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DEVELOPMENT OF DIAGNOSTIC AND PROGNOSTIC TECHNOLOGIES FOR AEROSPACE HEALTH MANAGEMENT APPLICATIONS

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Abstract: Effective aerospace health management integrates component, subsystem and system level health monitoring strategies, consisting of anomaly/diagnostic/prognostic technologies, with an integrated modeling architecture that addresses failure mode mitigation and life cycle costs. Included within such health management systems will be various failure mode diagnostic and prognostic (D/P) approaches ranging from generic signal processing and experience-based algorithms to the more complex knowledge and model-based techniques. While signal processing and experienced-based approaches to D/P have proven effective in many applications, knowledge and model-based strategies can provide further improvements and are not necessarily more costly to develop or maintain. This paper will describe some generic prognostic and health management technical approaches to confidently diagnose the presence of failure modes or prognose a distribution on remaining time to failure. Specific examples of D/P strategies are presented herein that address valves, hot section lifing and performance degradation of an Auxiliary Power Unit (APU) system. In addition, a model is presented for a Power Take Off (PTO) shaft and AMAD snout bearing.

Keywords: Prognostics, Diagnostics, Aerospace

Introduction: Various health monitoring technologies have been developed for aerospace applications that aid in the detection and classification of developing system faults. However, these technologies have traditionally focussed 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 addition, these technologies must be capable of communicating the root cause of a problem across subsystems and propagating the up/downstream effects across the health management architecture. This paper will introduce some generic prognostic and health management (PHM) system algorithmic approaches that are demonstrated within various aircraft subsystem components with the ability to predict the time to conditional or mechanical failure (on a real-time basis). Prognostic 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.

Generic Diagnostic and Prognostic Technologies: Prognostic and Health Management (PHM) 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 aerospace vehicle level. In general, A/D/P technologies observe features associated with anomalous system behavior and then relates these features to useful information. 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. These generic descriptions will be focussed more on the prognostic algorithm side because less information is currently published in this area than on diagnostics.

Prognostics simply denotes 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 will briefly describes five 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 form of prognostics that is practical. 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 1. 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 an electrical component or airframe component that has little or no sensed parameters and is not critical enough to warrant a physical model. 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 EFH) then updated as more data becomes available.

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 faults. Figure 2 is an illustration of the technique. Evolutionary prognostics may be implemented on systems or subsystems that experience conditional failures such as an APU gas 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 fault must be identifiable. While a physical model, such as a gas path analysis or control system simulation, is beneficial, it is not a 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.

Experienced/Inspection-Based PHM

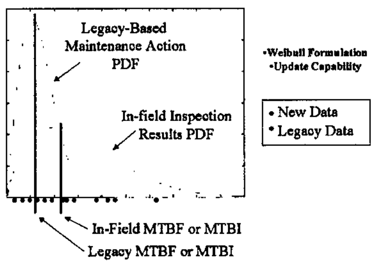

Figure 1 - Experienced-Based Approach

Feature/Evolutionary PHM

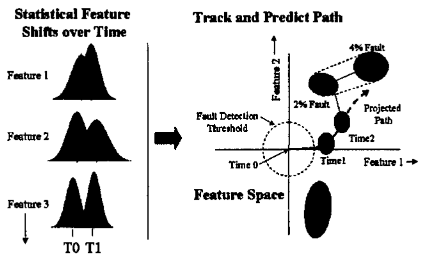

Figure 2 - Evolutionary Prognostics

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" which is required as a-priori information. The "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 it sees between the probability of failure curve and the correlated feature magnitudes. Once trained, the neural network architecture can be used to intelligently predict these same features progressions for a different test under similar operating conditions.

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 n^{th}-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 as an example. 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 predicting a failure.

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 remain consistent across the air vehicle. An example of a physical, model-based prognostic technique is shown in Figure 3 for a rotating blade.

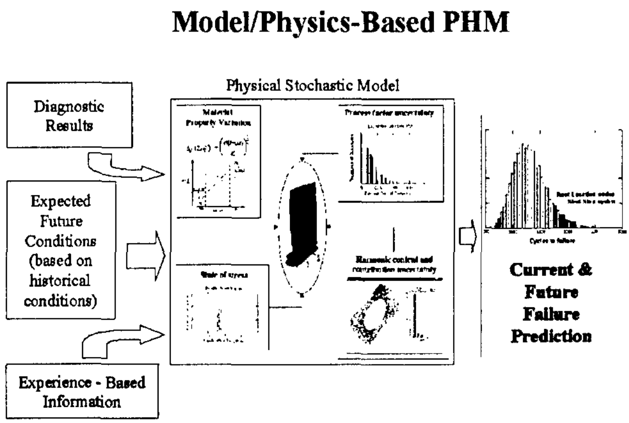

Figure 3 - Physics-Based Prognostics

Relationship to Failure Mode Model: It is important for a prognostic and health management system must to have a direct relationship to a model containing the information on how components, subsystems, and systems interact in operation. In addition, this model should contain information on how the system failure modes, sensors, and health monitoring technologies are related. This is necessary so that failure symptoms and failure propagation can be traced back to root cause failures for fault isolation purposes.

Essentially, information related to the signal and flow relationships between system components, failure modes and across system effects is linked to the sensors and A/D/P algorithms within the system architecture. This captured information is what allows A/D/P algorithms to remain as generic as possible and provides a "place holder" for the algorithms results. In a PHM system implementation, anomalous signals, indicted failure modes, diagnostic monitors or prognostic warning information is analyzed with this information in order to isolate the root cause of a problem. In addition, the reasoners will utilize this information to prioritize maintenance/operational actions that should be taken to prevent a failure.

An example of how the HM system architecture functions within such a failure mode model representation is given in Figure 4. In this figure, an anomaly detection algorithm (A) monitors four sensors (S). If the anomaly algorithm detects an off nominal condition, then only Failure modes FM1 and FM3 are "flagged" as potential failure modes (FM2 is not a possibility because there is no connectivity within this model).

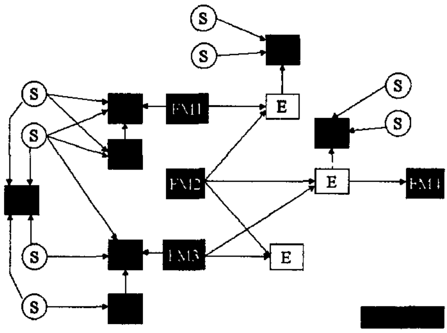

Figure 4 - Generic Representation of Failure Modes, Sensors and HM Technologies

In Figure 4, items to the left of the failure modes (FM's) are health monitoring aspects that attempt to detect the failure modes <u>before</u> they occur. Things to the right of the failure modes are the effects (E) of the failure mode or HM aspects that attempt the isolate which failure mode has already occurred.

Diagnostic Monitors (D) can either function as traditional BIT (Built In Tests) with 0 or 1 outputs denoting that a failure symptom or effect has been observed or they can provide "grayscale" measures of the confidence and severity of a symptom or effect. Continuing with the example, if a Diagnostic Monitor (D) were to observe a symptom of FM3, then the HM reasoner would then have some additional collaborative information to say that FM3 has the higher potential to have occurred. The Prognostic Monitor (P) on FM3 will provide the Mean Time to Failure (MTTF) with confidence bounds for that failure mode.

Let's imagine that Figure 4 represents the failure modes for a rolling element ball bearing. A physics-based prognostic model of the bearing (P) could calculate the current probability of a failure for failure mode (FM3) and project the future probability of failure based on speed and temperature (from sensed parameters) only. However, in this example, imagine that a diagnostic algorithm (D) uses data from a vibration transducer (S) to determine an unbalance or misalignment condition and uses vibration features (spike energy or kurtosis) to detect when significant spalling (FM3) of the outer race has occurred. For the majority of the life of the bearing, the diagnostic algorithms do not make any diagnostic reports and the physics-based prognostic model goes about evaluating remaining useful life. However, when the diagnostic elements diagnose higher than normal unbalance, the prognostic model would utilize this information and determine that life is being accumulated at a faster than expected rate. The HM system reasoners would then be capable of putting together these pieces of evidence to alert the maintainers to examine the bearing at an appropriate time. A prognostic module like this is presented later in this paper.

Now that the concepts for generic HM system technologies and their relationship failure mode models have been introduced, the remainder of the paper will be focussed on some specific model-based diagnostic and prognostic algorithms developed for different aerospace applications. Keep in mind that the output from these dedicated algorithms are processed within a failure mode model by the HM reasoners so that operations and maintenance decisions can be made with knowledge coming from all aspects of the system. A diagnostic algorithm for detecting unhealthy surge control valve operation and performance degradation associated with an APU is presented first. Next, prognostic algorithms for predicting when an APU will reach an EGT (exhaust gas temp.) limit or hot section remaining useful life limit is presented. The final example provides a prognostic model for a PTO (power take-off) shaft and associated bearings.

Surge Control Valve Diagnostics: Diagnostics is often defined as classification of anomalous system behavior to known fault conditions. While generic algorithms are sometimes capable of performing diagnostics, faults must be identified a-priori within an integrated modeling architecture that links anomalous conditions to particular failure modes. Often a more direct approach is to develop a specific fault classifier to diagnose a critical failure mode. Model-based diagnostic approaches are often implemented for these situations and they utilize knowledge (i.e. models) of a given system and compare expected outcomes to measured ones in order to help classify a fault condition.

It is always important to identify the sensory data that can enable a model-based diagnostic algorithm. Due to the fact that the failure mode model allows for a clear vision of inter-system relationships, the data required for diagnostics may already be present if the system is viewed on the whole. When existing or intra-system sensory data can be utilized for shared diagnostic purposes, the benefits of implementing such an approach becomes great and the expense of additional sensors is avoided. That was indeed the case for the surge control valve (SCV) diagnostic approach developed and described next.

In this case, the sensor information from the APU was used to diagnose the health of the surge control valve. Specifically, the response characteristics of the APU speed and EGT sensors after the surge control valve was commanded were used to predict the response time of the SCV and then infer the health condition. Figure 5 shows some of the data that was used to develop a Neural-Fuzzy classifier for diagnosing Surge Control and Load Control Valve sticking in a military fighter Auxiliary Power Unit (APU). To diagnose the health of the SCV or LCV (based on whether they were sticking or failed open/closed) a Neuro-Fuzzy classifier was trained on normal and faulty response characteristics of the APU responses to the valves being commanded. When the valve is sticking, the APU response characteristics are different in a predictable way (i.e. less overshoot in the EGT and speed responses).

A back-propagation neural network was trained on the overshoot levels and associated timing after either valve was commanded. A combination of laboratory results and modeling was used to develop the training data for healthy and faulty valve conditions. Based on these overshoot levels and timing, the valve response time is predicted by the neural network as shown in Figure 6. A healthy response time for the valves was in the range of 0.1 to 0.2 seconds, and anything greater than that would be suspect to sticking. Based on the valve response prediction of the neural network, a fuzzy logic reasoner translated the response time to a health measure of the valve. A value close to 1.0 was considered healthy and values lower than 0.75 would start to indicate a potential valve-sticking situation. It is important to note that the diagnostics achieved in this example was the result of a thorough understanding of the inter-component relationships captured in the modeling environment previously discussed. Also, in this case, prognostics was not feasible because of the highly unpredictable nature of this failure mode. Hence, this module only diagnosed the health of the valve and did not attempt to predict a MTTF.

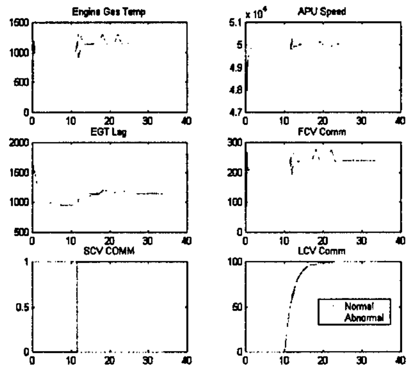

Figure 5(a) - Response in APU Speed and EGT After Surge Control Valve Command

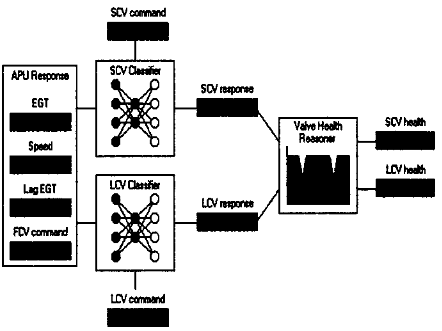

Figure 5(b) - Model-Based SCV Fault Diagnosis

APU Performance Diagnostics and Prognostics: The next example was specifically developed for monitoring the performance degradation of an APU and includes both a diagnostic and prognostic component. The combined algorithm is probabilistic in nature and utilizes statistically significant shifts in key APU performance parameters to diagnose a current level of degradation and then performs a multi-parameter, exponentially weighted projection to predict future degradation. This technique would be considered an evolutionary prognostic technique.

This feature-based diagnostic and prognostic approach relies on gauging the proximity and rate of change of the current system condition to known performance faults. This multi-parameter, evolutionary technique has already been shown to be capable of identifying degraded performance in propulsion systems (Roemer and Ghiocel, 1998).

The process involves assigning non-normal or normal Probability Density Functions (PDF's) to performance error patterns associated to known faults in N-dimensional space. Similarly, the current error exists as a PDF in the parameter space as well. The probability that the current condition (C, measured parameter shifts), may be attributed to a given fault (F, identified known fault conditions) is determined by the "overlap" (i.e. multi-dimensional integration) of their respective joint probability density functions. Figure 2 showed how this is done in 2-dimensional parameter space. If C and F can be assumed to be normally distributed (not a necessary assumption however), the probability of association (Pa) with a given fault condition F can be found using:

$$p_a = 2\Phi\left(-\frac{\overline{F-C}}{\sqrt{\sigma_f^2+\sigma_c^2}}\right) = 2\Phi(-\beta) \tag{3}$$

where:

$\overline{F},\overline{C} =$	the mean of the distributions F and C respectively
$\sigma_f,\sigma_c =$	the standard deviation of the F and C distributions

The function $\Phi(\,)$ is the standard normal cumulative distribution and the β is denoted as the reliability index. The β represents the Euclidean distance between the current conditional distribution (C) and a given fault distribution (F). Hence, this approach performs diagnostics by evaluating the likelihood of the current conditions to known fault conditions and prognostics by extrapolating a fault-weighted, evolutionary path.

The evolutionary prognotics approach was applied to APU degradation data on an Auxilary Power Unit for a military fighter aircraft. APU model simulations of performance degradation were utilized along with test cell data to identify known parameter shifts to particular performance faults. Incremental effeciency degradation of the turbine and compressor sections, which simulated the effects of seal leakage or fouling, were used to build the fault paths for compressor and turbine degradation in 5-dimensional feature space. This feature space was defined by deviations from the normal parametric curves for Compressor Discharge Pressure and Temperature, Exhaust Gas Temp, Speed, and Fuel Flow which are all derivable from information on the aircraft's data bus.

The results of the evolutionary diagnostic and prognostic algorithm is shown in Figures 6a and b. At each time interval, the degree of overlap of the current error pattern is compared with compressor and turbine efficiency faults. In this case, the fault initially looks equally like a turbine or compressor efficiency fault but then continues to evolve to confidently identify a compressor fault. The blue bars in the left chart of Figure 6 represent the confidence of identifying a compressor degradation and the red bars represent the confidence associated with a turbine degradation. The 3-D plot on the right of Figure 8 represents the mean shifts of all three parameters (CDT, N1 and CDP) as a function of the APU degradation. The red line shows that the actual degradation is moving along side the model-based prediction of compressor degradation, hence giving it a higher confidence.

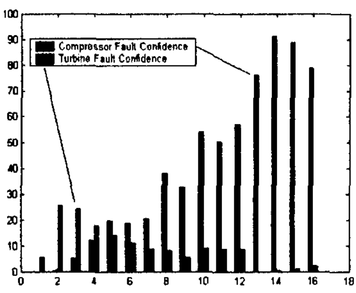

Figure 6(a) - Confidence Level in APU Compressor and Turbine Diagnosis

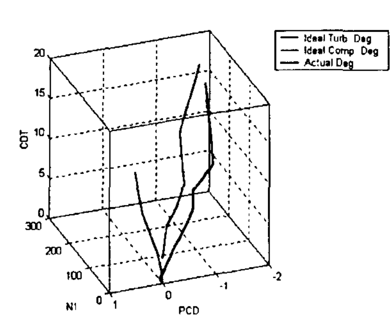

Figure 6(b) - Mean Degredation Path for Turbine and Compressor Faults

Figure 7 illustrates the concept for the prognostics algorithm in terms of what is important to predict associated with APU degradation. From an O&M point of view, any type of degradation that will lead to grounding the aircraft or putting the aircraft in danger is important to prognose. In this case, reaching an EGT limit that will prevent a main engine start (MES) will keep the aircraft on the ground and reduced air bleed from the compressor that effects the avionics cooling is also a concern. Predicting system-wide functional failure as opposed to just isolated LRU failures raises the standard for intergrated Health Management systems. Note that the expected to time to reach these critical events is displayed along side the actual time predicted to reach the event. In this case, these are the mean number of flight hours to No Main Engine Start (MES) and the point at which Avionics would overheat due to insufficient airflow. In Figure 7, the difference between the expected and actual MTTF (no MES) is shown as 231 APU operating hours. A threshold is typically set up a priori to alert maintenance personnel that accelerated degradation is occurring in the APU which will result in an EGT limit that would prevent the main engine from starting.

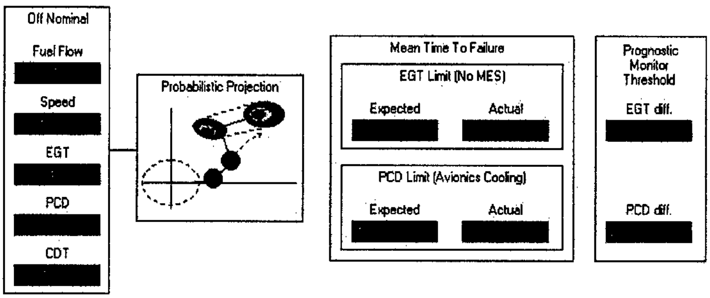

Figure 7 - Demonstration of Evolutionary Prognsotic Output

Power Take-Off Shaft Prognostics: Figure 8 shows a model-based prognsotic concept for a Power Take Off (PTO) shaft and AMAD snout bearing. In this prognostic module development, the first step is to relate processed per-rev vibration signals to different levels of PTO unbalance or misalignment. This inference (from measured vibration to unbalance/misalignment) is performed based on rigorous testing of vibrations measured on an AMAD gearbox under different levels of unbalance and misalignment on the PTO shaft. During the testing, different levels of unbalance were applied to a military fighter aircraft PTO shaft from 0.01 to 0.10 oz-in. Based on incremental levels of unbalance, the 1X vibration amplitudes were monitored and related to the level of unbalance. Some of the results from this testing are shown in Figure 9, with vibration spectrums associated with 0.01 and 0.05 oz-in unbalances shown. A simple back-propagation neural network was trained to represent this non-linear relationship between the 1X amplitudes and the unbalance level in oz-in.

Next, the unbalance prediction was applied to the rotordynamics (critical speed) model of the PTO staft including bearing stiffnesses. This model was run off-line under several different unbalance scenarios to obtain model-based estimates of the associated radial forces on the bearings under these conditions. A look-up table was then developed from which the real-time prediction of bearing radial forces are defined as a function of measured shaft unbalance (inferred from the 1X amplitudes). Based on these real-time predicted radial forces, the bearing model was utilized to assess the remaining B-10 life. A plot of the results from the bearing model are shown in Figure 10. From this figure, the B-10 bearing life can be accumulated based on the current level of unbalance force. The prognostic aspect of this model simply regresses the predicted radial bearing forces and applies them to the model to predict when the useful life of the bearing will be used up. Finally, the difference between the expected MTTF (under normal loading) was compared to the actual MTTF (predicted based on the actual operating conditions) to trigger an alarm if this difference becomes to large. In the case shown in Figure 8, the actual MTTF of the snout bearing was predicted to be 37,843 hours and the expected MTTF is 43,000 hours, resulting in a difference of over 5000 hours. This difference has triggered the PTOS prognostic monitor to report to the HM architecture discussed previously. Note, the expected and actual MTTF's are distributions as shown in the figure. Based on the severe consequences of a PTOS failure, only a small risk in the confidence interval of the distribution is acceptable and therefore the threshold of 5000 hours was choosen.

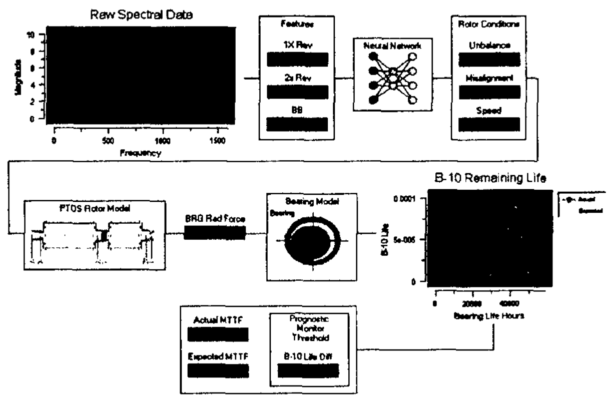

Figure 8 - Model-Based Prognostics for PTO Shaft and Bearings

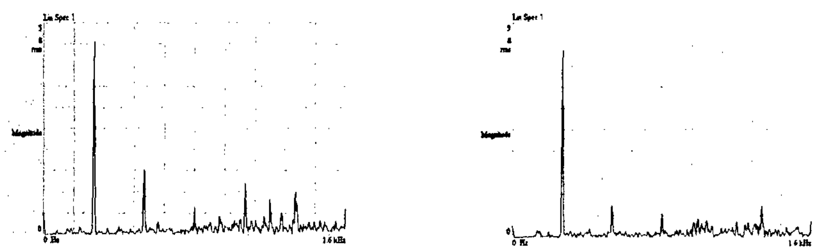

Figure 9 - Vibration Spectrums for 0.01 and 0.05 oz-in PTO Shaft Unbalance

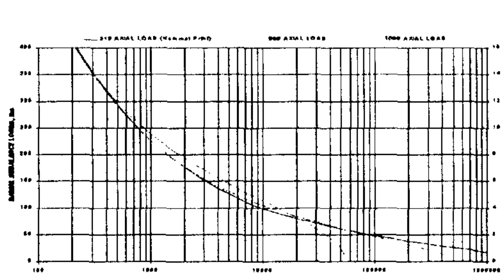

Figure 10 - B-10 Bearing Life Predictions for Various Radial Loads

APU Hot Section Prognostics: As a final example, a prognostic module was developed for the hot section blading for a military fighter APU. This hot section prognostics module is a simple extension of the OEM's life usage monitor for this APU. First, the module used the structural model to determine the creep fatigue damage done to the blading under various APU operating modes such as Main Engine Start, Landing Gear, Weapons Loading etc., as a function of speed, Turbine Inlet Temp (TIT) and Exhaust Gas Temperature (EGT). The OEM has developed event specific operating profiles that the APU is expected to see over the life of the APU. If this operating profile is adhered to, this Hot Section prognostic module will produce an actual MTTF probability distribution that is the same as the Expected MTTF; however, this is rarely the case. A particular APU may experience more Main Engine Starts (MES) than expected or have higher than expected TIT and therefore accumulate damage at a higher than expected rate. The inherent uncertainty in the remaining life is a function of many characteristics ranging from the material properties to the operating profile. Hence, the predicted probability of failure at some future time is performed by statistically sampling from these uncertainties in a probabilistic analysis.

The fundamental concept of this, and other "lifing-based" prognostic modules, is that a maintainer or auto-logistics system can simulate a future mission profile (based on past operating statistics), look at a risk-sorted list of components with potential failure modes for the mission, and be aware of all downstream effects if a failure does occur. In this manner, informed maintenance decisions may be made and aircraft readiness and availability may be assessed.

The implementation of this APU hot section is shown in Figure 11. As illustrated, the prognostic module utilizes the speed, EGT and calculated TIT as inputs to the model. As in the case of the PTO shaft model, the hot section model was run off-line under various design and off-design scenarios and a look-up table generated that related APU events at specific operating conditions to accumulated damage (in this case stress rupture due to creep). Based on this table and the monitored operating conditions, current levels of damage are continuously evaluated. The prognostic aspect utilizes the distribution of APU events specific to this APU to project future usage rates. As in the case of the other prognostic modules, this output produces two distributions on MTTF, one for the expected normal operation and one based on the actual operation. If this particular APU begins to experience high levels of hot section life, than the prognostic monitor threshold will warn the maintainers of significant differences between the actual and expected MTTF's.

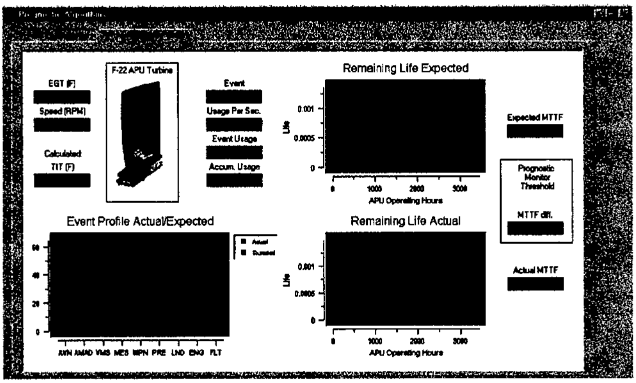

Figure 11 - APU Hot Section Prognostics Module

Conclusions:

This paper has discussed many concepts associated with next generation prognostic and health management systems for aerospace applications. First, a generic PHM architecture was presented that emphasized the integration of anomaly detection, diagnostic and prognostic reasoners through the use of an integrated model of the entire system. Next, direct links from the anomaly, diagnostic and prognostic algorithms were identified that trigger specific attributes in the integrated model for superior fault isolation and reasoning. With this type of overall algorithm integration across the system, system level reasoners can process collaborative evidence about particular failure modes more effectively so as to reduce the need for additional sensors. A few specific diagnostic and prognostic algorithmic approaches were also presented to illustrate how the results from these techniques are process by the integrated model and HM architecture.

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TOTAL OWNERSHIP COST

Chair: Dr. Kam W. Ng
Office of Naval Research