Title: Predictive Reliability of Tactical Missiles Using Health Monitoring Data And Probabilistic Engineering Analysis

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ABSTRACT

Tactical missiles within the U.S. Army are regularly subjected to severe stresses such as long-term exposure in harsh environments and transportation handling. These stresses factor into the aging, deterioration, and eventual decommissioning of some of the Army's critical warfighting assets. The negative reliability impacts associated with long-term aging and deterioration significantly affect the total life cycle cost of fielding these weapons in a high state of readiness.

Reliability evaluation of past data has indicated failures in missile structural, energetic, and electronic components associated with the long-term exposure to heat, humidity, and transportation shocks. Unlike strategic missiles, tactical missiles undergo a very minimum of field checks and non-destructive evaluation on a routine basis.

The Army Aviation and Missile Research and Development and Engineering Center have been developing a health monitoring system called Remote Readiness Asset Prognostics and Diagnostics System (RRAPDS) to assess and improve reliability of the missiles during storage and field exposures [3]. RRAPDS will use external and internal sensors to provide data to assess missile conditions and predict reliability.

This paper describes the approach to predict reliability of missile components like propellant, nozzles, and thermal batteries using sensor data from RRAPDS, and prognostic models for structural integrity and damage mechanisms. Probabilistic models will quantify all the uncertainties present in the health monitoring data and finite element models, to provide a realistic reliability evaluation.

INTRODUCTION

The US Army fields tactical missiles of various types all over the world. These missiles are exposed to different environments during storage, transportation, and operation. Typical environments include cyclic exposure to temperature and humidity extremes, vibration and shocks, and corrosive atmospheric conditions. Long-term environmental exposures affect a missile's performance and reliability as component material properties degrade, and this degradation negatively impacts critical performance parameters.

The reliability of the Army's missile stockpile and individual missile shelf life are monitored through dedicated programs of surveillance and testing. After fielding, the Army collects pertinent reliability data over a missile's lifecycle utilizing a variety of test methodologies both destructive and non-destructive. This data is analyzed for trends associated with age, manufacturing strata, and or unique environmental exposures.

If a missile system continued to perform reliably and safely based on surveillance data, then an extension of shelf life for that type missile is recommended to major decision makers and coordinated with the user and logistics community. If surveillance analysis indicates undesirable trends, then whole missile populations or subsets of populations are suspended for use or restricted for special use only. Obviously, the degradation and ageing of missile populations and their effects on

readiness of the stockpile can have major economic implications if new procurements are warranted.

A current surveillance and periodic test program is an essential element to maintain reliability of the missile stockpile by removing suspect assets before deployment. Analysis of test data identifies failure scenarios that include manufacturing defects, contamination during manufacturing and, most importantly, the degradation due to aging exposure and environmental exposure. In the case of environmental degradation and aging effects, the failure mechanism points towards accumulated damage resulting from exposure to temperature, humidity, and shock and vibration. It is evident from the failure mode analysis that real time monitoring and analysis of data may provide tools to predict the reliability of the missiles in storage and determine ways to improve it.

MISSILE FAILURE MODES:

Table 1 provides a snapshot of generic missile failure modes identified during storage. Fault tree analyses have been conducted to determine pathways from basic storage conditions to the top failure events. Basic events like thermal and humidity cycling, shocks and vibration during handling and transportation and corrosion are major causes of components failures during long-storage.

Table 1 shows generic failure modes classified under temperature, humidity, shock and corrosion related causes. RRAPDS provides data on these variables, which are then used and predict missile reliability, improve the shelf life and provide reliable hardware for operational use.

Table 1: Snapshot of Generic Missile Failure Modes due to Environmental Exposure

Temperature	Humidity	Shock	Corrosion
• Propellant Grain Cracking • Liner Unbond • Voids and Porosity in Propellant • Case Strength Degradation • Failure of Electronics Assemblies • Cracks in Packaging and Seals • Failure in Guidance Components o Gyros o Accelerometers	• Degradation of ballistic properties • Degradation of composite case • Degradation of O-rings • Degradation of Propellant properties • Failure of Electronics Assemblies • Cracks in Packaging and Seals • Failure in Guidance Components • Gyros • Accelerometers	• Case Damage • Liner Unbond • Propellant Cracking • Material Fatigue due to vibration • Loosening of components	• Failure of solder joints • Corrosion of metallic components • Stress corrosion cracking at interconnect /bends in electronic assemblies • Corrosion of actuators and bearings • Corrosion of contacts • Failure in squib wires

PROBABILISTIC PROGNOSTICS MODELING

Temperature, humidity, shock, vibration, and corrosion (chemicals) parameters can be measured in real time with an integrated health monitoring system. The data from this system can then be utilized to develop diagnostic and predictive models for components' health and integrity and to determine if a missile will operate successfully when fired.

The US Army has designed a system to monitor missile storage and transportation environments on a real time basis. The system, called the remote readiness asset prognostics and diagnostics system (RRAPDS), utilizes temperature, humidity, and shock sensors as an integral part of the weapon to monitor and perform diagnostic/prognostics analysis of the stockpiles during long-term storage [12].

RRAPDS is currently being field-tested and it is providing data to be used by probabilistic engineering models sufficient to predict the reliability of a weapon system at any point of time. Prognostic/predictive models are being developed to assess the reliability and structural integrity of the weapon system components and they can be used as a decision making tool for field deployment. Diagnostic and prognostic models will be utilized to translate health monitoring data into an assessment of reliability and performance of the weapon. The models are developed to determine if the component has or will degrade to a point where it cannot withstand the anticipated operating loads.

The models are developed to compute degradation in material properties as a result of exposure to thermal and humidity cycling, shock and vibration, and or a corrosive environment. The material properties data are determined using sensor information [1] that is then correlated with chemical kinetics or age-related relationships to determine change in modulus, strain energy, or other properties of this nature. Degraded material properties are then used in a finite-element method or other similar mathematical technique to evaluate induced internal stresses and predict current and future factors of safety. The factor of safety provides criteria for survivability of a component or weapon system in the actual field environment.

The prognostics and diagnostics models based on the deterministic approach stated above may not provide the actual quantification of uncertainty and variability presented in the health data and mathematical models. The real-time health monitoring data would consist of large variations in parameter values over time and the application of an average or worst-case value may overlook the occurrence of the failure frequency. Furthermore modeling uncertainty may not provide high confidence in the reliability assessment of the weapon system. The assumption of deterministic variables is an idealization that is not true in the real world. The extrapolation of the deterministic data to predict failure over time will be suspect and it adds another dimension of uncertainty.

A sound approach to modeling for prognostic and diagnostic analysis of the weapon system will be based on probabilistic engineering analysis. The probabilistic approach will attempt to quantify variability in the health monitoring data and modeling uncertainties and forecast the true failure frequency for decision-making purposes.

In this approach, the parameters of the prognostic and diagnostic models are specified as statistical distributions. These distributions are determined using statistical analysis of the health monitoring data. The model output response that includes the induced loads and component capabilities are also output as a statistical distribution. The synthesis of induced loads and component capabilities generate a failure function that can be analyzed to predict current and future reliability of the weapon system. The probabilistic approach will quantify increased variability in the failure function as data are extrapolated for future reliability assessment.

Several methods are available to analyze failure modes using the probabilistic engineering approach. The methods range from simple synthesis of material capability (strength) distribution with the applied (induced load) distribution to complex Monte Carlo simulation and sensitivity analysis. All of the analyses require the statistical analysis of all the input data to the failure function. The methods that are being evaluated for the army tactical systems are classified under three different categories: 1) probabilistic engineering evaluation using strength and stress interference; 2) probabilistic evaluation of the cumulative damage function; and, 3) prediction of component life based on Weibull analysis.

RRAPDS will provide data with information on exposed temperature, humidity, shock, vibration, and chemicals environment. Significant variables and trends can be identified using data mining techniques. Data collected can be analyzed to update design parameters such as failure rate of components, test costs, environmental thresholds, etc., and to predict spare parts requirements.

STRESS AND STRENGTH INTERFERENCE METHOD

In this approach, the material capability ($\overline{C}$) and the induced load distributions ($\overline{R}$) are used to compute the probability of failure at a point in time. If both parameters are normally distributed, the probability of failure is given by, [5]

$$P_f = 1 - \phi\left\{\frac{\overline{C} - \overline{R}}{\sqrt{(S_C^2 + S_R^2)}}\right\} \tag{1}$$

where $\overline{C}$ and $\overline{R}$ are average capabilities and s_c and s_r are standard deviation of the capability and induced loads, respectively. Φ is the normal probability function determined from standard normal table.

Figure 1 [5] shows the probability distributions as the material capability degrades while the induced stress due to long-term environmental effects increases.

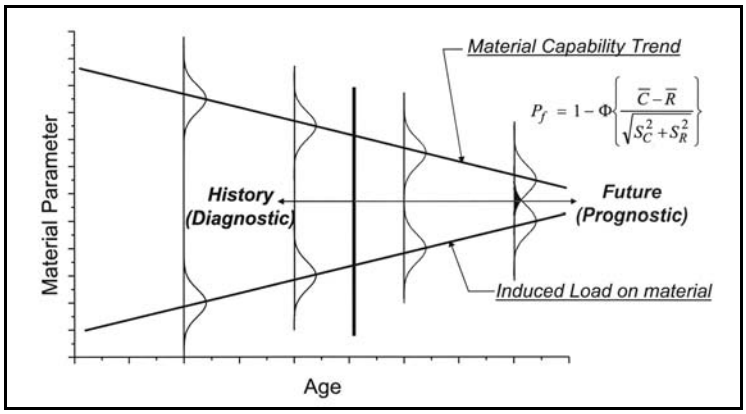

Figure 1: Component reliability with age.

In the stress and strength model, the capability or material strength (properties) is determined using a degradation mechanism resulting from humidity or temperature cycling, or shock and vibration. Some of the degradation functions include empirical Coffin-Manson functions, the Arrhenius law, or Boltzman formula [6]. The induced loads are determined using structural engineering models and input distribution from material properties (modulus, temperature) to compute the distribution of r. Statistics from these distributions are applied at any point of time to evaluate P_f.

An appropriate example for the stress and strength approach is to determine the reliability of the propellant/casebond system in the missile ordnance components like rocket motors and gas generators. Propellant modulus changes with age which impacts both the strength properties and the induced stress. Knowing propellant modulus at a given point of time, the propellant reliability can be determined using a finite element analysis model of induced stress and data on degraded material properties.

CUMULATIVE DAMAGE FUNCTION METHOD

Cumulative damage models evaluate the aggregate of small or microscopic damage within the component due to stress induced by environmental conditions over a time period. The incremental stresses are accumulated over time to determine the degradation in the component strength and to make predictions on whether the missile will withstand operational loads without failure. The rationale of the cumulative damage function is that eventually microscopic damage will accumulate and lead to failure. According to this theory, missile component failure will occur if the following is true:

$$D = \frac{\textit{stress accumuldated over time}(t)}{\textit{strength of material at time}(t)} + \frac{\textit{operating stress}}{\textit{predicted material strength at operation}} \geq 1.0 \quad .$$

The simplest form of the cumulative damage law is described by the Palmgren-Miner [7] rule as,

$$D = \sum \frac{n_i(t)}{N_f} \tag{2}$$

where d denotes the fatigue damage and n_i are the number of actual applied cycles at time t, and N_f is the total number of cycles to failure. At failure, d = 1 and n_i (t) = N_f.

Equation (2) represents a linear damage function that was originally proposed for the life prediction of metallic components undergoing fatigue. However, the linear damage function was found to give non-conservative results, as it predicts lives greater than those observed experimentally. Its main deficiencies are: 1) load level interdependence; 2) load sequence interdependence; and, 3) lack of load interaction accountability.

To make the cumulative damage law more appropriate to the real world, a simple non-linear form of Eq. 2 was presented using the definition of the power law as

$$D = \sum \left[\frac{n_i(t)}{N_f} \right]^{\beta} \tag{3}$$

where the power β is the load-dependent variable.

The cumulative damage [(D(t)] resulting from small steps in induced strength due temperature and humidity cycling or shock and vibration over a period of time is described by a damage function [2] as

$$D(t) = \int_0^{t_f} \frac{1}{t_f} dt \tag{4}$$

$$t_f = \left(\frac{\sigma_0}{\sigma(t)} \right)^{\beta} \tag{5}$$

$$D(t) = \int \left(\frac{\sigma(t)}{\sigma_0} \right)^{\beta} dt \tag{6}$$

where t_f is the time to failure, σ(t) is the induced stress as a function of time, σ_0 is the material strength, and β is the power law exponent showing the interaction between stress and strength parameters.

Equation 6 is shown graphically in Fig. 2 [2].

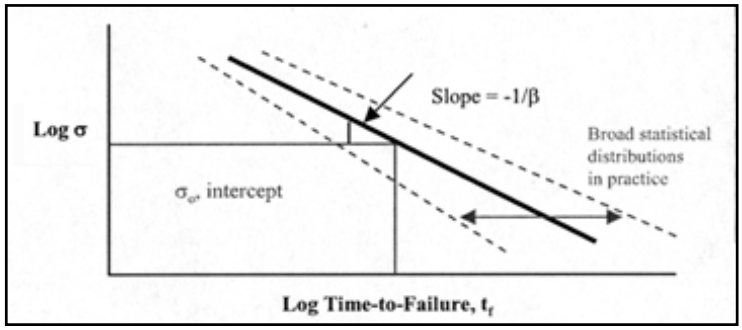

Figure 2: Time-to-failure versus damage due to increased stress.

Equation (6) can be evaluated using calculated stress values induced by temperature, humidity cycling, or shock and vibrations over time t. The value of the damage function at time (t) must be less than 1.0 to ensure the structural integrity of the component. Stress values are determined using finite element modeling or similar techniques.

The damage function D(t) evaluated in Eq. (6) represents a precise value and does not show any variability in D(t). It is calculated using specified values of temperature, humidity, or shock.

The data from the health monitoring systems will show a large variation in the measured parameters and the incorporation of average values to calculate stress will not provide an appropriate failure scenario. Since the damage function D(t) is very sensitive to applied stress, any variation in mechanical properties or other data could provide uncertainties in the results.

A probabilistic approach will be more appropriate to forecast the true failure frequency [10]. Figure 3 shows the comparison of mean damage (deterministic value) versus the failure probability.

According to Fig. 3, [4] the probability of failure as defined by the damage model is defined as,

$$P_f = P\,(d \geq 1.0) \tag{7}$$

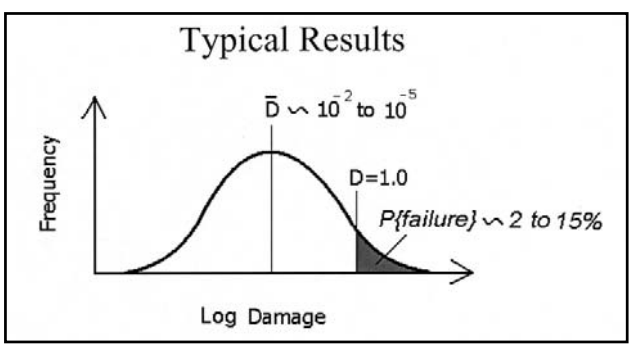

Figure 3: Failure probability distribution due to cumulative damage.

The probabilistic approach suggests that the damage model be developed as a failure distribution using statistical information on the input parameters such as temperature, humidity, and shock as measured by the health monitoring systems. The

variability in the input parameters could provide distribution of the damage function that can be evaluated for failure probability and reliability of the component.

WEIBULL SERVICE LIFE PREDICTION METHOD

Weibull analysis is widely used in reliability work to predict component service life and long-term aging degradation due to induced stress [9]. Weibull probability analysis provides a useful tool to predict time-dependent reliability and component service life [8].

The analysis methodology has a great advantage in stress and strength approach where non-linearity in the strength or stress function is involved. The application of Weibull distribution in the prognostic analysis is illustrated with an example of monitoring and predicting reliability of missile component like gyros in the guidance section.

PROBABILITY ANALYSIS OF GYROS:

Gyros are used in missile guidance and navigation systems and their precision is impacted due to long term exposure to humidity and temperature in storage environment. Failure mode analysis of gyros has identified several failure modes [16] in non-operating storage environment. Some of them are listed below:

- Separation in Spin Bearing lubrication due to temperature and humidity
- Creep and change in dimensional tolerances due to temperature variations
- Adhesive failure in Gimbals gas bearings due to humidity.

Data on gyros reliability as a function of storage time have been reported in reference [16]. To illustrate the application of probabilistic analysis for predicting failures and improve shelf life, some of the data from [16] are used. Weibull probability analysis has been performed to predict the reliability of gyros as a function of storage time.

According to Weibull analysis, the cumulative failure distribution is defined by function F(t) as follows:

$$F(t) = 1 - e^{-(t/\eta)^{\beta}} \qquad (8)$$

where

t = time in storage (hours, years, etc.)
η= scale parameter
β= shape parameter

Component reliability at a given storage time t is therefore,

$$R(t) = 1 - F(t) = e^{-(t/\eta)^{\beta}} \qquad (9)$$

Weibull parameters η and β can be estimated by using field reliability data and then used to predict the component reliability over time. Some of the data on gyros described in [16] are used to illustrate the methodology.

Taking the national log of both sides and negating both sides, (9), we get

$$\ln [1/R(t)] = (t/n)^{\beta} \qquad (10)$$

And, by taking the natural log again, we arrive at

$$\ln \{\ln [1/R(t)]\} = \beta \ln(t) - \beta \ln(\eta) \qquad (11)$$

Given component reliability versus storage time data, Weibull parameters (β, η) can be estimated using linear regression analysis of equation (11) An example of gyros field reliability versus storage time are taken from [16] and are shown in Table 2 below

Table 2: Reliability Data on Gyros

Storage Time (years) t	Reliability Success/Total tested R(t)	ln ln [(1/R(t)])	Ln (t)
1.14	0.9988	-6.718409	0.127061
1.50	0.9942	-5.154005	0.405592
3.27	0.9824	-4.030075	1.185539
4.35	0.9844	-4.150703	1.46978
5.00	0.9548	-3.074563	1.609438

The data are plotted in Figure 4. A least square fit of data in Table 2 gives the following values.

Slope (β) = 1.432
Intercept ($-\beta \ln(\eta)$) = -5.774

η, the scale parameter is equal to exp (5.774/1.432) = exp (4.032) = 56.4 years. Thus 63.21 % of gyros failures are expected to occur in 56.4 years.

Using the values of β and η, Figure 5 is constructed to show the predicted reliability of gyros as a function of time.

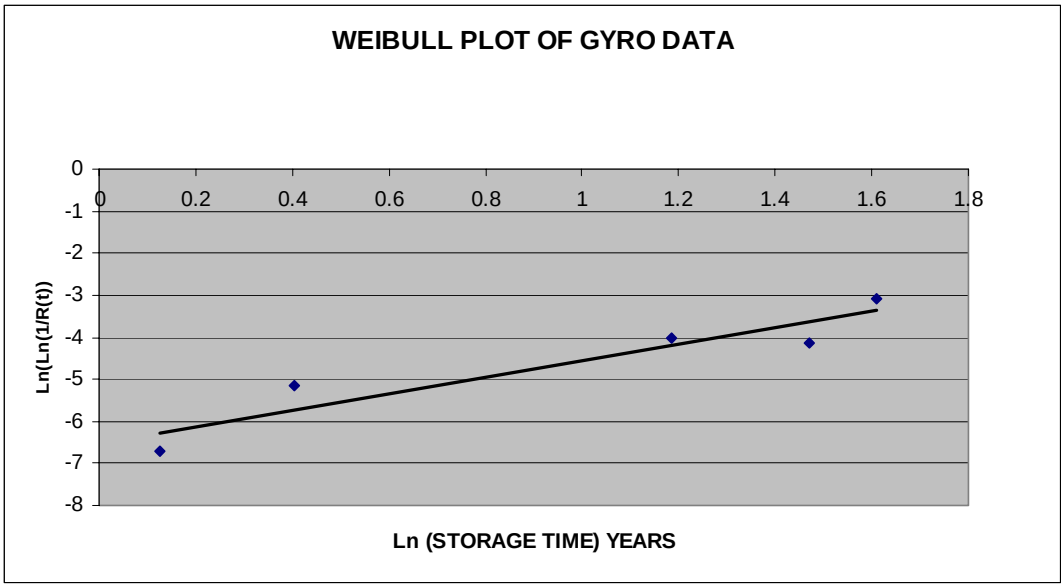

Figure 4: Weibull plot of gyro data.

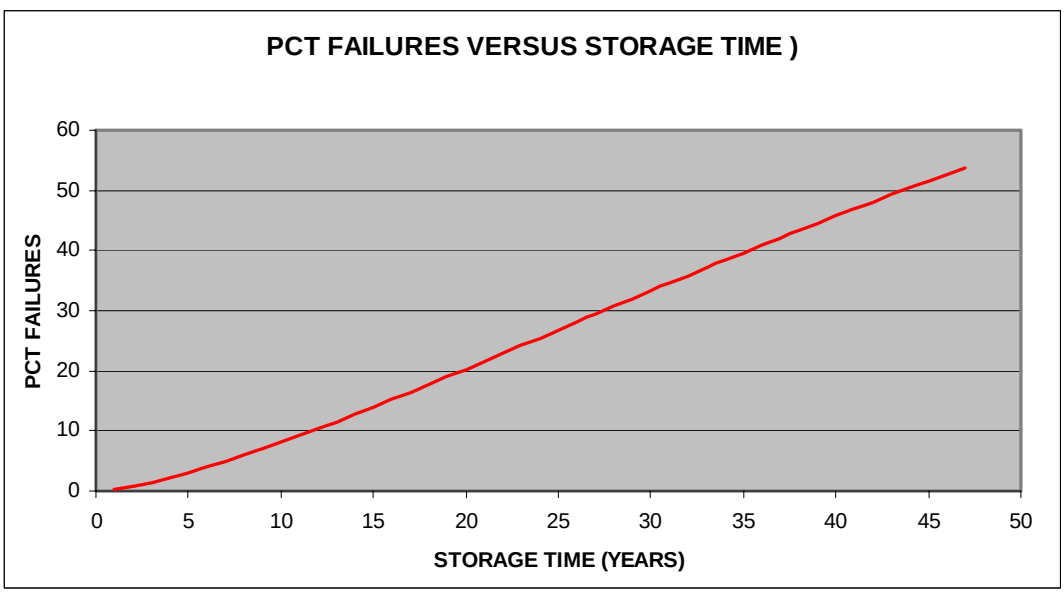

Figure 5: Pct failures versus storage (time).

Gyros failures in storage are generally caused by exposure to temperature and humidity cycling over a long period of time. Humidity and temperature cycling causes material degradation and induce stress which accumulates over time resulting in component failure. The Weibull analysis can be further extended by evaluating a relationship between stress and temperature/humidity cycling and integrating it over the storage time. Temperature, and humidity data from RRAPDS could then be directly input into the model to predict component reliability and shelf life.

In situations where there is a potential of crack initiation and/or crack propagation in materials due to environmental exposures, Weibull probability analysis provides a useful tool to predict time-dependent reliability and component service life [11]. In the case of tactical missiles, the potential for crack initiation and propagation exists in propellant, liners, solder joints and metallic hardware because of temperature and humidity cycling and exposure to corrosive environments.

The Weibull probability analysis for failure modes related to time-dependent crack propagation can be developed by defining the Weibull statistics in terms of parameters used in the fracture mechanics analysis. According to Weibull distribution, the reliability of a component under stress (σ) is given by:

$$R(\sigma) = \exp\left[-\frac{\sigma}{\sigma_o}\right]^{\beta} \qquad (12)$$

From the fracture mechanics model, the material fracture toughness at a given stress level and critical flaw size is given in reference [14]

$$K_{IC} = Y\sigma\sqrt{a}_c \qquad (13)$$

In equations (12) and (13),

a_c = critical crack length (mm)
σ = applied stress (psi)
y = is a geometrical factor (assumed = 1.0)
β = Weibull modulus or shape parameters
σ_o = Weibull scale factor (also characteristic value of ultimate material strength)
K_{ic} material fracture toughness properties to for a critical flaw size (determined by testing or handbooks)

The Weibull shape parameter (β) and the scale parameter σ_o are determined from material test data.

Fracture toughness (K_{ic}) is a measure of material toughness to withstand cracks [13] [14]. When both sides of equation (13) are equal, a material balance is maintained and the material is tough enough to withstand the effect of stress concentration about the crack. If stress (σ) or crack length (a) increases due to environmental thermal cycling or corrosive atmosphere, the balance is broken and the crack propagates and ultimately cause a failure.

The propagation of crack due to cyclic stress is defined by power law [15]

$$\frac{da}{dt} = A(K_1)^n \qquad (14)$$

where K_1 is as defined as in equation (13) for any crack length (a) below the critical length (A_c) and stress level (σ) is equal to $\sigma a^{0.5}$ for y =1. The variables A and n are two constants that are determined experimentally or from historical data.

The life time, t_f , can be determined by integrating equation (14) from initial crack length a_i to the critical length a_c as shown in equation (15) below:

$$t_f = \int_{a_1}^{a_c} \frac{da}{A(K_1)^n} \tag{15}$$

The integral steps are given in [15]. The final Weibull reliability model for crack propagation as a function of time is shown in equations (12) and (13).

$$R(t) = \exp\left[\frac{Ct^{1/(n-2)}\sigma^{n/(n-2)}}{\sigma_o}\right]^{\beta} \tag{16}$$

where C is given by

$$C = \left[\frac{A(n-2)}{2K_{IC}^{2-n}}\right]^{1/(n-2)} \tag{17}$$

Equation (16) provides a measure of component service life for given environmental conditions. If the initial defect or flaw size is known from manufacturing or historical data, the service life of the component can be predicted with equation (16). In the case of tactical missiles, the solder joint failures and or the failures of propellant, liners or other similar structures are caused by propagation of cracks when subjected to thermal cycling, shock, vibration or corrosive environment. Reliability models based on crack propagation theory are good prognostic tools for improving the reliability of the tactical missiles.

CONCLUSION

This paper addresses the application of an integrated health monitoring system to monitor health and perform prognostics and diagnostics analysis of army missile systems in storage and field deployment. The US Army has been field testing an integrated health monitoring system called RRAPDS that include diagnostic and prognostic models to assess the reliability of the weapons.

The application of probabilistic engineering methods to analyze RRAPDS data and predict component reliability during the life cycle of the weapon systems was discussed. Probabilistic methods in the diagnostic and prognostic analysis provide a realistic reliability assessment for decision making purposes.

The limitations of deterministic methods to predict component survivability were discussed. Probabilistic methodologies based on stress and strength approach, cumulative damage functions, and Weibull analysis were presented for use with data from health monitoring systems.

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