Expanding the Foundation for Prognostic Health Management in Complex Mechanical Systems

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One of the primary benefits of prognostic health management (PHM) is the ability to accurately assess whether a system can complete its intended mission. The system may be an automobile and the intended mission a family vacation, or the system may be a high-performance jet aircraft and the mission military in nature. Although the costs of unexpected system failure may differ, the general prognostic PHM system requirements are the same. The PHM system must be capable of detecting precursors to component or system failure, classifying the nature of the developing condition and accurately predicting the remaining useful life of the component or system. In addition, a comprehensive PHM system may also recommend changes in the current operating conditions to the operator that will prolong the life of the component or system or implement such life extending changes through the automatic control system. The fundamental components of a PHM system are advanced sensors and data acquisition systems, signal processing and data fusion, system models, pattern recognition and classification, automated reasoning, and interface to human users and asset management systems. The interests of system users (such as the power generation industry or the military) are driven by factors such as a need to decrease maintenance costs and improve operator safety. PHM offers potential added value to the system and eventually the ability to charge customers for actual usage and the opportunity to approach zero-downtime operation.

The Applied Research Laboratory (ARL) has assumed a role that includes expanding the knowledge base in the fundamental components of PHM systems and facilitating the cooperation of diverse members of the research, industrial supplier and user communities through the formation of consortia focused on particular prognostic health monitoring problems. Understanding the progression of faults in complex mechanical systems is one of the keys to reliable prognostic health management. ARL has constructed a number of test facilities designed to facilitate the acquisition of transitional machinery failure data. These include a mechanical diagnostics test bed, a lubrication systems test bench, a bearing test rig, an electrical generator test rig, a high-speed gearbox test rig, a torsional vibration test rig, and a battery test rig. In addition, ARL has constructed portable data acquisition systems for the collection of data in these facilities and on various fielded systems, and software test beds for the development and evaluation of processing and data fusion algorithms. This paper describes the facilities developed at the ARL and the contributions made to the field of prognostic machinery health management.

This paper describes research activities at the Applied Research Laboratory in the area of condition-based maintenance. It is a summary of previous work by the authors, co-authors and other researchers.

Introduction

Maintenance is widely considered to be the largest controllable cost in industry. In an era of increased global competition, producers continually strive to minimize costs, maintain or improve product quality, and increase their organization's market responsiveness. To that end, companies are seeking ways to optimize their maintenance practices by eliminating the expense of excessive maintenance, while concurrently reducing the likelihood of machinery failures and costly downtime. These seemingly contradictory goals have spawned a maintenance revolution.

In the past decade, maintenance practices have evolved as a result of several technological advancements. No longer must companies choose between periodic maintenance (e.g., changing bearings after X hours of operation) and run-to-failure operation (e.g., replacing bearings after a failure occurs and repairing the resulting damage). A wide range of maintenance practices has emerged, with Condition-Based Maintenance (CBM) representing one of the most promising philosophies.

The objective of Condition-Based Maintenance is to accurately assess the current state of machinery within its operational environments and use that information to schedule maintenance activities and predict systems' remaining useful lives. This enables organizations to perform maintenance only when needed—to prevent operational deficiencies or failures—essentially eliminating costly periodic maintenance and greatly reducing the likelihood of machinery failures. Prognostic Health Management uses Condition Based Maintenance to reduce maintenance costs and eliminate periodic maintenance and uses the health prognosis for the system in system planning and logistics.

BENEFITS OF CONDITION-BASED MAINTENANCE

Military
- Increased operational availability
- Reduced operating and maintenance (O&M) costs
- Increased readiness
- Improved safety

Industrial
- Improved product quality
- Fewer product repairs/returns
- Increased productivity via minimal downtime
- Reduced product costs and increased global competitiveness
- CBM as a product feature (i.e., products with built-in CBM systems)

Overall
- More efficient operations via better-informed decisions

CBM uses sensor systems to diagnose emerging equipment problems and to predict how long equipment can effectively serve its operational purpose. The sensors collect and evaluate real-time data using signal detection algorithms. The classification algorithms correlate the unique signals to their causes—for example, vibrations created by a developing fault. The system alerts maintenance personnel to the problem, enabling maintenance activities to be scheduled and performed before operational effectiveness is compromised.

The key to effectively implementing CBM is the ability to detect, classify, and predict the evolution of a failure mechanism with sufficient robustness—and at a low enough cost—to use that information as a basis to plan maintenance for mission- or safety-critical systems. "Mission critical" refers to those activities, which if interrupted, would prohibit the organization from meeting its primary objectives (e.g., completion of a military mission). "Safety critical" functions must remain operational to ensure the safety of humans (e.g., the safe transport of airline passengers). These concepts apply to both military and industrial endeavors.

A CBM system must be capable of:

1. Detecting the start of a failure evolution
2. Classifying the failure evolution
3. Predicting remaining useful life with a high degree of certainty
4. Recommending a remedial action to the operator
5. Taking the indicated action through the control system
6. Aiding the technician in making the repair
7. Providing feedback for the design process

These activities represent a closed-loop process with several levels of feedback, which differentiates CBM from preventive or time-directed maintenance. In a preventive maintenance system, time between overhaul (TBO) is set at design, based on reliability predictions, failure mode effects and criticality analyses (FMECA), and experience with like machines. Although feedback is possible to reduce or extend the TBO, the feedback process is lengthy and costly. This CBM closed-loop process is shown in Figure 1, with the steps in the process numbered to correspond to the activities listed above.

In the Beginning

In the early 1990s, CBM was little more than a concept. Both industry and the military demonstrated an interest. The evolution from primarily time-based maintenance to primarily condition-based maintenance will be a gradual change, as shown in Figure 2. A significant amount of research and technological development was needed to develop the capabilities necessary for CBM. Industry technology developers and users, government research and users, and university researchers, such as the Applied Research Laboratory (ARL), launched unprecedented collaborative efforts to design and develop the hardware, software, and services necessary for CBM solutions. ARL's Systems and Operations Automation Division has focused on this task, collaborating with a wide array of distinguished organizations in the areas of:

- Aircraft manufacturing
- Turbine manufacturing

- Ship manufacturing
- University-based research
- Power production (electric/nuclear)
- Sensors and control
- Human-interface technologies
- Mechanical and power systems
- Construction and land vehicle production
- Data and information technology

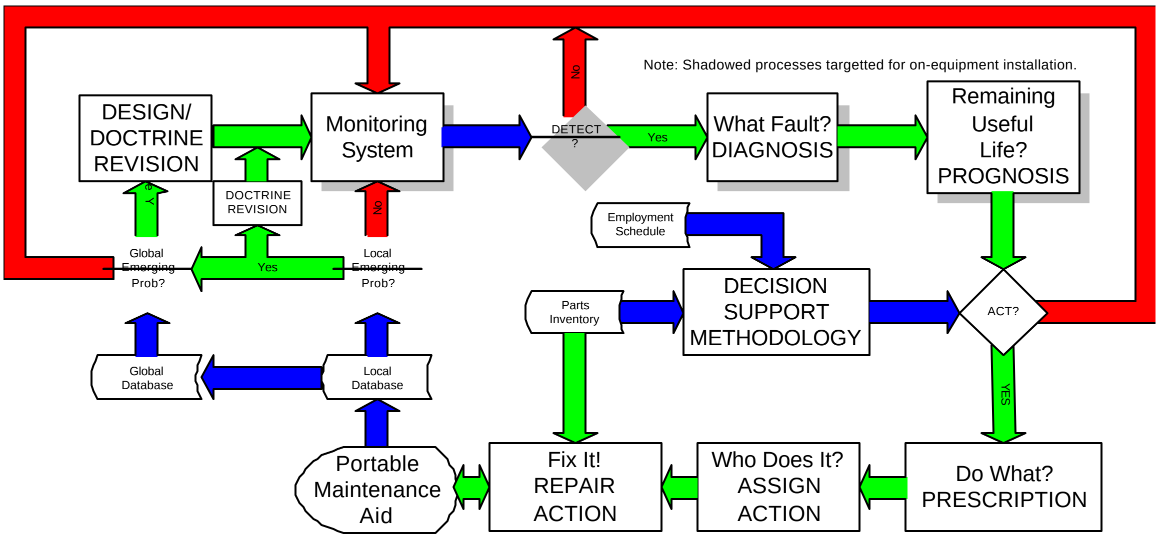

Figure 1 Condition-Based Maintenance as a closed-loop process.

ARL launched its CBM research efforts in the mid-1990s, recognizing that existing mechanical diagnostic equipment would be insufficient for prognostics purposes. Although that technology—designed to identify individual events or trends in the output of sensors mounted on components, subsystems, or systems—could indicate that a failure condition was developing, it could not provide reliable predictions of the remaining useful life. Such systems were limited to simply comparing the output of individual sensors against a priori thresholds to establish a measure of the system's health. Furthermore, the technology prevented implementers from taking advantage of synergy among sensors (i.e., making a multi-dimensional determination of health based on feedback from multiple sensors).

The general goal of "consistent" CBM research is to develop the physical understanding, sensors, signal processing methods, predictive models, classification, and reasoning to allow the development of accurate, reliable CBM systems. Figure 3 provides a high-level view of the elements and flow of the CBM process. ARL's goal has been the development of a conceptual framework, via a process model, which addresses the signal processing, data fusion, and decision processes for CBM. In particular, ARL seeks to determine the functional techniques, knowledge representation, and approximate reasoning formulations that are applicable to CBM for mechanical systems. Results of this research include a process model, a taxonomy of algorithms, and alternative architectures for CBM processing. In addition, ARL is establishing a criterion and metrics for CBM processing algorithm selection.

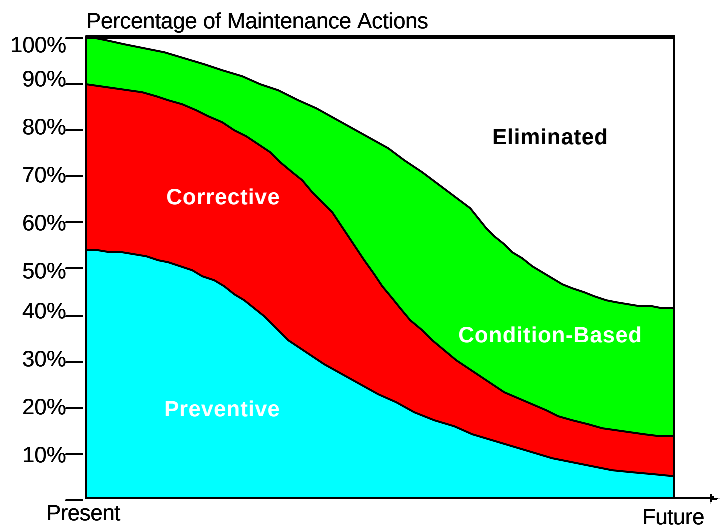

Figure 2 Evolution to Condition Based Maintenance.

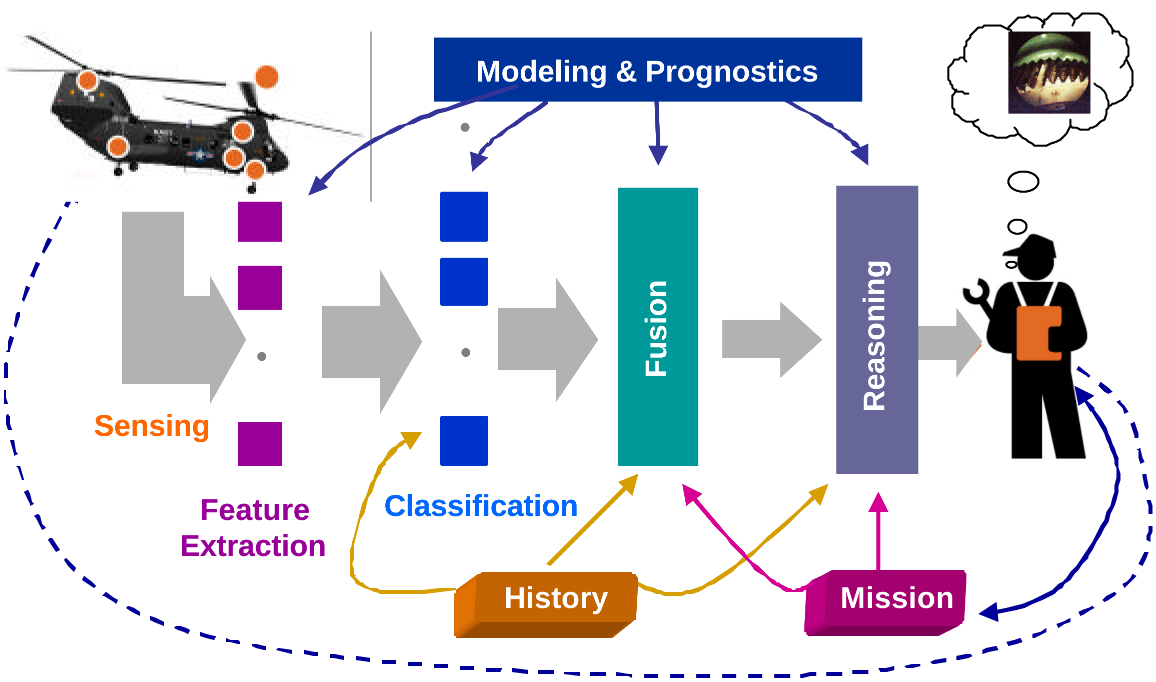

Figure 3 A CBM sytem example.

The Goal: Development of Machinery Prognostics

The primary research focus of ARL's Condition-Based Maintenance research program is the development of a prognostic capability—in other words, the ability to accurately and reliably predicts the remaining useful life of machinery in service. ARL's research is based on the Failure Trajectory Hypothesis, which contends that failures in mechanical systems follow a particular failure trajectory. Furthermore, this trajectory can be predicted within a multidimensional state-space sufficiently early to be useful to the operator and the maintainer.

A number of technologies are required to achieve the objective of prognosis. They include methods for understanding the material properties related to failure and failure propagation, sensors and control, monitoring and interrogation techniques and equipment, signal processing, model-based prediction techniques, and decision support methodologies. These are shown pictorially in Figure 4.

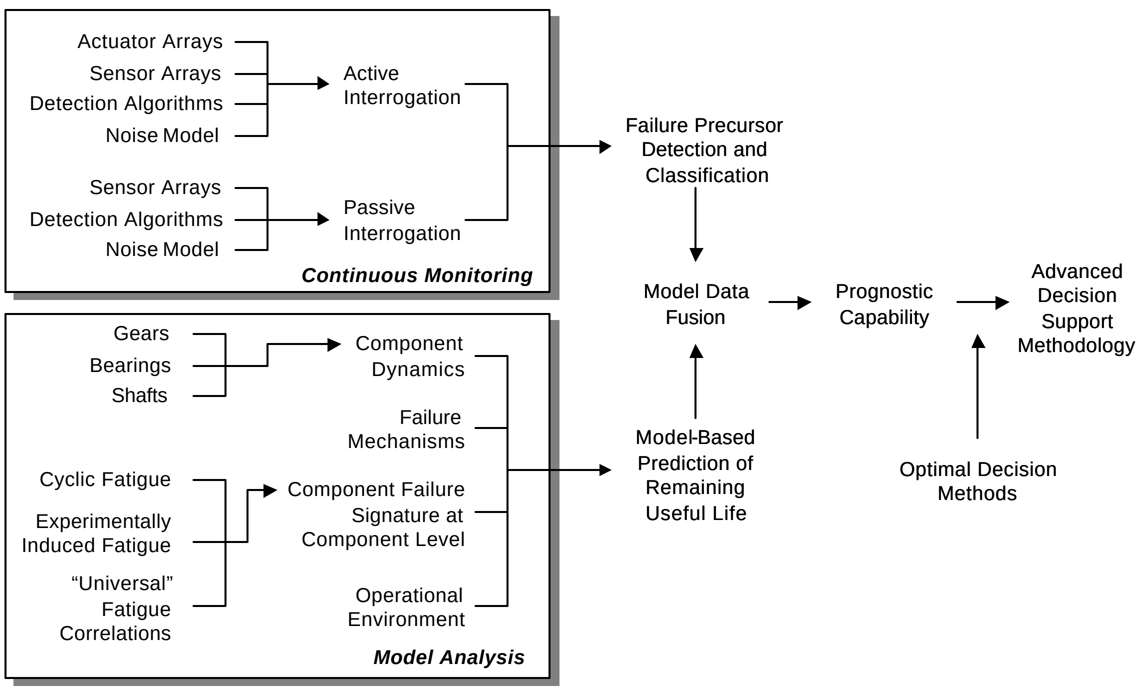

Figure 4 Prognostics development roadmap.

The top portion of Figure 4 shows the activities involved in monitoring the system's operation; the bottom portion reflects the analysis of collected data to develop models for predicting remaining useful life. Monitoring includes passive and active approaches. In active techniques, a known signal is introduced into the structure and the response of the structure is monitored. In the passive approach, the self-generated noise is monitored.

The analysis portion must consider all aspects of the physical system—including mechanical components such as gears, bearings, and shafts. The dynamics of those components must be taken into account. Analysis must also include an understanding of the mechanisms by which failure can initiate and evolve, the unique "signature" that a particular failure generates, and how the signature maps to something observable. Finally, to accurately predict life, the operational environment in which the system will operate must be projected.

ARL's Role

ARL recognized that, in addition to developing the knowledge base required to advance CBM technologies, researchers would have to engage in nonvested testing and evaluation. Testing would be needed in the form of a number of realistic scale test stands that effectively represent the real environment and bridge the chasm between typical university scale test facilities and the real world. Other requirements include: (1) evaluation metrics and procedures to ensure that all evaluations are on an even footing, (2) sufficient knowledge and experience to ensure credibility of findings, and (3) an evaluation data set that is the equivalent of a "primary standard." ARL has taken a leading role in developing these capabilities, creating innovative research tools, applying those tools to specific research efforts, and sharing our data and findings with the CBM community. ARL continues to provide CBM solutions and to develop and demonstrate prototypes of emerging techniques that will ultimately be commercialized.

Development of Innovative Research Tools

ARL has developed several significant test beds and software tools to support CBM research. The most prominent of these are described in the following paragraphs.

Mechanical Diagnostic Test Bed (MDTB) - ARL developed the MDTB, shown in Figure 5, to determine precursors to failure for rotating components (e.g., gearboxes) and other components, such as bearings. Components can be run to failure on the test bed, allowing researchers to collect data on temperature, vibration, and acoustic emission and analyze the findings using signal processing algorithms. This facility has been used to support several ARL CBM research programs. The resulting transitional failure data sets, which characterize fault inception and progression, are available for testing in the CBM community. ARL is currently building a Diesel Enhanced MDTB that can use either a diesel engine or a motor drive to explore seeded/transitional faults in closely coupled reciprocating sources and rotary drive systems.

Lubrication System Test Bench - This test bench reproduces the salient aspects of gas turbine engine lubrication systems and can be used to develop a validated, model-based diagnostics approach for many fault types. The test bench can simulate or produce lubricant degradation, contamination, internally or externally generated debris, flow blockage, and leakage—all important failure effects. A picture of the test bench is shown in Figure 6.

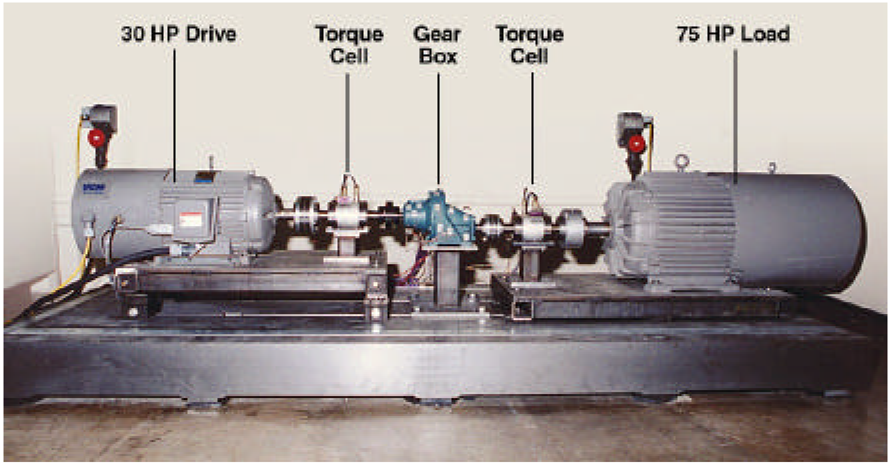

Figure 5 Mechanical Diagnostics Test Bed.

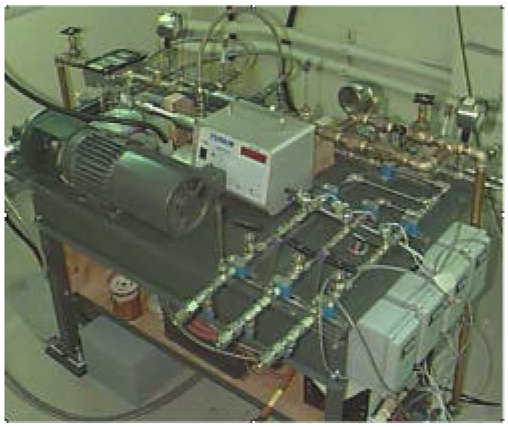

Figure 6 Lubrication System Test Bench.

Bearing Prognostics Test Rig - This test rig enables ARL to collect bearing transition-to-failure data to support development of bearing diagnostic and prognostic algorithms.

Electrical Generator Rig - This rig enables seeded and transitional testing for development of algorithms pertaining to bearing, diode and winding faults. Windings are brought out to a patch panel via electrical slip rings to facilitate the simulation of turn-to-turn short circuits and insulation failures. Diode faults can also be inserted into the electrical system. Figure 7 shows a photograph of the electrical generator test rig.

High-Speed Gearbox Rig - Currently under construction, this rig will simulate operation speeds (14,000 RPM input) for use in determining accessory gearbox health for gas turbine engines.

Torsional Vibration Test Rig - The Torsional Vibration Test Rig supports ARL's research into torsional vibration and its effectiveness in detecting and diagnosing turbine blade and shaft cracking. Figure 9 shows the torsional vibration test rig.

Battery Test Bench - This test bench has been used by ARL researchers to develop a more efficient, model-based approach for (1) accurately assessing the condition (i.e., state of charge) and capacity (i.e., amp-hour) of primary batteries and (2) predicting the remaining useful life (i.e., number of cycles remaining) of secondary batteries.

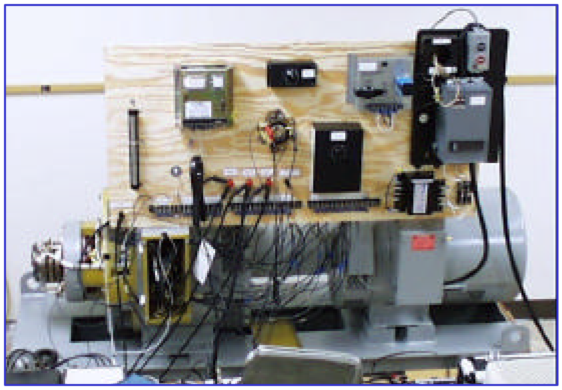

Figure 7 Electrical Generator Rig.

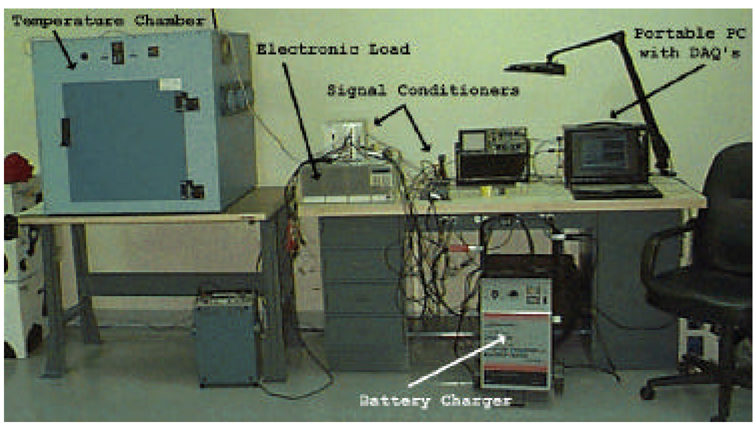

Figure 8 Battery Test Bench.

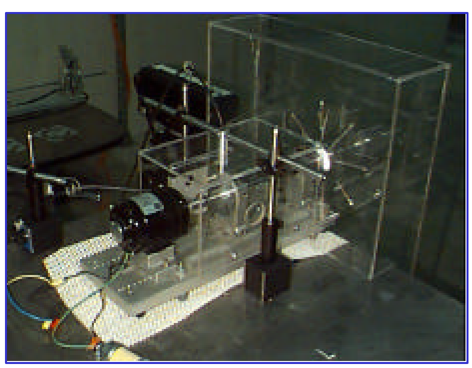

Figure 9 Torsional Vibration Test Rig.

Data Fusion Workbench - The Data Fusion Workbench combines data from multiple sensors and characterizes the state of electromechanical systems. The workbench incorporates multiple reasoning methods, including Auto Regressive Moving Average (ARMA) modeling, neural networks, and fuzzy logic systems, which previously required considerable effort to use.

CBM Features Toolbox - ARL's CBM Features Toolbox is a set of standard processing routines for machinery diagnostics and prognostics. The toolbox eliminates the need for users to code feature routines for each application and helps to standardize feature definition and implementation. It incorporates a mix of traditional and innovative features as well as all necessary signal preprocessing. The toolbox provides a straightforward interface, is easily expandable for new features, offers simplistic input/output file structures, and allows batch processing of features and data. Figure 10 shows the inputs and outputs of the toolbox.

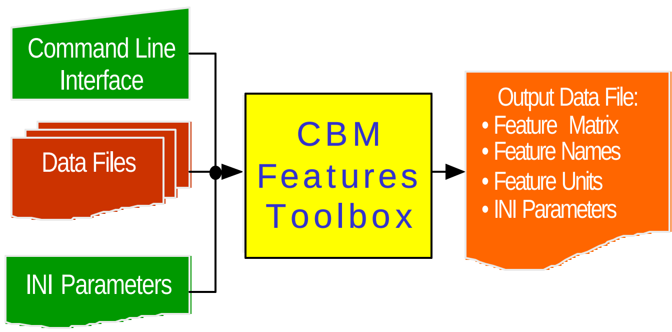

Figure 10 Functionality of the CBM Features Toolbox.

Portable Data Acquisition Systems - ARL developed several portable data acquisition systems to monitor machinery on-site and collect operational data for use in generating diagnostic and prognostic algorithms. These systems can monitor the performance of a variety of electromechanical systems under different operating requirements and in varying environments. The information obtained by these systems provides a dual benefit—it furthers CBM development and provides machinery owners with valuable diagnostic and prognostic data that is specific to their equipment and operating situation.

Key Research Areas

Through a variety of research programs performed in partnership with government, industry, and educational organizations, ARL has made significant strides in developing prognostics for various sponsors and platforms. Some of the most significant areas of research are described below.

Sensing, Modeling, and Reasoning Research – This effort focuses on developing technologies and methodologies to support consequence-driven sensing, modeling, and reasoning. It recognizes the hierarchical nature of failures and demands and responds with a vertically integrated approach that links material-level failure phenomena to platform-level effects. The results of this effort—hardware, software, models, and algorithms—are applicable to both helicopter and shipboard platforms.

CBM for Large Scale Equipment – This effort involves several NASA Ames Research Center wind tunnels. It focuses on providing an effective CBM system for the large equipment that is costly to repair and often impossible to replace. The program includes: building a highly flexible data acquisition system and fusion toolkit, isolating the causes of vibration, determining the most effective means of detecting vibrational changes related to operational degradation, using modeling to develop advanced reasoning schemes for collecting diagnostic/prognostic information and reducing false alerts, and tracking blade degradation on the National Full-Scale Aerodynamic Facility (NFAC), the largest wind tunnel in the world.

Battery Diagnostics – ARL research on the Battery Test Bench has led to the development of a new method of online battery charge density sensing. The new method represents a significant improvement in both effectiveness and efficiency over prior sensing technologies. A patent is pending on this new sensing technique, which can be applied to both battery diagnostics and prognostics.

Torsional Vibration Studies – ARL determined that torsional vibration could be used to detect changes in a rotor blade's natural frequency resulting from a crack or other defect. This research was based on the premise that excitation of the blades—by turbulence or other processes—results in a measurable frequency shift in the torsional domain. These findings are applicable to a wide range of industries, including electric power generation; aircraft, spacecraft, and shipboard applications; and petrochemical and paper production.

Advanced Sensors and Controls – This thrust focuses on the development of smart sensors and sensor technologies, along with the appropriate control architectures to implement health monitoring and other applications.

Fluid System Diagnostics – ARL's development of the lubrication system test bench has led to new model-based diagnostic approaches for fault detection based on fluid system diagnostics. Based on our research, we can characterize operational degradation and fault progressing by analyzing lubricant degradation, contamination, internally or externally generated debris, flow blockage, and leakage.

Intelligent Component Health Monitoring – ARL leads the Machinery Health Monitoring Consortium in developing a multi-layer hierarchical architecture and implementing machinery health monitoring at the platform, system, and component levels. This hierarchical approach enables fast, accurate identification of faults, based on a more integrated picture of machinery health, and will result in more useful, more timely recommendations for action. ARL is developing technology to support "smart components" capable of performing local algorithmic processing at the component level.

Research Horizon

The collection of machinery failure data at laboratory and operational levels has enabled ARL to develop an “implementable” CBM knowledge base and an evolving prediction capability. The next step will involve bridging the scientific gap between material failure and functional capability prediction for decision support. Future success will rely on developing effective strategies for incorporating passive/active interrogation methods with failure and functional models and automated reasoning, as well as advances in low-power sensors, self-calibrating sensors, and high performance sensors. Finally, by providing frameworks and linking the CBM knowledge with logistics and mission planning, ARL and its partners will provide a clear path to improved asset management and readiness.

Acknowledgements

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Outline

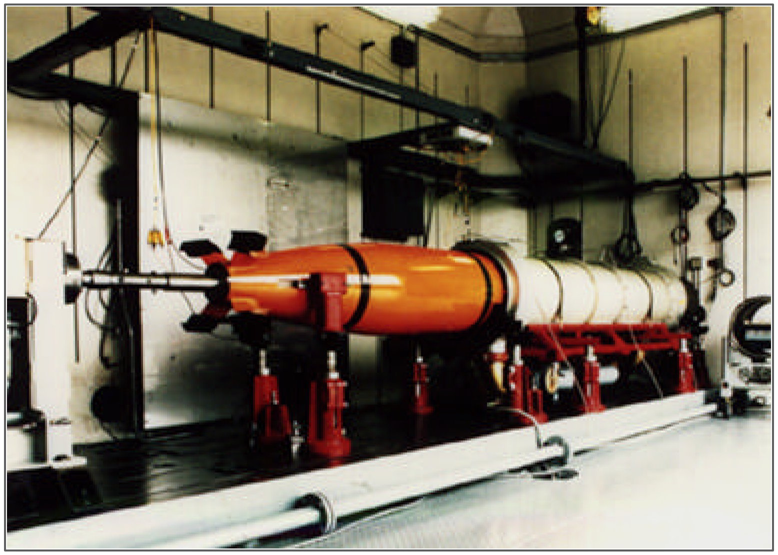
- Introduction to the Pennsylvania State University Applied Research Laboratory
- Prognostic health monitoring
- PHM system design and research approach
- ARL research test beds for the collection of transitional failure data
- Processing and data fusion efforts
- Challenges

PENNSTATE ARL

ARL Mission

As a university center of research excellence in naval science and technologies, with preeminence in undersea missions and related areas, the Applied Research Laboratory provides solutions to problems in national security, economic competitiveness, and quality of life.

ARL Role and Essential Capabilities

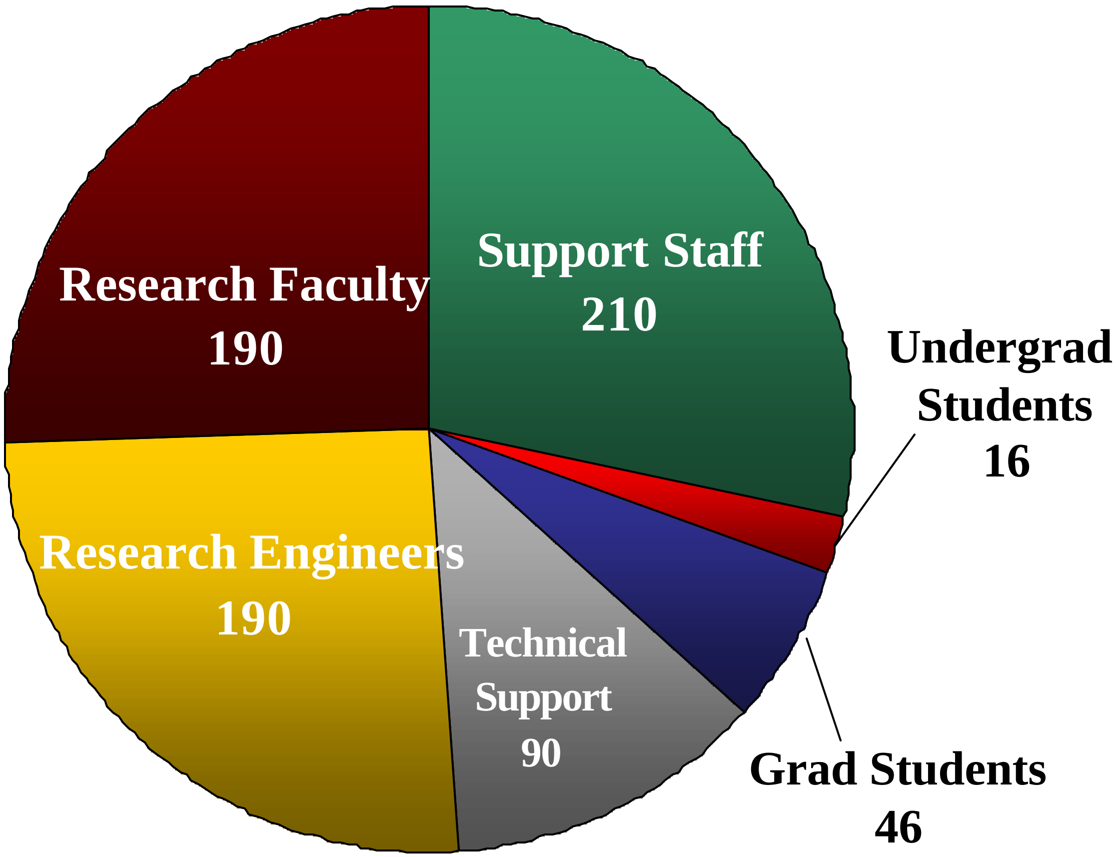


Primarily a science and technology base laboratory with leadership in the following core competencies:

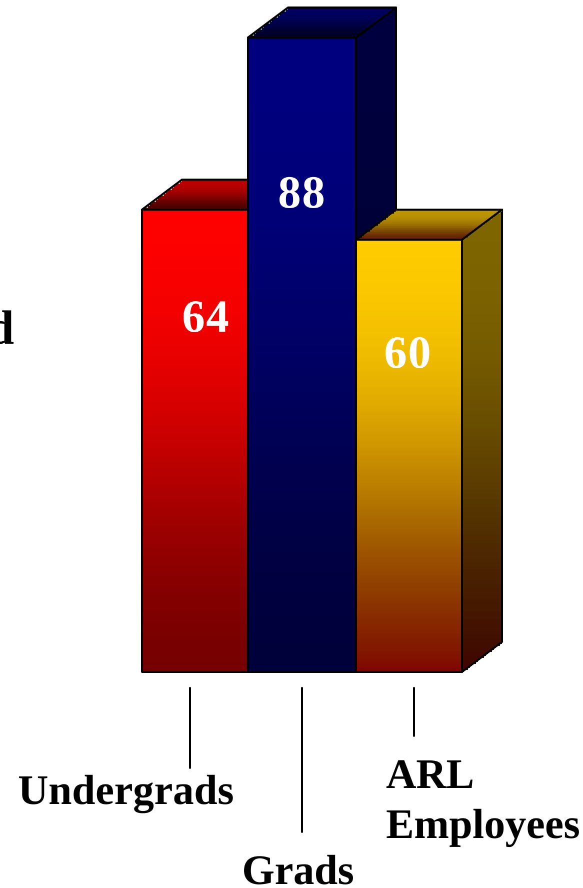
- Acoustics
- Guidance and control
- Navigation
- Advanced thermal propulsion systems
- Fluid dynamics and propulsor technology
- Information sciences
- Materials and manufacturing sciences
- Communications and remote sensing
- Education, training, and technology transfer

ARL People

FY00 Full-Time Equivalent Years of Effort



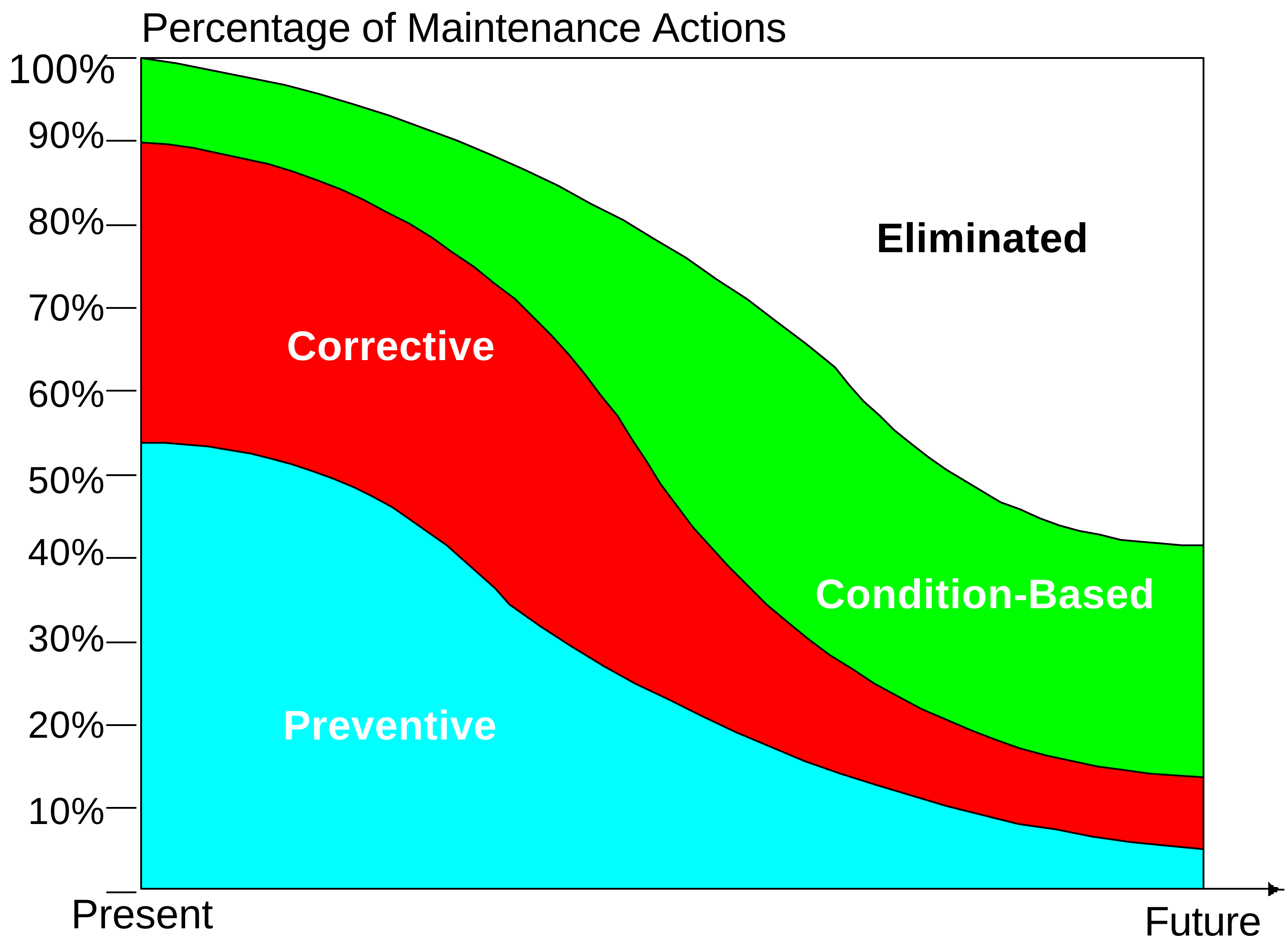
FY00 Degree Candidates



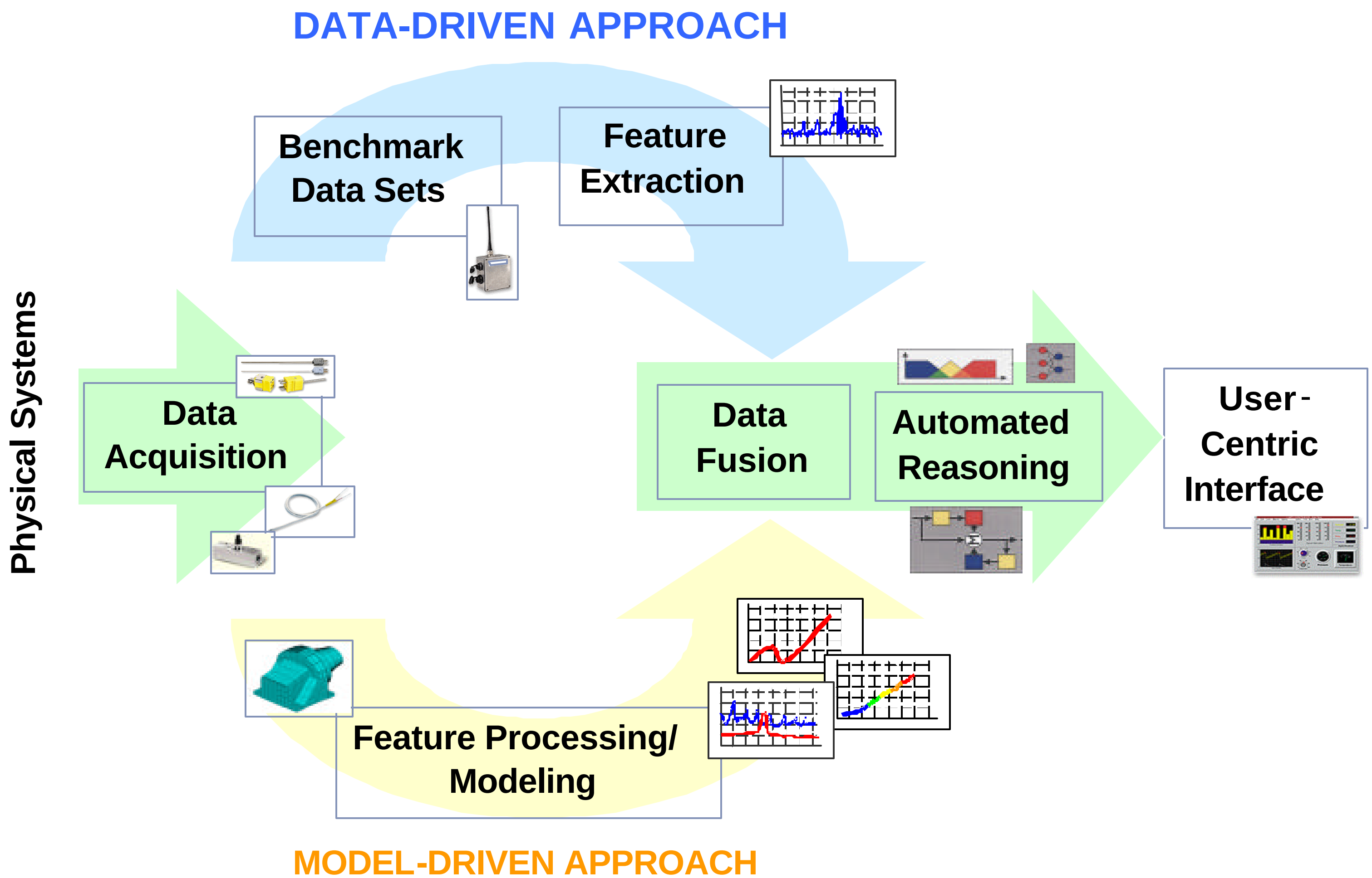
PHM System Functionality

- Detect the start of failure evolution
- Classify failure evolution
- Predict remaining useful life with a high degree of certainty
- Recommend remedial action to the operator
- Initiate indicated action through the control system
- Aid technician in making the repair
- Providing feedback for the design process

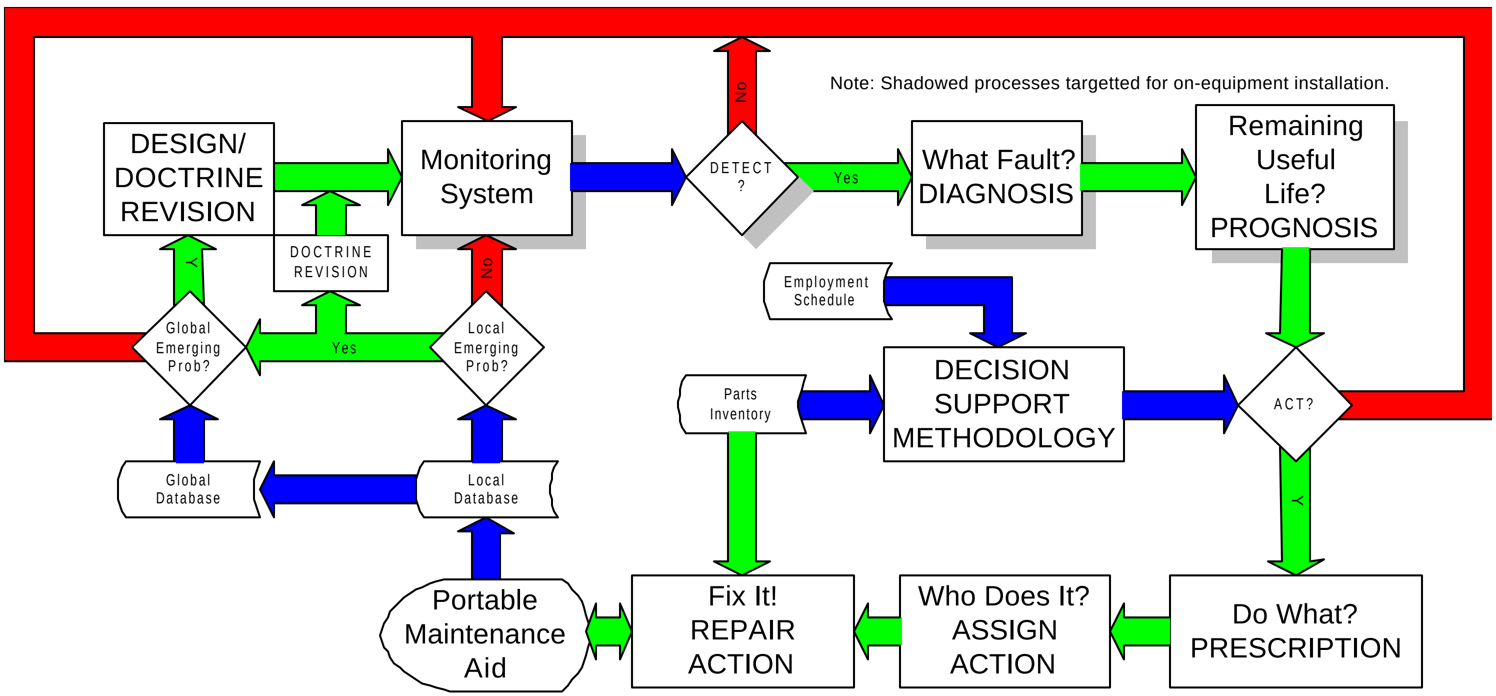
Evolution to PHM



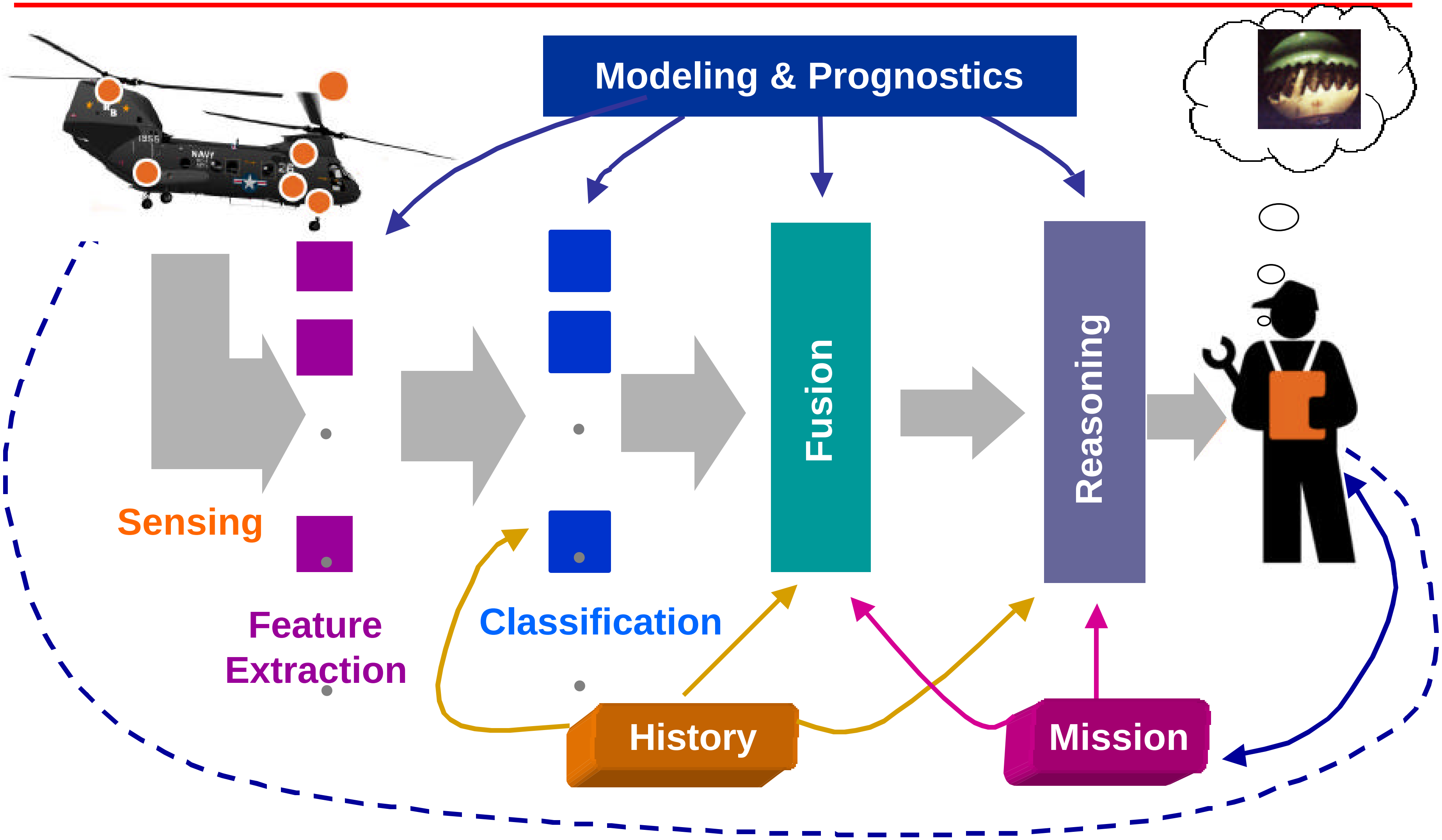
Systems-Level View of PHM



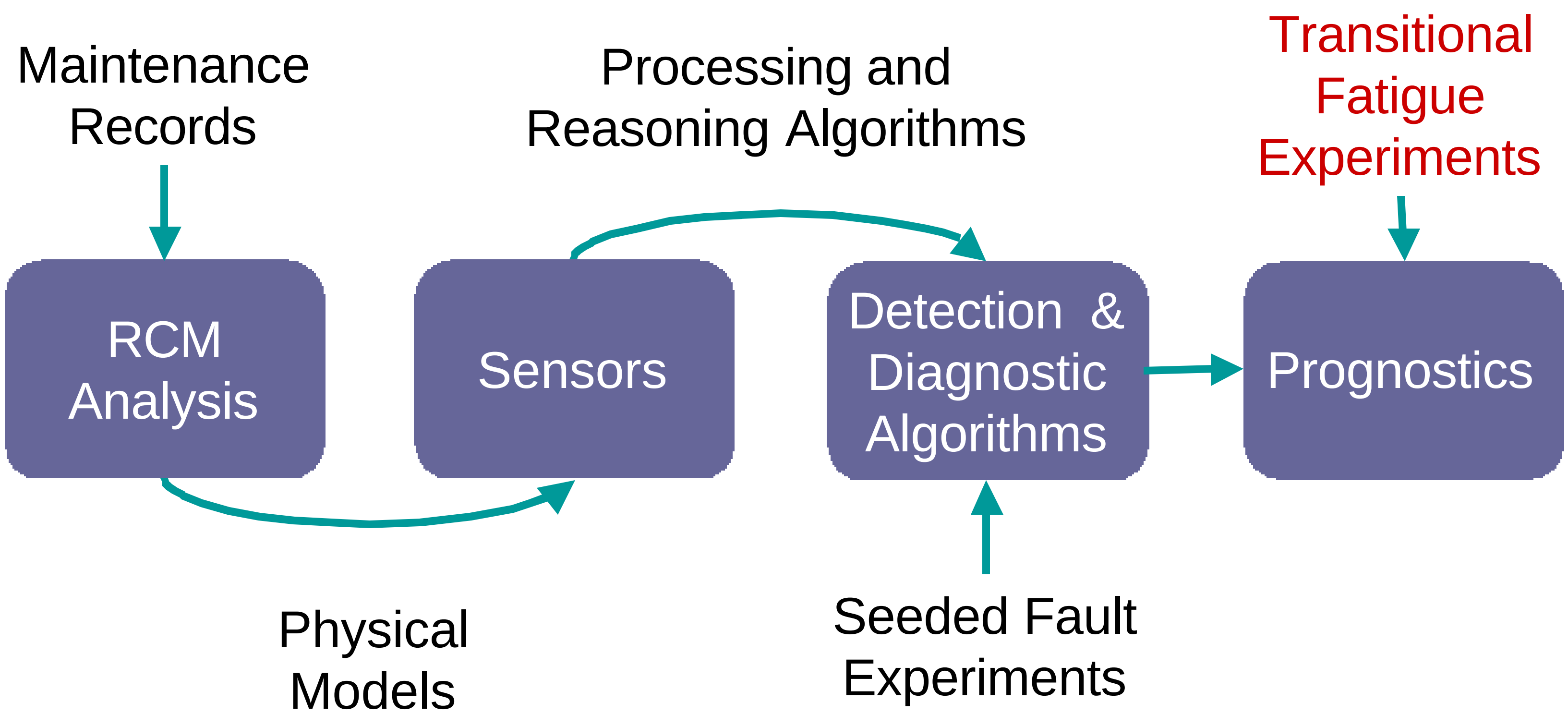
PHM as a Closed-Loop Process



Processing Flow

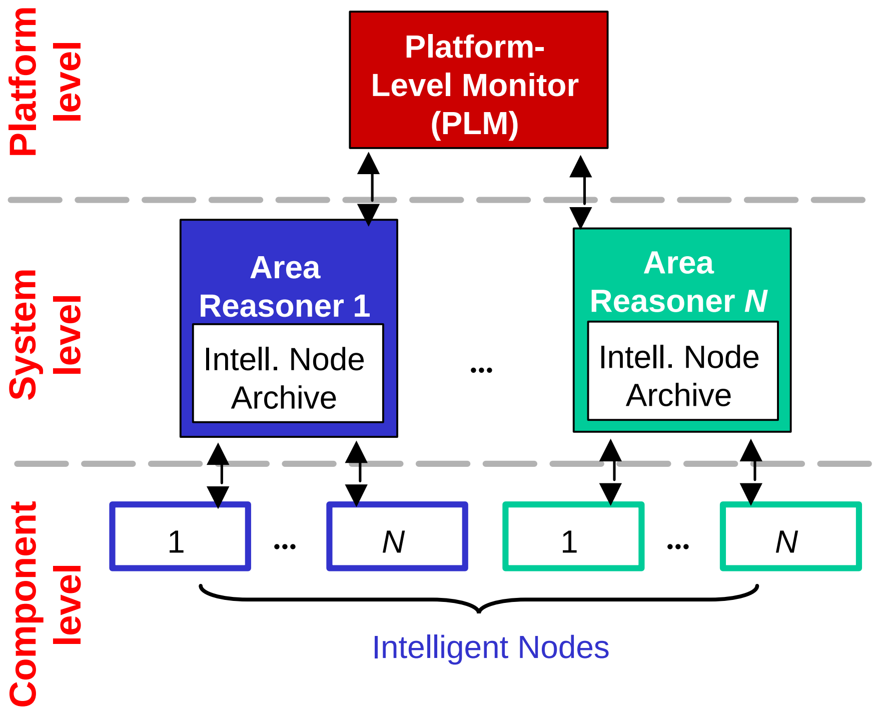


Role of Transitional Data



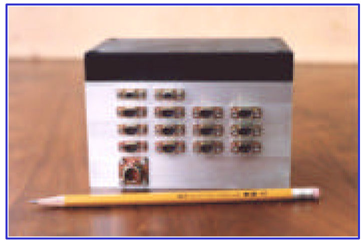
Hierarchical Monitoring Architecture

- Develop a multi-layer hierarchical architecture and implement machinery health monitoring at component, machine, and system levels
- Demonstrate the hierarchical system on a gas turbine generator
- Develop prototype hardware to accomplish PHM



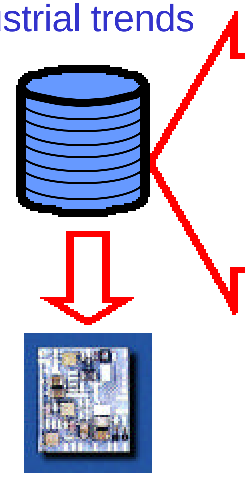
Hardware Options

Invocon Breadboard



Invocon Brassboard

Form factor consistent with industrial trends



- Communications
- Diagnostic Processor (ASIC)
- General Purpose Processing
- Signal Processing
- Signal Conditioning
- Power Interface/ Generation
- Sensing Element
- Self Calibration/ Active Cancellation

Future

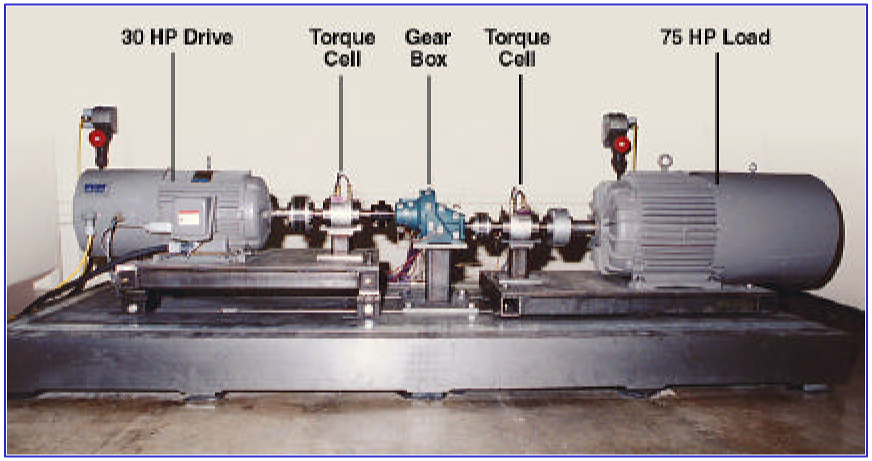
OST ICHM™

COTS PC-104

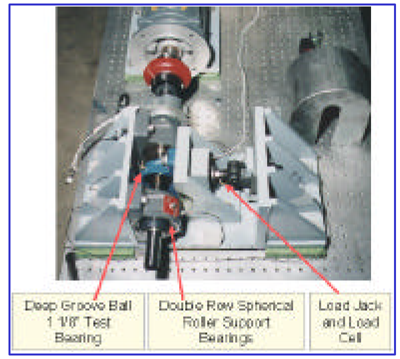
Data Acquisition Equipment

PENNSTATE ARL

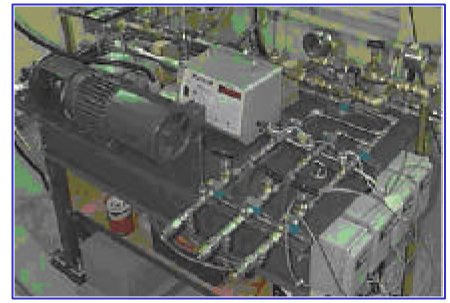
Test Beds



Mechanical Diagnostic Test Bed (MDTB)

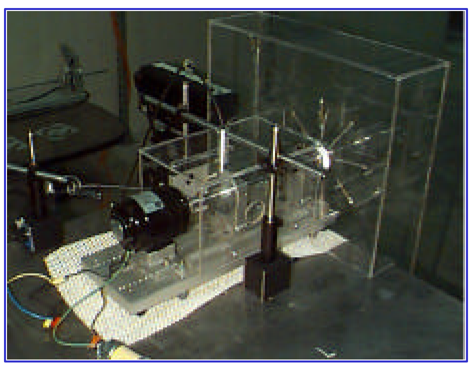


Bearing Test Rig

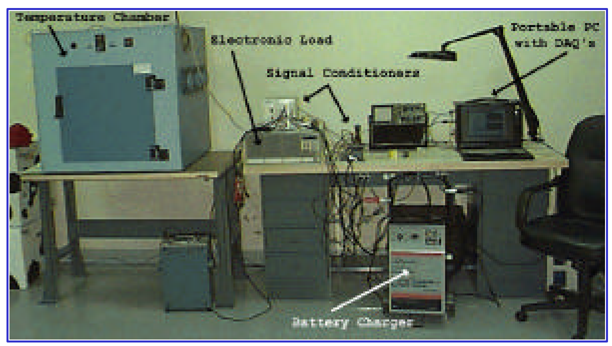


Lubrication Test Bed

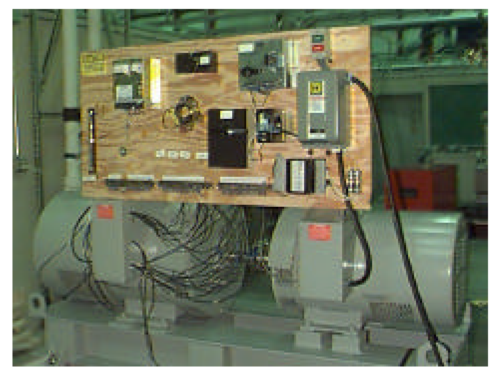
New in 2000:
- **Diesel-Enhanced MDTB**
- **High-Speed Gearbox Rig**



Shaft Torsional Test Rig



Battery Diagnostics Test Bed



Electric Generator Test Rig

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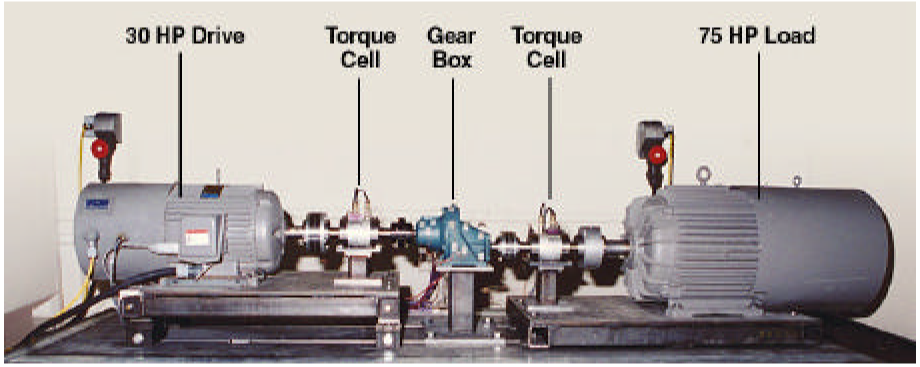
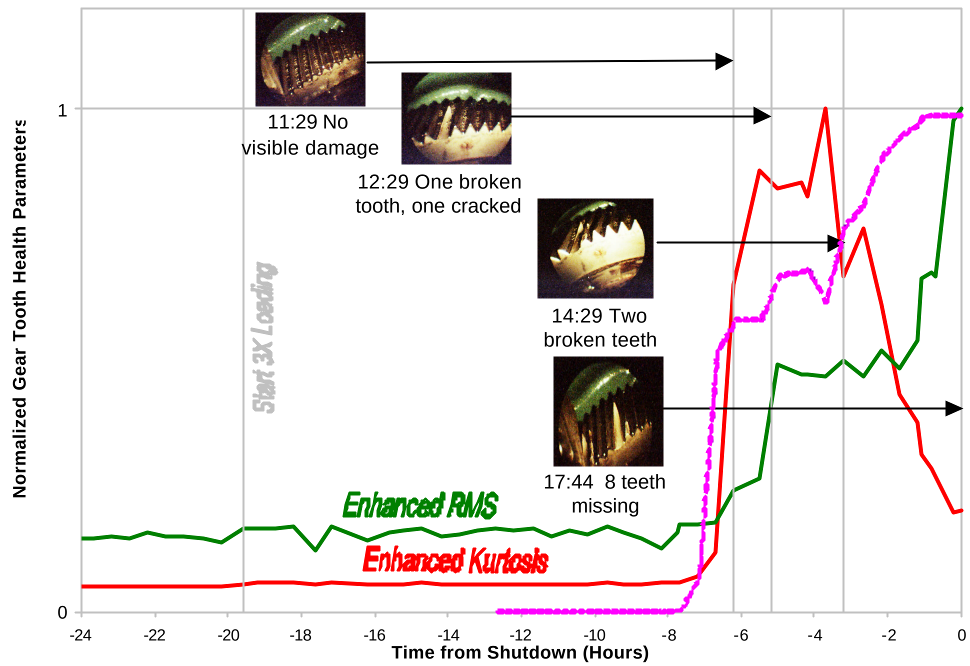
Mechanical Diagnostics Test Bed

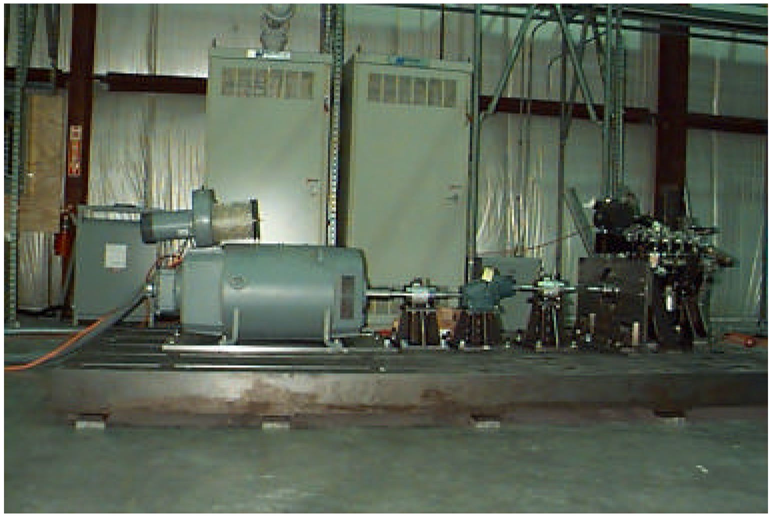


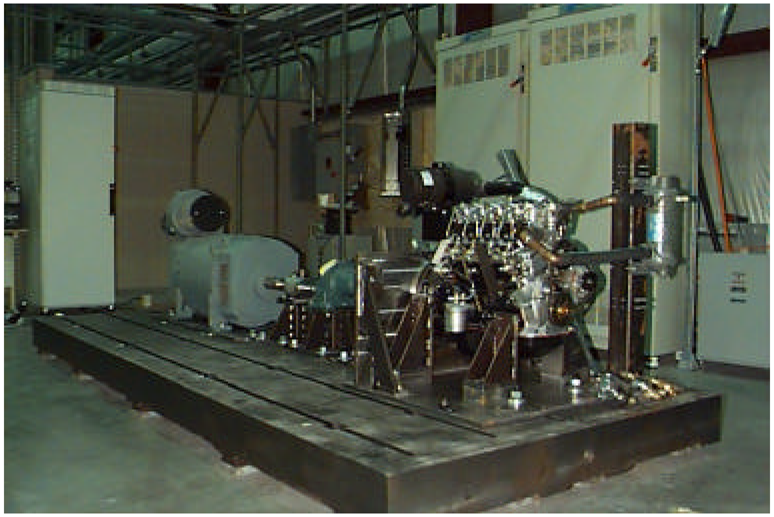
- Gearbox component failures through accelerated loading
- Transitional failure data to support diagnostics and prognostics development

- Vibration (Accelerometer, Laser Vibrometer)
- Acoustic Emission Events
- Strain Gauges
- Multi-point Temperatures
- Oil Quality and Sampling (Dielectric and Debris)
- Multiple Torque & Speed
- Motor Monitoring
- Shaft Encoder



Diesel-Enhanced MDTB

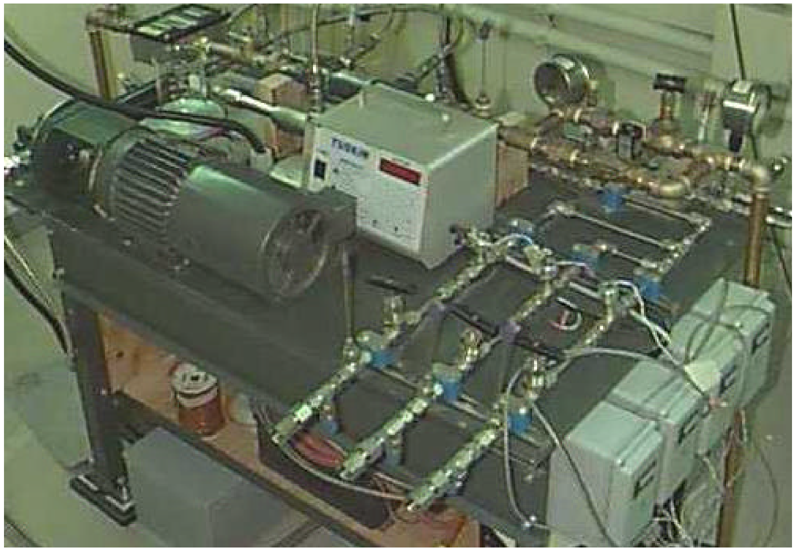




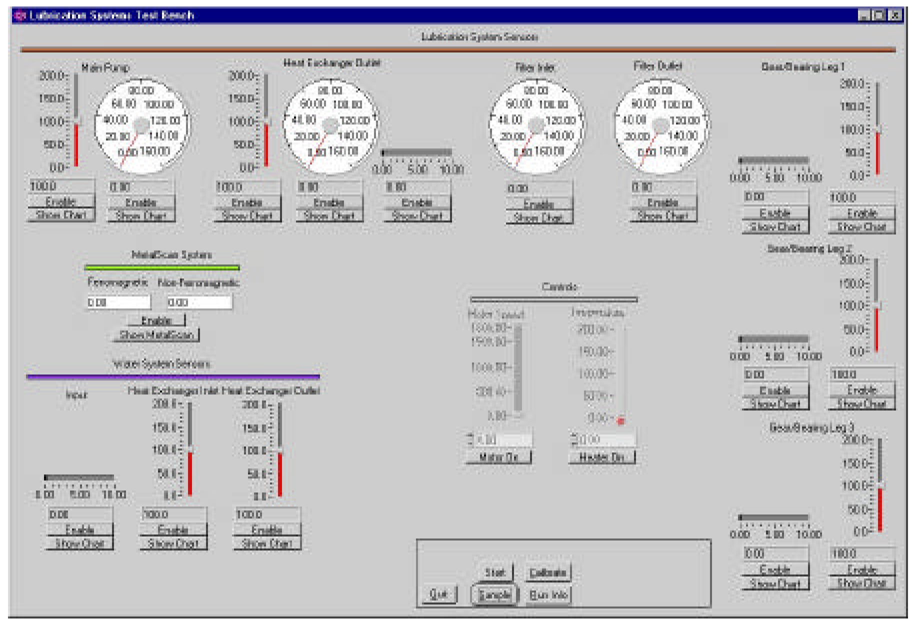
- Allows exploration of seeded/transitional faults in closely coupled reciprocating sources and rotary drive systems
- Has same basic driveline specification as MDTB
- Offers load-side power regeneration for high efficiency test operation
- Uses either a diesel engine or a motor drive as prime mover

* Funded by DURIP, Dr. Thomas McKenna

Lubrication System Testbed



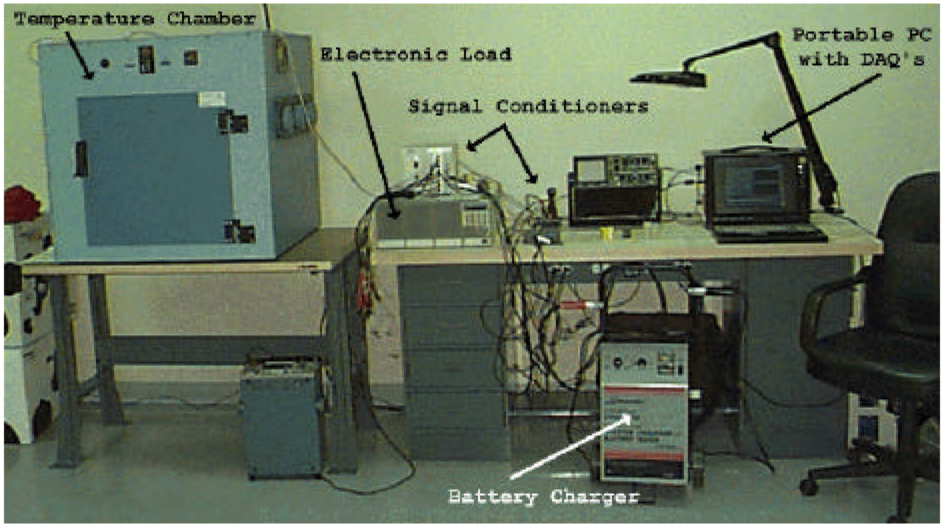
- Simulates pressure-fed lubrication system of gas turbine or transmission
- Pressure, mass flow, temperature, oil debris and contamination sensors



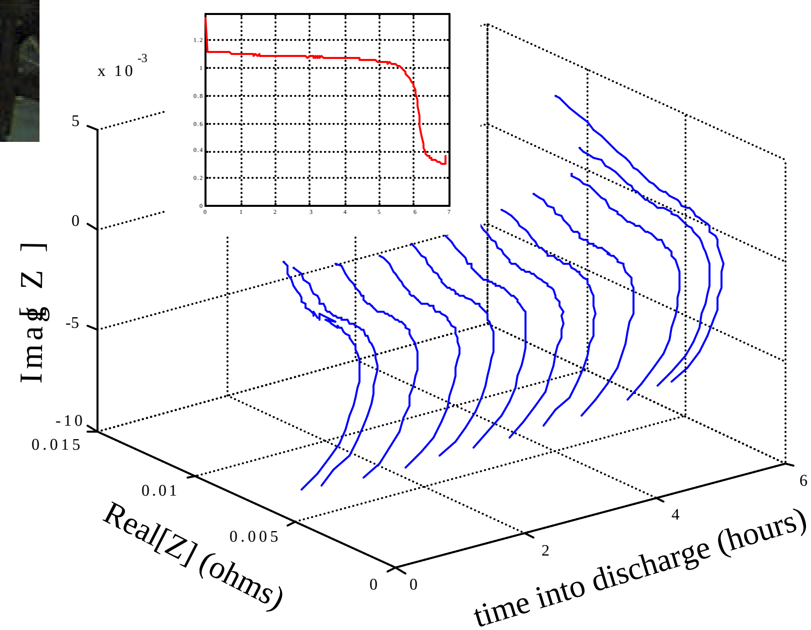
- Oil Delivery Issues
  - Mechanical faults
  - Flow blockage
  - System leakage
- Oil Quality Issues
  - Degradation
  - Fluid contamination
  - Internal/External Debris

* Funded by ONR Code 331, Dr. Phillip Abraham

Battery Prognostics Test Bench



- Evaluate model-based diagnostics for primary and secondary batteries
- Patented impedance technique, temperature, heat flux voltage, current

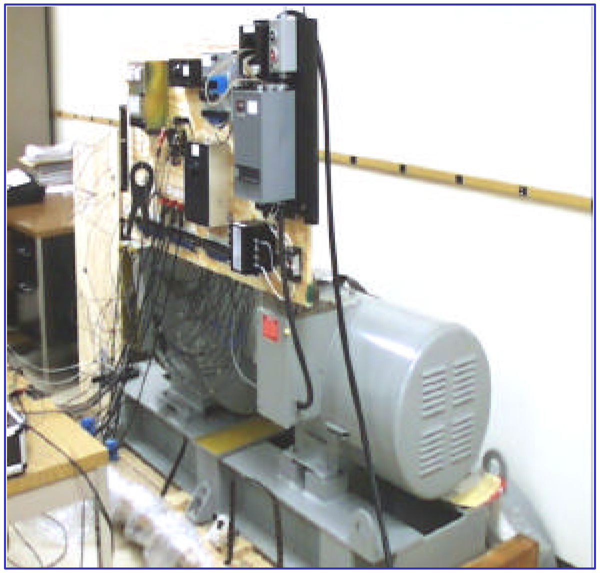


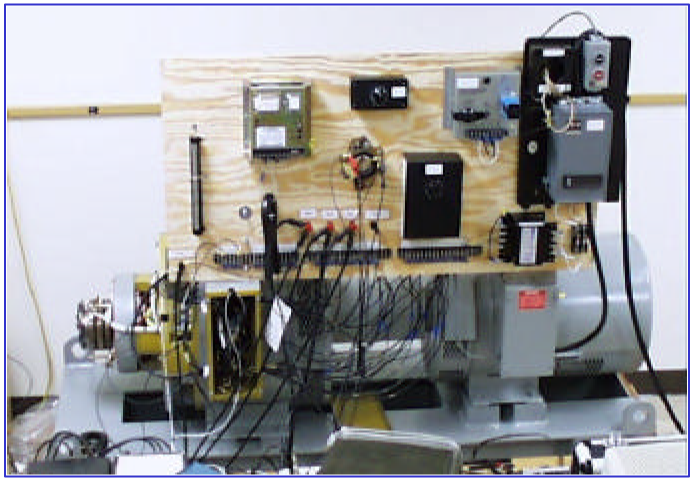
State of charge, health and life models for:

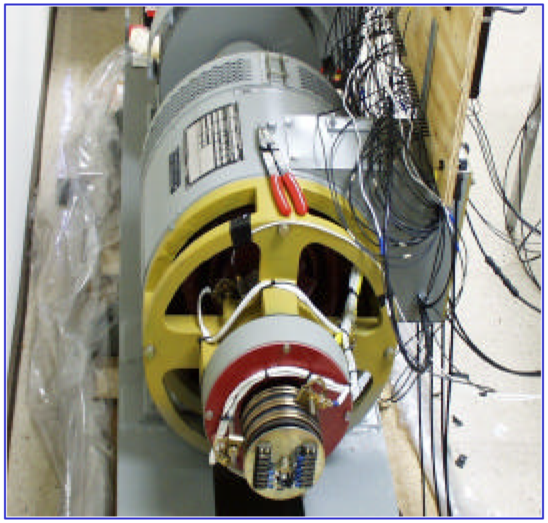
- Lead Acid
- Nickel Cadmium
- Alkaline
- Lithium Polycarbonate

* Funded by ONR Code 331, Dr. Phillip Abraham

Electrical Generator Test Rig

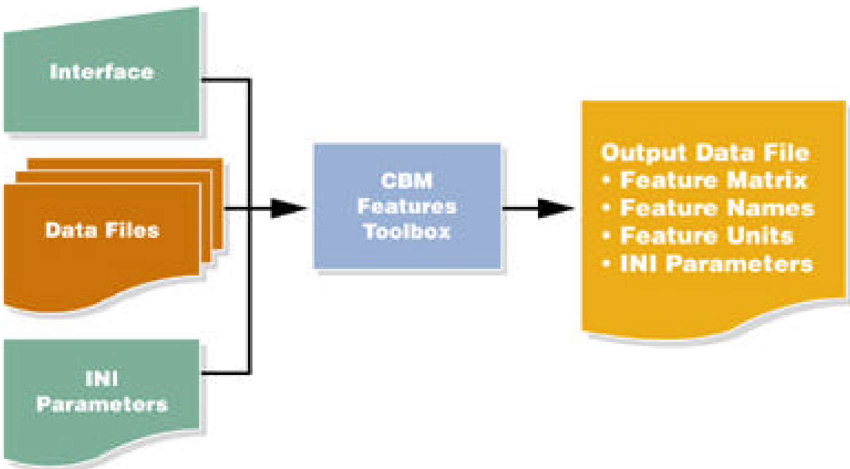




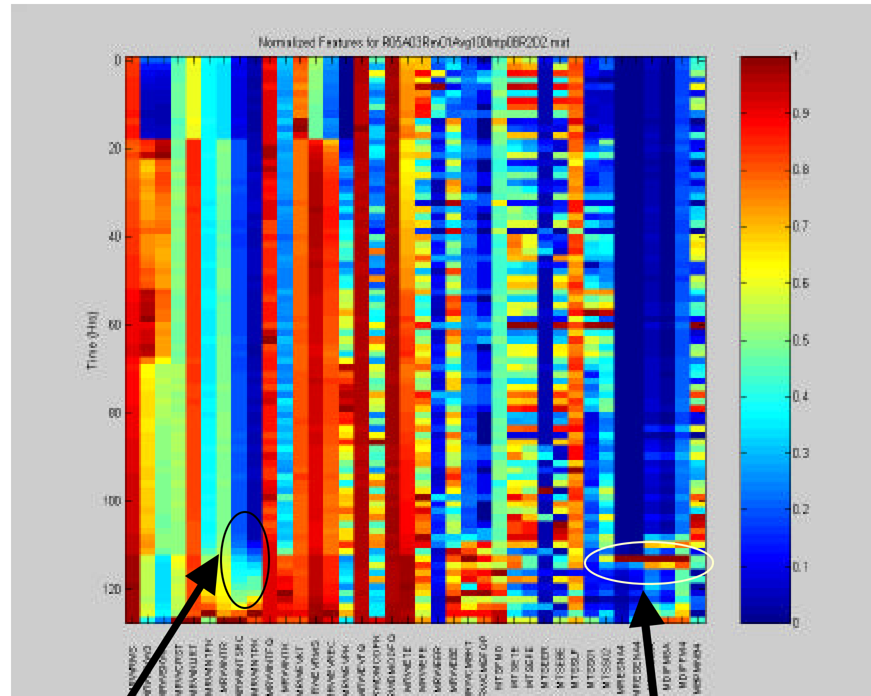


- Scale model for 501-K34 electrical generator
- Enable non-destructive
  - Stator short
  - Diode failure

Matlab® CBM Features Toolbox



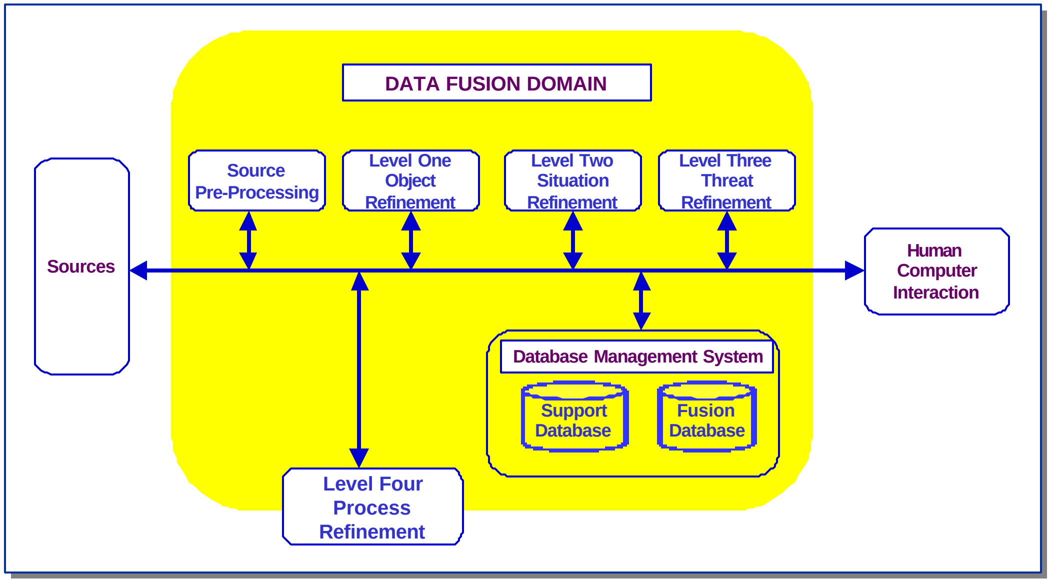
- Toolkit provides:
  - An objective process for evaluating features
  - Rapid prototyping of new features
  - An extensive set of calibrated algorithms for feature extraction

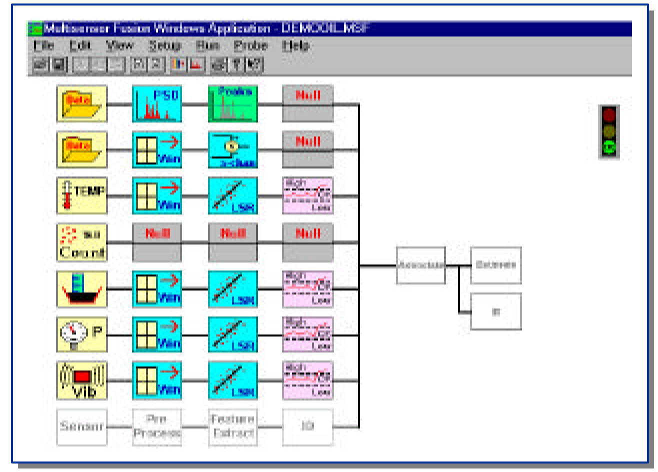


Prognostic Feature

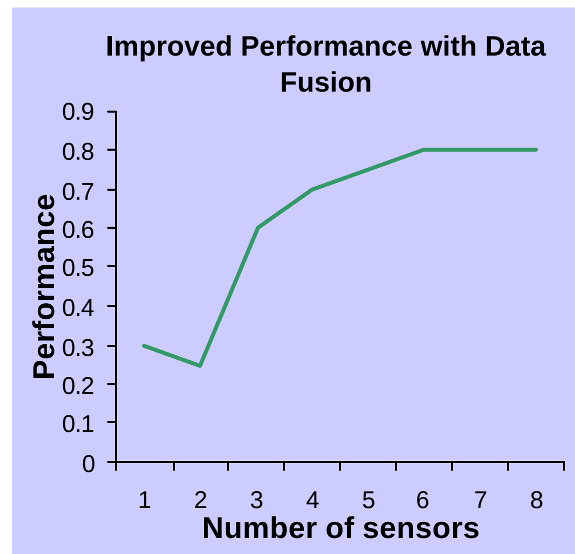
Diagnostic features-> strong jump & correlation

Multisensor Data Fusion



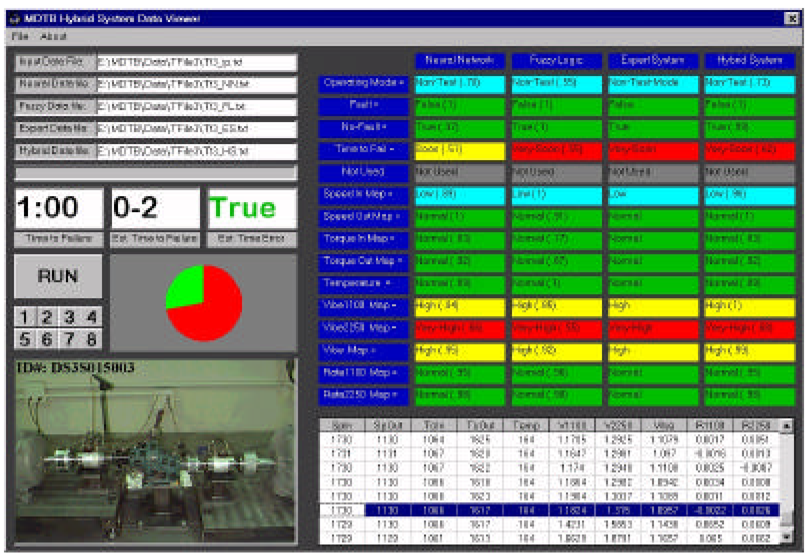


- Leverages JDL data fusion process model
- Multisensor Fusion Toolkit
  - rapid algorithm prototyping
  - MOP/MOE development
- Development of feature and decision-level fusion algorithms

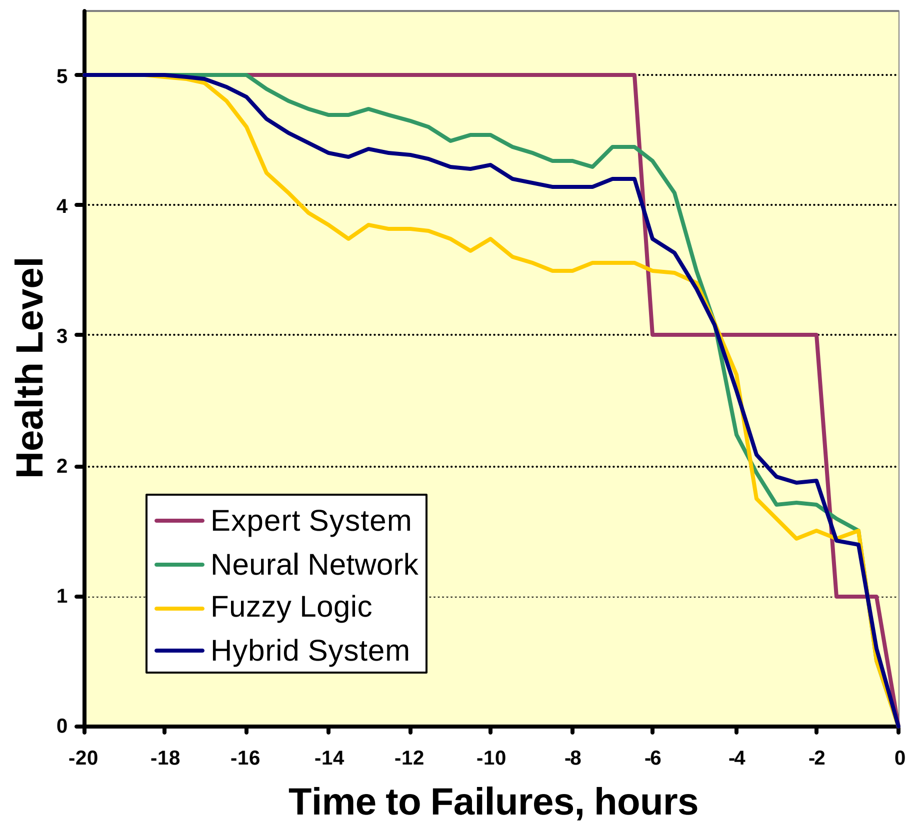


Reasoning and Prognostics

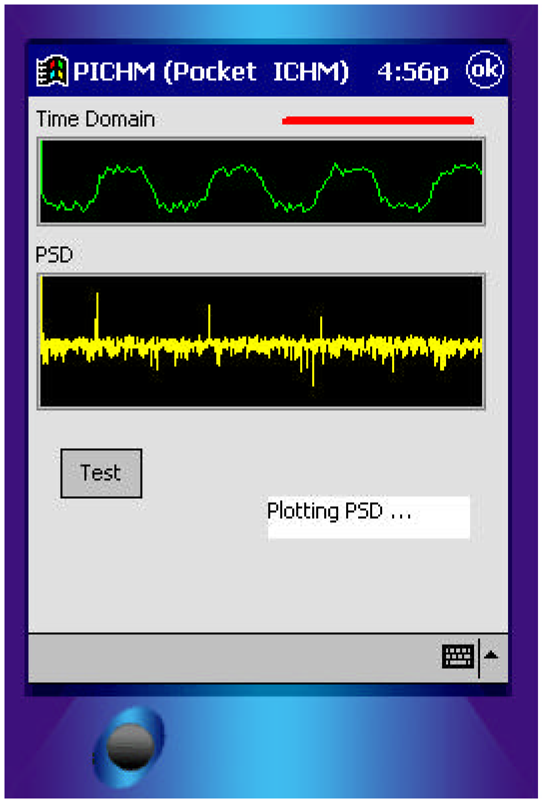
- Comparison of neural network, fuzzy logic, expert, and hybrid systems
- Hybrid system combined the estimates to provide improved robustness

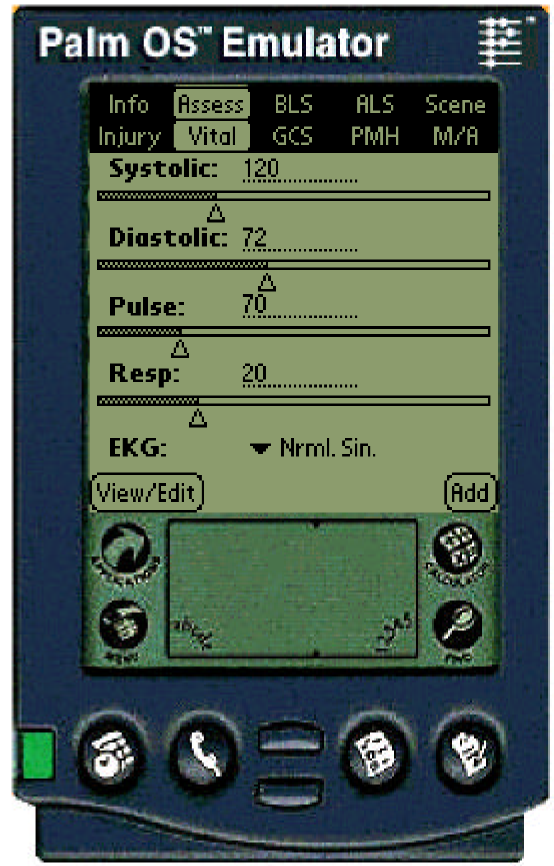


Gearbox Health Indications



Handheld User Interfaces





ARL PHM Research Areas

- Aircraft manufacturing
- Turbine manufacturing
- Ship manufacturing
- University-based research
- Power production (electric/nuclear)
- Sensors and control
- Human-interface technologies
- Mechanical and power systems
- Construction and land vehicle production
- Data and information technology

Continuing Challenges

- Sensing Challenges
  - Autonomous intelligent multisensor systems
  - Self-powered, self-calibrating sensors with wireless communications
- Modeling and Fusion Challenges
  - Physics-based models for failure phenomena and progression
  - Prediction of macro-scale effects from micro-scale phenomena
  - General theory of uncertainty and failure prediction
  - Automated feature extraction/selection for processing sensor data
  - Integration of non-commensurate sensor data
- Prognostics
  - Need for calibrated, transitional data
  - Scaling laboratory-based models to fielded systems and platforms
  - Continued evolution of prognostic theory and applications

(continued)

Continuing Challenges (cont'd)

- Automated Reasoning Challenges
  - Cognitive-based automated reasoning methods to mimic capability of expert mechanics
  - Hierarchical hybrid methods incorporating physics-based models
  - Integration of explicit and implicit knowledge and negative information
  - MOPs and MOEs for data fusion and reasoning
- System Control and Resource Utilization Challenges
  - Tasking and optimal use of 10^N sensors
  - Adaptive context-based sensing
  - Feedback and control of load conditions to extend life span
- Evolution of CBM to asset readiness for intelligent mission planning
  - Spanning the dimension from physics of failure to system capability and platform readiness
  - Translating mission profile demands to system loads and failure prognostics