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PROGNOSTIC ENHANCEMENTS TO NAVAL CONDITION-BASED MAINTENANCE SYSTEMS

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Abstract: In recent years, numerous machinery health monitoring technologies have been developed by the U.S. Navy to aid in the detection and classification of developing machinery faults for various Naval platforms. Existing Naval condition assessment systems such as ICAS (Integrated Condition Assessment System) employ several fault detection and diagnostic technologies ranging from simple thresholding to rule-based algorithms. However, these technologies have not specifically focussed on the ability to predict the future condition (prognostics) of a machine based on the current diagnostic state of the machinery and its available operating and failure history data. Prognostic capability is desired because the ability to forecast this future condition enables a higher level of condition-based maintenance for optimally managing total Life Cycle Costs (LCC). A second issue is that a framework does not exist for "plug 'n play" integration of new diagnostic and prognostic technologies into existing Naval platforms. This paper will outline a generic framework for developing plug 'n play prognostic "modules" as well as examples of specific prognostic modules developed for steam turbine journal bearings and auxiliary gearboxes. The gearbox prognostic module was calibrated and verified using gearbox seeded fault and accelerated failure data taken with the MDTB (Mechanical Diagnostic Test Bed) at the ARL Lab at Penn State University.

Keywords: Prognostics, Condition-based Maintenance, Open System architectures

Introduction: The U.S. Navy has identified the benefits of condition-based maintenance for reducing the life cycle costs of critical shipboard equipment, improving system readiness, and allow more efficient allocation of reduced human resources. Introducing CBM enabling technologies such as advanced diagnostics and prognostics onto Naval platforms that employ SMART and conventional Command, Control, and Communication (C3) systems, appropriate Human-System Interfaces, and various sensor technologies is paramount to achieving these goals. Specifically, these initiatives included:

- Integrating feature-based and model-based prognostics in a real-time environment.
- Developing a "Toolbox" of generic prognostic approaches useful for a wide variety of applications.
- Capitalizing on AI Technologies for fault identification, expert system development, and prediction.
- Designing a Human System Interface concept for knowledge-rich and efficient information access
- Making CBM enabling technologies "Plug 'n Play" in an Open Systems Architecture for ease of data transfer and continuous enhancement of shipboard technologies.

The technology development costs of advanced plug and play diagnostics and prognostics for steam and gas turbine components was validated for the reasons given below. They are aimed at reducing operations and maintenance costs by 50% and predicting component failures and/or degradation with 1-sigma confidence bound of 100 hours.

- Steam and gas turbine component failures and degradation can account for up to 5% of downtime associated with shipboard applications.
- The maintenance and operational costs can be in excess of approximately $5,000 per day for a DDG class ship.
- Prediction of component failure and degradation and maintenance optimization can reduce expected (risk*consequential cost) life cycle costs by up to 30% for steam and gas turbine applications.

Several technologies have been developed or transitioned to help achieve these goals which fundamentally fall in the categories of:

1) Automated sensor/data integrity assessment
2) Improved anomaly detection and feature extraction
3) Data and knowledge fusion processes
4) Feature and model-based prognostics

The capability of each category builds upon the functionality of the previous category with effective prognostics utilizing elements of data validation, anomaly detection, feature extraction and fusion. However, categories 1-3 are outside the scope of this paper. This paper will deal primarily with the design and functionality of prognostic modules, related open system architecture issues, and provide detailed examples of prognostics.

Prognostics Modules: A comprehensive prognostic capability for critical components and/or systems must be capable of integrating existing technologies such advanced features extraction (i.e. vibration, oil analysis, etc.) techniques and empirical/physics-based modeling approaches. In addition, due to the inherent uncertainty involved with predicting future events, prognostic modules should also incorporate a probabilistic framework to directly identify confidence bounds associated with specific component/system time-to-failure predictions. This approach should also be capable of integrating component reliability and inspection results, as well as provide statistical updating methods to accommodate modeling, operational and material property uncertainties known to exist.

To achieve this broad-based inclusion of prognostic technologies into Naval CBM systems, prognostics must utilized and implemented based on inputs from leading feature-based and model-based technologies. It is important to note the intrinsic differences between feature-based prognostics and physics-based prognostics, both in terms of accuracy and applicability, from the operations and maintenance perspectives. In short, the operational perspective relies on more near term predictions of remaining useful life (RUL). The feature-based prognostic approaches address this perspective because they can only make RUL estimates when a particular feature or features associated with a known fault condition has been observed. This characteristic of feature-based prognostics is illustrated in Figure 1. This plot shows how a feature-based RUL prediction becomes accurate only when diagnostic information or features become available. Without these features, no viable prediction can be calculated.

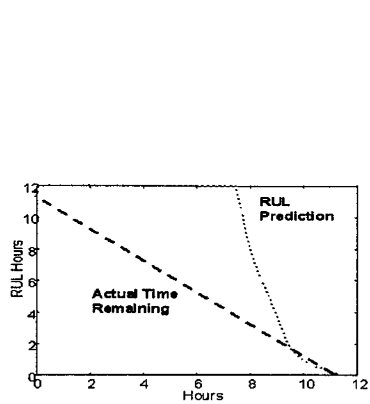

Figure 1 Typical RUL Prediction using Feature-Based Prognostics

Model-based prognostics differ from feature-based prognostics in that they can estimate RUL based only on operational conditions and can be "calibrated" based on any relevant diagnoses that are made. This form of prognostic relies upon high fidelity models (i.e. Finite Element or State Space) that are developed a-priori. Because this form of prognostics can make a RUL estimate in the absence of diagnostic information, it can be used for more long-term predictions as well as short-term ones [6]. It can address questions like what is the failure risk 6 months into the future if the expected future operational profile is known. Figure 2 shows the relationship between diagnostics and a-priori knowledge in the functionality of feature and model-based prognostics from the operations and maintenance perspectives.

One of the key aspects of this integrated prognostic approach is that it is flexible enough to accept input many different sources of information in order to contribute to better fault prediction on remaining useful life. Within this architecture, measured feature data is processed in the diagnostic block, with relevant processed feature information passed to the prognostic block. Next, this information is combined with the model-based estimate to examine the current and future risk associated with a particular failure mode. This block diagram is simplistic in order to highlight the important components of an integrated prognostic module. A more detailed description of the various technologies that have been implemented for particular applications is given in the following sections.

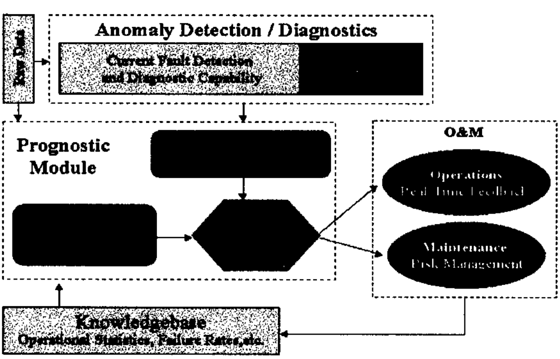

Figure 2 Generic Prognostic Process and Maintenance Integration

Gearbox Prognostic Module: A physics-based model for geartooth failure is the first prognostic model that will be presented. This model was chosen because it could be validated and calibrated on seeded fault / run-to-failure data available with the MDTB (Mechanical Diagnostic Test Bed) at the ARL Lab at Penn State University.

This prognostic module is a near real-time, self-calibrating, physics-based statistical RUL predictor of gear tooth failure due to tooth spalling or low cycle fatigue (LCF) cracking. Figure 3 is a block diagram that illustrates the functionality of this module.

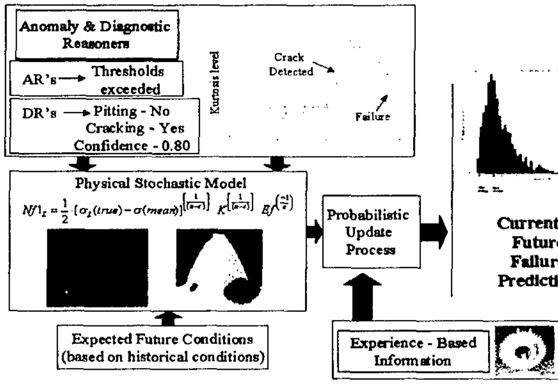

Figure 3 Gear Model-Based Prognostics

A shipboard gearbox of sufficient importance to warrant a dedicated prognostic module would be linked to a on-line data acquisition system capable of extracting vibration, speed and load data. This real-time data would be processed by a pre-developed prognostic module residing on the shipboard CBM system or on a remote server. The prognostic module encapsulates four primary capabilities.

1) Containment of real world calibrated, physic-based algorithms for accumulating the material damage of a gear as a function of operating parameters.
2) The ability to statistically examine past operating condition and extrapolate them into the future or allow for a simulated future operating profile.
3) Containment of algorithms for processing the vibration data and extracting vibration features that are most indicative of gear tooth cracking or pitting.
4) The ability to statistically calibrate the physic-based model results in the presence of a diagnosis of gear wear or with failure rates or inspection results from similar gearboxes.

The output of the prognostic module would be the probability of failure, with confidence bounds, for a specified time into the future.

This model uses American Gear Manufacturer's Association (AGMA) standards for calculation of tooth root stress as a function of transmitted load however sophisticated FE modeling of gear tooth contact could can been employed. The primary failure mode in the Penn State MDTB data was tooth root cracking which is an LCF phenomena. The mean number of cycles to root crack initiation is given in Eq. (1) which relates the LCF damage to localized true stress range.

$$Nf1_L = \frac{1}{2}\cdot[\sigma_L(true)-\sigma(mean)]^{\left[\frac{1}{(n-c)}\right]}\cdot K^{\left[\frac{1}{(n-c)}\right]}\cdot Ef^{\left(\frac{-1}{c}\right)} \quad (1)$$

Nfl_L = the LCF life for the gear (L)
$\sigma_L(true)$ = localized true plastic stress amplitude at a tooth root

n = cyclic strain hardening exponent, c = fatigue ductility exponent
K = cyclic strength coefficient, Ef= fatigue ductility coefficient

This tooth root stresses fully account for strain hardening and residual compressive stresses by completely modeling the material's hysteresis loop. A Monte Carlo simulation was used to generate a distribution on the time to crack initiation based on uncertainty in mechanical properties and operating conditions. Some examples of this uncertainty include the load application factor, which is a function of manufacturing quality and gear alignment, and the true root notch stress. Having developed a distribution on number of cycles to crack initiation at a given load level, the next step is to find the distribution on total damage level as a function of time.

The damage accumulated due to low-cycle fatigue at a particular time is based on a non-linear Miner's rule Eq. (2). A damage level greater than or equal to 1 would represent an initiated root crack.

$$Damage = \left(\frac{n}{Nf1_L} \right)^{r_1} \tag{2}$$

Where: n = number of cycles experienced, r1 = non-linear damage exponent, Nfl = Number cycles to crack initiation

To be functional as a calibrated prognostic tool, the physics-based model must also consider crack propagation so it can predict the time to gear tooth failure when a diagnostic tool discovers that a crack has initiated. To address crack propagation, a fracture mechanics model was created. The fracture mechanics package used was a 2-D version of Franc-XT. The 2-D analysis yielded the change in stress intensity factor with respect to crack length.

The fundamental differential equation used for the rate of crack growth per cycle (Paris Law) is:

$$\frac{\partial a}{\partial N} = C \Delta Ki^m \tag{3}$$

Where:
C, m = fracture related empirical constants, a = crack length, N = cycle (Low or High)

The total probability of failure is the combination of two independent events; the initiation of a crack and the propagation of that crack to failure. For independent events, the total probability is

$$P_{total} = P(i) * P(p) \tag{4}$$

where:

$$P(p) = \frac{\# Damage > 1}{\# MonteCarlo\_pts} \tag{5}$$

Figure 4 shows a screen capture of the notional, plug 'n play prognostic module for gear tooth failure prevention.

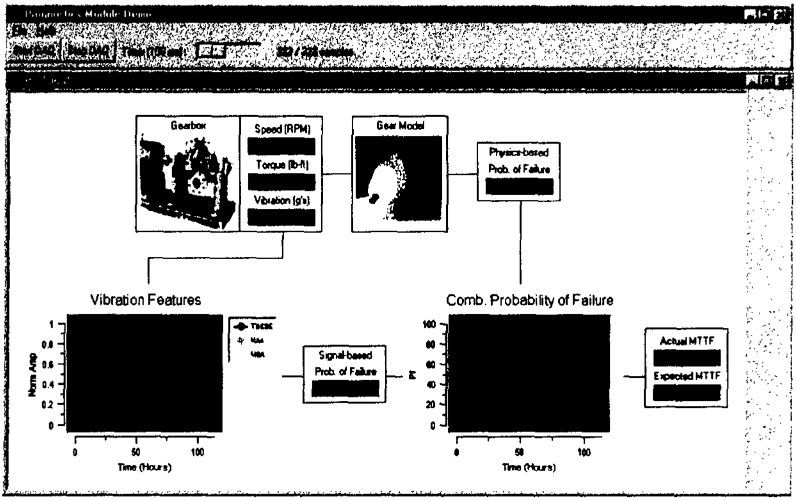

Figure 4 Gearbox Prognostic Module

The layout of this module (Figure 4) is intended to illustrate the knowledge fusion hierarchy that is "behind the scenes". The lower left plot shows three of the 25 vibration features as a function of time. Increases in the normalized amplitude levels have been shown to be indicative of gear tooth cracking [2]. The "Signal-based Prob. of Failure" number is based on the Dempster-Shafer combination of these features [7]. On a parallel path, the raw data gets evaluated by the physical-based prognostic model, which produces its own Prob. of Failure result called "Physics-based Prob. of Failure". A second Dempster-Shafer knowledge fusion process was used to combine the signal-based results with the Physics-based results. The "Actual MTTF" is generated based on the signal information while the Expected MTTF is based on the operational profile (speed and torque) from the physical model.

Actual and Expected MTTF have a higher purpose than just stating that a maintenance event should occur sooner (or later) than expected. The rate of change between actual and expected MTTF is a vital factor in maintenance optimization. Risk, defined as probability of failure multiplied by consequential costs, is always evaluated under two scenarios; 1) what is the risk of failure as a function of time if maintenance is performed in the present vs. 2) if it delayed until some future time. The future probability of failure is performed by extrapolating past speed and loading profile statistics over some future analysis time period.

Babbitted Journal Bearing: Large steam turbine babbitted bearings were identified as high-risk item for the Navy. Therefor a generic steam turbine bearing prognostic module was developed for a two axial groove or pressure bearing design with a tin-based babbitt atop a steel backing. The module is applicable for bearings of approximately 8-10" in length and 12-16" in diameter.

The failure mode of interest for steam turbine bearings is fatigue failure of the babbitt material as a result of fluid film pressure fluctuations [5]. The prognostic module developed would be used as follows:

1) A bearing prognostic module, initialized to specific application and design, would convert data from at least 2 proximity probes near the bearing into rotor eccentricity as a function of time.
2) Via the Reynolds equation and the short bearing model, the magnitude and location of the max fluid pressure will be calculated from the eccentricity
3) Using compiled experimental data relating max. fluid pressure to babbitt life, the mean time to failure (MTTF) with confidence bounds would be determined.

The Bearing Prognostic module is designed to accept two real-time rotor displacement measurements. Processing of the prox. probe data stream yields the eccentricity of the localized rotor motion as a function of time. The eccentricity or "orbit" of the rotor in the journal bearing is an input to a simplification of the Reynolds Equation chosen for this module called the Short Bearing Model. This model was chosen because for most steam turbine bearing designs the Length/Width ratio allows this assumption to be valid.

The Short Bearing Model, which relates non-dimensional fluid pressure to eccentricity is given by:

$$P_{ND} = 6\pi \left(L/D \right)^2 \left(\frac{1}{1 + er * \cos(\theta_{ar})} \right) (er \sin(\theta_{ar})) (z^2 - 1) + pa \tag{6}$$

This is converted to dimensional pressure via:

$$P = \mu * N * \left(\frac{R}{C} \right)^2 * P_{ND} \tag{7}$$

Where:

P_{ND} - Non Dimensional Pressure, L - Length of Bearing, D - Diameter of Bearing, er - Eccentricity Ratio
θ_{AP} – Angular position, R- Bearing Radius, μ – Fluid Viscosity, z- Non Dimensional axial direction

The solution to the model ultimately yields the fluid pressure distribution as a function of rotor displacement. A fluid pressure distribution is shown in Figure 5a. A sparse but significant set of experimental results have correlated max fluid pressure to number of cycles to babbitt fatigue failure [3]. This run-to-failure data taken from the EPRI Manual of Bearing Failure and Repair of Powerplant Rotating Equipment [4] is shown in Figure 5b. Standard Normal distributions were placed about the linear regression line to capture experimental uncertainty. Hence, with a given fluid pressure, a Mean Time To Failure (MTTF) with confidence bounds can be found.

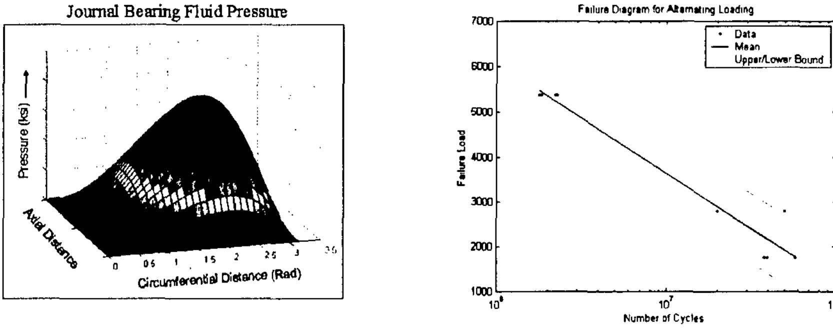

Figure 5a,b Journal Fluid Pressure Distribution and Failure Curve as Function of Load

A simulation was performed were the journal bearing had a normal amount of eccentricity for a period of time and then a rotor misalignment was simulated. The misalignment caused some high fluid pressure fluctuations as shown in Figure 6.

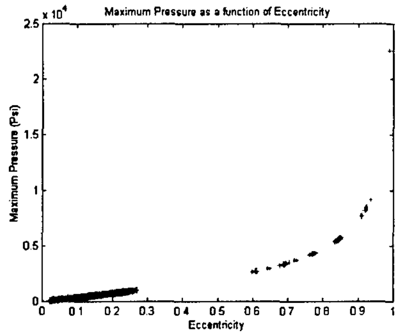

Figure 6 Maximum Pressure as a Function of Eccentricity

Like all the "prognostic" modules, the bearing module contains some components of anomaly detection, diagnostic and prognostic reasoning inherent to its architecture.

In this module an anomalous event that affects bearing life would be rotor misalignment. The model-based prognostic module continuously evaluates the remaining life of the bearing regardless of whether or not a misalignment diagnosis is made. However, the rate of damage accumulation increases dramatically when rotor misalignment is detected.

Figure 7 is a screen capture of a plug 'n play module for the Steam Turbine Bearing Prognostic Module. The real-time orbit of the rotor is shown in the upper left-hand corner along with the raw proximity probe data. The "Bearing Model" is meant to collectively represent FFT capability and the hydrodynamic model. 1 and 2 per rev. features are captured from the vibration spectrum. The severity level (0-100) of two conditions adversely affecting bearing life, rotor unbalance and misalignment are evaluated based on the amplitude levels of the 1 and 2 per rev. respectively. In the case illustrated, misalignment levels where mapped to rotor eccentricities.

Given the rotor eccentricity and Eq. (7), the maximum fluid pressure can be found. Finally, a probability of babbitt fatigue failure is found based on the number of cycles experienced and the known distribution of number of cycles to failure given max. fluid pressure level. Like all modules, a threshold level is placed on the difference between Actual and Expected Mean Time To Failure to alert when maintenance action should be taken.

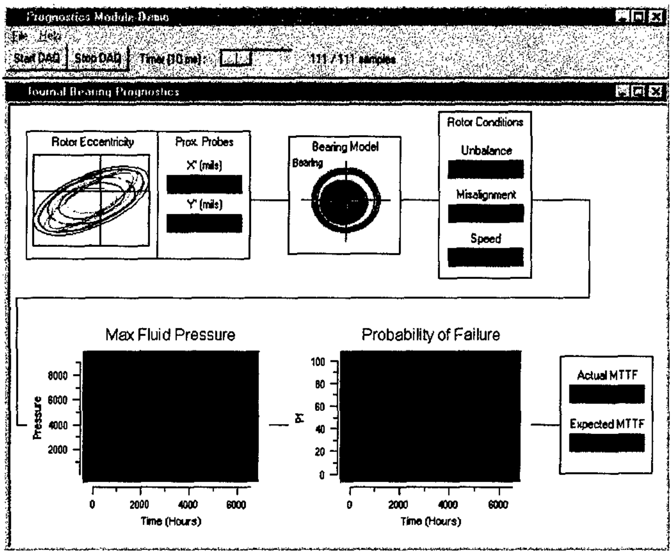

Figure 7 Journal Bearing Plug 'n Play Prognostic Module

Open Systems Architecture: Open systems architecture (OSA) is a design methodology that defines a set of standard publicly known interfaces for specific modules. This published interface standard allows systems to be broken down into independent sub-modules that can be replaced by another party's module as long as it meets the same non-propriety interface format. Each module is viewed as a collection of similar tasks or functions at different levels of abstraction. Figure 8 shows a flow chart of a proposed OSA for a machinery prognostics system. This OSA model has seven sub-components or modules: Human System Interface, Decision Reasoning, Prognostic Processing, Diagnostic Processing, Signal and Feature Processing, Data Acquisition and Sensor. Each module will have a standard input and output interface that enables communication between modules. The hub of the wheel structure represents the communications medium between the modules, which may be accomplished using popular Internet protocols such as TCP/IP or HTTP. This means that modules do not need to reside on the same machine but may reside anywhere on a local, wide area or worldwide network. Open systems architecture design is an essential part to a prognostic's system design to allow maximum flexibility and upgrade ability of the system.

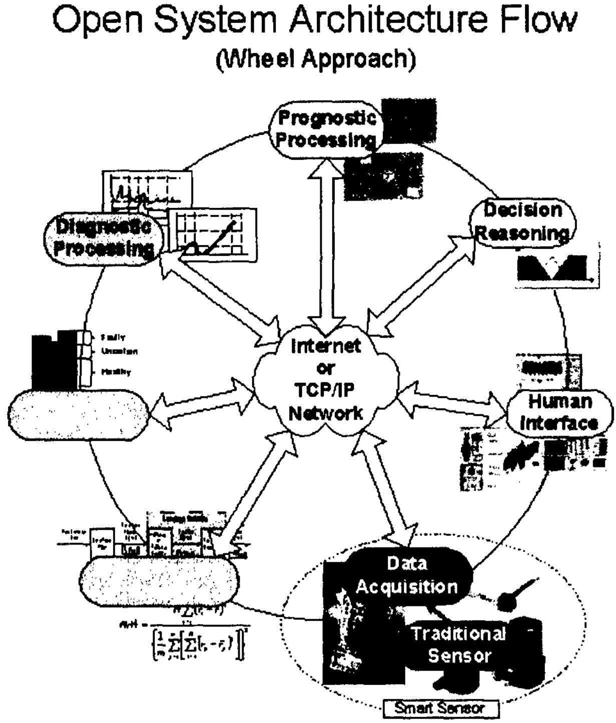

Figure 8 - Data Flow within an Open System Architecture

The requirements of an Open System Architecture (OSA) for prognostic modules such as the ones discussed herein will be further identified by incorporating current OSA formats such as those provided by MIMOSA. Some of the prognostic output protocols that have been considered are (as derived from MIMOSA): Status, State of Health, Rate of Change, Time to Action, Problem Identification, Components Affected, Recommendations, Work Request, Confidence, Remarks/Comments. A detailed discussion of OSAs can be found in [1].

Human System Interface: A proposed human system interface (HSI) concept for incorporating the prognostic modules into a multi-framed, single document interface (SDI) is illustrated in Figure 9. This approach will ensure that critical information is not obstructed or hidden from view by another window of the application. Tab buttons can be utilized to view multiple pages of information with the simple window and hot links will be incorporated to simplify navigation between pages.

The deck navigation frame allows the user to graphically locate compartments within the shipboard platform. This frame has two panels associated with it, allowing the user to graphically pinpoint a specific system or component within the ship. The left portion of the frame will provide a vertical cross-sectional view of the shipboard platform while the right portion of the frame will provide a graphical layout of the selected deck level. The deck level layout will show all the relevant compartments that a user may query. When a user selects the shipboard level and compartment, the equipment selection frame will then update to show all relevant equipment located in that selected compartment. The colors of the deck and compartment level will be color coded to indicate the current health of the system and components. A gray deck and compartment color may be used to indicate that all machinery within that location is of good health and operating normally, while the color red may indicate a system failure or alert message. A different color, maybe yellow, will be used to indicate a system with a low remaining useful life (RUL) or degraded condition. Blue will be used to indicate a selected region on the layout. If the item was originally red or yellow then the selected item will contain hatch diagonal blue lines in order to still indicate the critical condition of the compartment and deck level.

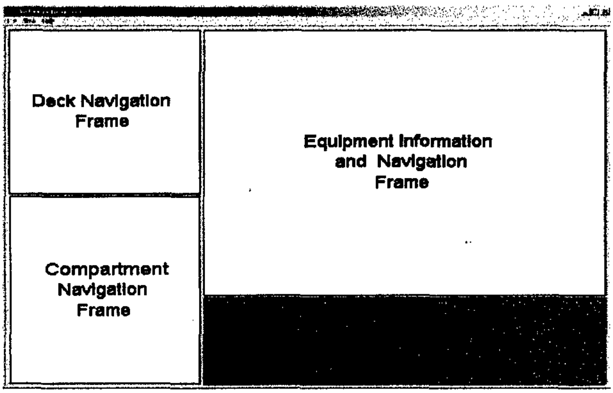

Figure 9 General HSI Layout

The compartment navigation frame will allow the user to visually monitor the heath of all equipment contained within a compartment. The user may then select a piece of equipment for further inspection. The color-coding of the equipment will also have the same methodology as the deck and compartment levels. Additional information may be displayed to the user as the mouse moves over a relevant deck, compartment or component. When a user clicks on a piece of equipment within the compartment, the equipment information and navigation frame will display additional information related to that specific component.

The equipment information and navigation frame allows the user retrieve information about a specific system and sub-components. The top portion of this frame will contain a set of tab controls to view different aspects and information about the system and sub-components. Six tab controls will be utilized for Overview, Detail, Diagnostics, Prognostic, Manuals and Procedures of the system. The "Overview" tab window will contain a picture of the system that will allow mouse-over information and short-cut links to sub-component information. This window will also display the current status and health of the system and sub-components. The current health panel will display the prognostic results for each component with indicated degradation. The current status panel will display information about the current operation configuration and output. The "Details" tab window will display current sensor readings such as temperature, pressures and vibration levels. An image of the system will be displayed in the top right-hand corner to allow the user to navigate between different sub-components. The "Diagnostics" screen will display information about the system's sub-components and an overall health rating for the system. The "Prognostics" window will display the RUL for each sub-component for the current loading profile. This screen will also allow the user to input a future mission profile to determine the RUL under different loading conditions of the system. The user will easily be able to located schematics and detailed drawings using the "Manuals" tab and the "Procedures" tab will give the operator quick access to operational, emergency and maintenance procedures with a list style view control. The results from the prognostics and diagnostics pages could incorporate a list of recommendation and short cuts or hot links to emergency and maintenance procedures based on the fault condition.

The Alert frame is meant to display important information to the user about critical alarms or abnormal events that are occurring across the shipboard platform. Each shipboard system module connected to this system will determine the information displayed in this panel. The alert information will be displayed in a tabular fashion along with date and time information. Each alert message will contain a short cut to allow the user to jump directly to the shipboard system in question by means of a double clicking the message.

A sample layout for a shipboard HSI used for an OSA prognostics system module is illustrated Figure 10. The figure shows the main overview screen from an HSI demonstration system developed as part of a Navy program on Prognostic Enhancements to Diagnostic Systems. A list view of shipboard equipment may also be implemented for the deck and compartment navigation frames. This would allow operators that are not familiar with the shipboard layout to located equipment based on name and not location.

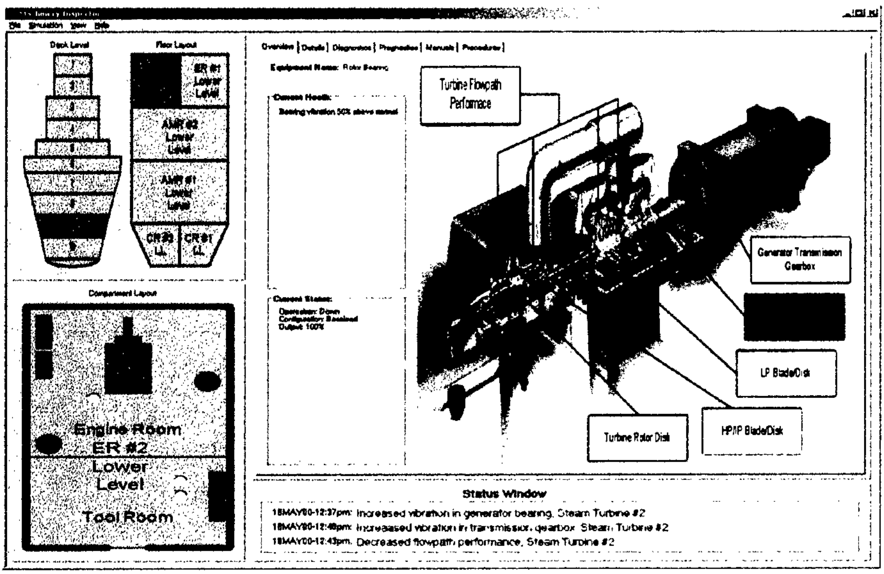

Figure 10 Prognostic Module HSI Demonstration Layout

Conclusions: A comprehensive prognostic capability for critical components and/or systems has been presented that integrates existing technologies such advanced features extraction techniques and empirical/physics-based modeling approaches. The demonstrated prognostic modules utilized a probabilistic framework for identifying confidence bounds associated with specific component time-to-failure or degradation predictions. The developed approach was also capable of integrating component reliability and inspection results with reference to operations and maintenance. The significance of having the developed prognostic modules follow a standard OSA format was highlighted with examples of current OSA considerations identified by MIMOSA. Finally, a human system interface concept was presented for illustrating how information from a complicated health management system could be presented to an end user.

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