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Probabilistic Approach to Component Condition Assessment, Remaining Life Prediction and Maintenance Engineering

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ABSTRACT

The paper illustrates how probabilistic physics-based models can be used for risk-based condition assessment and life prediction of aircraft jet engines, including the uncertainties in maintenance activities. Although this paper focuses on engines, the proposed approach can be extended elsewhere. Probabilistic modeling includes all significant uncertainties that affect engine reliability, such as flight conditions, loading history, manufacturing deviations, material properties and behavior under random loading and maintenance activities. Maintenance uncertainties include those related to NDI techniques and operator's skills. The paper shows the uncertainty effects of different NDI techniques, maintenance intervals, operator skills, etc. on the engine reliability. Unscheduled maintenance rates are computed for given a maintenance schedule.

INTRODUCTION

In contrast to the current engine maintenance engineering based on field data and empirical FMECA studies, *STI, in collaboration with GEAE, proposed a physics-based stochastic approach to maintenance engineering that is based on the detailed integration of all design and post-design aspects and uncertainties including significant manufacturing variabilities, maintenance activities and cost aspects*.

By developing physics-based stochastic models for idealizing the operating environment, aero-thermal loading, structural behavior and material progressive damage under variable loading*, the maintenance engineering and cost analysis is approached from an advanced physical understanding and modeling of the engine behavior.* Only by using such a physics-based stochastic approach, can the engine life-cycle cost process be adequately understood and controlled from the design stage.

The actual approaches to risk-based maintenance cost analysis, that are based solely on simple Weibull life models developed for only very limited tests or field data, suffer severely from having a weak foundation by neglecting the stochastic physics of failures. And the maintenance costs are very sensitive to the to the engine component failure risk estimates.

The overall scope of the research effort was to develop a prototype engineering computational tool for predicting the unscheduled maintenance event rates by developing physics-based stochastic models that are based on actual flight and component design data for current engines. Based on this physics-based stochastic models approach the key engine component reliability measures can be computed. These computed reliability estimates are used to perform a risk-based optimal-cost maintenance analysis

TECHNICAL APPROACH

The prototype engineering tool developed by STI under this project, called ProMACOR (Probabilistic Maintenance for Cost Reduction) is based on a *physics-based reliability engineering approach* that bridges and integrates intimately the *structural reliability* concepts and tools with the *classical reliability engineering* concepts and tools.

To increase ProMACOR's practicality, its computational reliability results are also converted to equivalent reliability (failure) models that are currently used in practice, such as the Weibull failure models and Uniform Hazard Rate (Exponential) reliability models.

PROMACOR APPROACH

The integration between the *structural reliability* tools and the *reliability engineering* tools is the essence of the ProMACOR approach. This integration brings with it the capability of stochastic modeling of the physics of failures within the classical reliability engineering framework (and further to cost modeling).

In the *classical reliability engineering* approach the designer or maintenance engineer has no ability to understand and control the effects of any environment or component changes on risk and maintenance costs. In contrast, in the *physics–based reliability engineering* approach the engineer understands the stochastic physics of failure and can control the effects of changes on risk and costs. The physics-based reliability engineering approach links engineering decision to reliability and costs. Of great importance is that this approach also reduces the needed amount of testing data.

ProMACOR brings a new dimension to engine design and maintenance by the fact that the comparison can be made directly in terms of risks and costs. This type of what-if cost analysis forms the basis for an optimized design-maintenance approach for fleets of aircraft engines. By examining how the variation of different parameters affects component risk prediction accuracy and life-cycle cost estimates, it would be possible to perform trade studies that maximize the value of the funding used in research for new and existing aircraft designs.

The ProMACOR prototype software has basically two important functional options: (i) For an accepted reliability it computes the required maintenance intervals to inspect the investigated component (the results depend also on uncertainties in operational environment, component behavior, selected inspection techniques) and (ii) For an anticipated maintenance strategy it computes component reliability and associated maintenance costs for obtaining an optimum engine design over a family of alternate designs.

Using ProMACOR a designer or maintenance engineer can quickly perform *what-if* analyses to see how different design modifications affect a component's risk of failure, the predicted life and/or the induced maintenance costs. For a designer, *what-if* analyses represent a key aspect for obtaining robust, affordable and durable cost-effective designs. Through *what-if* analyses, the designer understands, in much more detail, the behavior of his design, so that he can make the optimal technical decision.

The ProMACOR probabilistic condition assessment and life prediction analysis of an engine component include:

(i) stochastic modeling of flight profiles

(ii) stochastic modeling of component loading, environmental surface conditions, material and structural properties; this step may include modeling of the component surface boundary conditions, such as pressure and temperature variations, contact surface constraint effects on stiffness and damping, material property variations, manufacturing deviations from the baseline geometry, etc.

(iii) probabilistic component stress/strain analysis to compute multiaxial stress/strain state in the component for given steady and dynamic boundary conditions that are time dependent, such as variable blade stresses induced by speed variations or variable thermal stresses in a hot component due to the transient thermal effects, etc.

(iv) probabilistic component reliability analysis or risk analysis for initial no-usage conditions (no deterioration due to progressive failure mechanisms is included). This risk analysis is to identify the "infant mortality" failure risk due to a poor component design, material defects, or due to mishandling, etc. (this is the responsibility of OEM engine designer and in ProMACOR is considered to input by the analyst).

(v) stochastic modeling of component stress and strain histories at critical locations; this step includes the construction of equivalent stress random histories based on the stochastic mission profile inputs and component stress computations.

(vi) probabilistic condition assessment and life prediction based on stochastic cumulative damage mechanics models for crack nucleation stage and stochastic fracture mechanics-based models for crack propagation stage (effect of maintenance is not included). This step includes the maintenance uncertainties.

ProMACOR predicts probabilistic life of an engine component, including both the crack initiation and crack propagation stages, using the following cumulative damage models:

Crack Initiation: Stochastic Cumulative Damage Models (fatigue and creep)

1) Linear Damage Rule (Miner's Rule)
2) Damage Curve Approach
3) Double Damage Curve Approach
4) Lemaitre-Caboche CDM Model
5) Larson-Miller Model (pure creep rupture)

Crack Growth: Fracture Mechanics-based Models (fatigue and creep)

1) Forman Model
2) Sine Hyperbolic Model
3) Modified Sigmoidal Equation Model

PHYSICS-BASED RELIABILITY ENGINEERING

The current approaches to engine maintenance cost analysis are based solely on FMECA and simple Weibull life (failure) models that are developed for very limited tests or field data. These practical approaches suffer severely from having a weak foundation by neglecting the stochastic physics of failures.

ProMACOR is developed to handle all situations including the "break-in" and "wear-out" failure mode periods. However, ProMACOR is developed mainly to handle the "wear-out" failure types that are generated by progressive damage mechanisms. In the actual version, the "break-in" period failures can be included, but it is the analyst's responsibility to define the initial failure probabilities due to material defects or poor workmanship. Figures 1 and 2 show the failure probability curves and hazard rate curves computed for three critical crack limits with ProMACOR assuming an initial reliability condition defined by (i) a zero initial failure probability (at time zero) that corresponds to a situation with no "break-in" period, Figure 1, and (ii) a non-zero failure probability that corresponds to a situation that includes a "break-in" period, Figure 2.

The basic relationship that links the physics-based reliability engineering approach with the classical reliability engineering approach is

$$P[T_f \le t + \Delta t | T_f > t] =$$

$$P_f(t) + [1 - P_f(t)]\exp\left[- \int^{t+\Delta t} h(x)dx \right] \quad (1)$$

The above equation relates the failure probability within a time interval that in fact defines probabilistic distribution of component life, to the instantaneous failure probability computed at the starting time of the interval and to the hazard failure rate variation in the interval. Then, the MTBF can be computed integrating the reliability function that translates in the equation

$$MTBF = \int_0^\infty [1 - P_f(t)]dt \quad (2)$$

Equivalent Weibull failure models

For practicality purposes, equivalent Weibull component life models are determined based on the computational results of the physics-based reliability analysis. These equivalent "physics-based Weibull life models" have the advantage that they can be easily compared with the existing Weibull models developed based on component field failure data.

To compute the two parameters of the Weibull distribution a least-square error minimization technique is used to fit the random sample life data. It can be shown by doing some simple mathematical manipulations that the Weibull distribution assumes a linear relationship between ln(t) and ln(ln(1/1-F(t))) as follows:

$$\ln(\ln(1/(1 - F(t))) = \beta \ln(t) - \beta \ln(\theta) \quad (3)$$

By choosing ln(t) as x, the scale on the abscissa, and ln(ln(1/(1-F(t))) as y, the scale on the ordinate, the Weibull CFD is represented as a straight line in this transformed space (these are the coordinates of the Weibull paper). Thus, by a simple linear regression in the transformed space, the two Weibull parameters are easily computed. For equivalent Weibull model the instantaneous failure probability is computed by

$$P_f(t) = 1 - e^{-(\frac{t}{\theta})^\beta} \quad (4)$$

Also, the hazard failure rate at time t is given by

$$h(t) = \frac{1}{\theta\beta(\frac{t}{\theta})^{\beta-1}} \quad (5)$$

Computation of Optimal-Cost Replacement Time: If a part has a Weibull wear-out distribution and the cost of unplanned failures is greater than the cost of planned replacements, there is an optimal replacement interval. If the interval is too short, the replacement costs are too high. If it is too long, the unplanned failures drive the total cost too high. An optimal replacement strategy finds the most cost effective interval for replacing the hardware.

The optimal replacement interval is the time with the minimum ratio of the mean cost to the mean time to failure, $MainCost(t)$. The maintenance cost per unit can be expressed as follows:

$$MainCost(t) = \frac{C_p[1 - P_f(t)] + C_{up}P_f(t)}{\int_0^t [1 - P_f(t)]dt} = \min \quad (6)$$

where C_{up} = Cost of an unplanned on-line replacement, where $C_{up} > C_p$ and C_p = Cost of a planned off-line replacement before failure. If β is greater that one and the cost ratio is greater that one, the maintenance cost per unit time has a minimum.

Non-Destructive Inspection (NDI) Techniques

Inspection routines are adopted to detect and remove cracks with size larger than a rejection limit, resulting in the improvement of reliability towards an acceptable level. The advantages taken from regular inspections can be reduced or even completely lost if the inspection technique is not appropriately selected in view of the given component or the inspection is not able to detect damage indications that would lead to failure before any repair action could be taken.

The rejectable crack size can be used to evaluate the following probabilities, where independence between additive sizing error and detection is assumed:

1. The probability PR(a) of rejecting a crack with size a, calculated as the product of the detection probability and the probability of sizing the detected crack larger than aR:

$$P_R(a) = P_D(a)[1 - F_E(a_R - a)] \quad (7)$$

2. The probability PA(a) of accepting a crack with size a, calculated as the product of the detection probability and the probability of sizing the detected crack smaller than aR, added to non-detection probability:

$$P_A(a) = P_D(a)F_E(a_R - a) + [1 - P_D(a)] = 1 - P_R \quad (8)$$

For a given crack size a, the sum of these two probabilities equals unity, since a crack must always be either rejected or accepted. For a particular case where a > aR the function PR(a) is called the probability of correct rejection, while for a < aR the function PA(a) is called the probability of correct acceptance. It should be observed that PR(a) and PA(a), both depend on the reliability of the inspection technique and on the specified rejection limit aR.

ProMACOR can consider the uncertainties related to both the crack POD curve and the crack length sizing.

Reliability-Based Maintenance Analysis

The effect of NDE inspections on the crack propagation process is illustrated in Figure 3. The plots show the time evolution of the PDF of crack length in an axonometric view and using contour plots (time flows is from right to left). The left-side plot corresponds to no NDE inspection, while the right-side plot corresponds to four NDE inspections at 4000 EFH each. It can be visualized from Figure 3 that crack propagation process is a diffusion stochastic process with no boundary for no NDE inspection and with intermittent "mutation" (or reflective "jump-back") boundaries that have also a stochastic nature for repeated NDE inspections. For each NDE inspection a stochastic "mutation" boundary is placed at a random crack length crossing level. The "mutation" boundary has two functions: (i) accept a parent crack or (ii) reject a parent crack and produce a new kid crack (the crack of the replaced or repaired component).

Probabilistic Crack Growth Process Including Inspections

Thus, after each inspection new cracks are born due to the rejection of the old cracks, i.e. component replacement or local repair. The new crack populations are kids produced by the rejection of cracks from the previous populations. For example after two NDE inspections, the new kid cracks can have as parents (produced them by rejection-mutation) the rejected cracks form the original crack population that was born at the starting time or from the next generation of crack population produced by the rejected cracks at the first inspection. Thus, an accurate stochastic modeling of the crack growth process including inspections has to include the presence of evolutionary multiple statistical populations.

ProMACOR uses the non-normal probabilistic mixture model of populations for predicting component reliability. For each crack length population a lognormal probability distribution is assumed. This assumption appears to be reasonable and slightly on the conservative side as shown by repeated simulation studies performed. The use of Weibull distribution for crack length population is less accurate.

Component reliability is expressed in terms of the instantaneous failure probabilities and reliability indices. Based on physics-based reliability analysis, for each critical location of a component ProMACOR computes:

1. Crack Length Statistics Evolution with No or Multiple Inspection Intervals
2. Failure Risk Evolution with No or Multiple Inspection Intervals
3. Reliability Index Evolution with No or Multiple Inspection Intervals
4. Hazard Failure Rate Evolution with No or Multiple Inspection Intervals
5. Average Hazard Failure Rates per Inspection Intervals
6. Number of Failures (Removals) per Inspection Intervals
7. PDF of the Parent Crack Length Population after Each Inspection
8. Equivalent Weibull Failure (Life) Models
9. Posterior PDF of Life Via Bayesian Updating to Incorporate Failure Data
10. Posterior PDF of Crack Size Via Bayesian Updating to Include Inspection Data

For performing reliability-based maintenance analysis, ProMACOR has two functional options: (i) *For anticipated maintenance strategy it computes component reliability* (Figure 4) (ii) *For given reliability level it computes the required maintenance intervals* (Figure 5).

Based on reliability analysis results associated maintenance costs can be computed. A risk-based optimal-cost maintenance strategy can be identified (minimum cost with risk constraints).

The three curve plots in Figure 4 and 5 correspond to three different values of the critical crack lengths, namely 0.20 in, 0.50 in and 0.80 in. The figures compare the computed reliability estimates for two basic cases: (i) No Inspection and (ii) Multiple Inspections at 4000, 9000 and 11,000 FHs. The rationale behind selecting these inspection times was not to produce an optimum maintenance strategy, but to highlight some key aspects of problem. An average operator-skill ultrasonic POD curve was considered for this numerical investigation.

By exploring these types of results, important questions of the maintenance engineer can be answered. These questions include: What is the overall effect of maintenance strategy on failure risk evolution and overall associated costs? Is the selected maintenance strategy efficient from reliability and cost point of view? How much does the NDE technique influence the component reliability and the overall maintenance costs? How much does the operator skills influence the component reliability? How much does the crack rejection criteria influence reliability?

Figure 6 shows the failure probability evolutions for the two cases, without and with maintenance. From these plots it can be noted that if a failure probability of 0.001 is accepted, then the component life computed for this probability level and for the 0.50 in crack stability criteria is about 8,000 FH with no inspection and about 18,000 FH with three inspections. Further, it can be seen that the second inspection at 9000 FH is more efficient than the first inspection at 4000 FH. The first inspection is too early and therefore has a more reduced effect. The second inspection reduces the failure probability by a few orders of magnitude. The size of the downward jumps in failure probability evolution after each inspection time is a measure of how efficient the inspection at that time is.

Figure 7 shows the computed maintenance replacement costs assuming that the unscheduled on-line replacement is ten times more expensive than scheduled off-line replacement. It can be observed that the effect of the inspections is to double the optimal-cost replacement time and to reduce the overall replacement cost to half of one third.

Figure 8 shows the effects of the inspection NDE technique on the optimal-cost replacement time. It is interesting to note that the use of Eddy Current inspection instead of Visual inspection changes the optimal-cost replacement time from 13,000 FH to 17,000 FH and reduces the overall replacement cost by almost 35%.

Figures 9 and 10 show the main screens of the ProMACOR software for the "Maintenance Strategy" input options and the "Risk Analysis" output options, respectively.

CONCLUDING REMARKS

The paper presents a new, efficient risk-based maintenance cost analysis tool for aircraft engines, ProMACOR, based on an accurate physic-based stochastic modeling of material deterioration under random operational conditions.

Using ProMACOR, the maintenance and design engineers can take optimal-cost decisions based on accurate estimates of component failure risks including maintenance uncertainties

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CONTACT

Dr. Ghiocel is the Vice President of Advanced Engineering Applications at STI Technologies Inc., located in Rochester, New York. Dr. Ghiocel has 18 years plus of extensive research lab, university research and consulting engineering experience in advanced computational structural/mechanical analysis for systems and components, computational stochastic mechanics, nonlinear random vibration and bifurcation analysis, stochastic finite element analysis,damage mechanics, probabilistic risk assessment and component life prediction. He taught graduate courses on Structural Analysis, Dynamics, Random Vibration, Structural Reliability and supervised graduate research work and direct final theses of M.Sc. and Ph.D. students on related topics.

Currently, he is performing collaborative work with Carnegie Mellon, CWRU, Cornell, University of Colorado at Boulder, Toledo and Vanderbilt universities.

Since 2001, Dr. Ghiocel has received an Adjunct Professor position at Case Western Reserve University (CWRU), Cleveland, Ohio.

He is the Chair of the Engineering Probabilistic Methods projects and the Co-Chair of the Technology Transfer Subcommittee of the RMSL Division of the SAE International. He is also the Vice-Chair of the AIAA Working Technical Group on Non-Deterministic Approaches.

In 1999 Dr. Ghiocel received the prestigious SAE "Distinguished Probabilistic Methods Service Award" for "Demonstrated Excellence in Dedication to the Growth and Success of the SAE Probabilistic Methods Committee Through Production of Technical Documents and Ceasless Assistance to Probabilistic Methods Community".

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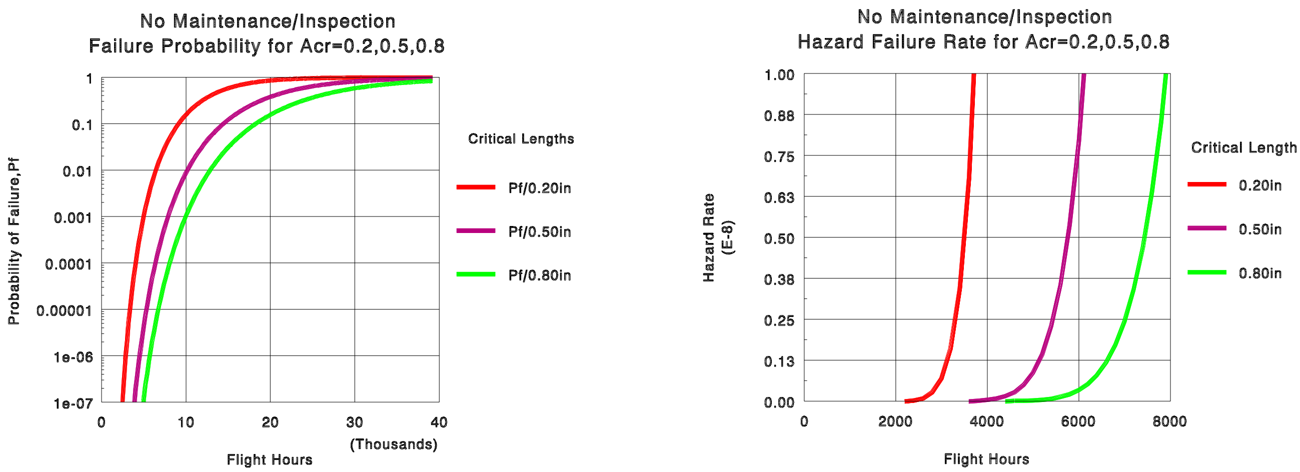

Figure 1 Failure Probability and Hazard Rate Evolution for Zero Initial Condition
("Wear-out" shape of hazard rate curve)

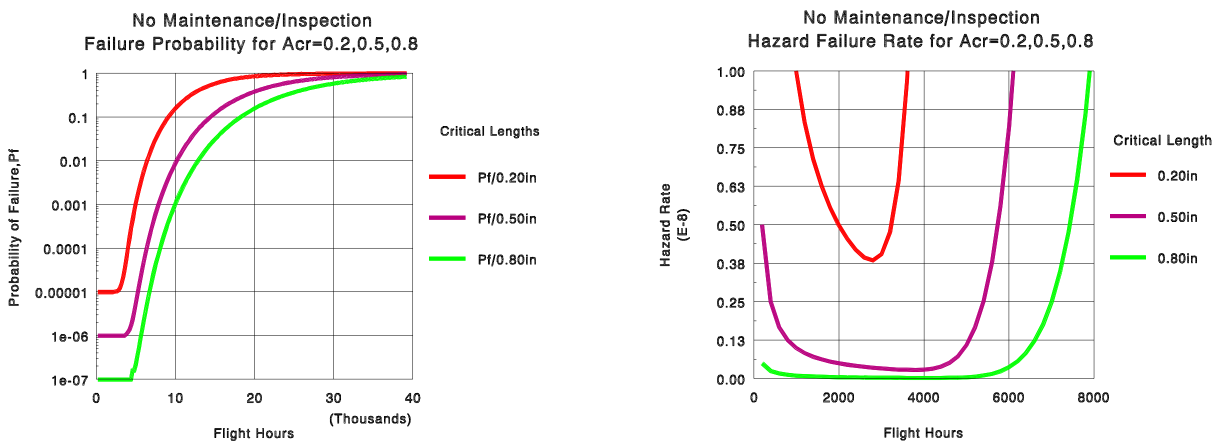

Figure 2 Failure Probability and Hazard Rate Evolution for Non-Zero Initial Condition
("Bath-Tub" shape of hazard rate curve)

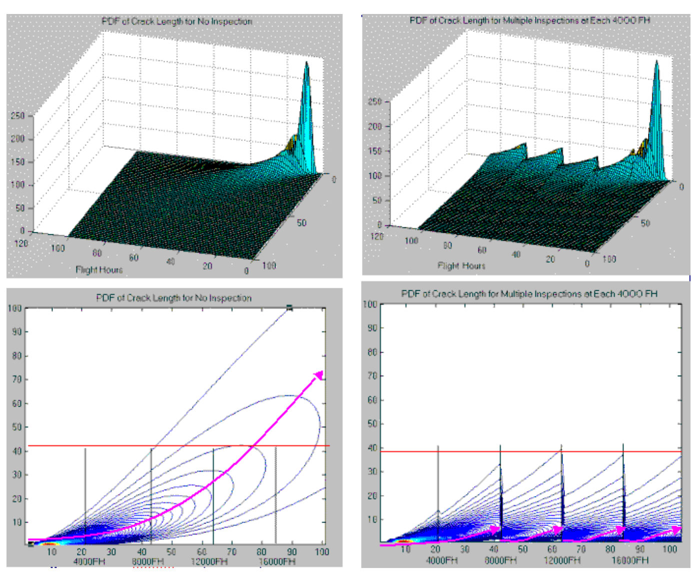

Figure 3. Effect of the NDE Inspection on Crack Length Probability Density

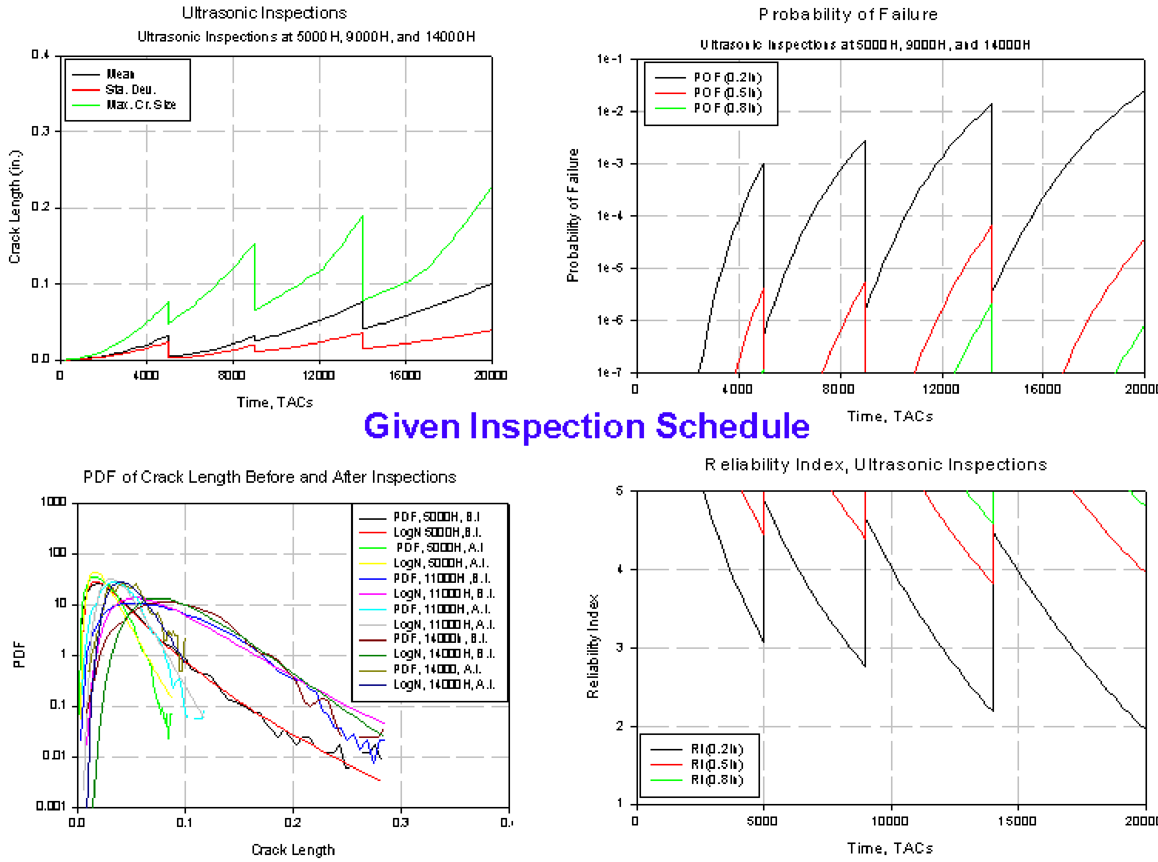

Figure 4. Reliability Analysis Results for Given Maintenance Strategy

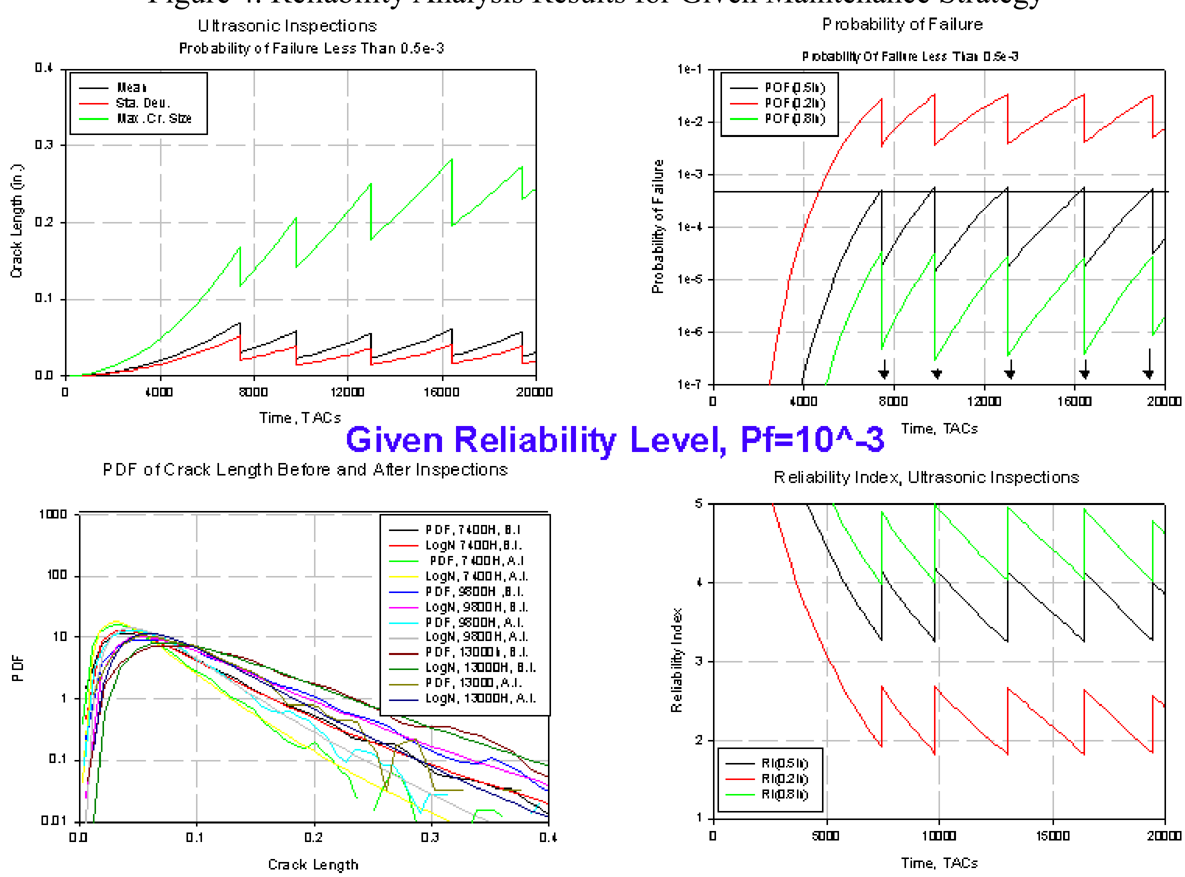

Figure 5. Reliability Analysis Results for Given Reliability Level

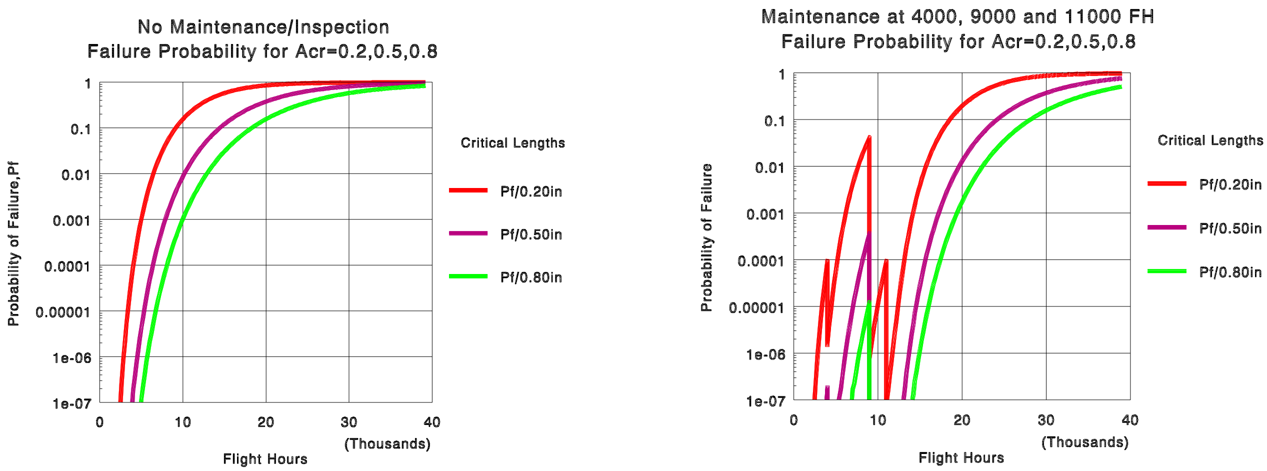

Figure 6. Failure Probability Evolution: (a) No Inspection, (b) With Inspections

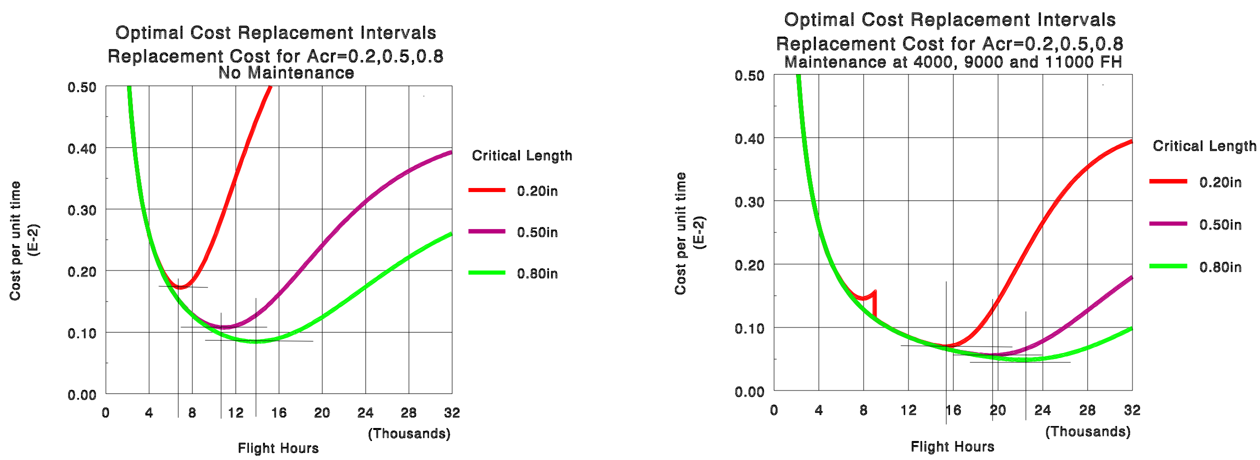

Figure 7. Maintenance Cost vs. Removal Time: (a) no Inspection, (b) with Inspections

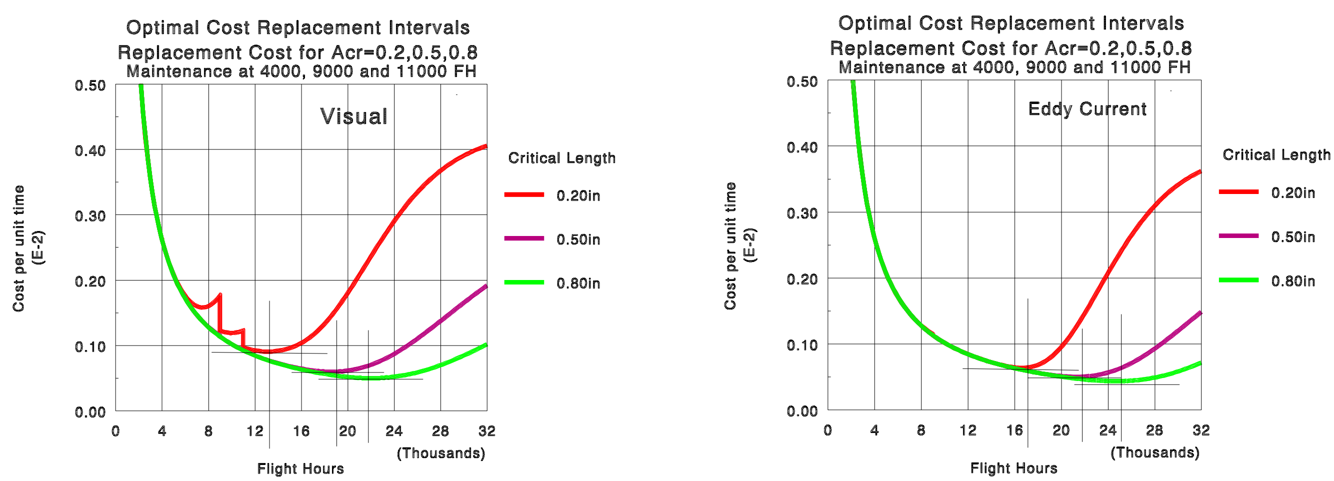

Figure 8. Maintenance Cost vs. Removal Time: (a) Visual, (b) Eddy Current

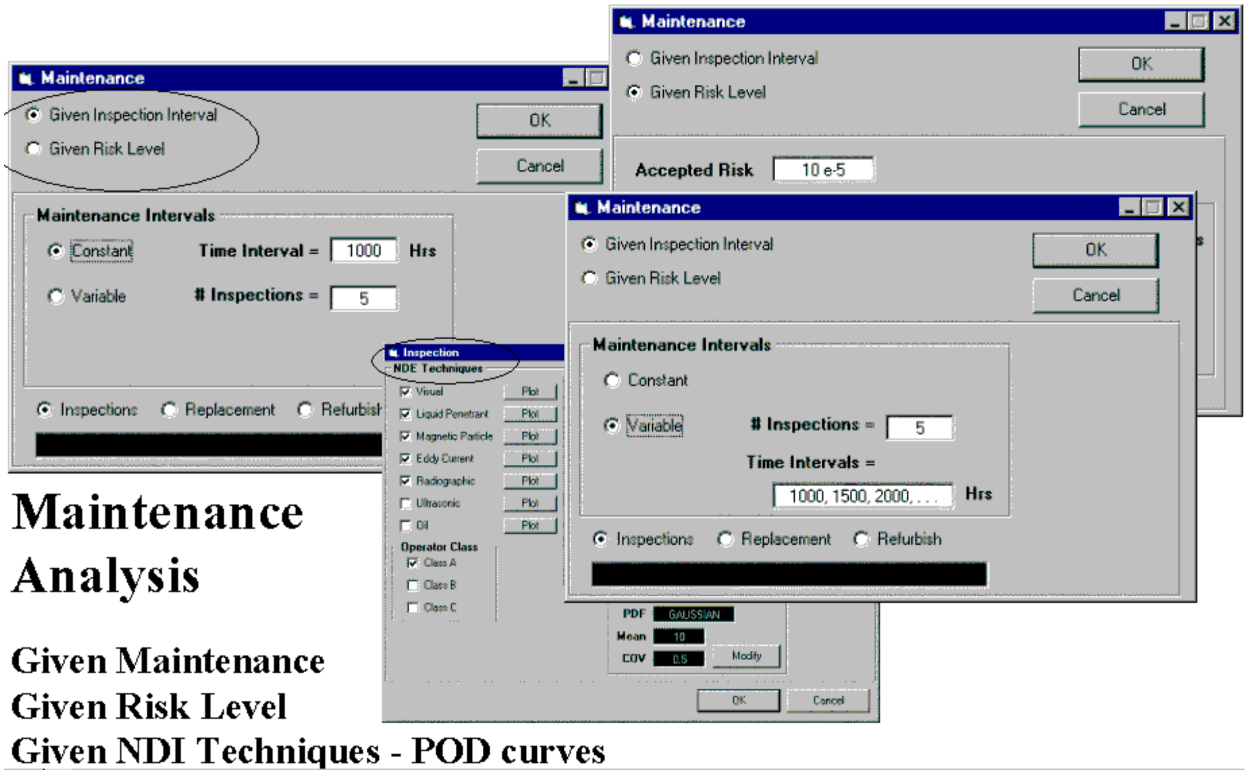

Figure 9. Maintenance Strategy Input Screens

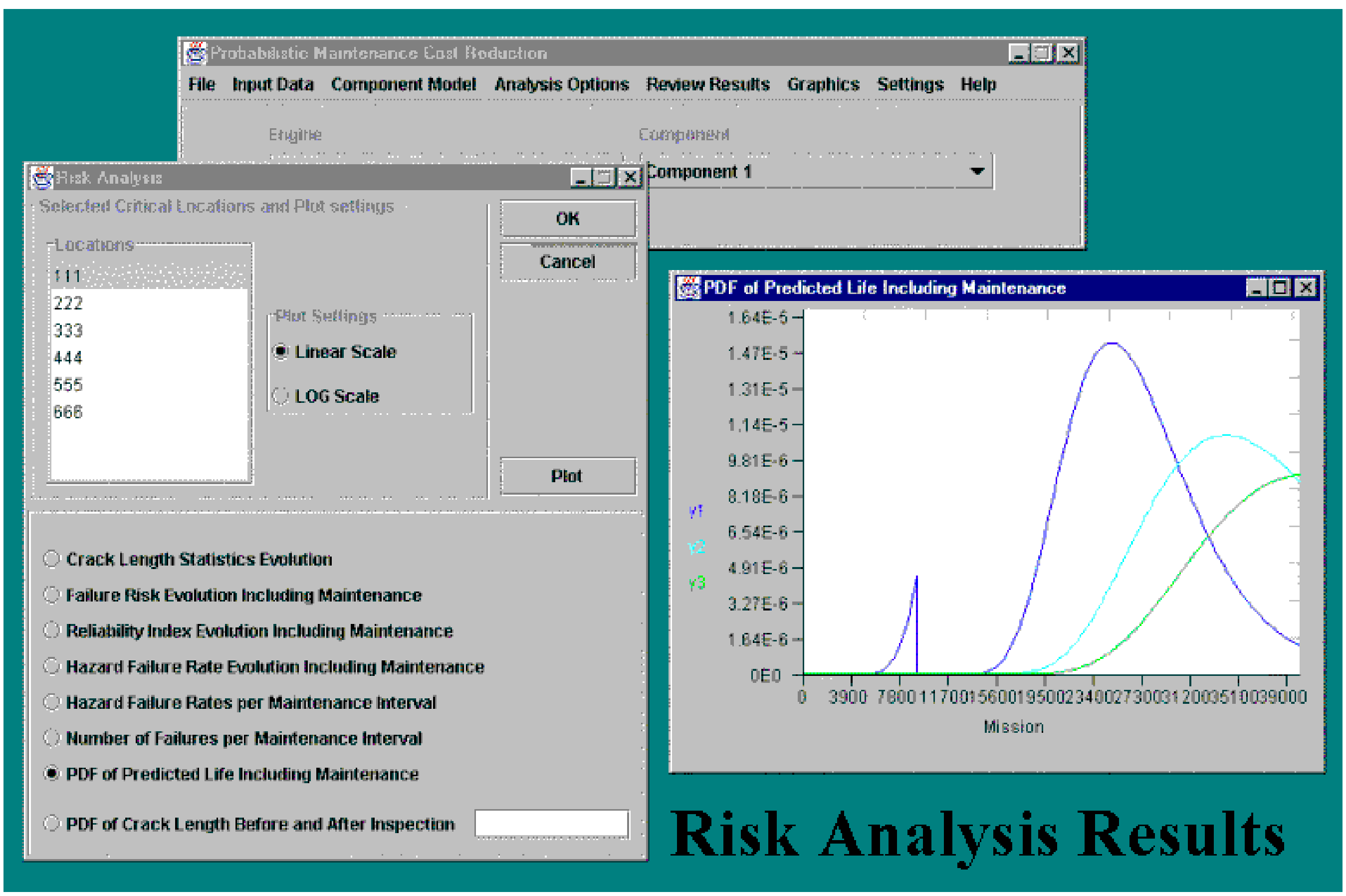

Figure 10. Probabilistic Risk Analysis Output Screen