Predicting Reliability of Tactical Missiles Using Health Monitoring Data and Probabilistic Engineering Analyses

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ABSTRACT

Tactical missiles within the US Army are regularly subjected to severe stresses such as long term exposure in harsh environments and transportation handling. These stresses factor into the ageing, deterioration, and eventual decommissioning of some of the Army's critical warfighting assets. The negative reliability impacts associated with long-term ageing and deterioration significantly affect the total lifecycle 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, 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 [1]. 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.

Recently, there has been a significant shift in how the Army builds and fields its missiles. This change has had a major impact on degradation factors affecting Army missiles as well as considerations needed to manage and assess degradation. Prior to Operation Desert Storm, the Army's missiles were designed for long-term storage in depots without extensive deployments. Additionally, these generations of Army missiles were designed and built to a government-owned specification resulting in highly homogeneous configurations.

Since Operation Desert Storm, missile deployments have become more frequent resulting in a greater stratification of aging and performance within the stockpile. The government has also reduced or eliminated control of lower level specifications resulting in further reducing stockpile homogeneity. Due to non-homogeneities in the stockpile, assessments of readiness are less certain and can be more costly.

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 of 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.

STOCKPILE SURVEILLANCE FINDINGS

Missile surveillance testing and subsequent failure analysis have identified a number of failure modes induced by extreme environmental exposure. These failure modes are divided into three component categories: 1) mechanical/structural components; 2) electrical components; and, (3) energetic components.

The mechanical category includes damage to missile storage containers, canisters, and launch tubes during severe transportation and handling.

The critical electrical components include guidance and control systems that are susceptible to failures due to corrosion, temperature, and humidity effects on sensors, and battery failures.

Components falling into energetic categories include propellant, thermal batteries, gas generators, etc. Some of the specific failure modes that resulted from temperature, humidity, and shock and vibration exposure are:

- Sealant materials that failed due to humidity.
- Missile cases damaged from handling and transportation.
- Flight motors ruptured anomaly during flight tests and static firings.
- Missile gyroscopes that failed due to bearing separator phenolic degradation.
- Seeker performance degradation in missiles exposed to high temperature storage environments.
- Corrosion and oxidization found inside deployed missiles.

The current surveillance and periodic test program by US Army is an essential element to maintain reliability of the missile stockpile by removing suspect assets before deployment. The analysis of test data has identified several 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.

The current surveillance and test program is more of a reactive procedure than a proactive tool. The surveillance and periodic testing for maintaining reliability and shelf life of the missiles can however, be further enhanced by implementing proactive tools such as equipment health monitoring and real time evaluation using prognostic models and probabilistic analysis.

Aging and surveillance testing has shown aging degradation in component material properties from exposure to high temperature and humidity environments. The effect of temperature and humidity cycling imposes additional stresses on the components and degrades the reliability over time. The impact of shock and vibration during transportation and handling have also caused component damage and reliability degradation. Another reliability concern is corrosion that degrades component life and affects performance.

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. 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 [2] that is then correlated with chemical kinetics or age-related relationships to determine change in modulus, strain energy, or other similar properties. 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.

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.

Table 1 shows the application of the three methods that are being evaluated in conjunction with the input data from RRAPDS to analyze various failure modes identified in the Army tactical missile program. RRAPDS will provide data with information on exposed temperature, humidity, shock, vibration, and chemicals environment. Each of these three methods is discussed in the sections that follow Table 1.

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.

For applications involving newly developed Strategically Tuned Absolutely Resilient Structures (STARS) [3,4], on-line health monitoring and smart diagnostics/ prognostics strategies will lead to significant savings in the total life cycle costs by improving a structure's reliability, maintainability, and availability. RRAPDS will allow for real-time access of source data and, in military applications, provide critical information needed for reduced sustainment costs and enhanced readiness. Sensor data analyzed by data mining algorithms and predictive trending has the potential to extend life and save millions in maintenance costs. Over time, data collected can be used to refine structural designs and improve reliability, resulting in an improved overall life cycle.

Stress and Strength Interference	Cumulative Damage Model	Weibull Service Life Predictions

Diagnostic:
• Determine current reliability of the structural components
    0 Propellant
    0 Liner
    0 Case/canister
	Prognostics/diagnostics
	• Fatigue related failures
	• Fracture mechanics
	    0 Crack propagation in propellant
	    0 Unbonds in liners
	    0 Thermal and humidity cycling effects on electrical components
	• Corrosion related failure modes of missile components
		Prognostics/diagnostics:
		• Age related failures of electrical and electronics components
		• Service life predictions
		    0 Thermal batteries
		    0 Gas generators
		    0 Guidance components

Table 1. Probabilistic engineering models.

1) 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],

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

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 a standard normal table.

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

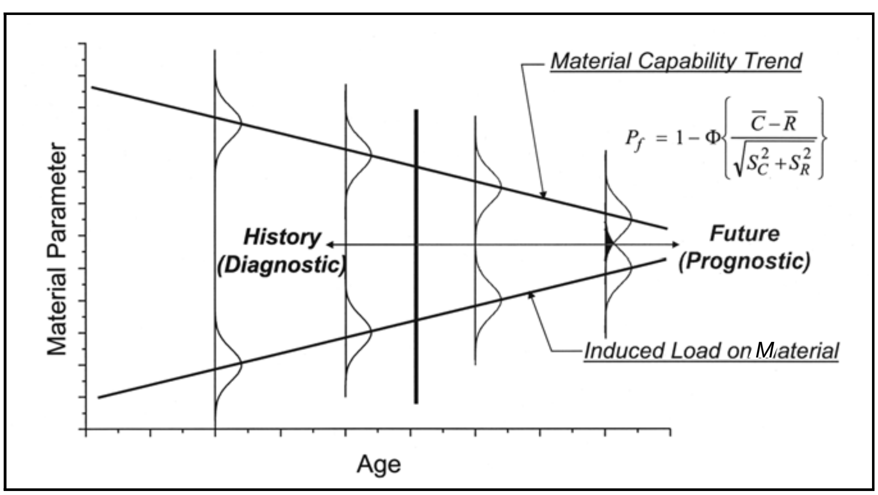

Figure 1. Component reliability with age.

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 to compute the distribution of R. Statistics from these distributions are applied at any point of time to evaluate P_f.

2) 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:

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

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

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

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 as [8],

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

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

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

where t_f is the time to failure, $\sigma(t)$ 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 [8].

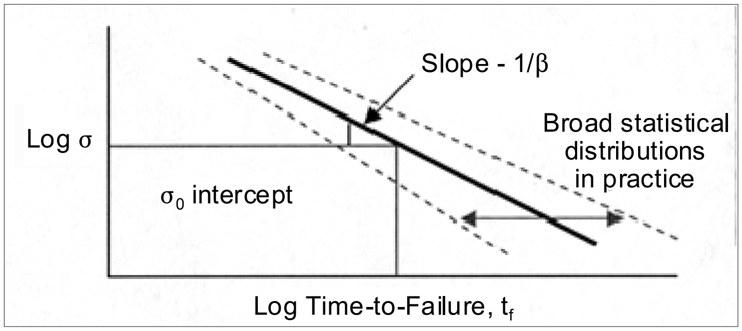

Figure 2. Time-to-failure versus damage due to increased stress.

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. Figure 3 shows the comparison of mean damage (deterministic value) versus the failure probability.

According to Fig. 3, the probability of failure as defined by the damage model is defined as [9],

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

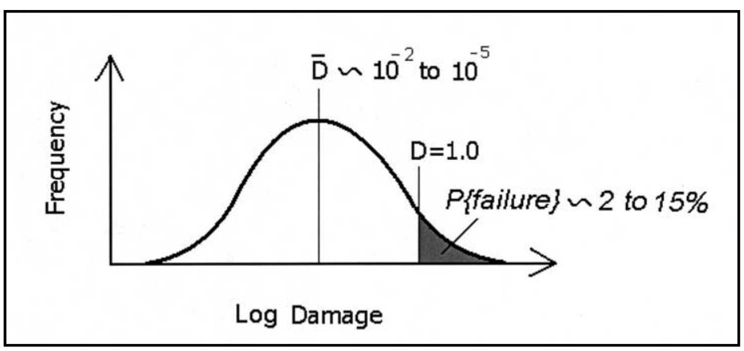

Figure 3. Failure probability distribution due to cumulative damage.

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.

When the damage function is normally distributed as shown in Fig. 1, the probability P_f is determined by the standard normal deviation as [10],

$$Z = \frac{\sqrt{\log D(t)} - 1.0}{\sigma_{D(t)}} \quad (8)$$

where $\sigma_{D(t)}$ is the standard deviation of the damage function.

The probability of failure, P_f , is given by Z from the standard normal table. The statistical variation of damage equation input, for example, includes:

$T = T_{avg} + s_t\, d_1\,(t)$
$H = H_{avg} + s_h\, d_2\,(t)$
$E = E_{avg} + s_e\, d_1\,(t)$

where E is the modulus, H is the humidity, T is the temperature, d_i are random deviations, and s_i is the standard deviation.

With this kind of prognostic models, the missile and components health and aging degradation are monitored on a real time basis.

3) 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 [11]. Accelerated aging data are generally analyzed using Weibull distribution to determine component characteristic life and probability of failure as a function of time [12]. The distribution is combined with Arrhenius or Boltzman principles to determine the effect of humidity and temperature on failure rates or reliability. The analysis provides estimates about the expected longevity of components in terms of probability and avoids data extrapolation with uncertainty.

The analysis is based on a Weibull probability distribution function that consists of a shaping factor, which allows it to be used in a many forms of data analysis. The Weibull distribution is used to determine degradation in both the electronic and mechanical parts under long-term exposure to the environment.

The Weibull distribution is a good tool for diagnostic and prognostics analysis of missile components such as mechanical and electrical components in the guidance system as well as degradation of sealant, adhesives and lube materials used in various missile subsystems. These materials degrade due to long-term exposure to temperature and humidity and have been the cause of missile failures.

The Weibull lifetime distribution is defined by the cumulative density function as [13],

$$F(t,S) = 1 - \exp\left[-\left(\frac{t}{\eta(S)}\right)^{\beta}\right] \quad (9)$$

where F(t) is the probability of failure at time t under stress s, β is the shape factor, η (s) is a scale factor that is a function of the stress (S) on the component. The latter is also defined as the component characteristic life, *i.e.*, the stress at which 66.33% of the failures occur.

The reliability function R(t,S) from Eq. (9) is,

$$R(t,S) = \exp\left[-\left(\frac{t}{\eta(S)}\right)^{\beta}\right] \quad (10)$$

Combining Eqn. (10) with the cumulative damage model represented by Eq. (4) and Eq. (5), the combined Weibull/cumulative damage reliability function becomes,

$$R(t,\sigma(t)) = \exp - \left[\int_0^t \frac{1}{\eta(t)}\,dt\right]^{\beta} \quad (11)$$

where $$\eta(t) = \left[\frac{\sigma_0}{\sigma(t)}\right]^{\alpha} \quad (12)$$

In Eq. (12), $\sigma(t)$ is a function of temperature, humidity, and vibration.

Equation (12) may require Monte Carlo simulations to predict and forecast component reliability, $R[t,\sigma(t)]$ over time. The Weibull parameters η, and β are evaluated using data from the induced stress calculated from finite element analysis and sensor data from the health monitoring network.

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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