Prognostic Enhancements to Diagnostic Systems for Improved Condition-Based Maintenance [1]

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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 focused 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. An advanced 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 such Prognostic Enhancements to Diagnostic Systems (PEDS) using a generic framework for developing interoperable prognostic "modules". Specific prognostic module examples developed for gas turbine engines and gearbox systems are also provided.

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1. INTRODUCTION

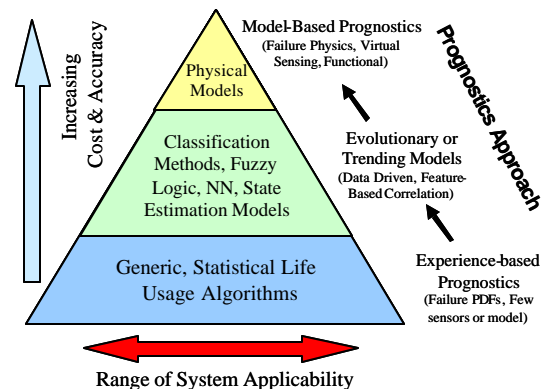Various prognostics and health monitoring technologies have been developed that aid in the detection and classification of developing system faults. However, these technologies have traditionally focused on fault detection and isolation within an individual subsystem. Health management system developers are just beginning to address the concepts of prognostics and the integration of anomaly, diagnostic and prognostic technologies across subsystems and systems. Hence, the ability to detect and isolate impending faults or to predict the future condition of a component or subsystem based on its current diagnostic state and available operating data is currently a high priority research topic.

In general, health management technologies will observe features associated with anomalous system behavior and then relate these features to useful information about the system's condition. In the case of prognostics, this information relates to the condition at some future time. Inherently probabilistic or uncertain in nature, prognostics can be applied to system/component failure modes governed by material condition or by functional loss. Like diagnostic algorithms, prognostic algorithms can be generic in design but specific in terms of application. Various approaches to prognostics have been developed that range in fidelity from simple historical failure rate models to high-fidelity physics-based models. Figure 1 illustrates the hierarchy of potential prognostic approaches in relation to their applicability and relative costs.

Figure 1 – Hierarchy of Prognostic Approaches

This paper will discuss some generic prognostic implementation approaches and provide some specific

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applications to various mechanical systems. The ability to predict the time to conditional or mechanical failure (on a real-time basis) is of enormous benefit and health management systems that can effectively implement the capabilities presented herein offer a great opportunity in terms of reducing the overall Life Cycle Costs (LCC) of operating systems as well as decreasing the operations/maintenance logistics footprint.

2. INCORPORATING PROGNOSTIC TECHNOLOGIES

Health management system architectures must allow for the integration of anomaly, diagnostic, and prognostic (A/D/P) technologies from the component level all the way up through the vehicle or platform level. In general, A/D/P technologies observe features associated with anomalous system behavior and relate them to useful information about component or system condition. Before getting into some specific examples of diagnostic and prognostic techniques applied to different aspects of an air vehicle, a brief description of some of the more common technical approaches are given. The software modules are currently in prototype development stage.
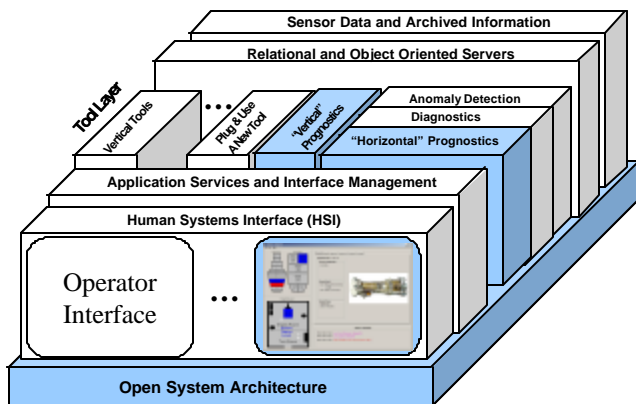

Figure 2 - PEDS Plug and Play "Toaster" Model

The approach for the PEDS program is to develop prognostic software that is modular and could have multiple transition opportunities. The "toaster" model (popular in software engineering) illustrates the concept for "plug and play" functionality of the modules. The areas in blue are the main focus areas of the current PEDS effort. They will be installed in an arrangement where data is gathered from equipment or archives and processed by the module. The results will be viewable and analyzed by both Navy and contractors through developed GUI's (Graphical User Interfaces).

From an implementation perspective, it is convenient to think of prognostics as horizontal or vertical modules in the architecture. This categorical differentiation should not be confused with the different prognostic approaches. It is merely a convenient way to define the information

and interface requirements that the prognostic module may or may not have. For instance, a horizontal module uses anomaly detection and failure mode diagnosis information to make a prognosis. This is usually the more accurate method, in which we integrate the knowledge about the type of failure and its severity into the time series prediction. The prediction is accomplished in a number of ways including: simple trending algorithms based on recursive curve fitting, artificial intelligence (implicit) predictions, state-space tracking algorithms, and higher-fidelity physics of failure algorithms to name just a few. A vertical prognostics module, by contrast, is not explicitly dependent on the diagnostics information and will either input just time and usage conditions or in addition, some measured data. Experience-based statistical failure distributions can be applied to determine the probability of failure within a future time period given the prior time/usage history. There exist many lifing models to do this type of prediction on turbomachinery components and bearings, for instance. Other vertical methods, such as signal correlation and pattern recognition methods, which identify patterns that can be projected forward in time, have also been proposed. These methods are data-driven and are usually less desirable as comprehensive failure examples need to be provided. This is usually not possible to do prior to fielding the system, so such algorithms must rely on "on-the-job" training, which is not acceptable for critical applications. Typically, we view horizontal prognostics as the preferred path towards more accurate predictions and vertical prognostics as a fall back position in situations where there does not exist sufficient sensor information or justification to develop horizontal prognostics. Either way, there exists a need to provide interoperability for both vertical and horizontal prognostics.

Evolving Open Systems Standards

Openness is a general concept that denotes free and unconstrained sharing of information. In its broadest interpretation, the term "open systems" applies to a systems design approach that facilitates the integration and interchangeability of components from a variety of sources. For a particular system integration task, an open systems approach requires a set of public component interface standards and may also require a separate set of public specifications for the functional behavior of the components. The development of the open-systems standards relevant to Condition-based Maintenance (CBM) and Prognostics and Health Management (PHM) development has been pursued by an International Standards Organization (ISO/TC 108/SC 5) committee, a consortium of condition monitoring companies (MIMOSA), and a DoD Dual-Use Science and Technology program (OSA/CBM) lead by Boeing.

The International Standards Organization (ISO) has formed a Subcommittee (SC 5) of the Mechanical Vibrations Technical Committee (TC 108). SC 5 "Condition Monitoring and Diagnostics of Machines." The scope of the committee is the *"standardization of the procedures, processes and equipment requirements uniquely related to the technical activity of*

condition monitoring and diagnostics of machines in which selected physical parameters associated with an operating machine are periodically or continuously sensed, measured and recorded for the interim purpose of reducing, analyzing, comparing and displaying the data and information so obtained and for the ultimate purpose of using this interim result to support decisions related to the operation and maintenance of the machine."

MIMOSA is a not-for-profit trade association founded in 1994 and incorporated in December of 1996. Their general purpose is the development and publication of open conventions for information exchange between plant and machinery maintenance information systems. The core of the MIMOSA development activity is the MIMOSA CRIS (Common Relational Information Schema). The second version of the CRIS (CRIS V2.1) was released in May 2000 and is publicly available at the MIMOSA website [*http://www.mimosa.org/*]. The CRIS defines a relational database schema for machinery maintenance information. The schema provides broad coverage of the types of data that need to be managed within the CBM domain.
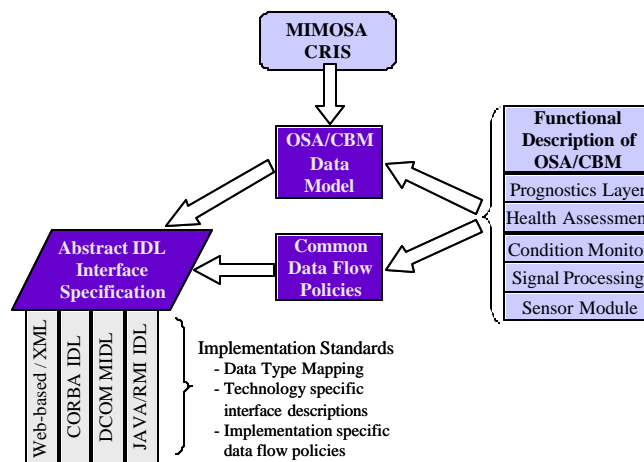

Figure 3 - Outline of the OSA/CBM Architecture

The OSA/CBM development approach was formulated based on the assumption that the large body of work that constitutes the MIMOSA open standards would be used as a basis for development. The MIMOSA interface standards define open data exchange conventions for sharing of static information between CBM systems (openness at the intra-system level). The goal of the OSA/CBM project is the development of an architecture (and data exchange conventions) that enables interoperability of CBM components (openness at the inter-system level). Within the open systems' approach, the proprietary system solution is addressed using a MIMOSA-compliant "wrapper" that exposes a set of public MIMOSA compliant server interfaces. The interface set allows external clients open access to the information generated within the proprietary system solution. Alternatively, a CBM system can operate openly

at the inter-system and intra-system levels also. In this case the individual components are exposed at the functional component interfaces. These component interfaces offer access to the data and services supplied by the component, and provide for open information flow between components during system operation. In addition, components may be readily replaced by components with improved capability as long as they follow the same public interface standards.

The components of the OSA/CBM architecture are shown in Figure 3. The primary inputs to the architecture definition are the functional description of the layers (as discussed above) and the MIMOSA CRIS, along with the general requirements described in the section on CBM Architecture. An object oriented data model has been defined (using Unified Modeling Language – UML - syntax) based upon a mapping of the MIMOSA relational schema to the OSA/CBM layers. The focus is on describing the structure of the information that might be of interest to clients of that layer. In fact, in the same way that the MIMOSA interface standard does not impose a structure on the components that comprise a MIMOSA compliant system, OSA/CBM does not impose any requirements on the internal structure of compliant software modules. The architectural constraints are applied to the structure of the public interface and to the behavior of the modules. This approach allows complete encapsulation of proprietary algorithms and software and is a key enabler to prognostic module implementation.

3. REVIEW OF PROGNOSTICS APPROACHES

For a health management or CBM system to possess prognostics implies the ability to predict a future condition. Inherently probabilistic or uncertain in nature, prognostics can be applied to system/ component failure modes governed by material condition or by functional loss. Like the diagnostic algorithms, prognostic algorithms can be generic in design but specific in terms of application. This section briefly describes some approaches to prognostics.

Experienced-Based Prognostics

In the case where a physical model of a subsystem or component is absent and there is an insufficient sensor network to assess condition, an experienced-based prognostic model may be the only alternative. This form of prognostic model is the least complex and requires the failure history or "by-design" recommendations of the component under similar operation. Typically, failure and/or inspection data is compiled from legacy systems and a Weibull distribution or other statistical distribution is fitted to the data. An example of these types of distributions is given in Figure 4. Although simplistic, an experienced-based prognostic distribution can be used to drive interval-based maintenance practices that can then be updated on regular intervals. An example may be the maintenance scheduling for a low criticality component that

has little or no sensed parameters associated with it. In this case, the prognosis of when the component will fail or degrade to an unacceptable condition must be based solely on analysis of past experience or OEM recommendations. Depending on the maintenance complexity and criticality associated with the component, the prognostics system may be set up for a maintenance interval (i.e. replace every 1000+/-20 Effective Operating Hrs) then updated as more data becomes available. Having an automated maintenance database is important for the application of experience-based prognostics.
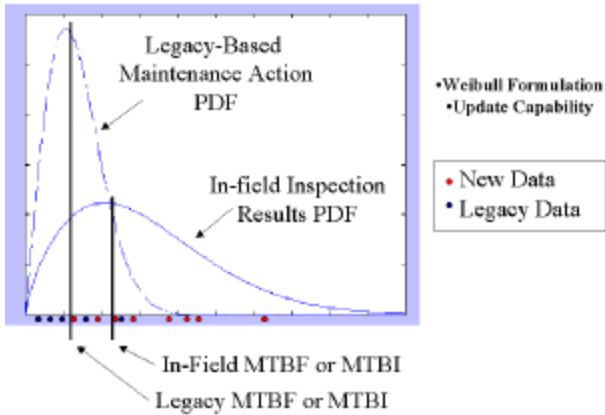

Figure 4 - Experienced-Based Approach

Evolutionary Prognostics

An evolutionary prognostic approach relies on gauging the proximity and rate of change of the current component condition (i.e. features) to known performance degradation or component faults. Figure 5 is an illustration of the technique. Evolutionary prognostics may be implemented on systems or subsystems that experience conditional failures such as compressor or turbine flow path degradation. Generally, evolutionary prognostics works well for system level degradation because conditional loss is typically the result of interaction of multiple components functioning improperly as a whole. This approach requires that sufficient sensor information is available to assess the current condition of the system or subsystem and relative level of uncertainty in this measurement. Furthermore, the parametric conditions that signify known performance related faults must be identifiable. While a physical model, such as a gas path analysis or control system simulation, is beneficial, it is not a strict requirement for this technical approach. An alternative to the physical model is built in "expert" knowledge of the fault condition and how it manifests itself in the measured and extracted features.
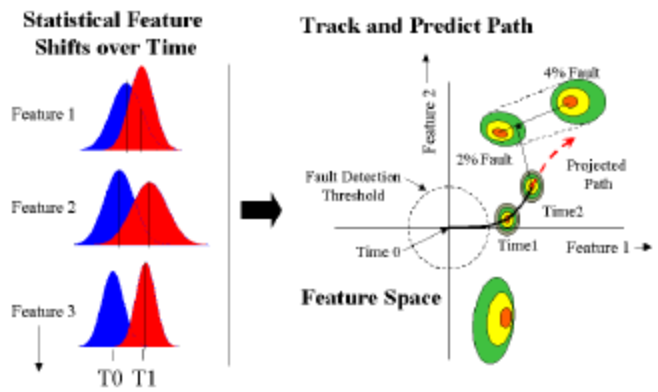

Figure 5 - Evolutionary Prognostics

Feature Progression and AI-Based Prognostics

Utilizing known transitional or seeded fault/failure degradation paths of measured/extracted feature(s) as they progress over time is another commonly utilized prognostic approach. In this approach, neural networks or other AI techniques are trained on features that progress through a failure. In such cases, the probability of failure as defined by some measure of the "ground truth" is required as a-priori information as described earlier. This "ground truth" information that is used to train the predictive network is usually obtained from inspection data. Based on the input features and desired output prediction, the network will automatically adjusts its weights and thresholds based on the relationships between the probability of failure curve and the correlated feature magnitudes. Figure 6 shows an example of a neural network after being trained by some vibration feature data sets. The difference between the neural network output and the "ground truth" probability of failure curve is due to error that still exists, after the network parameters have optimized, to minimize this error. Once trained, the neural network architecture can be used to intelligently predict these same features progressions for a different test under similar operating conditions.
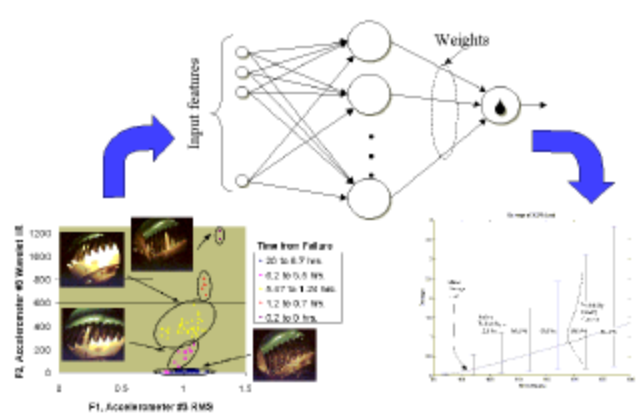

Figure 6 - Feature/AI-Based Prognostics

State Estimator Prognostics

State estimation techniques such as Kalman filters or various other tracking filters can also be implemented as a prognostic

technique. In this type of application, the minimization of error between a model and measurement is used to predict future feature behavior. Either fixed or adaptable filter gains can be utilized (Kalman is typically adapted, while Alpha-Beta-Gamma is fixed) within an nth-order state variable vector. For a given measured or extracted feature f, a state vector can be constructed as shown below.

$$x = \begin{bmatrix} f & \dot{f} & \ddot{f} \end{bmatrix}^T \tag{1}$$

Then, the state transition equation is used to update these states based upon a model. A simple Newtonian model of the relationship between the feature position, velocity and acceleration can be used if constant acceleration is assumed. This simple kinematic equation can be expressed as follows:

$$f(n+1) = f(n) + \dot{f}(n)t + \frac{1}{2}\ddot{f}(n)t^2 \tag{2}$$

where f is again the feature and t is the time period between updates. There is an assumed noise level on the measurements and model related to typical signal-to-noise problems and unmodeled physics. The error covariance associated with the measurement noise vectors is typically developed based on actual noise variances, while the process noise is assumed based on the kinematic model. In the end, the tracking filter approach is used to track and smooth the features related to the prediction of a given failure mode progression, and thus, it is used in conjunction with a diagnosis.

Physics-Based Prognostics

A physics-based stochastic model is a technically comprehensive modeling approach that has been traditionally used for component failure mode prognostics. It can be used to evaluate the distribution of remaining useful component life as a function of uncertainties in component strength/stress or condition for a particular fault. The results from such a model can then be used to create a neural network or probabilistic-based autonomous system for real-time failure prognostic predictions. Other information used as input to the prognostic model includes diagnostic results, current condition assessment data and operational profile predictions. This knowledge-rich information can be generated from multi-sensory data fusion combined with in-field experience and maintenance information that can be obtained from data mining processes. While the failure modes may be unique from component to component, the physics-based methodology can be applied to many different types of mechanical components. An example of a physical, model-based prognostic technique is shown in Figure 7 for a rotating blade.
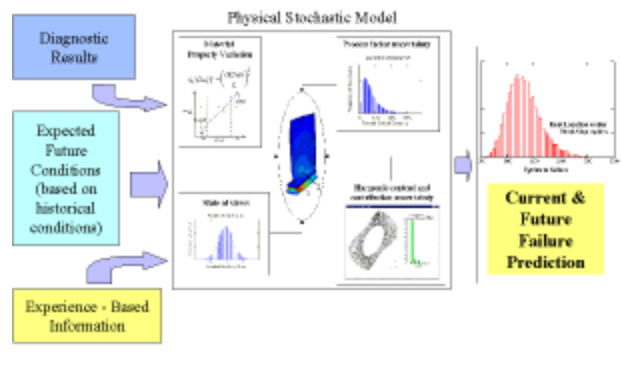

Figure 7 - Physics-Based Prognostics

4. SOME PROGNOSTIC MODULE EXAMPLES

Gas Turbine Fuel Nozzle Prognostics

The purpose of this investigation was to identify features that could be incorporated in an automated system for diagnosing clogged fuel nozzles. The main focus was diagnostics, but there is potential for incorporating a prognostics element given sufficient clogging progression data. This example focuses largely on a feature-based approach.

Figure 8 – Clean Nozzle and One with Severe Clogging

Clogging reduces the efficiency of the combustion process and can create potentially damaging hot spots in the combustor and turbine sections. At startup, this is especially true to the extent that "hot starts" or "no starts" may be produced. For this project, Impact Technologies used test data from several start-ups of an Allison 501-K17, taken at NAVSEA Philadelphia, comprising both clean and fouled fuel nozzles.

The diagnosis of fuel nozzle clogging was demonstrated using an analysis of gas turbine sensor values. Features were identified from the Fuel Manifold Pressure (FMP), Turbine Inlet Temperature (TIT), Engine speed (RPM), and Fuel Flow (Wf). Data from the four different tests is shown in histogram plot. The baseline data was the December 13th dataset, in which the nozzles were known to be clean. The three other data sets indicate progressive clogging conditions. The diagnostic scalars are as follows. The delta (1) is the time delay between the end of the FMP increase, as defined by the baseline, and the start of the TIT increase, again defined by the baseline (multiplied by 100 for scaling purposes). The Average FMP vs

RPM Difference is the average difference of the actual FMP values at a given RPM and the expected FMP values for that RPM. This was calculated for only the FMP points associated with the start event. The max FF/FMP ratio is the maximum Fuel Flow (FF) to FMP ratio for the start. The TIT slope is the slope of the TIT line. These features appear to be reliable indicators of fuel nozzle clogging that can provide ample warning prior to full start.
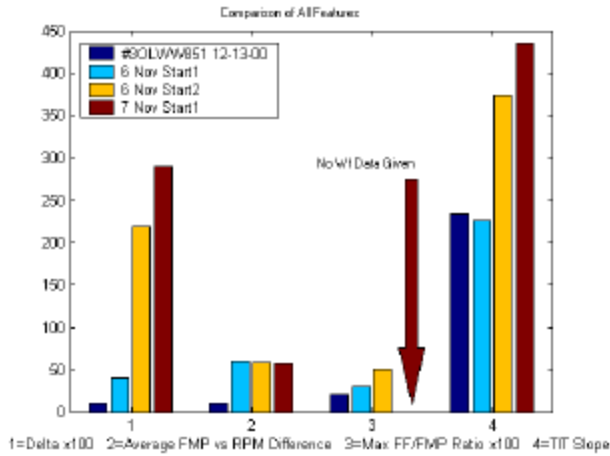

Figure 9 – Feature Diagnostic Scalars at Baseline and under Degraded (Fouling) Conditions

Prognostic adaptations focus on the automated interpretation of the nozzle clogging projected in time and a recommended change threshold based upon the features identified. The prognostic output should be a recommended number of starts or operational hours for a nozzle change.

Gas Turbine Compressor Wash Prognostics

The prognostic model was developed based on data from fouling tests taken at NSWCC in Philadelphia, PA and is an example of evolutionary prognostics approach. It is based upon some specific features and a simple model for compressor efficiency. In order to simulate the amount of salt the typical Navy gas turbine is exposed to on a normal deployment, a 9% salt solution was injected into the engine intake. Over the course of the entire test (3 days) approximately 0.0057m^3 of salt was used to induce compressor degradation at four different load levels (1/3, 2/3, standard and full load levels or "bells"). This method of testing was performed on both Allison 501 and LM2500 Units. Figure 10 shows a borescope image of the salt deposits on the LM2500 1st stage blading.
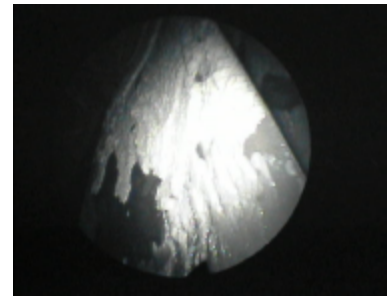

Figure 10 - Borescopic Image of Salt deposits: 1st stage Blading

In addition to fouling the two engines, testing was also performed on the effects of on-line washing for the Allison 501. The machine was crank washed and fouling was reinitiated. Specifically, at approximately 2% CDP drops, an on-line waterwash was performed using detergent. This cycle was completed 4 times at four different load levels.

During the testing, several of the critical parameters were monitored and their response to degradation was tended. Table 1 contains the measured parameters with their units and ranges (Shaft RPM and Ngg are for the LM2500 testing only)

Table 1 – Recorded Parameters from the Digital Control System

Parameter	Units	Ranges
N_{gg}	RPM	0 → 9575
Q_{fuel}	GPM	0 → 97
TIT	°F	0 → 2000
CDT	°F	0 → 1468
CDP	psig	0 → 300
CIT	°F	0 → 500
Load	k-lbf	0 → 300
Shaft RPM	RPM	0 → 274
$P_{barometric}$	inHg	

When a compressor undergoes fouling, several key performance factors are affected. The most sensitive of these factors is the compressor capacity or referred mass flow. (Peltier et al, 1995) This is because loss of capacity comes from throat blockage and increases in roughness on the suction side of the blading. Unfortunately, in most practical naval applications, compressor capacity is not reliably determinable. The compressor inlet temperature (CIT), outlet temperature (CDT), inlet total pressure (CIP$_T$) and discharge total pressure (CDP$_T$) can typically be used to find compressor efficiency. (Boyce 1995) However CDT, CDP$_T$ are not standard sensors in most Naval platforms.

$$?_{adb} = \frac{\left[\left(\dfrac{CDP_T}{CIP_T} \right)^{?-1/?} - 1 \right]}{\left[\left(\dfrac{CDT}{CIT} \right) - 1 \right]} \tag{3}$$

With total pressure measurements absent there is not enough information to calculate compressor adiabatic efficiency in its strict form (as was shown above).

Alternately, the following may be used to estimate the efficiency.

$$h_{adb} = \frac{(h_{3t} - h_{1t})_{ideal}}{(h_{3t} - h_{1t})_{actual}} \qquad (4)$$

Where h is the enthalpy of the discharge (3) or inlet (1) condition and the ideal refers to an isentropic process.

The compressor performance prognostic module consists of data preprocessing and specific diagnostic/prognostic algorithms for assessing the current and future conditions of the gas turbine. The data preprocessor algorithms examine the unit's operating data and automatically calculate key corrected performance parameters such as pressure ratios and efficiencies at specific load levels in the fashion already described. As fouling starts to occur in service, probabilistic classifiers match up corresponding parameter shifts to fouling severity levels attained from these tests with corresponding degrees of confidence.

A probabilistic-based technique was developed that utilizes the known information on how measured parameters degrade over time to assess the current severity of parameter distribution shifts and project their future state. The parameter space is populated by two main components. These are the current condition and the expected degradation path. Both are multi-variate Probability Density Function (PDFs) or 3D statistical distributions. Figure 11 shows a top view of these distributions. The highest degree of overlap between the expected degradation path and the current condition is the most likely level of compressor fouling.

In general, the probability that the current condition (C), may be attributed to a given fault (F) is determined by their joint probability density function. If we assume C and F to be normally distributed, the probability of association (Pa) can be found using:

$$p_a = 2\Phi(-\frac{\overline{F-C}}{\sqrt{s_f^2 + s_c^2}}) = 2\Phi(-b) \qquad (5)$$

where:

$\overline{F}, \overline{C}$ = the mean of the distributions F and C respectively

s_f, s_c = the standard deviation of the F and C distributions

The function F (β) is the standard normal cumulative distribution. The notation ß is defined as the fault index.

Once the current severity level is known with a high degree of confidence, a fault-weighted projection is performed using a modified double-exponential smoothing technique. This approach is more appropriate than a simple multi-variate regression because it weights the most recent performance degradation trends and evolves the current conditions toward the expected degradation path.

To manipulate the data into the form of this model, the time dependency of the test results had to be removed because of the unrealistic fouling rates. The percent changes in static pressure ratio, fuel flow, and CDT were recast in terms of ¼ % pseudo-efficiency drops. This increment was chosen because it was the highest resolution that still permitted statistical analysis. With the assimilation of the data into these discrete bands, the statistical parameters (e.g., mean and standard deviation) can be ascertained for use in the prognostic model. Figure 11 shows the evolution of the compressor degradation for the LM-2500 test at 1% pseudo-efficiency drops (for visual clarity). The top two plots illustrate the distributions of pressure ratio and fuel flow respectively while the bottom two provide the joint probability distributions.
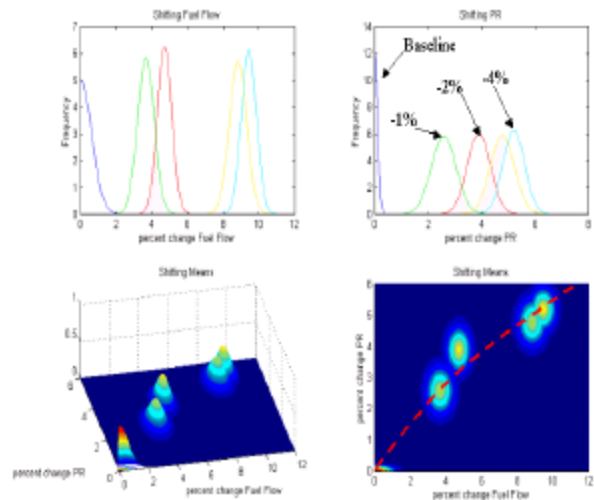

Figure 11 - Prognostic Model Visualization

Once the statistical performance degradation path is realized along with the capability to assess current degradation severity, the final step was to implement the predictive capability. The actual unit-specific fouling rate is combined with historical fouling rates with a double exponential smoothing method. This time series technique weights the two most recent data points over past observations. The following equations give the general formulation. (Bowerman, 1993). Figure 12 shows how this technique can give significantly different results than standard regression.

$$S_T = \alpha y_T + (1-\alpha)S_{T-1} \qquad (6)$$

$$S^{[2]}_T = \alpha S_T + (1-\alpha)S^{[2]}_{T-1} \qquad (7)$$

$$\hat{y}_{T+t}(T) = \left(2 + \frac{at}{(1-a)}\right)S_T - \left(1 + \frac{at}{1-a}\right)S_T^{[2]} \qquad (8)$$
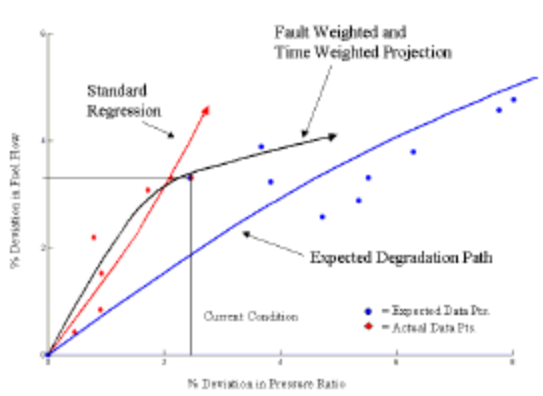

Figure 12 - Prediction of Degradation Rates

The test data made two essential contributions to the development of this prognostic model. First, it provided a means by which to validate an analytical model of how performance parameters change as a function of compressor fouling. Secondly, they gave insight into the sensitivity and statistical distributions of performance parameters as a function of load. Hence, having been developed and validated on real data, a large amount of knowledge is "built in" to the prognostic model.

Gearbox Prognostic Module

Under the Phase I SBIR effort a physics-based model for geartooth failure was developed. It illustrates the physics-based model approach. This model was chosen because it could be validated and calibrated on transitional (run-to-failure) data from the MDTB (Mechanical Diagnostics Test Bed) at the Penn State Applied Research Lab.
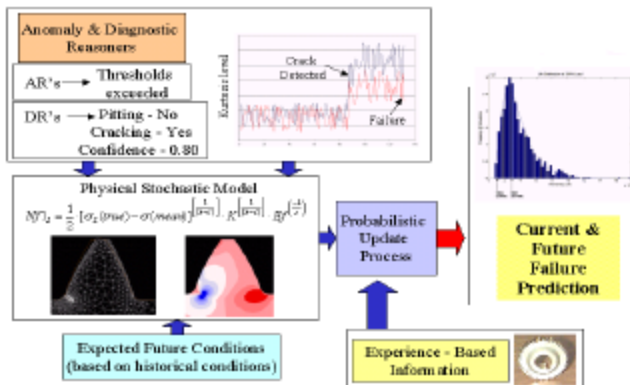

Figure 13 - Gear Model-Based Prognostics

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 13 is a block diagram that illustrates the functionality of this module.

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 and cracking could also be 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.

$$Nf1_L = \frac{1}{2} \cdot [s_L(true) - s(mean)]^{\left[\frac{1}{(n-c)}\right]} \cdot K^{\left[\frac{1}{(n-c)}\right]} \cdot Ef^{\left(\frac{-1}{c}\right)} \qquad (9)$$

where:

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 stress formulation accounts 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. Handling such uncertainties is an important real-world necessity when it comes to mechanical failure.

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

$$Damage = \left(\frac{n}{Nf1_L}\right)^{r_1} \qquad (10)$$

where:

n = number of cycles experienced
r1 = non-linear damage exponent
Nf1 = 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:

$$\frac{\partial a}{\partial N} = C \Delta Ki^m \qquad (11)$$

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

$$P_{total} = P(i) * P(p) \qquad (12)$$

where:

$$P(p) = \frac{\#Damage > 1}{\#MonteCarlo\_pts} \qquad (13)$$

The module considered about 25 vibration features as a function of time. Specific features that correlate with gear tooth cracking were used to generate a "Signal-based Prob. of Failure" number is based on a fusion (Dempster-Shafer) combination of these features. On a parallel path, the raw data is evaluated by the physics-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. An "Actual Mean Time To Failure (MTTF)" is generated based on the signal information while an "Expected MTTF" is estimated based on the operational profile (speed and torque) from the physical model. Extrapolating past speed and loading profile statistics over some future analysis time period provides a future probability of failure.

An aircraft or shipboard gearbox of sufficient importance to warrant a dedicated prognostic module would need to be linked to a on-line data acquisition system capable of extracting vibration, speed and load data. The module would need to contain real world calibrated, physic-based algorithms for accumulating the material damage of a gear as a function of operating parameters and algorithms for processing the vibration data to extract relevant vibration features. It would also need to access past operating condition and extrapolate them into the future and allow for a simulated future operating profile. Lastly, a means provide an update to the model using a diagnosis of gear wear or with failure rates or inspection results from similar gearboxes would be necessary.

5. CONCLUSIONS

This paper discussed many concepts associated with prognostic module development under the PEDS (Prognostic Enhancements to Diagnostic Systems) program. A review of prognostic approaches, implementation issues including current OSA developments, and several explicit examples were provided. The variations in data, modeling and reasoning for the different prognostic approaches was also discussed and illustrated with gas turbine fuel nozzle clogging, compressor wash interval prediction, and gearbox prognostic module developments. Data availability, dominant failure or degradation mode of interest, modeling and system knowledge, accuracies required and criticality of the application are some of the variables that determines the choice of prognostic approach. The ability to predict the time to conditional or mechanical failure (on a real-time basis) is of enormous benefit and health management systems that can effectively implement the capabilities presented herein offer a great opportunity in terms of reducing the overall Life Cycle Costs (LCC) of operating systems as well as decreasing the operations/maintenance logistics footprint.

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