

AN OVERVIEW OF SELECTED PROGNOSTIC TECHNOLOGIES WITH APPLICATION TO ENGINE HEALTH MANAGEMENT

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ABSTRACT

The DoD has various vehicle platforms powered by high performance gas turbine engines that would benefit greatly from predictive health management technologies that can detect, isolate and assess remaining useful life of critical line replaceable units (LRUs) or subsystems. In order to meet these needs for next generation engines, dedicated prognostic algorithms must be developed that are capable of operating in an autonomous and real-time engine health management system software architecture that is distributed in nature. This envisioned prognostic and health management system should allow engine-level reasoners to have visibility and insight into the results of local diagnostic and prognostic technologies implemented down at the LRU and subsystem levels. To accomplish this effectively requires an integrated suite of prognostic technologies that can be applied to critical engine systems and can capture fault/failure mode propagation and interactions that occur in these systems, all the way up through the engine and eventually vehicle level. In the paper, the authors will present a generic set of selected prognostic algorithm approaches that can be applied to gas turbine engines, as well as provide an overview of the required reasoning architecture needed to integrate the prognostic information across the engine.

INTRODUCTION

The focus of gas turbine engine health monitoring technologies being developed and deployed over the last several years has been on the detection and classification of critical engine system faults (Marko 1996, Schauz 1996, Shiroishi 1997). However, these technologies have traditionally used built in test (BIT) results and anomaly detections as a source for the fault isolation within an individual subsystem on the engine. Moving

forward, health management system developers are now beginning to address the concepts of prognostics and the integration of anomaly, diagnostic and prognostic technologies across subsystems of the engine systems as a whole. Hence, the ability to first detect and isolate impending faults and then predict their future progression based on its current diagnostic state and available operating data is currently a high priority in the DoD. Also, the capability for updating these failure predictions based on either measured or inferred features related to the progression of the fault over time is also desirable.

In addition, there are many sources of uncertainties that can affect the results in any prognosis system; thus achieving the best possible prediction on a LRU/subsystem's health is often implemented using various algorithmic techniques and data fusion concepts that can optimally combine sensor data, empirical/physics-based models and historical information. By utilizing a combination of health monitoring data and model-based techniques, a comprehensive prognostic capability can be achieved throughout an engine's life, using model-based estimates when no diagnostic indicators are present and monitored features at later stages when failure indications are detectable.

Finally, these technologies must be capable of communicating the root cause of a problem across subsystems on the engine and propagating the up/downstream effects across the engine health management (EHM) system architecture. This paper will introduce some generic prognostic and health management (PHM) system algorithmic approaches that have been demonstrated within various engine systems and subsystem components with the ability to predict the time to conditional or mechanical failure (on a real-time basis). Engine 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.

PROGNOSTIC ALGORITHM APPROACHES

In the engineering disciplines, fault prognosis has been approached via a variety of techniques ranging from Bayesian estimation and other probabilistic/statistical methods to artificial intelligence tools and methodologies based on notions from the computational intelligence arena. Specific enabling technologies include multi-step adaptive Kalman filtering (Lewis 1986), auto-regressive moving average models (Lewis 1992), stochastic auto-regressive integrated moving average models (Jardim-Goncalves 1996), Weibull models (Groer 2000) forecasting by pattern and cluster search (Frelicot 1996), and parameter estimation methods (Ljung 1999). From the artificial intelligence domain, case-based reasoning (Aha 1997), intelligent decision-based models and min-max graphs have been considered as potential candidates from prognostic algorithms. Other methodologies, such as Petri nets, neural networks, fuzzy systems and neuro-fuzzy systems (Studer 1996) have found ample utility as prognostic tools as well. Physics-based fatigue models (Ray 1996, Muench 2004) have been extensively employed to represent the initiation and propagation of structural anomalies.

Next, we will provide a brief overview of a representative sample of the multitude of enabling prognostic technologies that can be applied to gas turbine engine applications. Figure 1 summarizes the range of possible prognostic approaches as a function of the applicability to various systems and their relative implementation cost. Prognostic technologies typically utilize measured or inferred features, as well as data-driven and/or physics-based models to predict the condition of the system at some future time. Inherently probabilistic or uncertain in nature, prognostics can be applied to failure modes governed by material condition or by functional loss. Prognostic algorithms can be generic in design but specific in terms of application. Prognostic system developers have implemented various approaches and associated algorithmic libraries for customizing applications that range in fidelity from simple historical/usage models to approaches that utilize advanced feature analysis or physics-of-failure models.

Depending on the criticality of the engine LRU or subsystem being monitored, various levels of data, models and historical information will be needed to develop and implement the desired prognostic approach. Table 1 provides an overview of the recommended models and information necessary for implementing specific approaches. Of course, the resolution of this table only illustrates three levels of algorithms, from the simplest experienced-based (reliability) methods to the most advanced physics of failure approaches that are calibrated by sensor data.

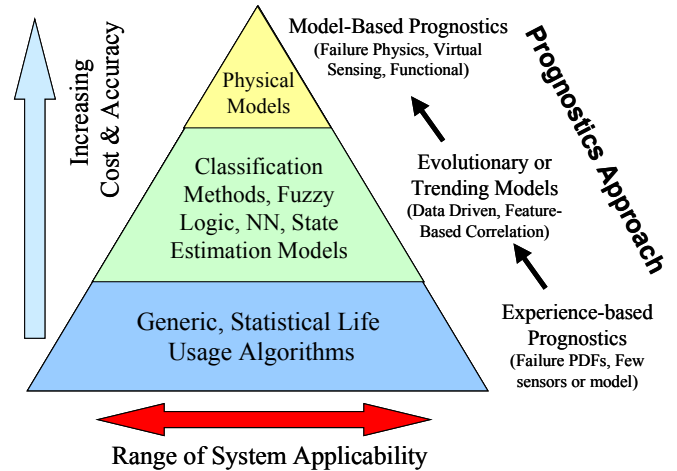


Figure 1. Prognosis Technical Approaches

Table 1

	Prognostic Accuracy →		
	<i>Experienced-based</i>	<i>Evolutionary</i>	<i>Physics-based</i>
Engineering Model	Not required	Beneficial	Required
Failure History	Required	Not required	Beneficial
Past Operating Conditions	Beneficial	Not required	Required
Current Conditions	Beneficial	Required	Required
Identified Fault patterns	Not required	Required	Required
Maintenance History	Beneficial	Not required	Beneficial
In General	No Sensors / No Model	Sensors / No Model	Sensors and Model

ENGINE COMPONENT RELIABILITY AND USAGE-BASED APPROACHES

In situations where sophisticated engine component prognostic models are not warranted due to the lower level of criticality or low failure occurrence rates and/or there is an insufficient sensor network to assess condition, a statistical reliability or usage-based prognostic approach may be the only alternative. This form of prognostic algorithm is the least complex and requires the engine component/LRU failure history data and/or operational usage profile data. Typically, failure and/or inspection data is compiled from legacy systems and a Weibull distribution or other statistical failure distribution can be fitted to the data (Groer 2000, Schomig, 2003). An example of these types of distributions is given in Figure 2. Although simplistic, a statistical reliability-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 few 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 reliability. 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 component every 1000+/-20 Engine Flight Hours) then updated as more data becomes available. The benefit to having a regularly updated maintenance database as happens in autonomic logistics applications is significant for this application.

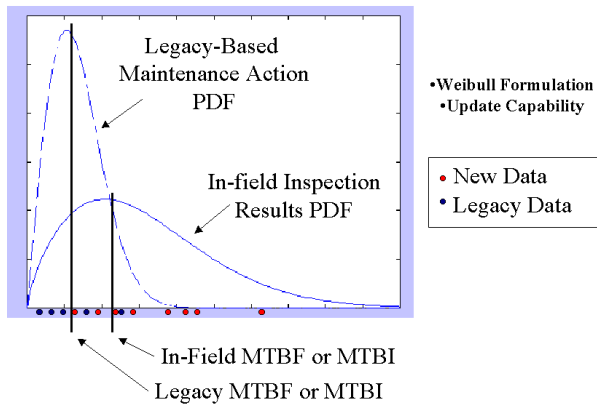


Figure 2. Statistical Reliability-Based Approach

The next logical extension to this type of reliability-based statistical model is to correlate the failure rate data with specific operational usage profiles that are more directly related to the way a specific engine is used. In this manner, statistical damage accumulation models or usage models for specific engine components/LRUs can be directly tied to the loading profiles inferred from the high-level operations data sets, for example, fatigue cycles that are a function of operating conditions such as speed or loading conditions. An example of this is shown in Figure 3, where a usage model (in this case damage accumulation on a turbine disk) was developed based on the operating speed of an engine. These type of usage models are often referred to as regime recognition in the helicopter community.

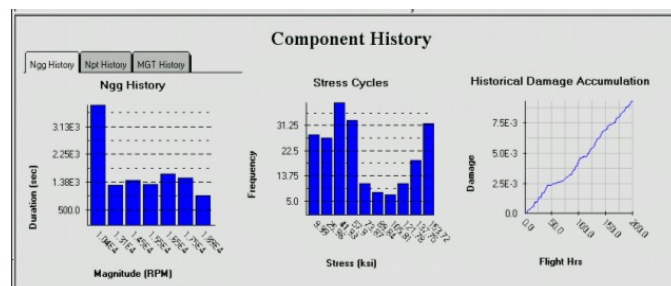


Figure 3. Usage-Based Damage Accumulation Approach

It is important to recognize that this is not another form of reliability-centered maintenance, in which we replace components based upon a conservative safe-life operational time. It is a method to include the operational profile information and up-to-date reliability/inspection data in an automated algorithm that will augment existing fault detection conclusions or provide a prediction when more accurate means are not justified. More accurate prognostic methods are described in the following sections.

ENGINE PERFORMANCE TREND-BASED APPROACHES

A trend-based or evolutionary prognostic approach relies on the ability to track and trend deviations and associated rates of change of these deviations of specific engine features or measurements from their normal operating condition. Figure 4 is an illustration of such a technique. Evolutionary prognostics may be implemented on engine failure modes with conditional or slow degradation type faults such as an efficiency loss. Generally, trend-based predictions work well for engine degradation because efficiency loss is typically the result of interaction of multiple trends in parameters such as fuel flow, pressure ratios and temperatures. This approach requires that sufficient sensor information is available to assess the current engine condition, which in most cases is true. Furthermore, the parametric conditions that signify a known performance related fault must be identifiable.

As an example of applying this type of prognostic approach, consider predicting the effects of fouling on compressor performance. In such an example, a preprocessing algorithm examines the engine operating data and automatically calculates key corrected performance parameters such as pressure ratios and efficiencies at specific power levels. As fouling starts to occur, corresponding parameter shifts in fuel flow, pressure ratios, temperatures, etc. are assessed with respect to fouling severity levels attained from existing models/tests with corresponding degrees of confidence.

Parameter distributions (shown in Figure 4) that utilize known information about the degradation of measured parameters as a function of fouling severity (efficiency degradation level) are used to directly assess the current and future condition of the compressor. The parameter space for this application is related to the fuel flow and pressure ratio changes that occur over time. These provide the current diagnosed condition and the expected degradation path. The bottom plot of Figure 4 shows a top view of these distributions. The highest degree of overlap between the expected degradation path and the current condition is the best estimate of compressor fouling.

$$\hat{y}_{T+\tau}(T) = \left(2 + \frac{\alpha\tau}{(1-\alpha)} \right) S_T - \left(1 + \frac{\alpha\tau}{1-\alpha} \right) S_T^{[2]} \quad (0)$$

DATA-DRIVEN ENGINE MODEL APPROACHES

In many instances, one has historical fault/failure data in terms of time domain or feature plots of various signals leading up to the failure, or statistical data sets. In many of these cases, it is either difficult or impractical to determine a physics-based model for prediction purposes. In such situations, one may use nonlinear network approximators that can be tuned using well-established formal algorithms to provide desired outputs directly in terms of the data. Nonlinear networks include the *neural network*, which is based on signal processing techniques in biological nervous systems, and *fuzzy logic systems*, which are based on the linguistic and reasoning abilities of humans. These are similar in that they provide structured nonlinear function mappings with very desirable properties between the available data and the desired outputs.

In prediction, Artificial Neural Networks (ANNs), fuzzy systems and other computational intelligence methods, have provided an alternative tool for both forecasting researchers and practitioners (Sharda 1994). Werbos (1988) reported that ANNs trained with the backpropagation algorithm outperform traditional statistical methods such as regression and Box-Jenkins approaches. In a recent forecasting competition organized by Weigend and Gerhenfeld (1993) through the Santa Fe Institute, all winners of each set of data used ANNs. Unlike the traditional model-based methods, ANNs are data-driven and self-adaptive and they make very few assumptions about the models for problems under study. ANNs learn from examples and attempt to capture the subtle functional relationship among the data. Thus, ANNs are well suited for practical problems where it is easier to have data than knowledge governing the underlying system being studied. Generally, they can be viewed as one of many multivariate nonlinear and nonparametric statistical methods (Cheng 1994). The main problem of ANNs is that the reasoning behind their decisions is not always evident. Nevertheless, they provide a feasible tool for practical prediction problems.

Hence, with an understanding of how the fault/failure signature is related to specific measurable or inferred features from the system being monitored, a data-driven modeling approach is a commonly utilized approach. Based on the selected input features that correlate with the failure progression, a desired output prediction of the time to failure is produced based on a training process in which the network will automatically adjust its weights and thresholds based on the relationships it sees between the time to failure and the correlated feature magnitudes. Figure 5 shows an example of a neural network after being trained by some vibration feature data sets for predicting a gear failure. The difference between the neural network output and the “ground truth” probability of failure curve is due to error that still exists after the

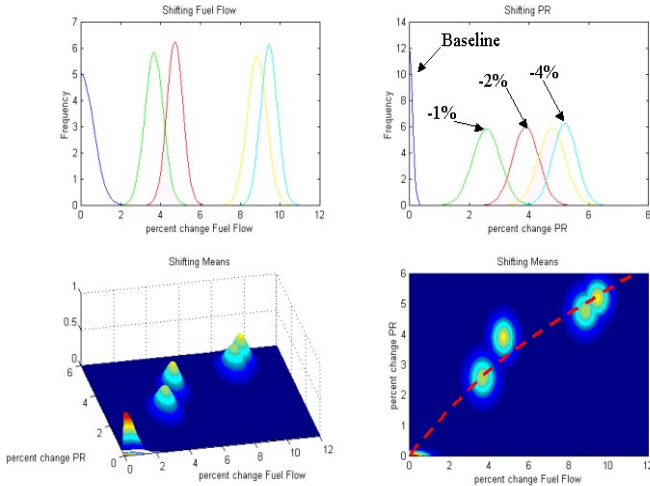


Figure 4. Trend-Based or Evolutionary Prognostic Approach

The top two plots illustrate the distributions of pressure ratio and fuel flow, respectively, while the bottom two provide the joint probability distributions. The red dotted line represents the path (either current or projected) of degradation for the compressor. 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). In the event that total pressure measurements are not available, other methods can be used to approximate this efficiency calculation with other specific sets of sensors. A typical efficiency calculation is shown below.

$$\eta_{adb} = \frac{\left[\left(\frac{CDP_T}{CIP_T} \right)^{\frac{\gamma-1}{\gamma}} - 1 \right]}{\left[\left(\frac{CDT}{CIT} \right) - 1 \right]} \quad (0)$$

Once the statistical performance degradation path is realized along with the capability to assess current degradation severity, the predictive capability is performed. The actual engine-specific fouling rate is combined with historical fouling rates with a double exponential smoothing method to accomplish this task. This time series technique weights the most recent data points over past observations. The following equations give the general formulation for the exponential smoothing prediction (Bowerman, 1993).

$$S_T = \alpha y_T + (1-\alpha) S_{T-1} \quad (0)$$

$$S_T^{[2]} = \alpha S_T + (1-\alpha) S_{T-1}^{[2]} \quad (0)$$

network parameters have optimized to minimize this error. Once trained, the neural network architecture can be used to predict the same features progressions for a different test under similar operating conditions.

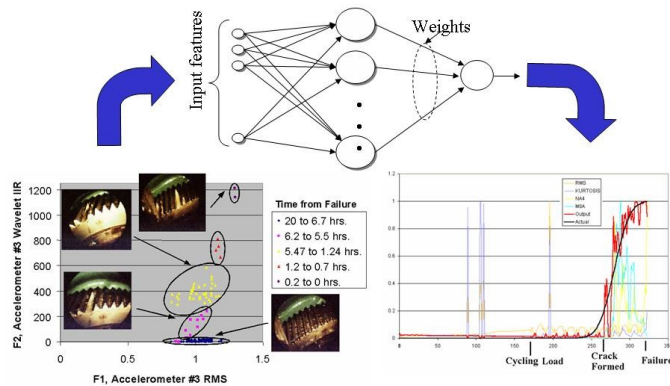


Figure 5. Data-Driven Model Based Approach

STATE ESTIMATOR BASED PROGNOSTICS

State estimation techniques such as Kalman filters or various other tracking filters can also be implemented as a prognostic technique. The Kalman filter (Lewis 1986, Drexel 2001) is a dynamical systems tool for estimating unknown states by combining current measurements with the most recent state estimate. It can be considered as a virtual sensor in that it takes current available sensor measurements and provides optimal estimates (or predictions) of quantities of interest that may in themselves not be directly be measurable. Knowledge of noise processes is used to minimize the estimation error covariance, via the optimal determination of the so-called Kalman gain.

It is typically implemented with the use of a linear system model, but can also be extended to non-linear systems through the use of the extended Kalman filter algorithm that linearizes the system about an operating point. The discrete-time system with internal state x_k and sensor measurements z_k may be described in terms of the recursive difference equation

$$x_{k+1} = A_k x_k + B_k u_k + G_k w_k$$

$$z_k = H_k x_k + v_k$$

where u_k is a control input, w_k is a *process noise* that captures uncertainties in the process dynamics, such as modeling errors and unknown disturbances (e.g. wind gusts in aircraft), and v_k is a *measurement noise*. This is depicted in Figure 6 shown below.

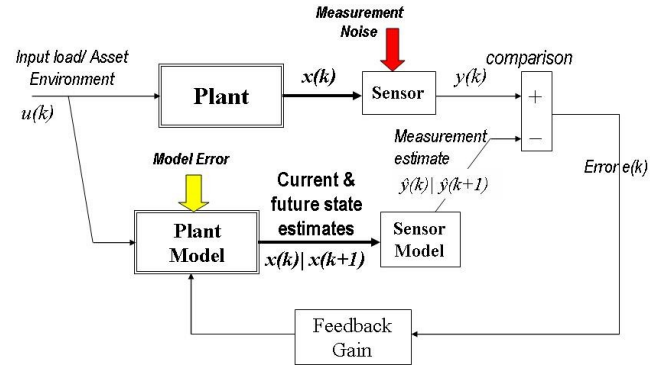


Figure 6. State Estimation (Kalman Filter Implementation) Approach

In this type of application, the minimization of error between a model and measurement can be used to predict future feature states and hence the behavior of the modeled system. 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.

In a slightly different application of the Kalman filter, measured or extracted features f , can be used to develop a state vector as shown below.

$$x = [f \quad \dot{f} \quad \ddot{f}]^T$$

Then, the state transition equation can be 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:

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

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 MODELING APPROACHES

A physics-based model is a technically comprehensive modeling approach that has been traditionally used to understand component failure mode progression. Physics-based models provide a means to calculate the damage to critical engine components as a function of operating conditions and assess the cumulative effects in terms of component life usage. By integrating physical and stochastic modeling techniques, the

model can be used to evaluate the distribution of remaining useful component life as a function of uncertainties in component strength/stress properties, loading or lubrication conditions for a particular fault. Statistical representations of historical operational profiles serve as the basis for calculating future damage accumulation. The results from such a model can then be used for real-time failure prognostic predictions with specified confidence bounds. A block diagram of this prognostic modeling approach is given in Figure 7. As illustrated at the core of this figure, the physics-based model utilizes the critical, life-dependent uncertainties so that current health assessment and future remaining useful life (RUL) projections can be examined with respect to a risk level.

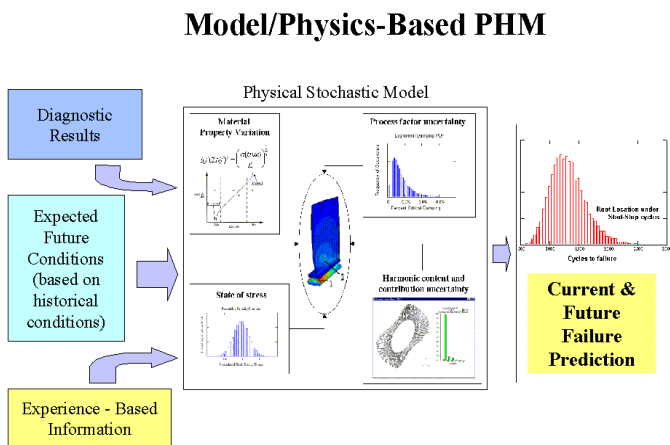


Figure 7. Physics-Based Modeling Approach

The results from such a model can then be used to create a neural network or probabilistic-based autonomous system to obtain real-time failure prognostic predictions. Other information used as input to the prognostic model may include 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 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 engine.

Model-based approaches to prognostics differ from feature-based approaches in that they can make RUL estimates in the absence of any measurable events, but when related diagnostic information is present (such as the feature described previously) the model can often be calibrated based on this new information. Therefore, a combination or fusion of the feature-based and model-based approaches provides full prognostic ability over the entire life of the component, thus providing valuable information for planning which components to inspect during specific overhauls periods. While failure modes may be unique from component to

component, this combined model-based and feature-based methodology can remain consistent across different types of critical components or LRUs.

To perform a prognosis with a physics-based model, an operational profile prediction must be developed using the steady state and transient loads, temperatures or other on-line measurements. With this capability, probabilistic critical component models can then be “run into the future” by creating statistical simulations of future operating profiles from the statistics of past operational profiles or expected future operating profiles.

Based on the author’s past experience correlating operational profile statistics and component or LRU life usage, the non-linear nature associated with many damage mechanisms is dependent on both the inherent characteristics of the profiles and operational mix types. Significant component damage resulting from the large variability in the operating environment and severity of the missions directly affects the vehicle component lifetimes. Very often, component lives driven by fatigue failure modes are dominated by unique operational usage profiles or a few, rare, severe, randomly occurring events, including abnormal operating conditions, random damage occurrences, etc. For this reason, the authors recommend a statistical characterization of loads, speeds, and conditions for the projected future usage in the prognostic models as shown below in Figure 8.

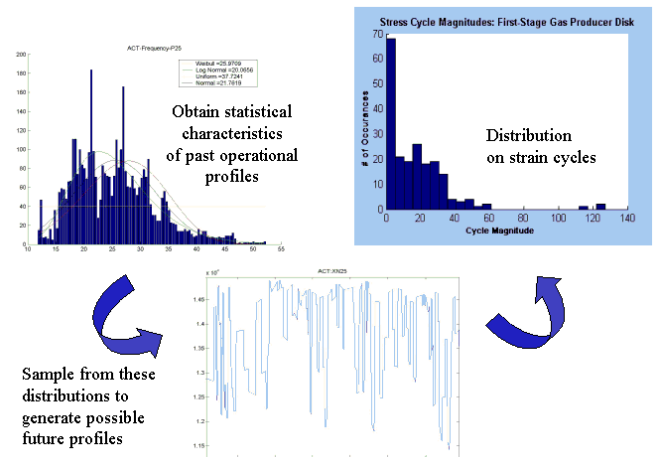


Figure 8. Operation Profile and Loading Model for Prognosis

PROGNOSIS REMAINING USEFUL LIFE PROBABILITY DENSITY FUNCTION

A comprehensive description on the probabilistic techniques in prognostics as related to predicting the remaining useful life (RUL) is given by Engel, Hess, et al. (2000). The seminal notions presented in this paper serve to clarify our thinking about remaining useful life prediction. A key concept in this framework is the *remaining useful life failure probability density function (PDF)*. In this

representation, an engine component or LRU is recommended to be removed from service prior to attaining a high probability of failure, set based on the criticality. This concept is depicted in below in Figure 9, in terms of the RUL PDF, where a *just in time point* is defined for removal from service that corresponds to a 95% probability that the component has not yet failed.

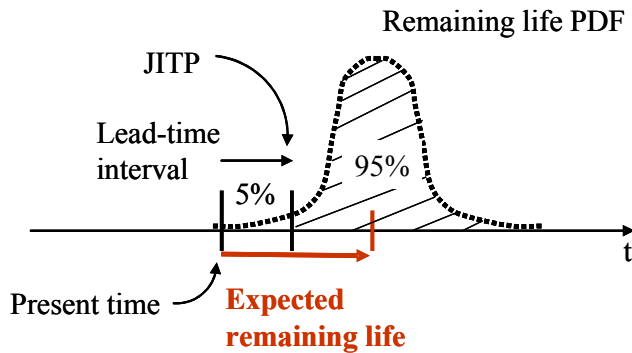


Figure 9. A Probability Density Function for Prognosis

A key issue, unfortunately, is that the RUL PDF is actually a *conditional PDF* that changes as time advances. In fact, one must recompute the RUL PDF at each time t based on the new information that *the component has not yet failed at that time*. This concept is shown in Figure 10. One starts with an a priori PDF similar to the hazard function. Then, as time passes, one must recompute the a posteriori RUL PDF based on the fact that the failure has not yet occurred. This involves renormalizing the PDF at each time so that its area is equal to one. As time passes, the variance of the RUL PDF decreases; that is the PDF becomes narrower. This corresponds to the fact that, as time passes and one approaches the failure point, one becomes more and more certain about the time of failure and its predicted value becomes more accurate.

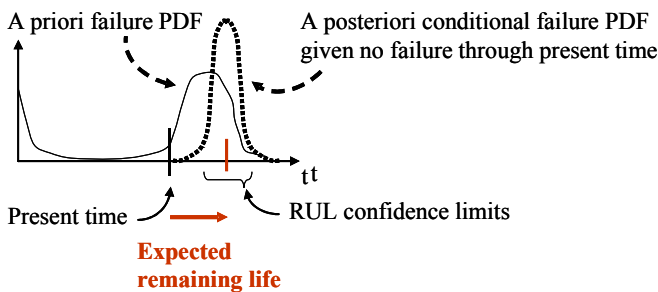


Figure 10. Updated Prognosis Probability Density Function

ADAPTIVE PROGNOSIS

As a direct extension to the concept presented above, the idea of updating the prognosis PDF based on additional state awareness (fault detection and diagnostic) information that can become available over time is also desirable. The adaptive prognosis concept entails that information available

at the current time (which may or may not be diagnostic in nature) be used to modify future predictions, hence updating the prognosis PDF. This idea is illustrated in Figure 11 (Engel 2000) and briefly described next.

Consider point d_0 in Figure 1 to be the mean initial damage condition for a prognostic model. A prognosis of life, from time k to predetermined damage level is found to be represented by RUL_0 or Remaining Useful Life. Suppose that some imperfect measurement $z(k)$ regarding the damage state becomes available at time $k=k+p\Delta T$. The challenge is to find optimal current damage state to re-initialize the model and/or adjust model parameters so that a calibrated and more accurate prognosis can be established.

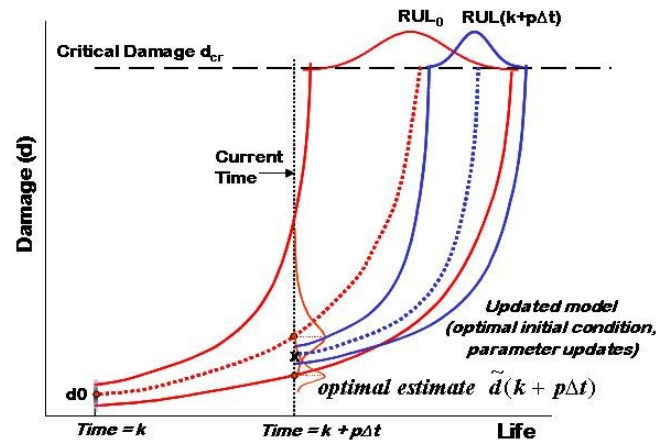


Figure 11. Adaptive Prognosis Concept

Though utilization of a new initial condition, $\tilde{d}(k)$ at time $k=k+p\Delta T$ as shown in Figure 11, it is apparent that the prediction mean has shifted and the confidence bounds on the resulting *RUL* has less variance than the original (blue prediction). The prediction accuracy improvement would generally mean that a decision to take action based on failure probability will likely reduce lost operational availability over a run-to-failure maintenance plan.

DISTRIBUTED PROGNOSIS SYSTEM ARCHITECTURE

The cornerstone of an effective Prognostic and Health Management (PHM) system for a gas turbine engine or other complex system is the information/data architecture and the ability for understanding and managing the anomaly, diagnostic, and prognostic (A/D/P) information from the LRU level all the way up through to the engine level reasoners. This concept is briefly illustrated in Figure 12, where faults detected and predicted at the LRU level are assessed through the hierarchy of reasoners in order to determine the root causes of engine malfunctions and contingency option for impending failures.

In general, the A/D/P technologies implemented at the lower levels (LRUs) are used to detect and predict off-nominal conditions or damage accumulating at an accelerated rate. In the distributed PHM architecture, this information is analyzed through the hierarchy of reasoners to make informed decisions on the health of the engine subsystems/systems and how they affect total engine capability. This integration across LRUs, subsystems and systems is vital to correctly isolating the root-cause of failures and understanding the propagation of up/downstream effects of the faults. Integration of the individual subsystem PHM results is eventually accomplished with the engine level reasoner, which will assess the intra-engine A/D/P results in order to prioritize the recommended maintenance action(s) to perform in order to correct the problem.

A distributed PHM architecture, such as that shown below, has many benefits including; (1) Optimal computational resource management (i.e. placing high bandwidth processing at the lowest level and only passing up critical features), (2) Supports the concept of “Smart LRU/Subsystem”, where the most detailed “intelligence” about the system exists (i.e. supplier/designer responsibility), (3) Provides the ability to isolate and assess the extent of multiple faults and battle damage, hence improving survivability of the engine, (4) Hierarchical reasoners have a “built in” data management capability for containing erroneous information and utilizing multiple data and information sources, and (5) Ability to capture and localize system degradations (as opposed to only hard failures), based on increased health awareness of the lowest-level LRUs, hence providing a more accurate engine and vehicle availability assessment.

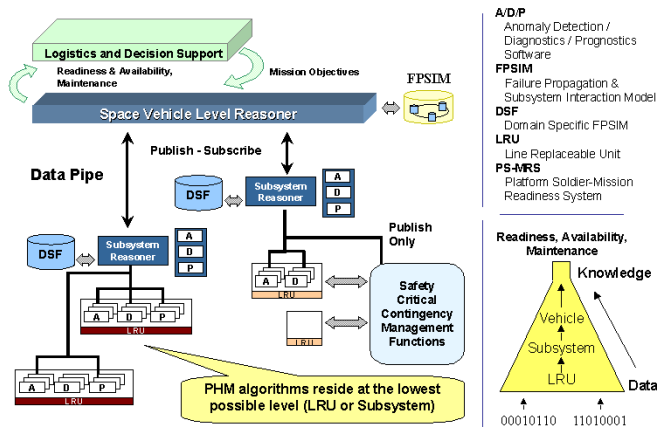


Figure 12. Distributed Prognostic System Architecture

CONCLUSIONS

This paper has briefly reviewed some generic prognosis algorithmic approaches and introduced the theoretical and notional foundations associated with probabilistic predictions and required software architectures for performing prognostics on critical gas turbine engine systems.

Prognosis is certainly the Achilles’ heel of the Prognostics and Health Management (PHM) system and presents major challenges to the CBM/PHM system designer primarily because it entails large-grain uncertainty. Long-term prediction of a fault evolution to the point that may result in a failure requires means to represent and manage the inherent uncertainty. Moreover, accurate and precise prognosis demands good probabilistic models of the fault growth and statistically sufficient samples of failure data to assist in training, validating and fine tuning prognostic algorithms. Prognosis performance metrics, robust algorithms and test platforms that may provide needed data have been the target of CBM/PHM researchers over the recent past. Many accomplishments have been reported but major challenges still remain to be addressed.

In addition, due to the inherent uncertainties in prognosis approaches, which are the aggregate of many unknowns and can result in considerable prediction variability, the concept of adaptive prognosis was also introduced. In that case, available, albeit imperfect, information is used to update elements of the prognostic model. Only one of many approaches for accomplishing this was briefly introduced, i.e. the Kalman Filter. Other statistical update techniques include Bayesian updating, constrained optimization and particle filtering.

The prognosis process by which extracted features and models are integrated to obtain the best possible prediction on remaining useful life still has many remaining challenges. It is a significant challenge to design systems so that measured data can be fused and used in conjunction with physics-based models to estimate current and future damage states. Furthermore, multiple models will often be required that may or may not use various feature inputs. Finally, the feedback mechanism in a prognosis system design cannot be ignored. Specifically, the prognosis system must be capable of intelligently calibrating a-priori initial conditions (i.e. humidity, strain and temperature have changed), random variable characteristics or switching prognostic models in an automated yet lucid process to empower better operational and logistical decisions for vehicle platforms.

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