A Probabilistic Approach for Reliability and Life Prediction of Electronics in Drilling and Evaluation Tools

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ABSTRACT

The capability to predict performance and lifetime of drilling electronics is the key to preventing costly downhole tool failures and ensuring success of any drilling operation. Drilling electronics operate under extremely harsh downhole environments with temperatures beyond 150C and vibration levels exceeding 15g. In addition to temperature and vibration, there are several factors affecting electronic reliability that have high uncertainty and cannot be accurately measured. There is a growing trend in the oil and gas industry to drill faster and operate at higher temperatures and pressures, forcing tools to operate beyond design specifications. This has resulted in increased failure rate leading to higher maintenance costs and system downtime for drilling operators as well as service providers. This paper develops a methodology to estimate the life of drilling electronics by using operational data, drilling dynamics and historical maintenance information. The methodology combines parameter estimation techniques, statistical reliability analysis and Bayesian math in a probabilistic framework. Parameter estimation is used to calibrate statistical equations to field data and probabilistic analysis is used to obtain the likelihood of failure. In the paper, the model parameters are represented as random variables, each with a probability distribution. Drilling electronics under downhole conditions can have several failure modes and each failure mode can be caused by the interaction of several variables. When information on each failure mechanism is not readily available, the failure is expressed in terms of several candidate models. Bayesian updating is used to incorporate real time operational history for a specific part and select the most accurate failure model for that part. Tis is for the first time, a systematic approach is developed for predicting the life of electronics in downhole drilling environments using statistical modeling and probabilistic methods on life cycle history and operational data from the field.

1. INTRODUCTION

Drilling and evaluation operations are becoming faster, more accurate and safer, thanks to modern electronics that enable measurements, storage and transmission of information in real time. Transmitting information in real time makes it possible to evaluate properties of earth's formation while drilling and enable directional drillers to steer wells towards target zones more efficiently. The reliability of electronic printed circuit board assemblies (PCBAs) in the bottomhole assembly (BHA) is the key to the success of any drilling operation. Drilling electronics operate in extremely harsh downhole environments with temperatures exceeding 150C, shock and vibration levels exceeding 15g. The impact of temperature, shock and vibration on the life of electronics is described by Barker et al. (1992), Duffek (2004), Garvey et al. (2009), Gingerich et al. (1999), Lall et al. (2005, 2007), Mirgkizoudi et al. (2010), Pecht et al. (1999), Vichare (2006), Vijayaragavan (2003), Wassell & Stroehlein (2010), White & Bernstein (2008). Other factors like power cycles, thermal ramp rates, electrical overstress, mechanical stress and manufacturing defects impact reliability of tools, but the factors cannot be accurately measured in downhole drilling environments and encompass high uncertainty. These factors can act alone or interact with each other to produce several degradation mechanisms that can cause failure. For example, Mirgkizoudi et al. (2010) demonstrated through tests that there is significant difference between the lives of electronic components subjected to thermal testing with vibration as compared to those with pure thermal loading. Failure of electronics because of fatigue, corrosion, electromigration, filament formation and dielectric breakdown has been established by the scientific community (e.g. Barker et al. 1992, Duffek 2004, Gingerich et al. 1999, Lall et al. (2005, 2007), and Pecht et al. 1999). Typical PCBAs used in the drilling industry are multiscale devices made from several components. The geometric dimensions of individual components may vary from nanometers to inches. This difference creates significant challenges in developing a predictive model for failure because individual components on a PCBA may fail by many failure modes based on the operating environmental conditions. Furthermore, diagnosis of faults and indicators of failure is difficult because degradation of individual components may not lead to a measurable loss of electrical function up until imminent failure. There is growing interest in the area of health prognostics for electronic components through the use of physics based models, operating data from fielded products, design qualification testing and in-service inspections (e.g. Pecht et al., 1999, Vichare 2006, and Garvey et al., 2009) The main drivers behind the efforts are preventing failure and system downtime, reducing costs of repair and maintenance, and supporting new product improvements. A discussion on state of the art techniques in prognostics and health management of electronics can be found in Pecht et al. (1999) and Vichare (2006).

The method of measuring failure precursors as indicators of impending failure is based on the hypothesis that degraded circuit boards produce significantly different signatures from defect free boards. Failure precursors are measurable indicators that can be correlated with subsequent part failures. Failure indicators for electronics like shifts and variation in temperature, voltage, current, surface insulation resistance and impedance have been proposed by Born & Boenning (1989) and Pecht et al. (1997, 1999). Another area of research in electronics prognostics and health management (PHM) is usage of sacrificial circuits like fuses, canaries, circuit breakers and self-diagnostics sensors for detecting if the device is operating outside of design limits. These devices are mounted along with the main electronic component but have accelerated failure rates to provide advance warning of failure (e.g. Mishra & Pecht 2002, and Ridgetop Semiconductor Sentinel Silicon report 2004).

The physics of failure (PoF) based approach for life prediction uses modeling and simulation to relate the fundamental physical and chemical behavior of materials to the surrounding environment and applied loads. The PoF based modeling process starts by exposing the product to the highly accelerated life test (HALT) and highly accelerated stress test (HAST) to find the significant modes and root cause of failure. Next, the governing equations of the failure mechanisms are combined with the data gathered from acceleration tests using statistical distributions. The PoF approach has been successfully applied to understand system performance, identify weak links and root cause of failure so that they can be mitigated before the product is launched. Chatterjee et al. (2012) gives a historical perspective of the evolution of the physics of failure approach. White & Bernstein (2008) present the state of the art methods for PoF modeling. Finite element analysis was used to model fatigue damage growth during cyclic loading (thermal, mechanical and combination of both) by Barker et al. (1992), Bailey et al. (2007), Dasgupta (1993), Duffek (2004), Shinohara & Yu (2010), and Vijayaragavan (2003). Material modeling to predict degradation of solder joints in the circuit board as results of thermo mechanical fatigue was developed by Nasser & Curtin (2006). Lall et al. (2007) used experimental tests in combination with finite element analysis to model solder joint failure from shock and vibration. Mirgkizoudi et al. (2010) developed a test plan to evaluate the reliability and service life of electronic components that are subject to a combination of mechanical, thermal, chemical or electrical inputs, and Wassell & Stroehlein (2010) use accelerated tests to derive accumulated damage models and failure thresholds as functions of vibration, shock levels, the number of shocks and the operating temperature. Young & Christou (1994) developed models for failure because of electromigration. The models obtained from accelerated tests are also widely used to estimate the life for fielded products by using the governing equation to scale accelerated test life to that under the actual operating environment in the field. However, such scaling is valid only if the following conditions are met (1) failure modes and mechanisms for accelerated stress levels are the same as those observed in the field and (2) variations of material properties with stress levels are incorporated in the governing equations. Because of these limitations, it has been shown for practical application that life obtained by scaling the highly accelerated life tests (HALT) and highly accelerated stress tests (HAST) is orders of magnitude different from those observed in actual field environments (e.g. Osterman 2001, Pecht (1997, 1999), and White & Bernstein 2008).

Field data driven methodologies for modeling time to failure have gained momentum because of the availability of large volumes of data and limitations of physics based methods to simulate actual operating environment in laboratory (e.g. Osterman, M., 2001 and Vichare 2006). This methods use operating environment measured in field, repair and maintenance information of fielded products in conjunction with statistical modeling to predict the life of parts in operation. For example, Hu et al. (1991) presented a probabilistic approach for predicting thermal fatigue life of wire bonding in microelectronics, and Vichare et al. (2007) developed an algorithm to extract load parameters necessary for assessing damage from commonly observed failure mechanisms in electronics. Sutherland et al. (2003) developed data mining methods and statistical approaches to obtain accurate life distribution for power plant maintenance optimization.

There is a growing trend in the oil and gas industry to drill faster and operate at higher temperatures and mechanical loads, forcing tools to operate beyond design limits. The capability to predict performance and life of drilling electronics is critical to preventing costly downhole tool failures and reducing cost of maintenance. This paper presents a systemic approach for deriving and updating models for time to failure of PCBAs used in drilling and evaluation tools using field data. The methodology combines parameter estimation techniques, statistical reliability analysis and Bayesian math in a probabilistic framework. Parameter estimation technique is used to calibrate statistical equations to field data and probabilistic analysis is used to obtain the likelihood of failure. The model parameters are represented as random variables with probability distribution. Drilling electronics within downhole conditions can have several failure modes and each failure mode can be caused by the interaction of several variables. When information on each failure mechanism is not available in real time, the failure is expressed in terms of several candidate models. Bayesian updating is used to incorporate the operational load history for a specific part and selecting the most accurate failure model for the part. Results presented in the paper show that the life of electronic assemblies used in drilling and evaluations can be predicted accurately by using the probabilistic model and incorporating operational effects. Interaction between different factors causes the components to degrade faster than individual factors acting alone.

2. OPTIMAL MAINTENANCE PLANNING

The framework for lifecycle management, optimal operations, repair and maintenance planning of drilling systems requires databases to record equipment lifecycle history, environment and operations data, telemetry and communication systems, sensor and measurement systems and algorithms for predicting performance and consumed life. Developing an optimal maintenance strategy requires the knowledge of component life as a function of usage. Predicting component life accurately requires knowledge of engineering design, physics of component behavior under operating loads, data from qualification tests, operating mission of fielded products and indicators of degradation of part life from inspection and maintenance shops. The information can be used in physics based or statistical data driven models (or a combination of both) to predict part life and risk of failure as a function of usage. Once accurate life models are developed, cost factors, performance and reliability targets can be incorporated to optimize maintenance plans for minimum life cycle cost. In field operations, life extension can be achieved by derating the mission (e.g. lowering rotational speed of drill to reduce impact of vibration induced damage on BHA components) so that parts degrade slower. Cost of repair and maintenance can be lowered by using a risk based maintenance level. For example, tools with low risk of failure can be given a quick turnaround, medium risk entails partial disassembly and inspection, and high risk tools require full piece part level disassembly and inspection. The goal of this method is to enable reliability and maintenance personnel to schedule timely maintenance and prevent costly downhole tool failures. Fig. 1 shows a high level overview of data, methods and decision process for optimizing operations and maintenance plans.

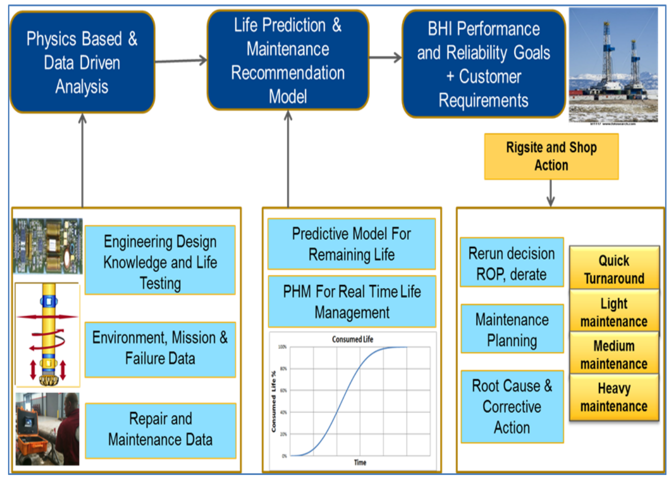

Figure 1. Methodology for optimal operations and life management of parts.

This paper develops a framework to provide advance warning of impending failure so that high risk components can be retired. The remainder of the paper focuses on algorithms to estimate part life using data from field and maintenance shops. Section 3 gives an overview of parts in the bottomhole assembly (BHA) for which reliability models are developed. Section 4 describes the algorithms used to analyze field data and develop mathematical models for time to failure. Section 5 describes the methodology to use load history from each drilling mission (also known as a "run") to update model weights and predict part life. Section 6 presents results for fielded component and Section 7 concludes the paper with a summary and future work.

3. DESIGN OF BOTTOM HOLE ASSEMBLY

A typical drilling system comprises a drill bit, bottomhole assembly (BHA); drill pipes and rig (Fig. 2). The drill bit is a rotary cutting tool that cuts through the earth's formation; the drilling rig is a structure on the surface that houses equipment, the drill pipes provide the required extension to reach a target depth and the bottomhole assembly (BHA) is a structure that houses drill collars, reamers, steering system and electronic components. The focus of the report is predicting life of electronic components in BHA of the AutoTrakG3 line of product manufactured by Baker Hughes Incorporated. A typical AutoTrakG3 contains three modules, namely (1) the

AutoTrak steering system (ASS) that provides the necessary drive to steer the bit (2) OnTrak sensor assembly contains the electronics used for measurement while drilling (MWD) and logging while drilling (LWD). The OnTrak tool takes measurements like resistivity, gamma ray, pressure and vibration. (3) Bi-directional communication and power module (BCPM). This module sends and receives data to and from the surface, enabling drillers to monitor drilling operations in real time and make adjustments when necessary. The BCPM also delivers power required by the other modules in BHA. The three assemblies have components that are critical to the drilling and evaluation operation. Failure of the components can lead to the loss of functionality and cause trip for failure which can cost several millions of dollars. The paper focuses on developing predictive life models of several such components in the drilling system.

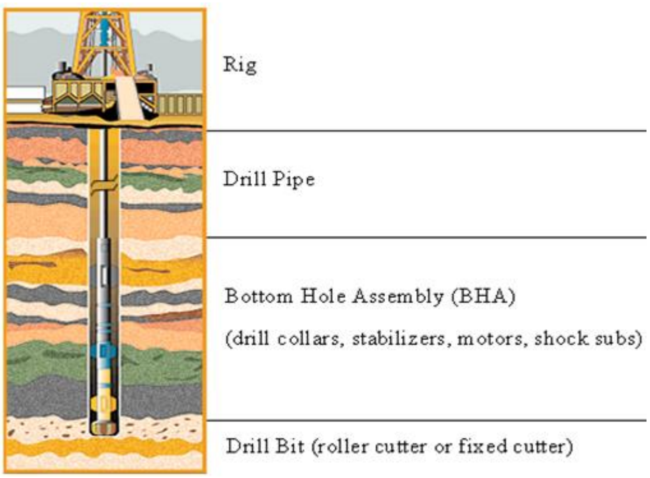

Figure 2. Illustration of drilling system.

4. FIELD DATA ANALYTICS

Developing field data driven models for life of electronic assemblies in drilling operations is challenging for two reasons. First, not all of the factors impacting component life can be measured in real time, and second, the data that can be measured has errors and noise because of limitations of the measurement system and human factors. This paper presents method to calculate the reliability of components that have been operated at varying stress level because of temperature and mechanical loads such as that caused due to shock and vibrations. The Maintenance and Performance System (MaPS^{TM}) is a state of the art database developed by Baker Hughes Incorporated to track equipment lifecycle data. Information related to operations, failure, repair and maintenance is stored for serialized parts. The downhole environment data like temperature, vibration, pressure and power cycles is also maintained in the MaPS database. The magnitude and cyclic variation of temperature can cause solder joint fatigue failure in electronic circuit components, chip delamination, corrosion, electro migration, diffusion voids and dielectric breakdown. Extreme vibrations influence the life of electronic components in the BHA. There are three principal modes of vibration: (1) axial vibration along the tool axis can cause damage to seal faces of modular connections, stabilizers and, in severe cases, can lead to buckling fatigue. Axial vibration is responsible for low rates of penetration and reduced efficiency, (2) lateral vibrations occur transversely to the tool axis. Historically, they are the most destructive type of vibrations and constant exposure to lateral vibrations can cause damage to tool electronics. Constant lateral shocks damage the tool body as well as greatly reduce drilling efficiency, (3) stick slip is a rotational phenomenon that occurs because of twisting of the drill string. Twisting can occur when the bit gets stuck downhole while the motor continues to turn the drill string. When the bit is free, the torsional energy stored in the drill string is released, causing the BHA to spin in the opposite direction. Stick slip can lead to material fatigue and physical damage to the tool and electronics. Figure 3 shows the three vibration modes.

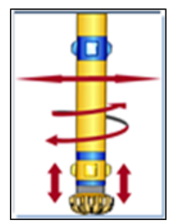

Figure 3. Vibration modes in drill string.

4.1. Consolidating Life Cycle Data

An important first step in developing a life model is to collect life cycle history for each part. Each serialized part undergoes one of three maintenance actions during its lifecycle: (1) repairs, which involve replacing damaged components on a PCBA, (2) revision upgrades which may include repairs and/or firmware updates, (3) scrapped because of failure or as a preventive measure. To accurately capture the life cycle of a part, the accumulated temperature and vibration hours for each serialized part are retrieved from MaPS database and grouped using the steps described in Table 1. The purpose of the steps described in Table 1 is to group the data into buckets that have three common characteristics, namely revision id flag, repair flag, and revision upgrade flag. Data in each bucket encompasses the same value for the three flags and any two buckets have at least one flag different between them. For example, the bucket in which the three flags are [“A”, N, N] implies that parts in that bucket are revision “A”, they have never been repaired and never received a revision upgrade. Another bucket with flags [“A”, N, Y] implies that parts in that bucket have never been repaired and have been upgraded to revision “A” from an older revision. A bucket with flags [“A”, Y, Y] implies that all parts in that bucket have been repaired and have been upgraded to revision "A" from an older revision.

Table 1. Process to group part life cycle data for failures, suspensions, repairs and revision upgrades.

(1) Find all the serial numbers of a given part number in the database
(2) Select a serial number and look up mission profile for that serial number starting with installation date
(3) Accumulate drilling hours, circulating hours and the operating environment variable (temperature, vibration, rotational speed (rpm), distance drilled) etc. for each run; store the accumulated data in a record with index *i*. Store the revision id flag, repair flag (*Y/N*), revision upgrade flag (*Y/N*), and failure/suspension flag (*F/S*)
(4) Check if the part underwent one of the following actions after the run (a) failed and scrapped, (b) failed and repaired to put back in service (c) upgraded to next revision (d) repaired to put back in service (e) scrapped because of preventive maintenance. If any of the above is true, then label the i^{th} record flag appropriately. Create a new record *i*+1 and go to step 3. If none of steps (a)–(d) happened, continue to accumulate the fields for the i^{th} record in step 3
(5) Check if all the runs have been accounted for the serial number. If no, go to step 3; otherwise, create a new record for a new serial number

It is important to make the distinction between revision upgrade and repair because not all revision upgrades lead to life extension (for example, if only firmware is changed in revision upgrade). Grouped data is filtered for outliers and weighted before building a life model using an algorithm described in the next section.

4.2. Iteratively Reweighted Maximum Likelihood Algorithm

The life cycle data for parts recorded in the maintenance database is large and complex because each part has several hundred serial numbers and each serial number has the operating history for several drilling runs. Like any other physical experiment, data can have errors or noise because of human factors and flaws in the measurement system. The impact of outliers on the quality of the predictive model can be minimized by optimally weighting the life cycle data. Outlier identification is done by first removing data points that lead to constraint violation in the estimation process. The likelihood equation is subjected to constraint that $\alpha_0 > 0$ *and* $\alpha_{1\ldots}\alpha_n \leq 0$ in Eq. A-1, A-5 and A-8. The inclusion of these constraints implies that life decreases with increase in stress level due to temperature and vibration. Next, iteratively reweighted maximum likelihood estimation (IRMLE) technique was developed to determine the optimal weight of each data point in the life cycle data. Unlike conventional likelihood maximization procedure where all points are weighted equally, the new technique iteratively maximizes the weighted likelihood function of life data until the quality of model shows no further improvement. Iteratively reweighted maximum likelihood estimation procedures assign weight that is inversely proportional to the log-likelihood of the data point, so that points with lower log-likelihood are weighted less than points with higher log-likelihood. Eventually, the model moves away from outliers. The procedure can be summarized in steps (1)-(4). The symbols used in these steps have the following description.

T is temperature, L is lateral vibration, S is stick slip or rotational vibration, RPM is revolutions per minute, α_0 is a constant term, $\alpha_{1\ldots}\alpha_n$ are coefficients on stress variables in the life equation (e.g. Eq. A-1, A-5 and A-8), $w^i_{updated}$ is the model weight, symbol £ is likelihood of i^{th} data point.

(1) Select $\bar{\boldsymbol{X}} = \{T, L, S, RPM, LT, ST, LS, SRPM\}$ for modeling characteristic life function described in Appendix A.

(2) Maximize weighted sum of likelihood of failure and suspension data to estimate the mean and variance of parameters of the characteristic life function (e.g. Eq. (A-1) α_0, $\alpha_{1\ldots}\alpha_n$). The initial weight of each data point is unity. The maximization of likelihood equation is subjected to constraint that $\alpha_0 > 0$ and $\alpha_{1\ldots}\alpha_n \leq 0$.

(3) Compute the value of likelihood of each data point at the values of α's estimated in step 2. Compute the mean and standard deviation of likelihood, $\mathcal{L}_{mean}$ and $\mathcal{L}_{stdev}$. The updated weight $w^i_{updated}$ of i_{th} data point is given by

$$w^i_{updated} = \frac{Total\ number\ of\ data\ points}{\sum \frac{\mathcal{L}^i}{\mathcal{L}_{stdev}}} \frac{\mathcal{L}^i}{\mathcal{L}_{stdev}} \qquad (1)$$

(4) Iterate step (2) – (3) with updated model weights until the sum of likelihood has converged within a specified tolerance (10^{-6} used in this paper).

In principle the IRMLE technique is similar to the iteratively reweighted least squares (IRLS) except that in IRMLE, the weighted sum of likelihood is maximized, whereas in IRLS the weighted sum of squares of difference between data and model response is minimized. The IRMLE algorithm is used to build transfer function for time to failure as a function of the operating mission for a serialized part. One of the challenges in using this model to accurately estimate remaining life is that the operating environment is variable throughout the life of a component. This is overcome by updating the remaining life estimate after each drilling mission (life of a part can span several drilling missions and each mission may have different load history and hours). The application of this algorithm in identifying outliers is presented in Fig. A1 through Fig. A6 in Appendix A.

5. RELIABILITY ANALYSIS

Statistical models are extensively used in reliability and life data analysis to estimate time to failure of parts in operation. The models are either computational simulations or a set of mathematical equations that explain the general state of a system under the influence of load and time. Typically, a mathematical model is an approximation of the physical phenomena and rarely matches the field observations. However, for practical commercial application where the models are used in design and operation of a product, it is desirable to have a model that matches the field or experimental data closely. The process of determining the unknown model parameters by tuning the model to field data is called parameter estimation or model calibration. The model parameter usually represents quantities that have physical significance and are determined by imposing some constraints during the calibration process. The constraints require that the parameters being estimated must have minimum variance from using one set of data to the next and the estimated value is bound to the true value. A reliability model that best represents the life cycle of a component can be developed when sufficient amount of operation, failure, and repair and maintenance data is available. This section outlines the method for calibrating a mathematical model to field data and its subsequent application to predict remaining life and reliability using real time mission profile for a specific part.

5.1. Generating Best Fit Model

A typical time to failure model comprises a life distribution function to incorporate the statistical scatter in failure time and a characteristics life function (Appendix A) that describe a general relation between failure time and stress levels. In this work, the Weibull, lognormal and exponential distributions are used to build time to failure models. The life characteristic can be any life measure such as the mean, median or hazard rate that represents a bulk property of the distribution. The life characteristic is expressed as a function of stress (as shown in Appendix A). The unknown parameter of the composite model is determined by tuning the model equation to field data using the Iterative Maximum Likelihood Estimation technique. The method for deriving the model that best fits the field data is described in the following steps:

(1) Retrieve life cycle data from maintenance database and bucketize it using the method described in Section 4.1.
(2) Select a revision identifier, trial function for stress η_i and trial function for probability distribution f_j from Appendix A. Initialize trial functions, i=1, j=1.
(3) Calibrate the reliability model $f(t,x)_{ij}$ to the bucketed field data using IRMLE technique. Compute standard deviation in parameter estimates.
(4) Compute goodness of fit for model $f(t,x)_{ij}$ by evaluating prediction error sum of squares (PRESS[1]).
(5) Select new probability distribution and trial function by updating values of i and j and repeat steps (2) – (4) until all trial functions are evaluated.
(6) Generate pareto of the solution obtained from steps (1) – (5) with two objectives namely, goodness of fit and Euclidean norm [2] on coefficient of variation of parameter estimates.

The models generated by steps (1)-(4) yield pareto of competing solutions, some solutions are better in terms of cross validation error while others are better in terms of confidence in value of estimated model parameters (α*'s* described in Appendix A). The time to failure for a part in operation is determined using the method described in the next section.

5.2. Model Selection and Updating Using Real Time Data

The best fit model is representative of a nominal[3] part. Drilling electronics under downhole conditions can fail because of several mechanisms that can be caused by the interaction of several variables (like temperature, vibration, and power cycles). The time to failure is expressed as weighted average of several competing models. Bayesian updating is used to select the most accurate failure model for a specific part by using the real time mission profile for that part. Bayesian updating provides a systematic process for incorporating real time operational data for model selection and updating. This section presents Bayesian formulation for updating probability of an event y based on recorded observations at time t (examples of observations include pass/fail event and mission profile parameters like temperature, lateral vibration, stick slip, etc.). More details on this formulation can be found in Zhang and Mahadevan, (2000). The symbol M_i is the i^{th} model, $p(M_i)$[4] is the probability of i^{th} model and reflects the belief that the model is accurate for the specific part in operation, $p(y|\bar{x_i}, t, M_i)$ is the probability of observing an outcome y at time t using the i^{th} model, the vector $\bar{x}_i$ is a set of parameters estimated by the calibration procedure. The term $f(\bar{x}_i|M_i)$ is the joint probability density function of the parameters of i^{th} model.

[1] PRESS is adding the squared of difference between data and model prediction, where the model is constructed by excluding one data point and repeating this over all the data points.
[2] Euclidean norm of an n-dimensional vector space is given by the geometric distance from origin to a point x.
[3] A representative part that has a life equal to the average of several part produced using same manufacturing process and operating under same condition
[4] Note that $\sum \mathrm{p(M_i)} = 1.0$

The event y is the state of the part at a time t that has one of the two values z = *pass* or *fail*.

$$p(y) = \sum_{i=1}^{m} p(M_i) \int_{x_i} p(y|\bar{x}_i, t, M_i) f(\bar{x}_i|M_i)\, d\bar{x}_i \tag{2}$$

The prior probability $p(G_i)$ of the parameters of i^{th} model is given by Eq. (3).

$$p(G_i) = p(M_i) f(\bar{x}_i|M_i) \tag{3}$$

$p(G_i)$ is the prior probability of $(M_i, \bar{x}_i)$ pair. The posterior probability after observing an outcome for y=z is given using Bayes theorem in Eq. (4).

$$p(G_i|y = z) = p\big((M_i|y = z)\big) f(\bar{x}_i|M_i, y = z)$$

$$= \frac{p(y = z|G_i) p(M_i) f(\bar{x}_i|M_i)}{\sum_{i=1}^{m} p(M_i) \int_{x_i} p(y = z|\bar{x}_i, t, M_i) f(\bar{x}_i|M_i)\, d\bar{x}_i} \tag{4}$$

Integrating over the probability distribution of $\bar{x}_i$ in Eq. (4), the posterior model weight of the i^{th} model after observing an outcome y=z is given by Eq. (5).

$$p(M_i|y = z) = \frac{p(M_i) \int_{\bar{x}_i} p(y=z|G_i) f(\bar{x}_i|M_i) d\bar{x}_i}{\sum_{i=1}^{m} p(M_i) \int_{x_i} p(y=z|\bar{x}_i,t,M_i) f(\bar{x}_i|M_i) d\bar{x}_i} \tag{5}$$

It is important to note that the time t used in Eq. (2) through Eq. (5) is not the failure time but it is the time at which an observation is made regarding the pass or fail state. The expected time to failure is obtained by weighted sum of time to failure predicted by each of the models as shown in Eq. (6).

$$tf_{predicted} = \sum_{i=1}^{m} p(M_i|y = z) \times tf_{M_i} \tag{6}$$

Where $tf_{predicted}$ is the expected life of a part being modeled and $tf_{M_i}$is the life predicted by the i^{th} model whose probability distribution is given in Appendix A. Equation 6 is solved using the Monte Carlo simulation technique. For drilling tools, probability of failure greater than 10% is unacceptable. To estimates this probability accurately we use a sample size of 10,000[5]in Monte Carlo simulation.

6. RESULTS

The methodology developed in this paper is used to predict life of fielded electronic assemblies used in drilling and evaluation tools and advance warning of impending failure so that preventive maintenance can be scheduled. The life cycle data for a typical low voltage power supply (LVPS) modem used in drilling operations is shown in Fig. 4 for parts that failed in field and Fig. 5 for suspensions (i.e. parts that are operating in field.). The x axis on the plots represents the average temperature (lateral vibration, stick slip and interaction effects are shown in Fig. A1-Fig. A6 in Appendix A). The y-axis represents drilling hours. Each point on the figure is a unique serial number of the part and undergoes different mission profile during their life. The data shown in Fig. 4 is derived from the failure of parts in operation that are root caused and Fig. 5 shows data for parts that are either currently being operated or those that are retired for precautionary measures.

Fig. 4 and 5 show field data with scatter and noise. As such, errors and noise cannot be totally eliminated and are part of field data because of limitations of the measurement system and human factors. The methodology developed in the paper is used to reduce the scatter in the life prediction by incorporating the cumulative effect of temperature, vibration and their interaction on life consumption. The IRMLE algorithm described in Section 4.2 is applied to the data in Fig. 4 and Fig. 5 and the outliers (shown in red dots) are identified by the algorithm. The data in Fig. 4 and Fig. A1 through Fig. A3 shows that temperature and vibration have a detrimental effect on life.

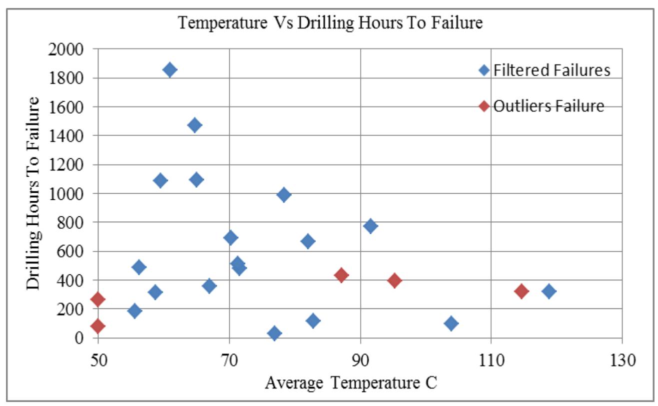

Figure 4. Time to failure vs. temperature severity for fielded LVPS modem serialized parts.

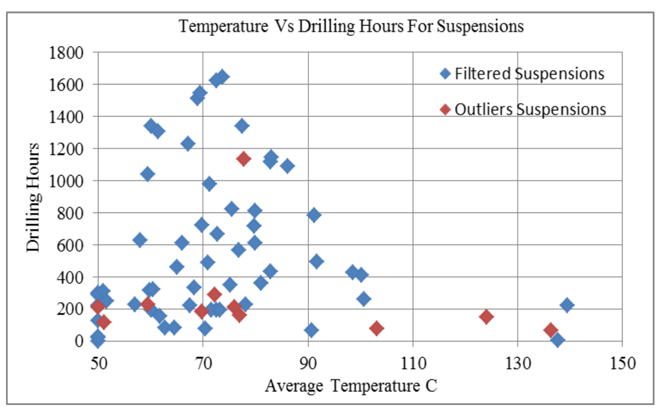

Figure 5. Suspension and operational severity for fielded LVPS modem serialized parts.

[5] The standard deviation in probability calculated by Monte Carlo integration is given by $\sqrt{\frac{p(1-p)}{10,000}}$. For a target probability of 50% the standard deviation is 0.005. Hence 10,000 samples are sufficient to estimate probabilities level of interest in this paper.

Table 2 show the parameters of the time to failure model built from the data in Fig. 4 and 5. The best fit model is a Weibull distribution with a characteristic life function whose parameters are α and β. The models are generated using the best fit procedure described in Section 5. The values in parenthesis are the mean and standard deviation of the parameter estimates. Each of the models in Table 2 is comparable in terms of likelihood value and confidence level in coefficients. Model M_1 shows the interaction of temperature and lateral are significant factors affecting the life of the part; model M_2 shows the temperature by itself is significant; and model M_3 shows the temperature plus interaction of temperature and stick slip are significant factors.

Table 2. Competing Weibull models for time to failure of apart as a function of operating stress.

Parameter	$\boldsymbol{M_1}$	$\boldsymbol{M_2}$	$\boldsymbol{M_3}$
$P(M_i)$	0.29	0.40	0.31
$\alpha_0\ (\mu, \sigma)$	(7.5, 0.07)	(8.0 0.1)	(8.6, 0.1)
$T,\ \alpha_1\ (\mu, \sigma)$	**0**	(-10.3, 0.7)	(-7.9, 0.5)
$S{\times}L,\ \alpha_2\ (\mu, \sigma)$	**0**	**0**	(-43.8, 3.1)
$T{\times}L,\ \alpha_3\ (\mu, \sigma)$	(-39.3, 2.5)	**0**	**0**
$\beta(\mu, \sigma)$	(1.6, 0.08)	(1.7, 0.07)	(1.8, 0.05)

The models in Table 2 represent failure time for a nominal part representative of the population. To obtain an individual part specific prediction, the time to failure is expressed as a weighted sum of failure times from each of the models using the operational history from each run of that specific part and adjusting the relative contribution of each model using the Bayesian formulation in Section 5.2. An example is shown for predicting the time to failure for a single part in operation. Table 3 shows the load history on an LVPS modem operated for 1000 drilling hours at varying levels of temperature and vibration. The first column of Table 3 shows the run number which represents the mission between the start and stop of the drilling operation; the second column shows the average temperature for the run; the third column shows the average lateral vibration level for the run; and the fourth column shows the average torsional vibration level. The lateral and stick slip vibrations (reported as root mean square in units of acceleration because of gravity *g*) are measured by accelerometers placed in the drilling assembly. The algorithm described in Section 5 is applied to the operational history after each drilling mission (referred as a "run"). Starting with an equal model weight of 0.33 for the three models, the life prediction and model weight is updated after each run to obtain a more accurate estimate of remaining life after each run (using Eq. 3 through Eq. 6). The final value of model weights prior to the eighteenth run is shown in second row of Table 2 for each of the three candidate model.

The life expectancy predicted by Eq. 6 (shown in Table 2) and the actual hours accumulated on the part after each drilling run and the operating environment is shown in Fig. 6 and Table 3. Figure 6 shows the true remaining useful life (RUL) and 95 percent confidence bounds on predicted life. It can be seen that the true RUL is bounded between the predicted 95% confidence interval. This interval represents statistical variation in part life of the population of identical parts subjected to same load history. The variation is caused by defects in manufacturing, limitations of the measurement system and human factors that are unknown or cannot be modeled. The purple diamonds represent the actual RUL on the part. Fig. 6 shows during the early part of the part life cycle, the life expectancy is high, but with usage and application of operating loads, the accumulated hours begin falling within the range of variation of expected life. At that point, the component is retired to prevent downhole tool failure. The part failed during the nineteenth drilling run. In retrospect, the model accurately predicted impending failure when it showed that the part was at high risk (>75% risk of failure) from the seventeenth run and should have been retired at that time.

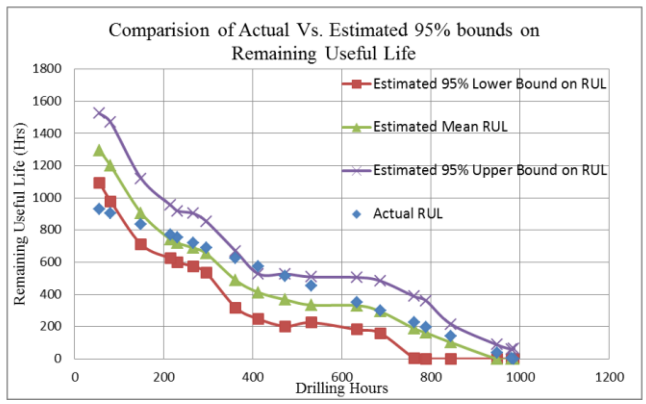

Figure 6. Predicted life vs. actual drilling hours after each run for LVPS modem.

Fig. 6 shows that the expected life of a part can increase or decrease with each run and are not a constant number (because expected life is a function of usage). Table 3 illustrates the concept where the average value of operational temperature and vibration over all the previous runs is calculated in columns two through four. The first run is the least severe and has the highest life expectancy. In subsequent runs, the life expectancy reduces as the severity of operation increases as shown by the values of temperature, lateral and stick slip vibrations. The trend continues until the ninth run, after which the operational severity starts reducing, leading to higher life expectancy until the thirteenth run. In summary, the life expectancy can vary through the operation depending on the severity of operating environment.

Table 3. Average operating environment and risk of failure after each drilling mission (run) during life of a part

Run No.	Average Temperature C	Average Lateral (g_RMS)	Average StickSlip (g_RMS)	DrillHrs [h]	Risk
1	57.6	1.6	0.2	55.3	0.00
2	63.8	1.5	0.1	80.8	0.00
3	57.6	1.3	0.3	149.2	0.00
4	71.9	1.1	0.2	215.4	0.00
5	74.9	1.1	0.2	231.0	0.00
6	72.0	1.1	0.2	266.1	0.00
7	70.1	1.1	0.2	295.1	0.00
8	77.3	1.0	0.3	361.4	0.00
9	81.8	0.9	0.3	412.6	0.00
10	78.9	0.9	0.3	472.6	0.00
11	76.5	0.8	0.3	530.6	0.00
12	73.0	0.9	0.2	633.8	0.00
13	71.2	0.9	0.2	686.4	0.00
14	71.7	0.9	0.3	761.5	0.00
15	73.3	0.9	0.3	788.5	0.03
16	75.5	0.9	0.2	844.9	0.25
17	79.6	0.9	0.2	948.0	0.85
18	78.6	0.9	0.2	981.0	0.90
19	78.4	0.9	0.2	986.0	0.87

7. CONCLUSIONS

The paper presents a generic methodology to predict the life of electronic components used in drilling and evaluation tools. Statistical modeling techniques are used to derive best fit mathematical equations for durability of parts from field data. The method is applied to predict life of electronic printed circuit boards (PCBAs) and retire high risk components. The key challenges associated with developing durability models for PCBAs in drilling environment are:

(a) Life of parts is impacted by several factors, not all which can be measured accurately because of limitations of measurement systems and human factors.
(b) Field data may have noise and errors that may affect the quality of predictive model.
(c) Statistical model do not incorporate physics of degradation and may not be applicable for all failure mechanisms.

The methodology addresses the aforementioned challenges for the first time vis-à-vis application to lifing parts operating in downhole drilling environments. The key features of the analysis methodology include:

(a) Algorithm to determine life from cumulative damage over time and the best-fit mathematical model using a combination of statistical distribution and characteristic life function.
(b) Clustering mechanism to group parts life cycle data by upgrades, repair, failures and suspensions.
(c) A pattern search and outlier detection algorithm to identify data from a physical degradation trend.
(d) Iteratively reweighted maximum likelihood estimation method to determine optimal weights of data points.
(e) A Bayesian model selection technique to incorporate part specific operational history to obtain improved accuracy in life prediction.

Future work will focus on improving model predictions by using additional environment variables as well as integrating data from design and qualification tests.

NOMENCLATURE

ASS = AutoTrak steering system
BCPM = Bi-directional communication and power module
BHA = Bottomhole assembly
HALT = Highly accelerated life test
HAST = Highly accelerated stress test
IRMLE= Iteratively reweighted maximum likelihood estimation.
LVPS = Low voltage power supply
LWD = Logging while drilling
MaPS = Maintenance and performance system
MLE = Maximum likelihood estimation
MWD = Measurement while drilling
PCBA = Printed circuit board assembly
PHM = Prognostics and health management
PoF = Physics of failure
RPM = Revolutions per minute
F = Failure
L = Lateral vibration
M_i = i^{th} model identifier
N = Symbol used to represent negative decision, generally "no" or "0"
S = Symbol used to represent stick slip or suspensions
T = Temperature
X = Vector of parameters like temperature and vibrations
Y = Symbol used to represent affirmative decision, generally "yes" or "1"
f = Probability density function
m = Number of models
n = Number of records
p = Probability
$p(a|b)$ = Conditional probability of occurrence of event a provided b is true
revid = Revision identifier
tf = Time to failure (drilling hours)
w_i = Weight of i^{th} data point

x_{ave} = Average value of parameter x
x_{stdev} = Standard deviation of parameter x
α = Calibration parameters of reliability model
$\mathcal{L}$ = Likelihood
η = Characteristic life or scale factor of a probability distribution
β = Shape factor of a probability distribution
σ = Standard deviation
λ= Hazard function
$\{CF\}$ = Set of life data for confirmed failure
$\{O\}$ = Set of outliers
$\{S\}$ = Set of life data for suspension
$\{UF\}$ = Set of life data for unconfirmed failure
Load, *Stress* and *Severity* are used interchangeably to describe the impact of an operational environment (mechanical and thermal) on the durability of parts.
Nominal part is a representative part that has a life equal to the average of several parts produced using the same manufacturing process and operating under the same condition.
Run refers to a drilling mission that can last for several hours.
Suspensions are used in reliability modeling to represent hours accumulated on parts that are in operation or removed from service for reasons other than failure.

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BIOGRAPHIES

Amit A. Kale was born in Bhopal, India on October 25 1978. He earned PhD in 2005 and MS in 2004 in Mechanical Engineering from University of Florida, Gainesville, Florida, USA and BTech in Aerospace engineering from Indian Institute of Technology, Kharagpur, India in 2000. He joined Baker Hughes Inc. in 2012 and currently works on health prognostics of drilling system in Houston, Texas. Prior to that he worked in GE Global Research, Niskayuna, New York from 2005-2012.

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APPENDIX A

A. General Log-Linear Model

The relation between characteristics of life and stress variables are represented by using one of the three models: generalized log-linear (*GLL*), proportional hazard (*PH*) or cumulative damage (*CD*). The *GLL* model represents life using Eq. (A-1)

$$\eta(\bar{x}) = e^{a_0+\sum_{i=1}^{n} a_i x_i + \sum_{i=1}^{n}\sum_{j=1,j\neq i}^{n} a_{i,j}\, x_i x_j} \tag{A-1}$$

Where $\bar{x} = \{T,\ L,\ S\}$. For a Weibull distribution, the probability density function is shown in Eq. (A-2), where β is the shape parameter, η is the scale parameter and α*'s* are unknown parameters calculated from field data using the maximum likelihood estimation technique.

$$f(t,\bar{x}) = \beta t^{\beta-1} e^{-\beta.\eta(\bar{x})} e^{-t^{\beta} e^{-\beta.\eta(\bar{x})}} \tag{A-2}$$

The probability density function (PDF) for an exponential distribution can be obtained by putting $\beta=1$ in Eq. (A-1). For lognormal distribution, the probability density function for a *GLL* stress function is shown in Eq. (A-3):

$$f(t,\bar{x}) = \frac{1}{t\sigma\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{ln(t)-\eta(\bar{x})}{\sigma}\right)^2} \tag{A-3}$$

B. Proportional Hazard Model

For a proportional hazard model, the hazard rate of a component is affected by hours in operation and stress variables. The instantaneous hazard rate of a part is given by the equation as:

$$\lambda(t,\bar{x}) = \frac{f(t,\bar{x})}{R(t,\bar{x})} = \lambda_0(t)\, \eta(\bar{x},\bar{a}) \tag{A-4}$$

where f is the probability density function and R is the reliability function. The instantaneous hazard rate λ_0 is a function of time only and the stress function η is function of operating stresses like temperature or vibration. The list of unknown model parameter $\bar{a}$ is obtained by calibrating model-to-test data using maximum likelihood estimation (MLE). The stress function η is given by Eq. (A-5):

$$\eta(\bar{x}) = e^{\sum_{i=1}^{n} a_i x_i + \sum_{i=1}^{n}\sum_{j=1,j\neq i}^{n} a_{i,j}\, x_i x_j} \tag{A-5}$$

Substituting Eq. (A-5) in Eq. (A-2), the hazard function can be written for a Weibull distribution using Eq. (A-6):

$$\lambda(t,\bar{x}) = \frac{\beta}{\eta}\left(\frac{t}{\eta}\right)^{\beta-1} e^{\sum_{i=1}^{n} a_i x_i + \sum_{i=1}^{n}\sum_{j=1,j\neq i}^{n} a_{i,j}\, x_i x_j} \tag{A-6}$$

C. Cumulative Damage Model

The cumulative damage model is designed to incorporate the effect of varying stress on life of components. The model takes into account the impact of damage accumulated at each stress level on the reliability of the part. Damage accumulation can take place at different rates for different stress levels and can be determined using the linear damage sum (Miner's rule), inverse power law or cycle counting techniques like rain flow counting. The cumulative damage model used in the paper is established from Miner's rule, which is based on the hypothesis that if there are *n* different stress levels and the time to failure at the i^{th} stress σ_i is Tf_i, then the damage fraction, *p*, is given by Eq. (A-7):

$$p = \sum_{i=1}^{n} \frac{t_i}{Tf_i} \tag{A-7}$$

Where t_i is the number of cycles accumulated at stress σ_i and failure occurs when the damage fraction equals unity. The probability distribution functions for Weibull and lognormal distributions are obtained by substituting Eq. (A-7) in Eqs (A-2) and (A-3), respectively. Given the stress variables $\boldsymbol{\bar{X}} = \{T, L, S, RPM, L\times T, S\times T, L\times S, S\times RPM\}$, the PDF for a Weibull distribution is given by:

$$I(t,\bar{x}) = \int_0^t \frac{e^{a_0+\sum_{i=1}^{n} a_i x_i(t) + \sum_{i=1}^{n}\sum_{j=1,j\neq i}^{n} a_{i,j}\, x_i(t) x_j(t)}}{p}\, dt$$

$$f(t,\bar{x}) = \beta s(t,\bar{x})\big(I(t,\bar{x})\big)^{\beta-1} e^{-\left(\left(I(t,\bar{x})\right)\right)^{\beta}} \tag{A-8}$$

D. Characteristic Life Function

The life characteristic function describes a general relation between failure time and stress levels. The life characteristic can be any time-to-failure measure such as the mean, median or hazard rate that represents a bulk property of a probability distribution. Ideally, the function incorporates the governing equations that represent the physical phenomenon of degradation of the material under application of load. Typical electronic circuit boards used in drilling and evaluations are complex and the governing equations representing degradation and failure mechanisms are difficult to model; hence, the paper evaluates several empirical functions between stress variables and selects the one that best fits the field data.

E. Maximum Likelihood Estimation and Outlier Detection

The maximum likelihood estimation (MLE) obtains the most likely values of parameters that best describes lifecycle data. Typically, the life cycle data of a part contain two sets of populations (a) hours to failure on samples that failed in an experiment or in field and (b) hours in operation for parts that are either currently being operated or those that are retired for precautionary measures but were fully functional at that time.

$$ln(L) = \sum_{i=1}^{F_e} W_i^F \times N_i^F \times ln\big(f(T_i,\eta,\beta)\big) + \sum_{i=1}^{S} W_i^S \times N_i^S \times ln\big(1-F(Ts_i,\eta,\beta)\big) - \sum_{i=1}^{I} W_i^I \times N_i^I \times ln\left\{\left(1-F(T_i^L,\eta,\beta)\right)-\left(1-F(T_i^R,\eta,\beta)\right)\right\} \qquad \text{(A-9)}$$

Where the initial weight of each data point is given by

$$W_i^* = \frac{1}{\sum_{i=1}^{Fe} N_i^F + \sum_{i=1}^{S} N_i^S + \sum_{i=1}^{I} N_i^I} \qquad \text{(A-10)}$$

F_e is the number of samples for which the exact times-to-failure is known, N_i^F is the number samples for which the exact time-to-failure is T_i, f is the probability density function (pdf) for time to failure, η is the scale factor and β shape factor of the pdf, N_i^S is the number samples for which the right censoring time is Ts_i, N_i^I is the number samples for which the left censoring time is T_i^L and right censoring time is T_i^R. The W_i^* is the weight of i^{th} data subgroup is determined by the IRMLE algorithm. The outliers identified by the algorithm are shown in Fig. A1-Fig. A6 and the comparison of estimated life versus actual drilling hours to failure is shown in Fig. A7.

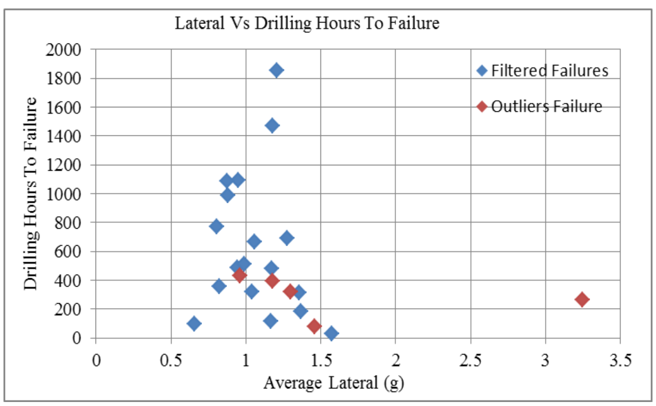

Figure A1. Time to failure Vs. lateral vibration severity for fielded LVPS-modem serialized parts.

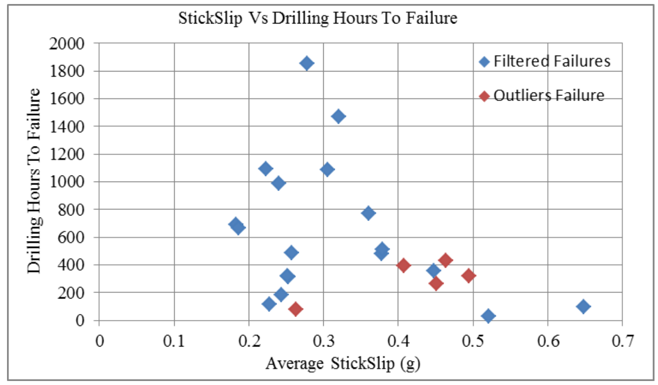

Figure A2. Time to failure Vs. stickslip vibration severity for fielded LVPS-modem serialized parts.

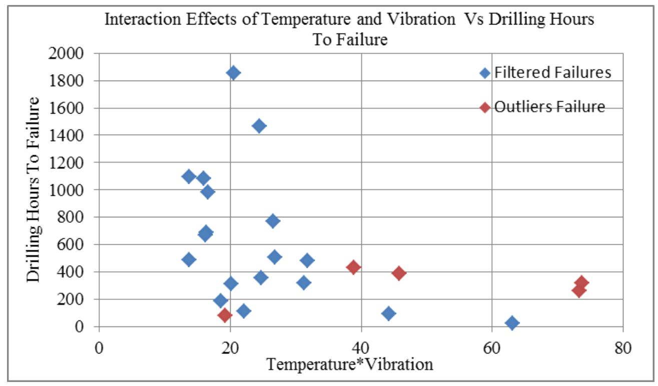

Figure A3. Impact of interaction of temperature and vibration on failure of LVPS-modem serialized parts.

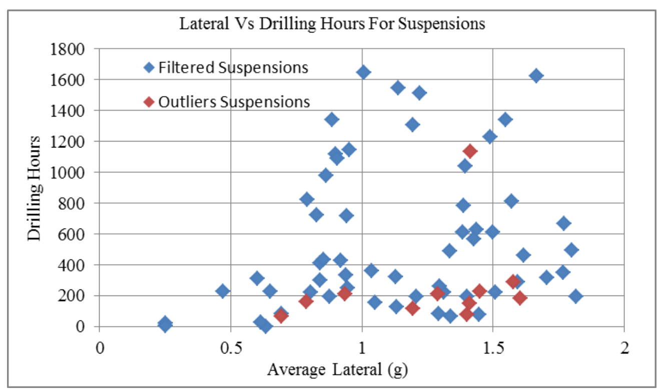

Figure A4. Suspension time Vs. lateral vibration severity for fielded LVPS-modem serialized parts.

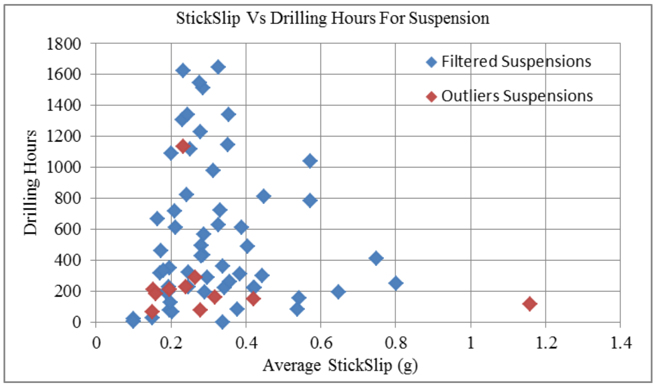

Figure A5. Suspension time Vs. stickslip vibration severity for fielded LVPS-modem serialized parts.

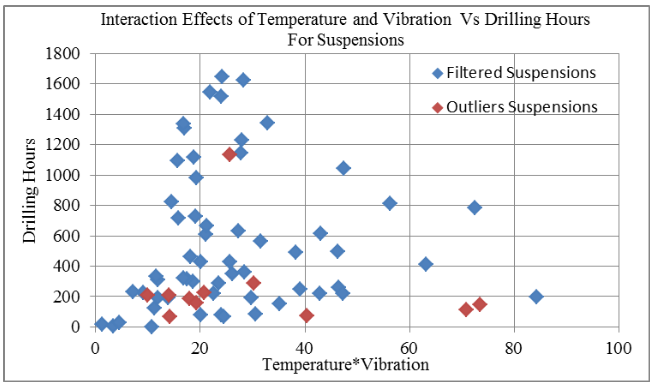

Figure A6. Suspension time Vs. interaction effect for fielded LVPS-modem serialized parts.

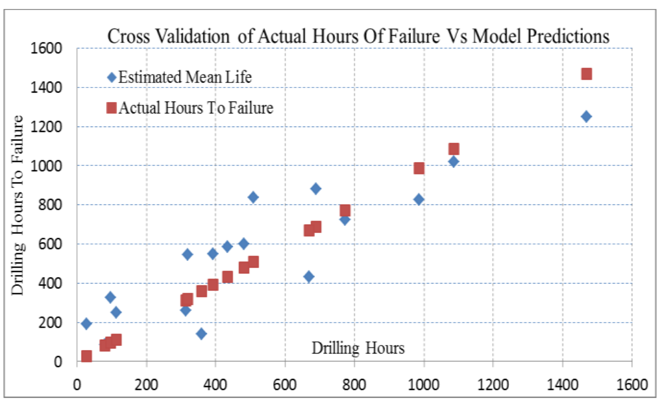

Figure A7. Comparison of actual life Vs. predicted mean life for parts that failed in field