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Prognostics for Gas Turbine Engines

RATIONALE

AIR5871 has been reaffirmed to comply with the SAE five-year review policy.

FOREWORD

Gas turbine engine prognostic technologies that are capable of predicting critical component failures or performance degradation rates are expected to improve safety and availability, reduce life cycle costs, and optimize the timing of scheduled maintenance intervals. For many critical engine components and subsystems, prognostic approaches are currently being developed that utilize state-of-the-art modeling and analysis technologies. This document introduces and provides examples of leading prognostic modeling approaches that integrate state-of-the-art analytical and empirical models with component testing and inspection results. Specific examples related to failures of engine fan blades and engine performance degradation are described, along with a representative range of different technical approaches. The process of prognostic model calibration and verification is also discussed.

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1. SCOPE AND PURPOSE

1.1 Purpose

This document applies to prognostics of gas turbine engines and its related auxiliary and subsystems. Its purpose is to define the meaning of prognostics with regard to gas turbine engines and related subsystems, explain its potential and limitations, and to provide guidelines for potential approaches for use in existing condition monitoring environments. It also includes some examples.

1.2 Field of Application

This document seeks to meet the increasing interest in gas turbine engine prognostics. Specifically, the document tries to provide a timely guideline for applying prognostic technologies to enhance the capability of current monitoring and diagnostic systems. Some examples are provided that are intended to illustrate different approaches and methodologies.

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2.2 Definition

Prognostics is the ability to predict the future condition of a component and/or system of components. For the purposes of gas turbine engine prognostics, this definition is often further described in terms of hard failures of components or condition/degradation of performance related problems. These are further defined as follows:

Failure Prognostics: Failure prognostics is focused on the prediction of damage state or failure rate of a component or system of components in an engine. Failure prognostics can either be directly or indirectly affected by the diagnosis of specific engine faults, depending on the level of impact the component experiences from the fault condition. Prognostic models are required to project the future condition of these components and/or system of components.

Condition Prognostics: Condition prognostics is associated with the slower degradation (wear related) processes that an engine is exposed to throughout its life. It is usually associated with the diagnosis of fault(s) conditions and the capability of predicting when the symptoms of the identified fault(s) will reach an undesirable state in which system operation will be adversely affected. Prognostic models are required to project the future “path” of these identified fault(s) on total system performance or reliability.

2.3 Potential Benefits of Prognostics

- Improved Safety of Flight
- Improved Operational Availability
- Reduced Life Cycle Costs
- Optimized Maintenance/Inspection Intervals

2.4 Needed Terminology

Monte-Carlo Simulation: A process for making multiple analyses of a particular deterministic problem by changing the associated parameters that effect the results/outcome of the process based on the uncertainties that exist in those parameters, usually in the form of a distribution.

Diagnostics: A technique for classifying or isolating a particular “non-normal” condition associated with a system, subsystem or component down to a piece of information that is useful in understanding the off-design condition.

2.5 Acronyms

AI	Artificial Intelligence
TBO	Time Between Overhaul
D&P	Diagnostic and Prognostic
MTBF	Mean Time Between Failures
EFH	Engine Flight Hours
FEA	Finite Element Analysis
LP	Low Pressure (engine section)
HP	High Pressure (engine section)
OEM	Original Equipment Manufacturer
FOD	Foreign Object Damage
HCF	High Cycle Fatigue
LCF	Low Cycle Fatigue
PDF	Probability Density Function
PHM	Prognostics and Health Management
MTB	Mean Time Between Inspections

2.6 Prognostic Requirements

An integral part of propulsion system prognostics is fault isolation and diagnosis. Fault isolation and diagnosis consists of utilizing the available evidence associated with a fault detection in order to identify the location of the fault within the propulsion system. Condition prognosis can then be used to forecast the remaining useful life (the operating time between detection and an unacceptable level of degradation). If the identified fault affects the life of a critical component, then the failure prognosis models must also reflect this diagnosis.

For the diagnosis and prognosis of critical failure modes, specific requirements for confidence intervals and severity levels must be identified by the developer and/or end user. In general, the fault detection statistics and diagnostics accuracy should be specified separately from prognostic accuracy.

To specify fault detection and diagnostic accuracy, the following probabilities should be used: as a minimum:

1. The probability of fault detection in terms of false alarm rate and real fault probability.

2. The probability of specific fault diagnosis confidence and severity.

To specify prognostic accuracy requirements, the developer/end-user must first define:

1. The level of condition degradation beyond which operation is undesirable.

2. A minimum warning level of acceptable operation, given a failure mode or degraded condition.

3. A minimum probability level that remaining useful life will be equal to or greater than the minimum warning level.

3. EXAMPLE PROGNOSTIC STRATEGIES

3.1 Analytical Prediction

The total available useful life of an engine component is typically calculated from design parameters and an assumed operational envelope. In the simplest case, operating hours can then be tracked and projected into the future to provide a very crude forecast of remaining useful life. This is analogous to cycle counting methods such as minors rule and implementations of it such as TAC (Total Accumulated Cycles) that are often used today. More advanced methods are now being considered (discussed in a later example) that use stochastic models to represent failure mode uncertainties, projected operational parameters, and rare/random events to help improve the prediction of specific failure mode and their propagation for remaining-useful-life.

Another example of a simple analytical prediction strategy is assigning a Time Between Overhaul (TBO) index to a component. This number can be derived from fatigue life predictions, under assumed operating loads, for various parts (gears, bearings, etc.) within a propulsion system assembly. The shortest predicted life of all the critical elements will then determine the maximum number of operating hours between required removal from service for overhaul, regardless of the actual condition of the specific component. A more advanced analytical modeling approach will be described in a later section.

3.2 Measured and Trend-Based Predictions of Wear and Degradation

Sensors provide a continuous view of the physical data that are directly related to a component's performance characteristics. These data can be processed into trendable measures of the component "health" and projections of remaining useful life can be made based upon assumed operational profiles and removal limits of the trendable health measures.

An example of this approach is the measurement and trending of pressure head and flow for a positive displacement pump. As the performance parameters deteriorate towards an undesirable level, a remaining useful life estimate is generated by applying tools such linear regression analysis to the trended measurements. In more sophisticated examples, a database of physical measurements can be further processed by techniques such as feature extraction, decision making networks, and rule based expert systems.

In the following section, a summary of five of the leading data-driven and model-based analytical approaches for performing predictions on remaining useful life or wear/degradation of specific components or engine systems are discussed.

4. GENERIC PROGNOSTIC TECHNOLOGIES

Prognostics simply denotes the ability to predict a future condition. Inherently probabilistic or uncertain in nature, prognostics can be applied to a system or component's 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 describe five approaches to prognostics.

4.1 Experience-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 experience-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 operating conditions (also basis for Reliability Centered Maintenance). Typically, failure and/or inspection data are 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 experience-based prognostic distribution can be used to drive interval-based maintenance practices that can then be updated at regular intervals. An example may be the maintenance scheduling for an electrical 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 (e.g., replace every 1000+/-20 EFH (Engine Flight Hours)) and later updated as more data become available. Regularly updated maintenance databases, as often used in autonomic logistics applications, have important benefits for this type of prognostics.

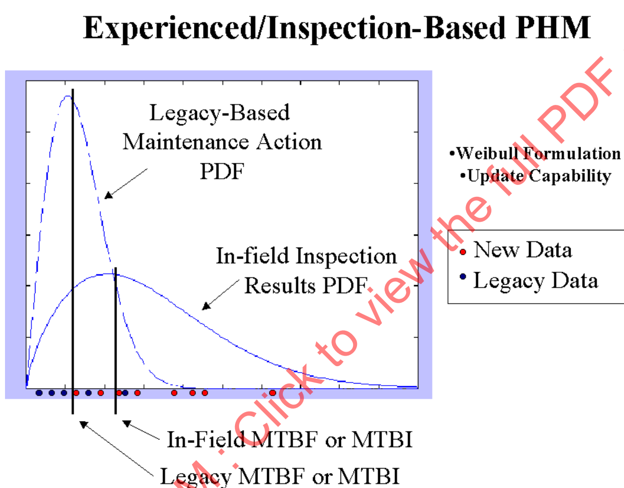


FIGURE 1 - EXPERIENCE-BASED APPROACH

4.2 Evolutionary Prognostics

An evolutionary prognostic approach relies on gauging the proximity and rate of change of the current component condition (i.e., features) by analyzing the known performance faults. Figure 2 is an illustration of the technique. Evolutionary prognostics may be implemented on systems or subsystems that experience conditional failures, e.g., an auxiliary power unit (APU) gas path degradation. Generally, evolutionary prognostics works well for system level degradation because conditional loss is typically the result of interactions 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 the 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 requirement for this technical approach. An alternative to the physical model is built in "expert" knowledge of the fault condition and how that knowledge manifests itself in the measured and extracted features.

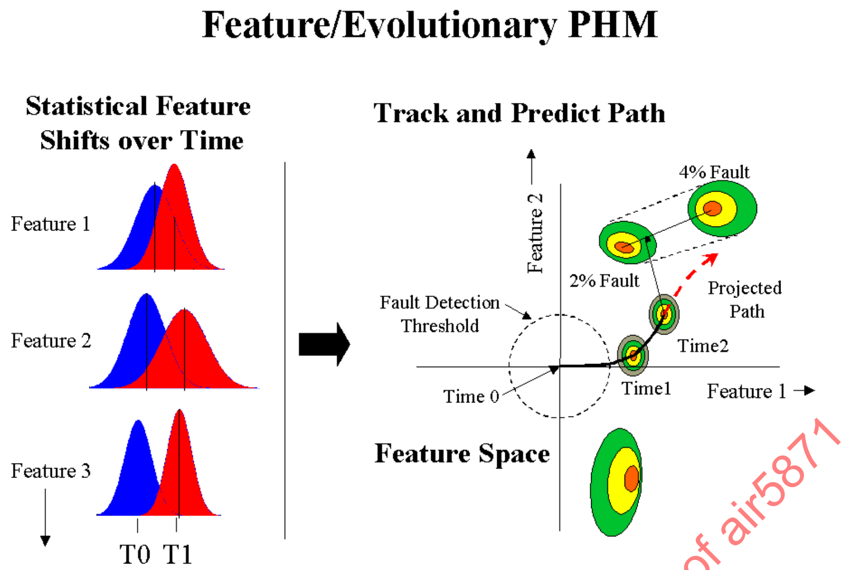


FIGURE 2 - EVOLUTIONARY PROGNOSTICS

4.3 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 to a failure. In such cases, the probability of failure, as defined by some measure of the "ground truth," is required as a-priori information. This "ground truth" information needed to train the predictive network is usually obtained from inspection data. Based on the input features and desired output prediction, the network will automatically adjust its weights and thresholds based on the relationships it sees between the probability-of-failure curve and the correlated feature magnitudes. Figure 3 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 feature progressions for a different test under similar operating conditions.

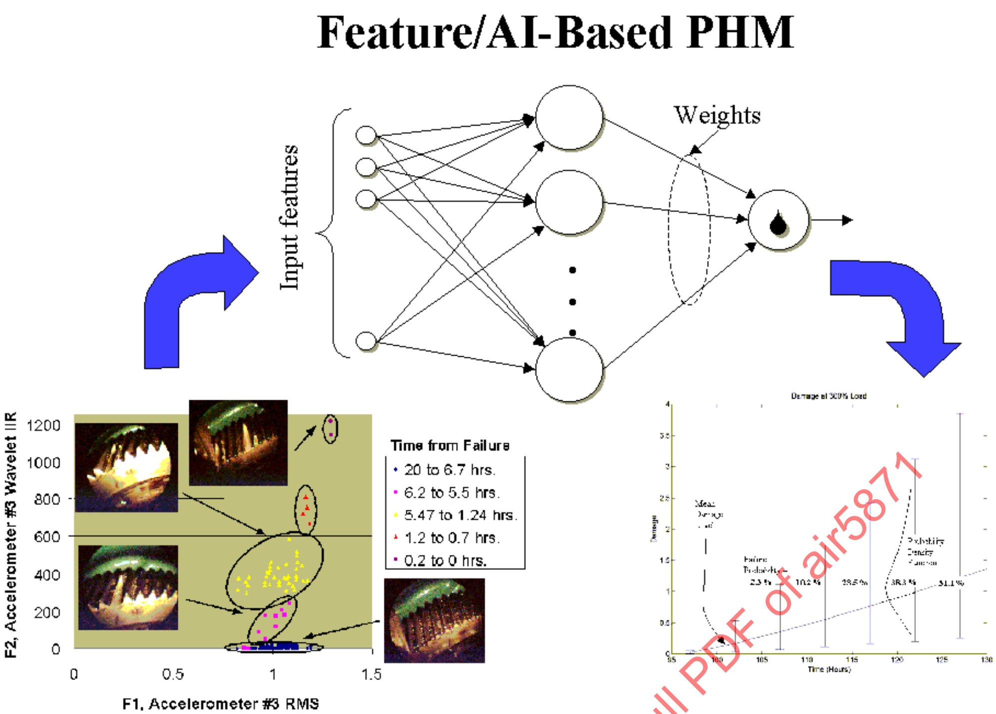


FIGURE 3 - FEATURE/AI-BASED PROGNOSTICS

4.4 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.

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

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:

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

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. Figure 4 is an illustration of this approach.

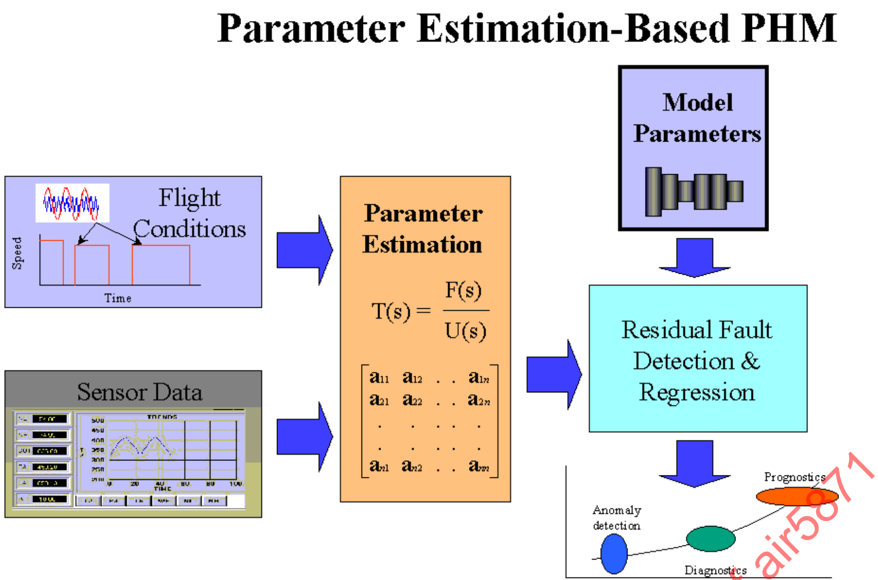


FIGURE 4 - STATE ESTIMATOR PROGNOSTICS

4.5 Physics-Based Prognostics

A physics-based stochastic model is a technically comprehensive modeling approach that has been traditionally used for component failure mode prognostics. For a particular fault, it can be used to evaluate the distribution of remaining useful component life as a function of uncertainties in component strength/stress or condition. 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. An example of a physical, model-based prognostic technique is shown in Figure 5 for a rotating blade.

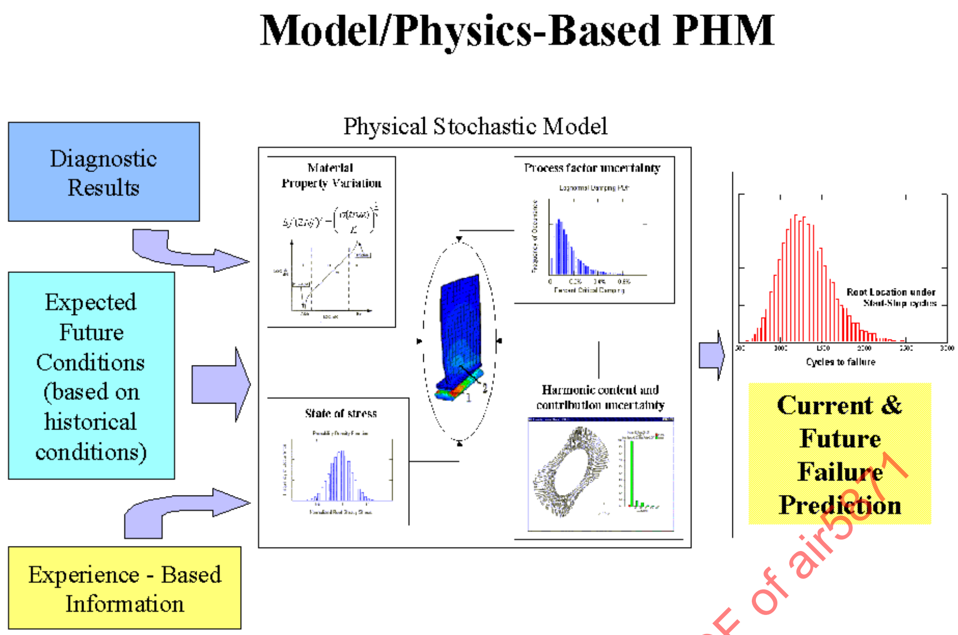


FIGURE 5 - PHYSICS-BASED PROGNOSTICS

5. PROGNOSTIC IMPLEMENTATIONS

Cost effective implementation of a prognostic system will vary depending on the design maturity and operational/logistics environment of the monitored equipment. One common element to successful implementation is feedback. As components are removed from service, disassembly inspections must be performed to assess the accuracy of the diagnostic and prognostic system decisions. Based upon this feedback, system software and warning/alarm limits should be optimized until desired system accuracy and warning intervals are achieved. In addition, selected examples of degraded component parts should be retained for testing that can better define failure progression intervals.

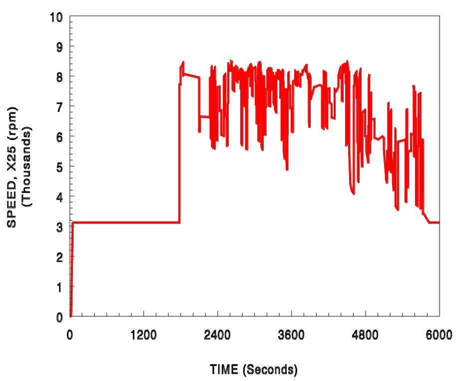
5.1 Example: Gas Turbine Engine Blade Prognostics

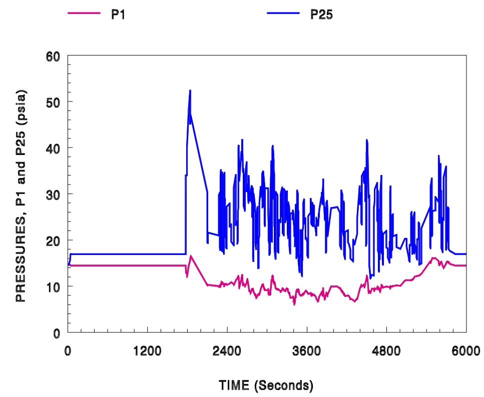
A pictorial representation of a failure prognostic modeling approach that was developed for a combined HCF/LCF blade failure mode is shown in the next series of figures (Note: Figure 6 is extended on two pages). This sequence of steps was implemented to demonstrate a probabilistic approach to prognosing the HCF/LCF failure mode life of a gas turbine engine fan blade. The sequence of probabilistic/prognostic modeling aspects included: (i) probabilistic mission type mixture, (ii) probabilistic mission profile simulations, (iii) probabilistic aerodynamic forcing function, steady and unsteady, derived from the mission profile measurements of pressure differential and power consumed along the fan stages, (iv) probabilistic blade steady-state and dynamic stress analysis, including all modes which generate vibratory stresses, (v) probabilistic equivalent stress profiles for both the steady state and the vibratory stress components, (vi) probabilistic stress-life transformation, including modeling uncertainties due to multi-axial stress effects, local plasticity effects using Neuber's approach, and rainflow counting, (vii) probabilistic damage mechanism using a nonlinear damage accumulation model for crack initiation. The last plot is a comparison of life prediction showing the effects of FOD random occurrences and laser shot peening on the fan-blade HCF/LCF life.

For component failure prognostics, a probabilistic model capable of simulating projected mission profile scenarios for all critical parameters is a desirable feature. In such a model, the random mission profiles are modeled by multipulse, continuous, non-normal stochastic processes. The rare accidental events, such as random FOD events, engine malfunctions, material defects, maintenance-induced damage, large flow distortion, etc. which have a discrete occurrence in time, are modeled by discrete impulse processes, such as Poisson or Weibull shot-noise processes. For a large time macro-scale, the typical mission environment represents a continuous component, while the rare events represent discrete components. A pictorial schematic representing this type of mission environment is shown in Figure 6. A detailed probabilistic model capable of simulating future mission profiles and FOD events is needed due to the non-linearity involved by the progressive damage mechanism, which includes the significant HCF/LCF/Creep interactions. An additional reason for having such a model is that a component's prognosis can be significantly affected by the large variability in the engine operating environment in cases where severe missions or FOD events occur.

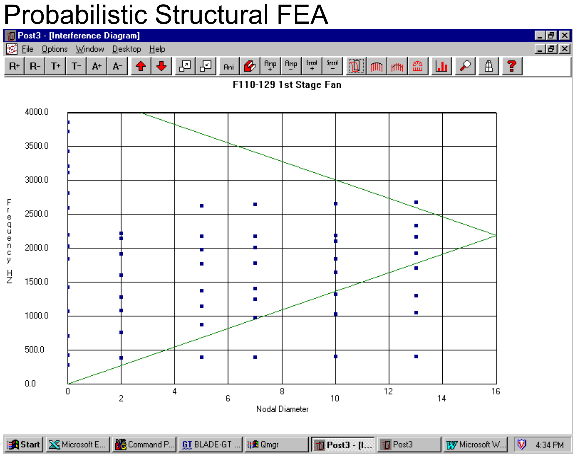
Due to the complexity of these stochastic models which involve high non-linearity, (i.e., very skewed probability distributions, multi-modal densities, and delicate non-stationary or non-homogeneous aspects), the use of pure analytical process models limited to classical probability distributions and stationary assumptions are not always possible. However, simple models can be used for defining the random variability of the parameters within the complex stochastic models describing the mission profiles.

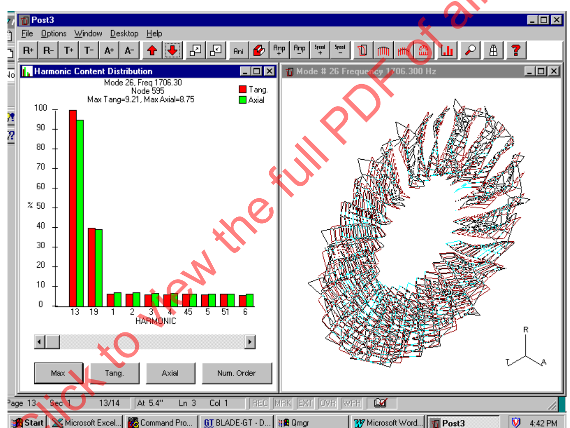
Stochastic Mission Profiles and Forcing Function Projections



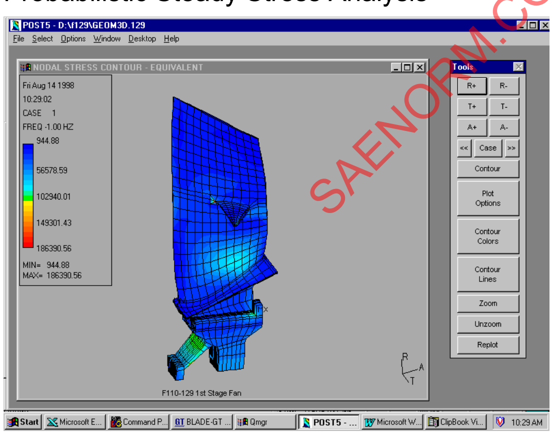


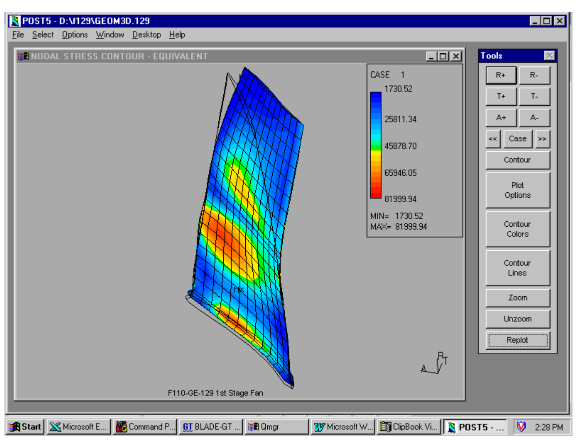
Probabilistic Structural FEA



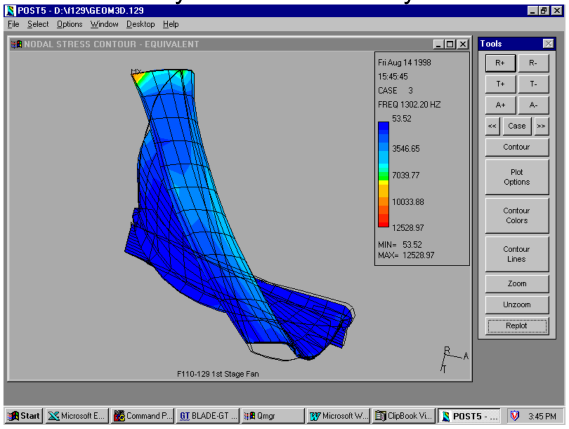


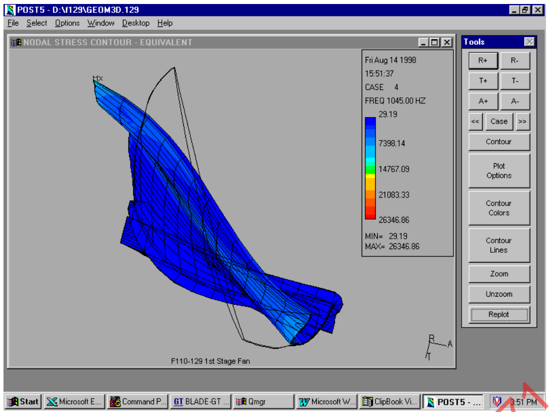
Probabilistic Steady Stress Analysis



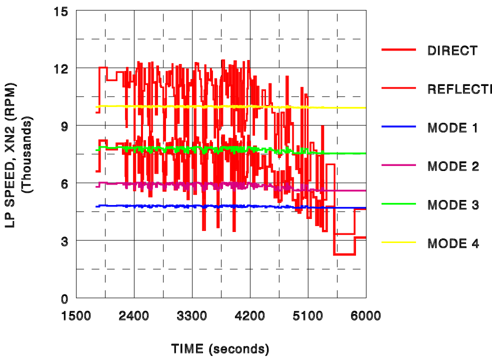


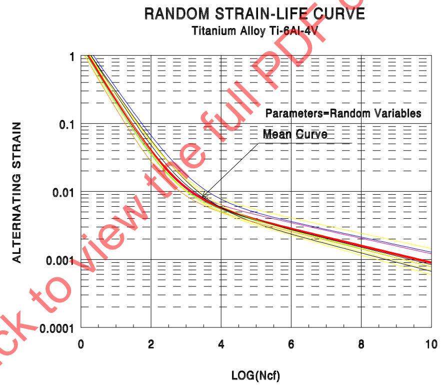
Probabilistic Dynamic Stress Analysis



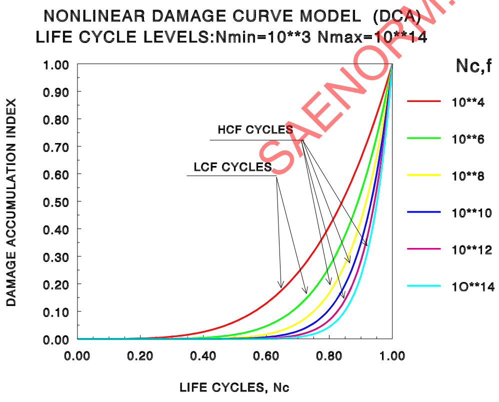


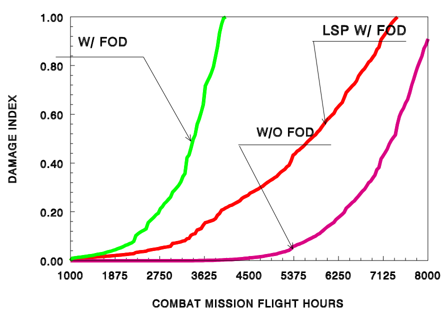
Probabilistic Stress-Life Transformation





Probabilistic Damage Accumulation and Life Prognostics





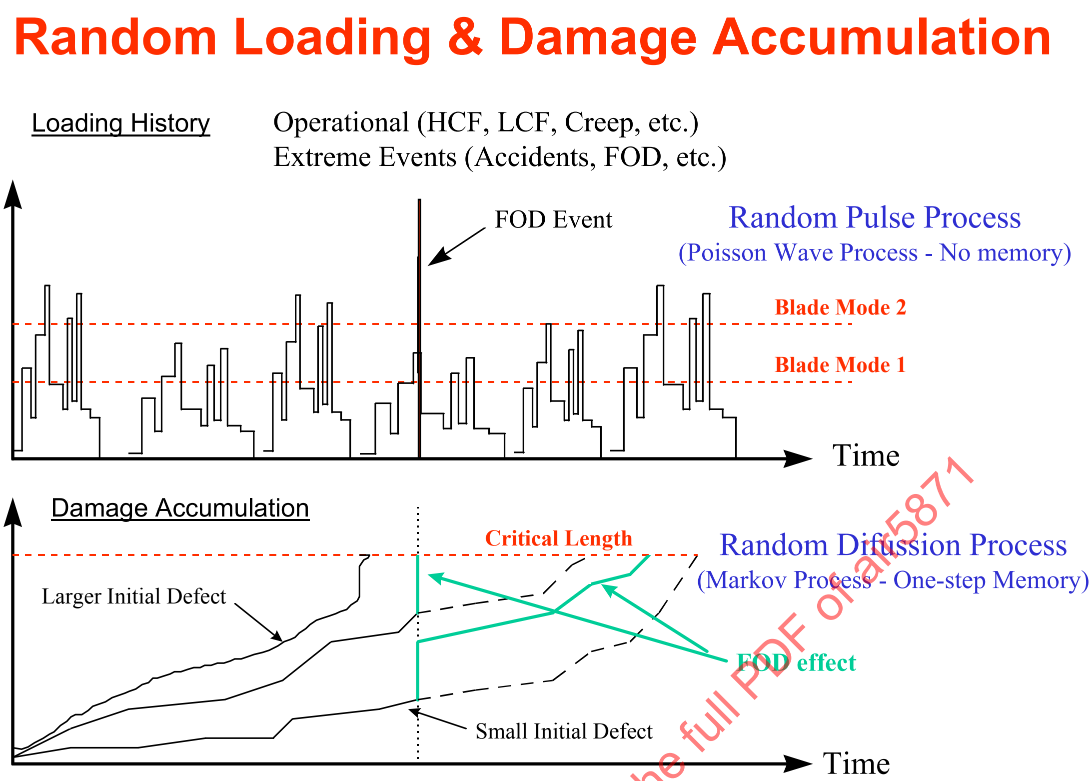


FIGURE 6 - MISSION ENVIRONMENT AND DAMAGE ACCUMULATION PROCESS

To develop the stochastic mission profile models, significant statistical aspects of recorded mission profiles are analyzed in detail. These aspects include the random characteristics of the LP/HP speed profiles in which random speed changes correspond to pilot combat maneuvers that also have random duration. It should be noted that the mission profiles are described by sequences of correlated random pulses. The structure of these pulse processes reveals the non-stationary characteristics. It can be observed that the maneuver pulses for particular mission types occur in clusters and with different random arrival times. Another important aspect for the probabilistic modeling of the mission profiles is the non-normality of their probabilistic distributions. Typically, the probability density functions (PDF) of the LP speed profile and pulse durations (or time between maneuvers) reveal a large skewness, indicating a large deviation from a normal (or Gaussian) PDF. A large collection of these mission statistics, including signal correlation analysis, is used to simulate new mission random profiles for probabilistic life prognostics.

5.2 Example: Gas Turbine Performance Prognostics

Fouling degradation of gas turbine engine compressors causes significant efficiency loss, which incurs operational losses through increased fuel usage or reduced power output. Scheduling maintenance actions based upon predicted condition minimizes unnecessary washes and saves maintenance dollars. The effect of the various maintenance tasks (washing and overhaul) on gas turbine engine efficiency is shown in the figure below.