Advanced System-Level Reliability Analysis and Prediction with Field Data Integration

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ABSTRACT

As the acquisition, operating and support costs rise for mission-critical ground and air vehicles, the need for new and innovative life prediction methodologies that incorporate emerging probabilistic lifing techniques as well as advanced physics-of-failure durability modeling techniques is becoming more imperative. This is because of interest in not only extending the life of current structures, but also in optimizing the design for new components and subsystems for next generation vehicles that are smaller, lighter, and more reliable with increased agility, lethality, and survivability.

The component level physics-based durability models, although widely adopted and used in various applications, are often based on simplifying assumptions and their predictions may suffer from different sources of uncertainty. For instance, one source of uncertainty is the fact that the model itself is often a simplified mathematical representation of complex physical phenomena. Another source of uncertainty is that the parameters of such models should be estimated from material-level test data which itself could be unavailable, noisy or uncertain. At the system level, most modeling approaches focus on life prediction for single components and fail to account for the interdependencies that may result from interactive loading or common-cause failures among components in the system.

In this paper, a hybrid approach for structural health prediction and model updating for a multi-component system is presented. This approach uses physics-of-failure and reliability modeling techniques to predict the underlying degradation process and utilizes field data coming from findings of scheduled maintenance inspections (or potentially, a real-time onboard health monitoring data) as feedback to update the model and improve the predictions. The integration of field data and model updating is realized via the Bayesian updating technique. The approach is being evaluated by an OEM to a ground vehicle suspension design enhancement.

Two different failure mechanisms, corrosion and thermal mechanical fatigue, are taken into consideration for physics-of-failure modeling. Finite element analysis (FEA) is performed on the components to calculate the stress values needed as inputs to the life prediction models. Once the expected life of individual components is calculated (considering multiple failure modes and composite of usage profiles), a

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As the acquisition, operating and support costs rise for mission-critical ground and air vehicles, the need for new and innovative life prediction methodologies that incorporate emerging probabilistic lifing techniques as well as advanced physics-offailure durability modeling techniques is becoming more imperative. This is because of interest in not only extending the life of current structures, but also in optimizing the design for new components and subsystems for next generation vehicles that are smaller, lighter, and more reliable with increased agility, lethality, and survivability. The component level physics-based durability models, although widely adopted and used in various applications, are often based on simplifying assumptions and their predictions may suffer from different sources of uncertainty. For instance, one source of uncertainty is the fact that the model itself is often a simplified mathematical representation of complex physical phenomena. Another source of uncertainty is that the parameters of such models should be estimated from material-level test data which itself could be unavailable, noisy or uncertain. At the system level, most modeling approaches focus on life prediction for single components and fail to account for the interdependencies that may result from interactive loading or common-cause failures among components in the system. In this paper, a hybrid approach for structural health prediction and model updating for a multi-component system is presented. This approach uses physics-offailure and reliability modeling techniques to predict the underlying degradation process and utilizes field data coming from findings of scheduled maintenance inspections (or potentially, a real-time onboard health monitoring data) as feedback to update the model and improve the predictions. The integration of field data and model updating is realized via the Bayesian updating technique. The approach is being evaluated by an OEM to a ground vehicle suspension design enhancement. Two different failure mechanisms, corrosion and thermal mechanical fatigue, are taken into consideration for physics-of-failure modeling. Finite element analysis (FEA) is performed on the components to calculate the stress values needed as inputs to the life prediction models. Once the expected life of individual components is calculated (considering multiple failure modes and composite of usage profiles), a reliability model is used to calculate the system-level reliability from the reliability of individual components. To perform the Bayesian updating, the Markov Chain Monte Carlo (MCMC) technique is employed to 'tune' the model parameters based on available field data and update the reliability estimates. This process results in an enhanced life prediction model that compensates for the aforementioned modeling uncertainties by utilizing feedback from the field behavior of an actual structure to tune the life-prediction model parameters.

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INTRODUCTION

A software framework for performing component and system durability calculations at the design stage has been developed. The initial target for this software is ground vehicles. This framework incorporates the following aspects:

- System Durability Explorer – Combines reliability predictions across multiple components and failure modes in an assembly to estimate the system reliability. The system level assessment is based on a system relational model, component level reliabilities, and a user defined usage or mission profile.
- Durability Analysis Enhancement Modules – Compute component life and reliability under corrosion and thermo-mechanical fatigue for specific combinations of finite element results (composite usage profiles). Parameters for life-prediction models are considered probabilistically via the use of Monte Carlo simulations.
- Parameter Updating – Incorporates feedback from field observations to enhance the prediction accuracy using Bayesian theory.

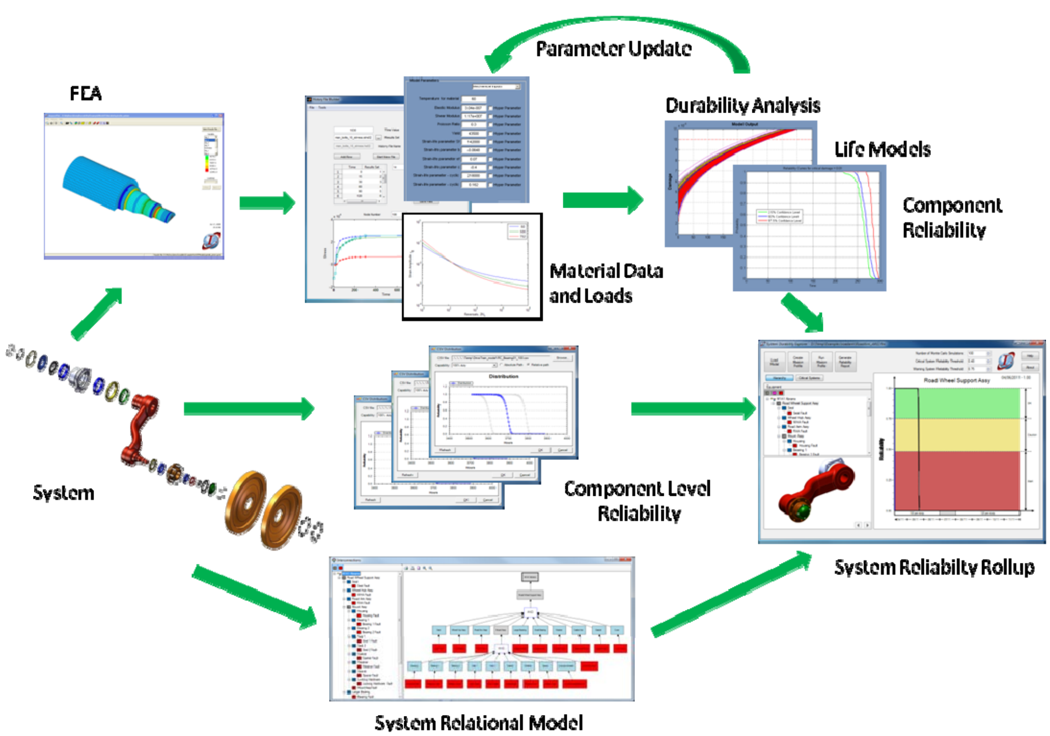

Figure 1: Architecture of the Advanced System Durability Analysis Software.

SYSTEM DURABILTY EXPLORER

The System Durability Explorer is a software tool that conducts system level reliability computations given the reliability of individual components or subsystems, considering various failure modes. The component or subsystem reliability is "rolled up" to a higher system level by combining reliability of each individual component that comprises the system. In order to accomplish this task, information about the internal system connectivity and the expected usage or mission profiles is required, in addition to component and failure mode specific reliability curves with uncertainty bounds. The specific reliability curves can be determined from a lifing calculation, experience, or vendor supplied information. A graphical modeling environment has been developed to establish a system-level inter-relational model. A full lifetime operational profile for the system can be specified as a combination of results from individual lifing analyses.

System reliabilities are calculated by modeling the system as an interconnection of components and failure modes in series or in parallel. If the failure of one component in the assembly would result in the system becoming inoperable, this component is modeled in series. If one component can fail, but the system continues to function since another component assumes the role of the failed component through redundancy, the two components are considered to be operating in parallel [1].

Assuming the failures in the components are independent, the system reliability distribution of M serial components can be calculated based on the probability of failure at time t as shown:

$$F_S(t) = 1 - \prod_{i=1}^{M} (1 - F_i(t)) \tag{1}$$

Where $F_s(t)$ is the cumulative distribution function (CDF) for system reliability prediction, and $F_i(t)$ is the CDF of reliability prediction for component i.

Similarly, the system reliability CDF of M parallel components can be calculated from:

$$F_S(t) = \prod_{i=1}^{M} F_i(t) \tag{2}$$

DURABILITY ANALYSIS ENHANCEMENT MODULES

A software framework for computing component life and reliability with uncertainty bounds has been implemented. Two specific failure modes are considered: corrosion and thermo-mechanical fatigue. These durability analysis enhancement modules are made independent of the FE package employed by utilizing a neutral file format for the computed nodal stress / strain and temperature inputs. Results sets are combined according to a loading spectrum definition. The output from each of these modules is a component-specific reliability curve as a function of time, with uncertainty bounds that are derived from the input parameter uncertainties through a Monte Carlo simulation.

Corrosion Modeling

For structural and drivetrain applications, two possible corrosion forms are corrosion fatigue and stress corrosion cracking. Corrosion fatigue describes the mechanism where localized corrosion pits form and become local stress risers, leading to crack formation under cyclic loading. The second failure mode is stress corrosion cracking under high mean stresses in the presence of a corrosive environment [2].

The model proposed by Harlow and Wei [3, 4] for corrosion fatigue incorporates localized pit growth by electrochemical means. In this model, the pit is assumed to grow at constant volumetric rate according to the Faraday and Arrhenius laws. The pitting model parameters are generally physics-based rather than empirical, and most can be found in the literature or derived. Once a critical pit size has been reached, the flaw behaves more like a crack and mechanically driven crack propagation dominates.

To account for stress corrosion cracking (SCC), two methods for crack rate calculation have been investigated and are incorporated into the module. The first method, as discussed by Jones and Ricker [5], is based on anodic dissolution of a metal utilizing the Faradaic relation. Some of the parameters in this equation are identical to those in the Harlow-Wei model. This SCC model is very aggressive and can be viewed as an upper limit since it neglects any passivation at the crack/pit surface. For SCC, once the stress corrosion cracking stress intensity threshold is reached (KISCC), crack growth progresses at a constant rate based on this relationship independent of stress until the stress intensity approaches the fracture toughness. Below the KISCC threshold, no crack growth due to SCC is assumed to occur. A second SCC calculation method has been developed in the power generation industry to predict SCC in power turbine blades. This approach, as explained by Rosario et al. [6], has been in use for the past few decades and is based on empirically derived material constants. This method also assumes that the crack growth rate due to SCC is constant above the KISCC threshold. Published data for this approach is based on materials commonly used for power turbines. However, the material constants can be also derived from test data.

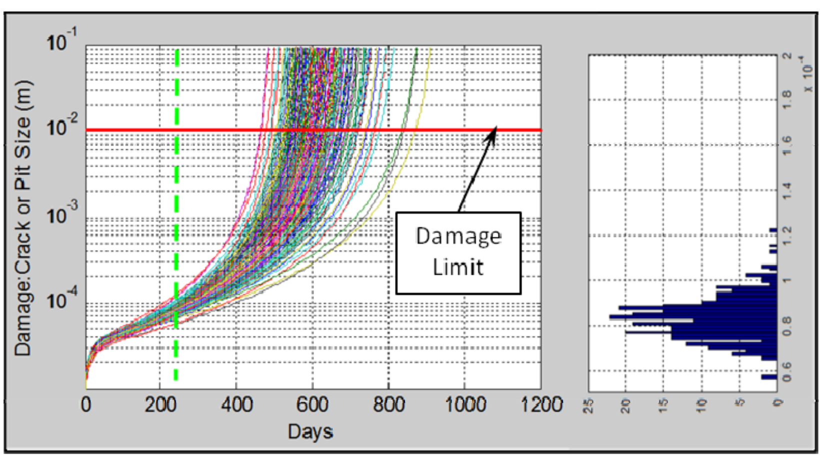

Figure 2: Example Probabilistic Corrosion Damage Progression Curves

Thermo-Mechanical Fatigue Modeling

Thermo-Mechanical Fatigue, or TMF, is caused by cyclic thermal gradients in components. Constrained thermal growth that results from these thermal gradients leads to material strains. Further, the effects of mechanical property changes as a function of temperature and compounding high temperature effects such as creep and oxidation makes TMF different from traditional low cycle fatigue (LCF) analyses where component temperatures can be assumed to be reasonably uniform and constant. In general, TMF can be broken into two categories, based on the temperatures experienced by the component: 1) moderately high temperatures, where the predominant failure driver is fatigue, and 2) very high temperatures (above roughly 30% of the melting temperature for example) where creep and oxidation are significant.

A review of thermo-mechanical fatigue literature (for example, see [8]) reveals that there are a number of approaches available for analyzing these types of problems. For the software development effort described here, fatigue due to a combination of applied loads and thermal expansion/gradients is considered to be the primary life driver, and very high temperature effects are neglected. The strain life approach [9, 10] has been selected for implementation, with a Finite Element model providing the nodal stress and temperature inputs. Damage from an applied cyclic loading history is then accumulated linearly according to Miner's Rule.

Two key effects in TMF that are handled in this software implementation include the temperature dependence of material properties, and the phase between mechanical loads and component temperatures. When isothermal test data is used, there are several choices of temperatures to choose for material properties over the course of a thermal stress cycle. One approach is to simply use material properties at either the maximum or mean cycle temperature. A method for determining whether the mean or maximum is more appropriate is described by Kang et al. [11], and Nagode and Hack [12]. An alternative method to handle this problem of temperature choice is through the computation of a Spanning Factor that allows the life to be estimated by combining N_f at the temperature extremes of the cycle [13]. The loading phase refers to the relationship between mechanical loading and thermal loading. For in-phase loading, the maximum temperature occurs at the same time as the maximum stress or strain. In the software implementation, fatigue properties obtained from fully in-phase and fully out-of-phase tests are accepted as inputs, and estimated properties are obtained by interpolating to the phase relation that is present in the loading data.

Probabilistic Analysis using Inner-Outer Loop Approach

The probabilistic nature of component dimensions, assembly conditions, material properties and loading conditions involved in lifing analysis is an important fact of life that influences structural safety. Durability and reliability analyses lead to safety measures that a design engineer has to take into account due to the uncertainties in model parameters, data variation, environmental factors, etc. Each of the model input parameters are allowed to vary within this software framework. The material properties as well as the load profile inputs for corrosion and TMF modules can be selectively considered probabilistic.

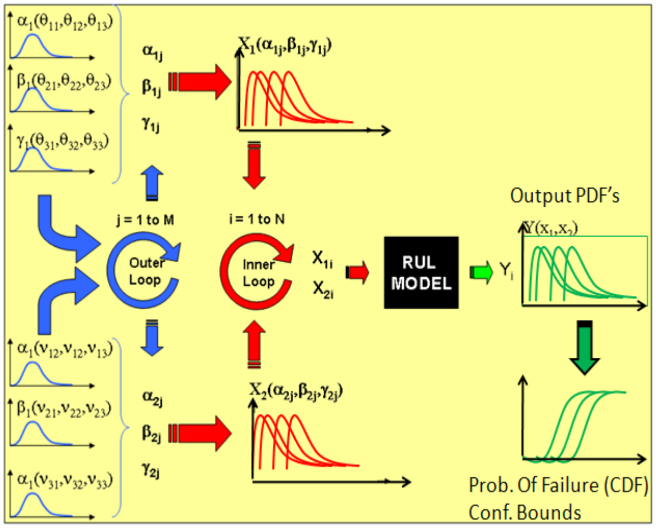

Figure 3: Overview of Inner-Outer Loop Procedure to Estimate Prediction Uncertainty

The uncertainty on the life prediction is determined through an inner-outer loop Monte Carlo approach (see additional discussion in [14]). To illustrate, a specific material property variation could be described with a Weibull distribution, with shape parameter α, scale parameter β, and offset γ. This inherent variability represents the inner loop. The Monte Carlo simulation in the inner loop will determine the probability of failure or reliability as a function of time for a specific set of model inputs, but it does not provide a confidence interval on that risk assessment. If variables α, β, and γ that describe a given input parameter are allowed to vary (for example, due to manufacturing or assembly variability across different batches of components), the uncertainty in the predicted probability of failure or reliability curve can be characterized. The variables that describe an input parameter may take on random values each with individual probability distributions. For example, parameter α may be described by a normal distribution with mean μ_1 and standard deviation σ_1. Likewise, β and γ may be represented by μ_2 and σ_2, and μ_3 and σ_3 respectively. These "hyper-parameters" (μ_1, σ_1), (μ_2, σ_2), and (μ_3, σ_3) that express the "hyper-distributions" are varied in an outer loop Monte Carlo simulation to establish the confidence bounds. The simulation approach consisting of two Monte Carlo Simulation loops is shown in Figure 3.

MODEL PARAMETER UPDATING

The model input parameters and their hyper-distributions that are initially based on a-priori experience or expert knowledge can be updated by applying Bayesian analysis to obtain a posterior distribution when evidence (inspection data, observations, or real time sensor data) becomes available. This evidence might be in the form of statistical samples of field failure incidence rates, or damage level inspection reports. The Bayesian updating addresses model parameter uncertainty when the model physics are assumed to be known and fixed. This type of Bayesian approach combines information contained in the observed data in the form of a likelihood function with the prior prediction from a model.

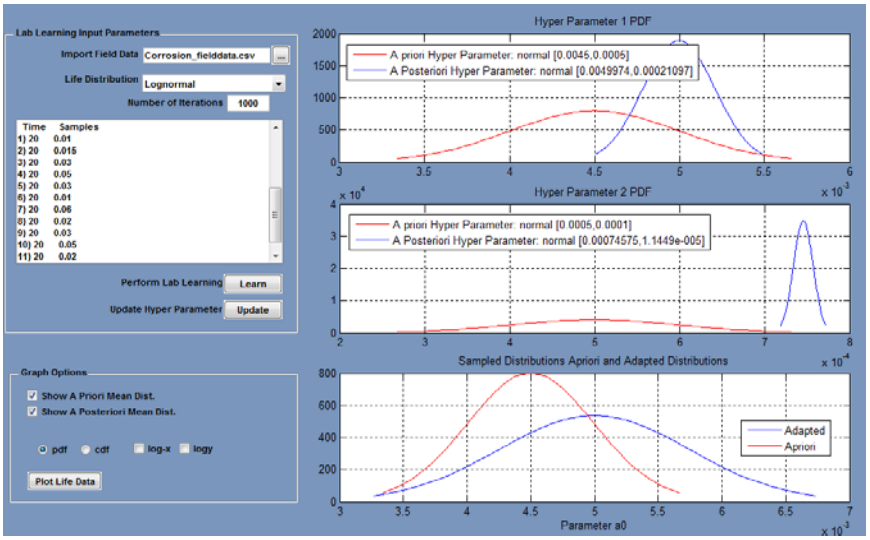

Figure 4: Bayesian Updating Interface

Based on Bayes' theorem, the data D influences the posterior probability distribution through the likelihood function p(D | θ), where θ represents the set of model input parameters. The updated probability distribution $p_D(\theta) = p(\theta \mid D,M)$ is obtained according to:

$$p_D(\theta) = C * p(D \mid \theta, M) * p_0(\theta \mid M) \tag{3}$$

Where, $p_0(\theta \mid M)$ is the a-priori probability distribution, and $C = 1 / p(D \mid M)$ is a normalizing constant. M signifies that the probability distribution was derived from a model prediction. The input parameters are treated as random variables, providing a feedback mechanism to update the original assumed values of the parameters. A Markov Chain Monte Carlo Simulation (MCMCS) is used for systematically extracting samples from a probability distribution during the updating process [15].

The benefit of performing this parameter updating step for a fielded component is realized when a new untested design requires similar input parameters to determine its life expectancy. Uncertainty can be reduced for parameters that are difficult to ascertain, leading to more accurate and realistic life predictions.

CONCLUSIONS

A set of software tools for estimating system durability at the design stage has been developed, along with an approach for incorporating field observations to improve the prediction. Software modules have been created to perform life predictions based on corrosion and thermo-mechanical fatigue induced failures. The corrosion module considers corrosion pitting/fatigue and stress corrosion cracking. The thermo-mechanical fatigue module includes the strain life approach with temperature compensated material properties, and is applicable for temperatures where creep and oxidation are minimal. The flexible architecture allows other failure mode-specific lifing modules to be integrated if needed. Component and failure mode specific reliability data is aggregated at the system level to provide an overall reliability estimate and identify the life-limiting components using reliability concepts. A model builder application has been designed to provide a means for creating system relational models. Interfaces are provided for updating model input parameters based on field observations or test data using Bayesian updating techniques. The initial target application for this software package is in the design of Army ground vehicle subsystems.

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