reduce the dimension of the dataset acquired, by projecting the dataset to a new coordination system while retaining as much variance of the original dataset as possible.

Support Vector Machine (SVM) is used to train a classification model based on the transformed data, or principal components. SVM finds the separating planes that maximize the distance between the two classes of surge & not-surge, and therefore can potentially minimize the misclassification.

The data acquisition process took approximately 80 days. Different tests including 25 surge and 22 not-surge data points were collected and 15 from each class are used for training the separation plane. For the training dataset, there is no misclassification hence there is no unpredicted surge and false alarms. The rest of the data points were used to test model performance and there were 6 false alarms among the 22 not-surge data. The model was further developed and used for open-loop surge avoidance control.

Project Deliverables and Results

Eventually as deliverables of the project, a validated IMS tool is ported into existing compressor controller. The compressor manufacturer that supplies for TMMK was asked to provide such capability of on-line surge detection and control optimization.
3.2.2 General Motors: Prognostics of Vehicle Components

General Background

This project is collaboration between IMS center and General Motors Technical Center. The project will aim at implementing IMS tools and methodology for prognostics of vehicle components. The project is divided into several phases; the first phase of the project focused on prognostics of wheel speed sensors of the Anti-lock Braking System (ABS); the second phase of the project is currently dealing with prognostics of the alternator/starter system; later phases of the project will focus on on-board prognostics.

Project Duration

Phase 1: July 2000 - July 2008; Phase 2: September 2008 - January 2009

Project Objectives

§ Design a prognostic model to assess the health of the wheel speed sensor and differentiate sensor faults from system faults.

§ Design a prognostic model to assess the health of the alternator/starter system.

§ Study the feasibility of using IMS tools and methodology to perform on-board prognostics for vehicle components.

Summary of Technical Approach

For phase 1 of the project, a thorough study of the existing techniques for sensor diagnostics/prognostics was conducted through a literature review and a patent search. A prognostic decision model based on the Watchdog Agent® was built. The model consists of two steps: off-line training and on-line testing.

In the step of off-line training, the basic task is to establish the data model for the normal characteristics based on the features extracted from the direct sensor readings, and train the artificial intelligence algorithms off-line. For this project two algorithms from the Watchdog Agent® were used: logistic regression (LR) and statistical pattern recognition (SPR). Data was initially collected directly from the vehicles sensors, then a test-rig was assembled at the IMS Center that allowed inducing faults to sensors and collecting data. Features extracted from the active wheel speed sensor data are: mean pulse duty factor, mean upper level amplitude, and mean lower level amplitude. Different features can reflect different physical characteristics of monitored sensor. Pulse duty factors can reflect the wear or broken of tooth ring, and amplitude related features can reflect the magnetic field change of the sensor. Therefore, changes of certain feature can be used to indicate the potential faulty element.

In the step of on-line testing, the real-time sensor readings are captured and the corresponding features can be extracted, which are further input into the trained model. A CV value can be obtained to show the current health status. The features are also analyzed and visualized through SOM. Finally, a comprehensive analysis decision is given, which include the CV value, the possible physical reason if CV is abruptly changed and corresponding solutions.

For phase 2 of the project, a test-rig is currently being built at the IMS center to run the alternator and collect data from both a healthy and faulty alternator. After that a prognostic model will be developed at the IMS center for the alternator/starter system.
3.2.3 Harley-Davidson: Spindle Bearing Monitoring

General Background

The integration of the Watchdog Agent® prognostics platform and wireless sensor network successfully realized real-time multiple networked machines health monitoring and prognostics. It would be directly helping production become more cost effective at Harley-Davidson motor company as it says in the article Harley-Davidson: Born to be predictable in Lean Tools for Maintenance & Reliability Magazine.

Project Duration

Phase 1: June 2006 - August 2006; Phase 2: June 2007 - August 2007

Project Objectives

§ Automate the data acquisition without interfering with the machine operation.

§ Save the investment of health monitoring and prognosis - upgrade the machine health monitoring capabilities by using a single platform to monitor multiple machines with multi-speed and various spindle loads.

§ Seamless integration of wireless vibration accelerometer with the Watchdog Agent® platform.

§ Reduce the data analysis time by providing autonomous data processing capabilities with logistic regression and statistical pattern recognition algorithms.

§ Enhance the trend prediction method by providing autoregressive moving average model (ARMA) and neural network algorithms.

Summary of Technical Approach

Generate Feature Vector: The feature vector is a signature describing a state of bearing health, which is formed from features that are considered to be correlated to those that indicate machine health condition. Features are extracted by Fast Fourier Transform (FFT).

Evaluate Bearing Health: Patterns of the feature vectors that describe up-to-now states of bearing health are grouped into a health map, using a clustering algorithm such as the method of self-organizing map, k-means algorithm, neural networks-based algorithm, and others, depending on available information about patterns of the feature vectors.

Trend Prediction: Autonomous algorithms (ARMA and Neural Network) are used to predict the trend of the extracted feature or the trend of the health assessment results (confidence values).

The uniqueness of the technique is the Watchdog Agent platform which provides the health information of the bearing performance instead of the raw signal data obtained from the sensors. Utilizing the current signal as a triggering mechanism, the system is able to monitor the vibration signals within any machining process of the machine without interaction with the controller. Based on the vibration signals, data processing tools are used to convert data into health information for the bearing performance. Hence, the information is presented in a radar chart for visualization. This platform is also designed for integration in the enterprise asset management systems.
3.2.4 Komatsu: Diagnostics and Prognostics of Truck Diesel Engines

General Background

This project was quite different in format, in that a Komatsu engineer spent 1 year at the Center for Intelligent Maintenance Systems (IMS) at the University of Cincinnati to understand the algorithms and data processing methods that were appropriate to his application (monitoring needs). Based on the guidance from researchers at the center, the Komatsu engineer would then apply those techniques to the Komatsu heavy truck diesel engine data collected in the field.

Project Objectives

- Study the feasibility of using IMS tools and methodology to improve the diagnostic and prognostic monitoring capabilities for the diesel engines used on Komatsu heavy duty trucks.
- Development of a decision aid tool that can be provided to the engine maintenance technician.

Summary of Technical Approach

This particular application was for a heavy duty equipment vehicle used in mining and construction. The remote prognostics and monitoring system focused on assessing and predicting the health of the diesel engine component. For this remote monitoring application, the previously developed architecture for data acquisition and data storage consisted of sending a daily data set of parameters from the diesel engine to the remote location. The parameters included pressures, fuel flow rate, temperature, and rotational speed of the engine. These parameters were taken at key operating points for the engine, such as at idle engine speed or at maximum exhaust gas temperature. The previously developed architecture was missing the necessary algorithms to process the data and assess the current health of the engine, determine the root cause of the anomalous behavior, as well as predict the remaining life of the diesel engine. The earth-moving equipment manufacturer in collaboration with the Center for Intelligent Maintenance Systems (IMS) developed a systematic approach utilizing several algorithms from the set of algorithms in the Watchdog Agent toolbox to convert the diesel engine data into health information.

The data preprocessing step consisted of using the Huber Method for outlier removal, as well as the use of an auto-regressing moving average approach to predict a time series value a few steps ahead to replace missing values. The missing values could be due to an error in the transmission of the data to the remote location or from an outlier removal preprocessing step. After preprocessing the data, the next step was to develop a methodology to classify the different engine patterns in the data to particular engine related problems. Bayesian Belief Network (BBN) classification technique allowed the use of the manufacturers experience on engine related problems along with the pattern history of the data to build the model. This classification model was able to interpret the anomalous engine behavior in the data and identify the root cause of the problem at the early stage of degradation.

The last remaining step is the remaining life prediction, and this used a fuzzy logic based algorithm. The fuzzy membership functions were based on engineering experience as well as features extracted from the data patterns; this hybrid approach accounts for the uncertainty in the data and combines data driven and expert knowledge for a more robust approach.
3.2.5 Caterpillar: Machine Tool Health Monitoring

General Background

This project is subcontracted to the IMS Center as part of Caterpillars project called Manufacturing Asset Capability Information Tools (MACIT). IMS provides consultancy and technical assistance to Caterpillar. In addition, two PhD students from the IMS Center were hired as internship by Caterpillar in 2007 and 2008 respectively to help Caterpillar develop their own technology for machine tool health monitoring.

Project Duration


Project Objectives

§ Develop an autonomous, online machine tool health monitoring system on a CNC lath test-bed with emphasis on spindle bearing health, tool wear and tool crashes.

§ Find the appropriate machine tool health monitoring practices that have strong generality in principle and are quickly duplicable for a variety of machine tools.

§ Replicate the prognostic system by developing a machine tool health monitoring system on a grinding test-bed with emphasis on the grinding wheel and coolant condition.

Summary of Technical Approach

The work starts with the common approach for spindle bearing health and tool wear monitoring based on the previous experience of IMS Center on machine tool prognosis. This approach implements the data-driven prognostic methodology developed at the IMS Center to machine tool health monitoring, which includes four key steps: data acquisition, signal processing and feature extraction, health assessment, presentation and reporting. Spindle bearing vibrations, spindle motor current and feeding motor current are instrumented. However controller-dependent communications and signals are avoided in order to maintain the generality of the approach. Several algorithms from the Watchdog Agent toolbox are selected and applied. Since autonomy is required for the health monitoring system, another key step, called process alignment and identification, is inserted immediately after data acquisition; the corresponding technology is developed and validated during the work. This technology enables the health monitoring system to function well when the machine switches among many jobs frequently, for example in manual or small-batch production.

Project Deliverables

§ A machine tool health monitoring system is built on the test-bed machine. The system can run online 24 hours per day and 7 days per week, automatically collecting data as well as doing analysis and displaying the machine health conditions for spindle bearing and tools. The system is also capable to manage the raw data and health information in order for engineers to track the history and find out reasons of critical events (e.g. spindle crashes).

§ Several signal streamlining algorithms for process alignment and identification are newly developed, enabling the whole system to be quickly ported to other type of machines.
3.2.6 Omron: Precision Energy Management System

General Background

This project will form a value-added collaboration between two participants: the Center for Intelligent Maintenance Systems (IMS) and the Omron Corporation in Japan. The project will establish a Precision Energy Management Systems (PEMS) that will aim to reduce energy consumptions by linking IMS tools and techniques to Omron products, processes, and business level.

Project Duration

April 2008 - April 2011

Project Objectives

§ PRODUCT: the PEMS must be able to define, measure, analyze, and predict energy consumption per product manufactured. This will allow each product, such as a switch or sensor, leaving the Omron process line to have an Energy Label that resembles the amount of energy consumed in manufacturing this product. Such an energy label can also be part of the Eco-Label initiative which is an integrated within Omrons Eco-Product vision.

§ PROCESS: the PEMS must be able to use the developed energy metrics and parameters for detailed operational analytics. In other words, the PEMS will assess both equipment-level and process-level degradation and integrity. Such a correlation between maintenance activities on the shop floor and energy consumed through the machines as well as the processes is an essential part of the PEMS initiative and is a large gap in todays industry operations.

§ PLANT: the PEMS will enable a strategic IT-centric evolution of Omrons QCD (Quality, Cost, Delivery) to consider energy analytics, thus inducing an Eco-IT framework for effective QCDÉ development and implementation.

Summary of Technical Approach

Figure 3.3: Overall Methodology of Precision Energy Management System
3.2.7 General Electric: Intelligent Prognostics for Machine Health Monitoring

General Background

General Electric is planning to develop an Intelligent Prognostic System (IPS) to monitor machine health using information available in the Computer Numerical Controller (CNC). The Center for Intelligent Maintenance Systems (IMS), as a collaborator with GE, proposes to design the Offline Prognostic Analysis System (OPAS). The system will periodically conduct Fixed Cycle Feature Tests (FCFT), collect data, process the data and conduct offline prognostic analysis for identifying machine degradation. Finally it should be responsible for notifying users of poor machine health in a clear and intelligent way.

Project Duration

March 2011 - December 2011

Project Objectives

Develop an OPAS that can learn the critical factors of machine health and analyze data collected from online Fixed Cycle Feature Test (FCFT), and report the analysis results.

Summary of Technical Approach

GE’s existing machine testing system periodically conducts fixed cycle tests on all five axes (X, Y, Z, A and B) of their machine tools, as well as the tool spindles. The MTConnect system collects data from machine controller signals, such as motor current and position delay, which are then saved to an offline database. This database is dedicated as a data-repository of the OPAS and buffers a snapshot of the machine every day for analysis. The OPAS proposed by the IMS center, will draw the FCFT data from the database for the purpose of machine tool health assessment. The data-sets drawn from the database will undergo pre-processing, including critical variable identification, segmentation, and feature extraction.

After pre-processing, extracted data features from identified critical variables will be organized into the database for every machine. The prognostic analysis will be conducted from two aspects, anomaly detection and degradation assessment. For anomaly detection, we will target our algorithm development towards candidate abnormal features such as spikes, shifting, periodical variation and trending. Secondly, algorithms will be developed to recognize normal conditions of individual machines and to track changes of these normal conditions. Lastly, suspected degradation will be modeled to quantitatively assess machine health. Analysis results will be reported by a human machine interface (in Matlab) and automatic notification email. During the analysis, information such as raw data, extracted features, detected anomalies and suspected degradation with severity index will be stored for manual inspection and historical record; otherwise the data will be discarded.

Project Deliverables

§ Demonstrate anomaly detection and data visualization capability; self-learning capability and validate classification algorithm with different machine normal conditions.

§ Demonstrate critical degradation modeling and assessment; system reporting and notification mechanism.
3.2.8 Hongkong EMSD: Health Monitoring of Airport Chiller

General Background

Collaborating with Hong Kong Electrical and Mechanical Services Department (EMSD) on this specific project, IMS designed and employed a systematic method called FCFT (Fixed Cycle Features Test) to identify the incipient faults of the chiller before it completely shuts down. Instead of acquiring data continuously, the chiller is run through several possible work conditions (e.g. 25%, 50%, 75% and 100% load) for two minutes every day. The overall health condition of different components will be assessed by comparing the readings acquired during these periods to the baseline.

Project Objectives

§ Identifying the incipient faults of the chiller before it completely shuts down.

§ Developing an entire platform that integrates data acquisition, preprocessing, health assessment and visualization for implementation in the airport.

Summary of Technical Approach

The data acquisition system used in this project consisted of 6 accelerometers installed on the housing of 6 bearings on the chiller (Figure 3.4). In addition, a National Instruments PXI-4472 was used to obtain data from the 6 accelerometers simultaneously. The data logging system also obtained data from the Johnson Controls OPC (Object-linking-and-embedding for Process Control) server of the chiller system through an Ethernet connection. As the working load is subject to change, the proposed method focused on identifying system behaviors during the transient period between different working loads (Figure 3.5). Wavelet Packet Analysis (WPA) method was applied to extract component health related features from the non-stationery vibration data obtained during these transient periods. Gaussian Mixture Model (GMM) was used as the health assessment model to calculate the confidence value (CV) of the different components of the chiller. Hence, a CV (using a 0-1 scale, 0 being unacceptable or faulty and 1 being normal) was derived from both acceleration data and OPC data were converted into 0 to 1 (0-unacceptable or faulty; 1-normal) information to indicate the health condition of the chiller components. Finally, a radar chart, as shown in Figure 3.6, was generated to show the health condition of all the components, including the shaft, four bearings, the evaporator, the condenser, the compressor oil and the refrigerant circuit. A drop in confidence value was displayed close to the center of the radar chart, which indicated an unexpected fault was likely to happen. The method employed successfully detected the abnormal health condition of the chiller during validation.

Project Deliverable

The entire platform that integrates data acquisition, preprocessing, health assessment and visualization is compiled into one integrated user interface and is being used by the airport staff.
Figure 3.4: Sensor Placement on Chiller

Figure 3.5: Fixed Cycle Feature Test (FCFT)

Figure 3.6: Overall Methodology of Airport Chiller Monitoring
3.2.9 TechSolve: Smart Machine Platform Initiative

General Background

The project is subcontracted to the IMS Center as part of the TechSolve program called Smart Machine Platform Initiative (SMPI). IMS provides consultancy and technical assistance to TechSolve. The first major task that was done was to perform a state-of-the-art survey of machine tool health and maintenance activities and research. The results of this task were used to identify specific prognostics tasks that need to be addressed such as tool unbalance detection, bearing health monitoring, coolant condition monitoring, axes/ball screw health monitoring and guide monitoring. The primary result of undertaking such a survey was to be able to identify the overall goal of the Smart Machine Health and Maintenance System and it is summarized in the Figure 3.7.

![Figure 3.7: Overall Approach to Smart Machine Monitoring](image)

Project Duration

July 2006 - June 2011

Project Objectives

Develop a scalable predictive maintenance system platform to demonstrate self-assessment and self-prognostics capabilities for machine tool makers and users. The specific tasks are:

- Develop a LabVIEW based predictive health monitoring system for machine tools.
- Develop suitable algorithms for predicting the future health state of spindle bearings.
- Develop a health monitoring system for the feed-axis.
- Evaluate a health model that relates tool-holder unbalance to surface quality.
Summary of Technical Approach

**Bearing RUL Modeling** - The objective is to develop a set of algorithms that can estimate the health of spindle bearings and also predict the remaining useful life. The proposed approach monitors the degradation of the spindle bearings using a self-organizing map algorithm and features extracted from the vibration, motor current, and temperature signals. The vibration based feature extraction methods include the use of time domain statistics and peaks in the frequency and envelope spectrum. The health monitoring algorithm and prediction approach are highlighted in Figure 3.8.

Figure 3.8: (a) Health Assessment Algorithm (b) Prediction Approach

The health and prediction results using this proposed approach are shown in Figure 3.9. This is shown for one of the two run-to-failure data sets from the spindle bearing test-rig. The results for these two data sets have been encouraging and future work looks to further validate this method with additional run-to-failure data sets.

Figure 3.9: (a) Bearing Health Trend (b) Prediction Results
Feed-Axis Health Monitoring - The feed-axis is a key subsystem on the machine tool which is subjected to a variety of operating conditions and loads, which over time can lead to the degradation of this particular subsystem. Also, a loss in performance in a particular axis of the machine tool would have a detrimental effect on position accuracy and perhaps the quality of the part manufactured. The proposed approach for monitoring the degradation of the feed-axis is provided in Figure 3.10.

![Feed-Axis Health Model Development Flowchart](image)

For developing the health model in this proposed approach, signals such as the torque, position, vibration, and temperature are further processed and features are extracted. Furthermore, a feature selection routine is used to obtain a subset of features that are best at discriminating between the good and faulty states. These selected features are used as an input into a health assessment algorithm that quantifies the level of degradation as a function of the deviation from normal behavior. Lastly, a classification algorithm can be used to isolate the particular fault that is occurring. After developing this health assessment and fault identification method, a model refinement and validation step is used to further test the model with additional data sets. Preliminary results using the proposed approach have been tested with data collected from a feed-axis test-bed. Figure 3.11 shows the feed-axis test-rig and Figure 3.12 shows the preliminary health assessment results. The preliminary results use data collected from a healthy system and from a feed-axis system with different induced faults.

![Feed-axis Test-rig](image)

![Preliminary Health Assessment Results](image)
Tool-Holder Unbalance Health and Surface Quality Model - The overall methodology for quantifying the tool holder unbalance condition and then relating this to work piece surface quality is shown in Figure 3.13. In the proposed approach, vibration features related to the fundamental frequency and harmonics are used to train a health assessment algorithm. As an extension of this health model, a regression or neural network model is used to relate the surface quality to the measured inputs such as machining parameters and the tool-holder unbalance condition. Data collected from a machine tool with different levels of tool-holder unbalance is used to build and validate the health model.

![Figure 3.13: Tool Holder Unbalance Health and Quality Model Methodology](image)

LabVIEW Interface - A LabVIEW-based software tool for specific machine tool components or subsystems, such as the spindle bearings and the feed-axis are part of the scope of this project. An example of the bearing LabVIEW monitoring program that is currently in development is shown in Figure 3.14; the tab shown in this screen capture is for feature plotting. There are respective tabs for feature extraction, feature selection, health assessment, and prediction as well.

![Figure 3.14: Example of Bearing Health Monitoring and Prediction Software in LabVIEW](image)

Project Deliverables

- LabVIEW based monitoring system configured for monitoring the critical machine tool components and subsystems
- Documented report that highlights the methodology and results for each monitored machine tool component or subsystem.
3.2.10 Data Challenge 2008: Trajectory Similarity Based Prediction (TSBP) of Jet Engine Remaining Useful Life

General Background

Each year the Prognostics and Health Management Society (PHM Society) sponsors a data challenge to both professional and student participants; participants use the available data and their prior experience and algorithm knowhow for developing their health monitoring algorithms for the given application. The accuracy of the health monitoring algorithm output is compared with the true health state; the true health state is unknown to the participants but is known by the organizers of the data challenge. The 2008 data challenge deals with jet engine remaining useful life prediction; the Center for Intelligent Maintenance Systems won the 1st and 3rd places of the competition, including both Professional and Students categories.

Competition Duration

May 2008 - August 2008 (3 months)

Competition Objectives

§ To develop accurate health prediction methods, with given full lifecycle datasets as training input.

§ To benchmark with other competing university and industry methods.

Technical Approach

![Flowchart of the TSBP algorithm for jet engine remaining useful life prediction]

The simulated data set consists of multivariate time series that are collected from multiple units. Each time series is from a different instance of the same engine. There are three operational settings that have a substantial effect on unit performance. The data for each cycle of each unit includes the unit ID, cycle...
index, 3 values for the operational settings and 21 values for 21 sensor measurements. The sensor data are contaminated with noise. Each unit starts with different degrees of initial degradation and manufacturing variation that is unknown. The unit is operating normally at the start of each time series, and develops a fault at some point during the series. The data set is further divided into training and testing subsets. In the training data set (218 units), the fault grows in magnitude until system failure. There is no “hard” failure in the data set; however, the remaining useful life of the last operational cycle of each unit in the training data is considered as zero. In the testing data set, the time series ends some time prior to system failure. The objective is to predict the number of remaining operational cycles before failure. A portion of the testing data set (218 units) is provided first to assist algorithm development and the remaining data (435 units) is released towards the end of the competition as the validation data set to score the algorithm.

The algorithm flowchart is shown in Figure 3.15 where seven steps are divided into two stages—training (model development) and testing (RUL estimation).

During the training stage, the training dataset is first partitioned into different operating regimes based on the operation settings. Selected sensor readings are used for performance assessment modeling; the model is obtained by fitting the sensor reading with parametric curve models. The best model is then selected during the model identification step. The first three steps in training stage are utilized first to classify the testing data of each testing unit. The testing data is then filtered with moving average method, compared with each of the training models with a certain distance metric (e.g., Euclidean Distance), and the prediction result is obtained by fusing all the comparisons. Algorithms applied in each step are briefly introduced in 3.16.

Figure 3.16: Key algorithms applied in each step

**Competition Deliverables**

- The design and configuration of an innovative prediction algorithm, based on abundant training life cycles
- Publications (both conference and journal)
4. Biography: Professor Jay Lee

Dr. Jay Lee is Ohio Eminent Scholar and L.W. Scott Alter Chair Professor in Advanced Manufacturing at the University of Cincinnati. Previously, he held a position as Wisconsin Distinguished Professor and Rockwell Automation Professor at the University of Wisconsin-Milwaukee and is founding director of National Science Foundation (NSF) Industry/University Cooperative Research Center (I/UCRC) on Intelligent Maintenance Systems (IMS, www.imscenter.net) which is a multi-campus NSF Center of Excellence between the University of Cincinnati (lead institution), the University of Michigan, and the Missouri University of Science and Technology.

Prior to joining UWM, he served as R&D Director for Product Development and Manufacturing Department at United Technologies Research Center (UTRC), E. Hartford, CT, and was responsible for the strategic direction and R&D activities for next-generation products and manufacturing, and service technologies. Prior to joining UTRC, he served as Program Directors for a number of programs at NSF during 1991-1998, including the Engineering Research Centers (ERCs) Program, the Industry/University Cooperative Research Centers (I/UCRCs) Program, and the Materials Processing and Manufacturing Program (MPM). In addition, he had served as an adjunct professor for a number of academic institutions, including Johns Hopkins University, where he was an adjunct faculty member for the School of Engineering and Applied Science as well as for the Hopkins Technical Management Program during 1992-1998. He conducted research work at the Mechanical Engineering Lab. of the Ministry of International Trades and Industry (MITI) as a Japan Science and Technology Agency (STA) Fellow in 1995, a Japan Society for Promotion of Science (JSPS) Fellow at the Univ. of Tokyo as in 1997, and a visiting professor at Swiss Institute of Technology (EFFL), Lausanne, Switzerland in July 2004. His current research focuses on autonomous computing and smart prognostics technologies including predictive machine degradation assessment, remote monitoring, embedded prognostics, and self-maintenance systems. He had served on Board on Manufacturing and Engineering Design (BMAED) of National Research Council, Board of Directors for the National Center for Manufacturing Science (NCMS), Chairman of the Manufacturing Engineering Division and Materials Handling Engineering Division of ASME, etc. He has authored/co-authored over 100 technical publications, edited two books, contributed numerous book chapters, three U.S. patents, 2 trademarks, and had delivered numerous invited lectures and speeches, including over 100 invited keynote and plenary speeches at major international conferences.

Dr. Lee received his B.S degree from Taiwan, a M.S. in Mechanical Engineering from the University of Wisconsin-Madison, a M.S. in Industrial Management from the State University of New York at Stony Brook, and D.Sc. in Mechanical Engineering from the George Washington University. He received Milwaukee Mayor Technology Award in 2003 and was a recipient of SME Outstanding Young Manufacturing Engineering Award in 1992. He is also a Fellow of ASME and SME.
5. Appendix: IMS Membership

5.1 IMS Organization and Operation Structure

IMS Center is an NSF Industry/University Cooperative Research Center which focuses on industrially relevant research, education, and outreach activities using a well-established operation structure supported by National Science Foundation and company members. The organization chart of the IMS Center is shown in Figure 5.1. Co-Directors report to their corresponding academic institutions (for intellectual property (IP) and sponsored research support). The Industry Advisory Board (IAB) is the main body of the operation which consists of the representative from each company and advises the Center’s management on all aspects of the Center from research project evaluation to strategic planning. The IAB meets twice per year at the membership meetings of the Center to select the project, review the progresses of research and operations, as well as discuss critical issues that are relevant to Centers development.

The Center co-Directors manage the operations of the Center, including administration of Center fund-
semi-annual IAB meetings, attending semi-annual NSF sponsored evaluator meetings, and providing information and feedback to both the NSF and the Center Director.

5.2 Membership Levels

There are two kinds of memberships:

§ Full Membership
Annual membership fee is $40K.

§ Affiliate Membership
Annual membership is $12K. It is primarily for small businesses (employees less than 500 people).

5.3 Benefits to Company Members

The following is a list of the benefits and rights for IMS members:

§ All IMS members will have non-exclusive and royalty free licensing rights in using all technologies and information developed by the Center.

§ The university will waive the overhead for the membership as the contribution to the Center.

§ The university will contribute to the Center by supporting Center Director’s summer salary as well as the annual salary of the administrative secretary for 5 years.

§ Company members can receive the leveraged research results (at least 15:1 ratio) from its membership investment. All projects funded through membership fund will be shared among companies.

§ Company members can share the best practices and experiences in different IMS testbeds and develop partnerships.

§ The Center can work with company members to develop company specific projects. In addition, these projects can be executed by either a research team at the Center or with dedicated full-time on-side researchers working at company site and assist companies to deploy and implement IMS technologies. The Center will work with the Company to develop a separate research contract and IP agreement based on company’s interests.

§ Company members mentor the IMS testbed projects and can hire and recruit experienced IMS researchers with great impacts.

§ The Center will develop short courses and training courses for companies who are interested in deploying and implementing the developed IMS technologies.
5.4 Technology Transfer Model

The most critical mission of the IMS Center is to nurture and cultivate new breed of engineers, scientists, and leaders in intelligent maintenance systems through a closely dovetailed industry/university collaborative model (Figure 5.2). This model has been used by over 80 NSF sponsored Industry/University Cooperative Research Centers (I/UCRCs) and has impacted large number of students, faculty, and industry members since 1972.

As shown in Figure 5.2, the Industry Advisory Board (IAB) and industrial practitioners serve as many roles within the IMS Center. In the roadmap definition phase, they serve as an advisor to help the Center define the strategic vision, path, and focus, and align them with industry needs. In addition, they work with faculty and company members to harness industry/university partnerships. In the research exploration and demonstration phase, they serve as a mentor to participate in research projects and provide guidance to faculty and students. In the prototype and validation phase, they serve as a champion to identify company prototype project with right point of contacts in the company. Faculty and students have opportunities to learn about business realities and constraints in risks, costs, and time. To bring the research results to impact company’s next-generation products and processes, they serve as users to recruit and hire Center’s students to join company team. In addition, they help faculty develop career experiences by strategically position them with company line organization to involve in real-world project assignment. The entire education program serves this purpose.

Technology transfers are executed by either proprietary interests or collective benefits sharing. At the IMS Center, membership cuts across all competitive lines and advancements in intelligent maintenance systems can be shared collectively. A competitive advantage for any IMS Center member is the ability to immediately transfer these engineering advances and thereby gain the leveraging advantage.
5.5 Maximizing Your IMS Membership

The IMS Center actively engages with member companies, satellite centers and partner institutions to advance research and broaden the knowledge in the area of PHM. Listed below are several opportunities for collaboration that the Center pursues.

§ **Core Membership Research Projects** target areas that are central furthering the IMS Center’s overall mission and that are of interest to the majority of the Center’s members. These areas are identified by IMS researchers as well as the Center’s members. Core Research Projects are presented to the members at the Industrial Advisory Board (IAB) Meetings, held every six months. At these meetings, members have the opportunity to indicate their interest or support for these projects, and can give targeted feedback to the researchers to help guide these projects to mutually beneficial results.

§ **Feasibility Studies** - Prior to a sponsored project, a feasibility study may need to be conducted. The purpose of such studies is to help determine the specific needs of the sponsor-member, as well as the technologies required to meet those needs. Such studies are funded by membership funds, with the ultimate result being a member-specific sponsored project.

§ **Member-specific Sponsored Project (Includes new IP)** When a member company has a specific research goal, or its needs go beyond the abilities of existing technologies, a member-specific sponsored project is generated, the outcomes of which are owned by the sponsor and will not be shared with other IMS members. Specific intellectual property terms are decided upon based on the sponsors input, and in keeping with the terms of the IMS membership agreement, and the policies of the IMS Center Site’s host institution.

§ **Technical Assistance Agreement** A Technical Assistance Agreement (TAA) can be generated for situations in which a member has a specific issue that can be addressed using existing technologies. For such projects, no new IP will be created, though some customization work may be required. TAAs work well for projects involving consultation, training, test-bed validation, existing tool deployment, and any other project involving the application of existing core technologies.

§ **Internships (for graduate students and post-doctoral fellows)** As an alternative to developing a member-specific project or technical assistance agreement, an IMS member has the opportunity to host a researcher from the Center at their facility. Such internships are common, and serve as an excellent way to promote collaboration, as well as to share information, experiences, technologies, etc. The work conducted by an IMS researcher while on internship is owned solely by the host member.

§ **Technical Training** The IMS Center offers training courses for engineers from member organizations in the use of its prognostics methods and its Watchdog Agent Toolbox. These courses can be tailored to the interests and level of experience of the attendees. Such courses can run from 3 days to 3 weeks, depending on the level of detail required.

§ **Corporate Training** The IMS Center also provides training for engineers and executives in Dominant Innovation: a tool developed by Professor Jay Lee (IMS Center Director) for helping organizations to identify and develop value-added services to achieve improved productivity and performance. Participation in this training can transform an existing business into a smart product service business.

§ **Joint Proposal Writing** Many opportunities exist for IMS members for joint proposal writing; this is especially true for small companies (SBIRs, STTRs, etc.) and research institutes.
5.6 Current IMS Members