Reliability engineering methods are widely applied in design and manufacturing. The process of deploying this collection of tools appropriately is known as Design for Reliability (DFR). Some reliability engineering tools and methods have also been applied in the maintenance sector (i.e., equipment operators) but, in many cases, not as extensively. In this article, we will review the reliability methodologies that are applicable for asset performance management (APM) and propose a process for deploying the appropriate tools at the appropriate stages.

Introduction to Reliability Engineering Methods

Reliability engineering is a discipline that combines practical experience, maintenance, safety, physics and engineering. Observational data is combined with experience to create models in order to understand the behavior of the equipment, optimize its performance and minimize the life cycle/operational costs. It is important to note that reliability engineering is not simply statistics and it is not always quantitative. Even though quantitative analysis plays a major role in the reliability discipline, many of the available tools and methods are also process-related. It is therefore useful to separate these methods and tools into quantitative and qualitative categories.

Asset Performance Management Supported by Reliability Engineering

In the quantitative category, the typical tools are:
- Life Data Analysis (a.k.a. "Distribution Analysis" or "Weibull Analysis")
- Reliability Growth Analysis
- Accelerated Testing (a.k.a. "Life-Stress Analysis")
- System modeling using Reliability Block Diagrams (RBDs)
- Simulation
- Fault Tree Analysis (FTA)
- Design of Experiments (DOE)
- Standards-based Reliability Predictions (e.g., MIL-217)

In the qualitative category, the typical tools are:
- Failure Modes, Effects and Criticality Analysis (FMEA/FMECA)
- Reliability Centered Maintenance (RCM)
- Failure Reporting, Analysis and Corrective Action Systems (FRACAS)
- Root Cause Analysis (RCA)

Avoiding Common Mistakes and Misapplications in Design for Reliability (DFR)

Design for Reliability (DFR) is a process that describes the entire set of tools that support the effort to increase a product’s reliability. These methodologies are applied from the early concept stage of a design all the way through to product obsolescence. The success of a DFR process is directly related to the selection of the appropriate reliability tools for each phase of the product development life cycle and the correct implementation of those tools.

This article has been adapted from a paper delivered by ReliaSoft engineers at the 2011 Annual Reliability and Maintainability Symposium (RAMS) [1]. It examines certain areas of the DFR process where mistakes are common due to misunderstood "common practices" or due to attempts to either oversimplify the process or introduce unnecessary complexity. The observations presented here are based on the authors’ collective experience from interactions with customers during consulting projects, training seminars and reliability engineering software development.

Reliability Requirements

Setting well-defined and meaningful reliability requirements is one of the most important steps in a DFR process. Mean Time Between Failures (MTBF) is an example of a reliability requirement that is a standard in many industries, yet is often misused and is inappropriate in most cases. (Note that when referring to non-repairable systems, the most appropriate term is Mean Time To Failure (MTTF), but these terms are often interchangeable in practice. Here we will use the more common term MTBF.)

The use of an MTBF as a sole reliability requirement implies a constant failure rate, which is not the case for most systems or components. Even if the assumption of a constant failure rate is not made, the MTBF does not tell the whole story about reliability. For example, consider three components

Also Inside...

- Accelerated Testing Data Analysis Without a Known Physical Failure Model
- Information on the latest software product releases
In this article, we will focus on some of the reliability engineering tools that are the most applicable in asset performance management. This will include a discussion of how and when each method should be deployed in order to maximize effectiveness.

The APM Process

Understanding when, how and where to use the wide variety of available reliability engineering tools will help to achieve the reliability mission of an organization. This is becoming more and more important with the increasing complexity of systems and sophistication of the methods available for determining their reliability. With increasing complexity in all aspects of asset performance management, it becomes a necessity to have a well-defined process for integrating reliability activities. Without such a process, trying to implement all of the different reliability activities involved in asset management can become a chaotic situation in which reliability tools may be deployed too late, randomly or not at all. This can result in the waste of time and resources as well as a situation in which the organization is constantly operating in a reactive mode.

Managers and engineers in the asset management discipline have come to this realization, and a push for a more structured process has been seen in recent years. The circumstances are very similar to what happened with the quality assurance discipline back in the 1980s, which spawned successful processes such as Six Sigma and Design for Six Sigma (DFSS). In more recent years, the same realization occurred in product development with the resulting Design for Reliability (DFR) process. It is therefore natural to look into these successful processes in order to create a process for asset performance management.

The process proposed in this article is based on the Design, Measure, Analyze, Improve and Control (DMAIC) methodology that is widely used in Six Sigma for projects aimed at improving an existing business process. It includes five phases:

- **Define** the problem, the voice of the customer and the project goals.
- **Measure** key aspects of the current process and collect relevant data.
- **Analyze** the data to investigate and verify cause-and-effect relationships. Seek out the root cause of the defect under investigation.
- **Improve** or optimize the current process based upon data analysis and standard work to create a new, **future state** process. Set up pilot runs to establish process capability.
- **Control** the future state process to ensure that any deviations from target are corrected before they result in defects. Control systems are implemented – such as statistical process control, production boards and visual workplaces – and the process is continuously monitored.

To develop the new APM-focused process, we first determined the asset performance management activities within each of these phases. Then we identified the reliability methods and tools that pertain to each activity/phase.

The proposed process can be used as a guide to the sequence of deploying different reliability engineering tools in order to maximize their effectiveness and to ensure high reliability. The process to advance the state-of-the-art by developing improved methods and tools, and c) share knowledge with practitioners across a variety of industries via participation in conferences, journals, online publications, training seminars and consulting projects.

—Lisa Hacker

---

**From the Editor’s Desk**

In this issue of *Reliability Edge*, we are proud to once again provide a variety of articles that were researched and prepared by ReliaSoft's world class R&D group. This dedicated team of engineers, statisticians, mathematicians and software programmers regularly collaborate to a) stay up-to-date on the latest advances in the discipline, b) help

---

In this issue of *Reliability Edge*: “Asset Management Supported by Reliability Engineering”
can be adapted and customized based on the specific industry, corporate culture and existing processes. In addition, the sequence of the activities within the APM process will vary based on the nature of the asset and the amount of information available. It is important to note that even though this process is presented in a linear sequence, in reality some activities would be performed in parallel and/or in a loop based on the knowledge gained as a project moves forward. Figure 1 shows a diagram of the proposed process. Each phase in the process is briefly introduced in the following sections.

Define Phase

The first step of any project is to define its objectives. This phase of the process is very important because it identifies the requirements and goals that will provide a direction for all future phases and activities to be performed. All too often, projects are initiated without a clear direction and without a clear definition of the objectives. This leads to poor project execution. Therefore, it is essential for the organization to do all of the following during the "Define" phase:

- Define the asset performance/reliability objectives.
- Define requirements and goals.
- Define the scope of the analysis.
- Determine budgetary and time constraints.
- Determine personnel resources and their responsibilities.
- Plan activities and set criteria for success.
- Define the appropriate key performance indicators (KPIs) for the organization.
- Establish the KPI targets.

The next section provides a brief discussion of the activity that will have the biggest impact on the application of reliability methods/tools in subsequent phases: defining KPIs.

Defining Key Performance Indicators

A performance indicator or key performance indicator (KPI) is a measure of performance. Such measures are commonly used to help an organization define and evaluate how successful it is, typically in terms of making progress toward long-term organizational goals. These performance metrics should be monitored in order to assess the present state of the business at any given time, and to assist in prescribing a course of action when improvements are needed.

It is very important that time is spent at the start of a project to define the KPIs that are important to the organization, as well as to review any existing performance indicators to determine their usefulness and how they are obtained from data. Reviewing and understanding the current indicators can also provide a benchmark for judging the success of a project.

KPIs can be specified by answering the question, "What is really important to different stakeholders?" As such, different levels of performance indicators – corporate, financial, efficiency/effectiveness, tactical/functional – can be specified and aligned to the organization's business objectives.

Figure 1: The proposed asset performance management process with applicable reliability engineering tools/methods

Please Turn to Page 5
Weibull++ is the industry standard for reliability and life data analysis (Weibull analysis) for thousands of companies worldwide.

- Supports all forms of the Weibull distribution along with the exponential, normal, lognormal, generalized gamma, gamma, logistic, loglogistic, Gumbel and Weibull-Bayesian distributions. The Distribution Wizard helps you select the appropriate distribution for your data.
- Supports rank regression and maximum likelihood estimation for parameter estimation and offers Fisher matrix, likelihood ratio, beta binomial and Bayesian methods for confidence bounds.
- Quickly returns calculated reliability results and automatically generates a complete array of related plots and reports.
- Provides integrated utilities for related analyses, including warranty analysis, reliability block diagrams, parametric and non-parametric recurrent event data analysis, degradation analysis, non-parametric life data analysis and reliability test design.

http://Weibull.ReliaSoft.com

Accelerated life testing techniques, in conjunction with powerful quantitative accelerated life data analysis methodologies, give design and reliability engineers the power to significantly reduce test times, which can provide faster time to market, lower product development costs, lower warranty costs and many other benefits.

ReliaSoft’s ALTA is still the only commercially available software tool designed expressly for quantitative accelerated life testing data analysis using rigorous scientific analysis methods. The software is available in two versions:

- **ALTA Standard** provides the life-stress relationship models required to analyze accelerated life test data with 1 or 2 constant stresses.
- **ALTA PRO** offers advanced capabilities for analyzing accelerated life test data with up to 8 simultaneous stress types where stress is constant or varies with time!

Both versions provide a complete array of utilities for designing accelerated life tests, evaluating the fit of the model, calculating reliability metrics, generating plots and performing related statistical analyses.

http://ALTA.ReliaSoft.com
Another reason for the critical importance of defining the KPIs at this stage is the impact on future data requirements. In other words, the chosen KPIs will determine what information needs to be captured and analyzed in subsequent phases of the process.

Measure Phase

Prior to conducting any type of reliability analysis, it is important to collect all the data required to support the analysis objectives. It is also crucial to determine what kinds of data are available and where the information resides. The types of data available will determine which analyses can be performed, so, if sufficient information is not currently available, it may be necessary to identify future steps for obtaining it. Therefore, the typical steps in the "Measure" phase are to perform a reliability gap assessment, then gather the data and select the appropriate analysis techniques.

Reliability Gap Assessment

The purpose of a reliability gap assessment is to identify the shortcomings in achieving the asset performance management objectives so that a reliability program plan can be properly developed. Many companies implement APM tasks without first understanding what drives reliability task selection. The gaps are those issues or shortcomings that, if closed or resolved, would move the company in the direction of achieving its APM targets. In addition, the available data sources can be identified during this activity. If they are inadequate, the analysts may resort to other sources of information. During the gap assessment, answers to the following questions are sought:

- What reliability activities are currently in place? For example, is an existing RCM study available? Has it been successfully executed?
- What personnel are currently supporting the reliability activities?
- What procedures document the current reliability and APM practices?
- How does the organization currently collect reliability data? For example, is there a CMMS (computerized maintenance management system), EAM (enterprise asset management) system, FRACAS (failure reporting, analysis and corrective action system), production loss database, etc.?
- How are the asset reliability and performance metrics currently computed (i.e., methods and tools)?
- Can we compute all KPIs defined in the previous phase?

Gather Data

Data, and specifically failure time data, are like gold to a reliability engineer. Of course, on the flip side, the more failures that are available to be analyzed, the worse the condition of the asset! In any case, data represent the most important aspect in performing quantitative reliability analyses. It is therefore crucial for data to be collected and categorized appropriately. The data will be used in computing the different KPIs, as well as in performing a variety of reliability calculations.

In addition to failure data, the repair duration is also a very important input in the reliability, availability and maintainability (RAM) model because it determines the equipment availability. Other types of data will also be necessary for a thorough RAM analysis for assets. The following lists provide a summary of the information typically used.

Minimal information required:

- Failure times/intervals.
- Repair durations.
- Failure codes/IDs (causes of failure).
- Current maintenance task types and intervals.

Additional information that would improve the analysis if available:

- Throughput (capability) of each piece of equipment.
- Repair crew availability (e.g., number of crews and corresponding logistic delays).
- Repair costs (e.g., parts, labor, etc.).
- Spare parts availability and costs.
- Inspection policies (e.g., condition monitoring).

There are multiple sources of data. For example, failure time data can be obtained from maintenance records (work orders, downtime logs, etc.), from the original equipment manufacturer (OEM) reliability specs, or from published generic equipment data.

For existing equipment, historical data can also be used. There may be a great deal of historical data that has been generated over many years. It is necessary to find out where this information resides, and to determine which information can assist in meeting the organization's analysis objectives.

Once the data sources have been identified, the quality and consistency of the data must be evaluated. One of the most common problems for analysis is insufficient quality of the collected data. All too often, even though records are kept, it turns out that the data are not really usable. The most common problems with available data include:

- No data tracking system.
- Not specifying the cause of the failure (i.e., the component, subsystem, etc. that was responsible for the downtime).
- Not having the appropriate system hierarchy in the CMMS for reliability data purposes. For example, in many maintenance management systems, the asset hierarchy is set up in a way that prevents the "roll-up" of failure frequency information from the component to the subsystem to the equipment. So the analyst might be able to see that a valve failed, for example, but cannot see where this valve belongs for equipment-level analysis. In
ReliaSoft’s XFRACAS provides all of the tools that your organization will need to troubleshoot issues as they occur in the lab or in the field, capture the data required for important reliability, quality and safety analyses, work as a team to resolve underlying problems and build a knowledge base of lessons learned that will be instrumental to future troubleshooting and development efforts.

- The system provides complete support for Failure Reporting, Analysis and Corrective Action (FRACAS) activities as well as problem resolution methods such as 8D, Six Sigma DMAIC, and others.
- XFRACAS is configurable, flexible and scalable to fit your organization’s particular products or processes and to grow with your needs.
- The system’s web-based user interface allows for easy access, collaboration and deployment for multiple sites, suppliers and dealers.
- Powerful configuration utilities allow you to control the look and feel of user interfaces and establish specific permissions based on user and “entity” (e.g., product line or business unit), with no custom programming required!

http://XFRACAS.ReliaSoft.com

ReliaSoft's Orion eAPI (enterprise Asset Performance Intelligence) software is an enterprise solution for asset performance management. This web-based system provides a centralized, searchable knowledge base for asset performance data, which is integrated with powerful analysis tools for transforming raw data into meaningful information that supports strategic decisions for your organization.

- Collect raw data from a variety of databases and CMMS/EAM systems (such as SAP®, Maximo®, Oracle®, Access®, SQL Server®, etc.).
- Apply the most effective reliability, availability and maintainability (RAM) analysis techniques including, but not limited to, Life Data Analysis (Weibull analysis), Root Cause Analysis (RCA), Optimum Preventive Maintenance Intervals, Spare Parts Forecasting and Reliability Growth Tracking (Crow-AMSAA).
- Display and track Key Performance Indicators (KPIs). Each user can configure the display to fit his/her particular needs, and the system can send automated e-mail notifications ("KPI Alerts") when a metric moves beyond a specified range.
- Manage improvement projects to control costs and improve availability.

http://Orion.ReliaSoft.com
addition, if there is another valve failure, the analyst may not be able to determine if it was the same valve that failed before.

- Poor implementation of the process for recording work order details. For example, if work orders are left open after the work has been completed, and the repair duration is based on the date/time when the work order was closed, this will give a false indication of downtime.
- A CMMS or EAM system is in place but it is not capturing production loss data.
- Information is not captured regarding inspection intervals and the results of each inspection. These details can be very useful in determining Safety Integrity Levels (SIL), and for use in the Risk-Based Inspection (RBI) methodology.

To avoid such problems, it is imperative for the organization to implement corrective actions to ensure that good data collection processes and management are in place.

Select Analysis Techniques

Finally, assuming that all the relevant information is available, the appropriate simulation and analysis techniques can be selected to estimate the system availability, downtime, production output (a.k.a. throughput), maintenance costs and other metrics of interest.

Analyze Phase

Depending on the objectives agreed upon during the "Define" phase and the data sources/analysis techniques identified in the "Measure" phase, the next step is to execute the appropriate analysis techniques in order to optimize the performance of the asset. In the following sections, we will briefly highlight the objectives, applications and benefits of some of the most effective reliability-related methodologies that can be used in asset performance management.

Reliability Centered Maintenance (RCM)

RCM analysis provides a structured framework for analyzing the functions and potential failures of physical assets in order to develop a scheduled maintenance plan that will provide an acceptable level of operability, with an acceptable level of risk, in an efficient and cost-effective manner. RCM can be:

- Quantitative and based on reliability analysis.
- Qualitative and following a published step-by-step methodology (such as MSG-3).
- A combination of both of the above.

A lot has been written about RCM and its benefits. A full discussion of the topic is outside the scope of this article but it is worth mentioning some of the widely accepted benefits, which include:

- Prioritizing actions based on equipment criticality (multiple criticality classifications exist).
- Reducing and ultimately eliminating chronic failures and reliability problems.
- Documenting the maintenance program and practices.
- Reducing unscheduled maintenance.
- Reducing risk.
- Documenting the reasons for current activities and for future changes.

Life Data Analysis

Life data analysis (also called distribution analysis or Weibull analysis) refers to the application of statistical methods in determining the reliability behavior of equipment based on failure time data. Life data analysis utilizes sound statistical methodologies to build probabilistic models from life data (i.e., lifetime distributions, such Weibull, lognormal, etc.). The following graphic shows how a statistical distribution is fitted to failure data.

The probabilistic models are then utilized to compute the reliability, make predictions and determine maintenance policies and maintenance task intervals. These models should be applied at the lowest replaceable unit (LRU) level. Some of the applications for this type of analysis include:

- Understanding failure patterns.
- Understanding life expectancy of components.
- Understanding repair duration patterns.
- Using these models in the RAM analysis.
- Using the results in the "Improve" phase for spare part provisions, determining optimum maintenance intervals, making design changes, etc.

Degradation Analysis

Another way to calculate reliability metrics involves a type of analysis known as degradation analysis. Many failure mechanisms can be directly linked to the degradation of part of the product. Assuming that this type of information is captured (e.g., condition based maintenance – CBM – data), degradation analysis allows the engineer to extrapolate to an
assumed failure time based on the measurements of degradation over time. This analysis essentially determines the P-F curve that is often discussed by RCM practitioners (i.e., the period from when it is possible to start to recognize a potential failure, P, until it becomes an actual failure, F). The degradation analysis results can be used to:

- Understand failure patterns.
- Understand life expectancy of components.
- Build lifetime distributions that will be used in the "Improve" phase for RAM analysis and optimizations.

Recurrent Event Data Analysis (RDA)

RDA is different than “traditional” life data analysis (distribution analysis) because RDA builds a model at the equipment/subsystem level rather than the component/part level. Furthermore, whereas life data analysis uses time-to-failure data (in which each failure represents an independent event), the data utilized in RDA are the cumulative operating time and the cumulative number of failure events. Therefore, while life data analysis is used to estimate the reliability of non-repairable components, RDA models are applied to data from repairable systems in order to track the behavior of the number of events over time and understand the effectiveness of repairs. The most commonly used models for analyzing recurrent event data are the non-homogeneous Poisson process (NHPP) and the general renewal process (GRP).

System Modeling/RAM Analysis

A reliability, availability and maintainability (RAM) analysis typically starts from the creation of a diagram that represents the overall system/process and the corresponding major subsystems. This diagram is known as a reliability block diagram (RBD). The next step is to expand the major subsystems into subsubsystems and keep repeating until you reach the level where reliability information is available (ideally at the LRU level). The analysis will be based on the failure and repair duration properties for the items in the diagram. The failure properties (i.e., reliability) determine the frequency of occurrence of failure of each LRU; the repair durations determine the downtime. The effect of the failure on the overall system is determined based on the configuration of the block diagram. The effect could be that the entire system fails or it could be a percent reduction in the total output (throughput) of the system.

To perform a complete RAM analysis, the following information is required:

- System diagrams/drawings.
- Failure data.
- Repair duration data.
- Process capabilities of individual machines.
- Repair costs.
- Maintenance types and intervals.
- Repair crew availability.
- Spare parts availability and costs.

The results of such an analysis may include:

- Availability
- Downtime
- Number of failures
- Number of spares used
- Production output
- Life cycle costs

Having the system RBD model will also help later in the “Improve” phase to perform what-if analyses and investigate the effect of any proposed changes/improvements.

Root Cause Analysis (RCA)

RCA is a method to logically analyze failure events, identify all the causes (physical, human and primary) and define corrective actions to prevent their recurrence. It is a critical activity in understanding failures and being able to determine corrective actions. Without a formal RCA procedure, the wrong remedies might be frequently implemented.

Improve Phase

The main objective of an APM process is to drive improvements, thus the “Improve” phase represents the most critical step of the process. During this phase, the objective is to identify the improvements that can increase the performance of the asset and optimize it, including:

- Defining the most appropriate maintenance policy.
- Determining the optimum maintenance task intervals.
- Determining adequate spare part provisions.
- Applying design changes when necessary/feasible.
- Driving new requirements to suppliers.
- Adding cost information to the simulation in order to run a dynamic life cycle cost (LCC) analysis.

As an example, the following section provides a brief overview of one of the most commonly used reliability tools that can be employed in this phase: calculating the optimum preventive maintenance (PM) interval.

Calculating the Optimum PM Interval

Engineers can use the following equation to find the optimum interval for a preventive maintenance action. The equation is solved for the time, $t$, that results in the least possible cost per unit of time.

$$CPUT(t) = C_p \cdot R(t) + C_u \cdot \int_0^t R(s) ds$$

where:

- $R(t) = \text{reliability at time } t$. This is determined by performing life data analysis on available data.
- $C_p = \text{Cost per incident for planned (preventive) maintenance.}$
Another critical function in this phase is sustaining the knowledge acquired by all previous activities, as well as retaining the analyses that have led to a particular action or change. Failing to retain this knowledge can lead to “reinventing the wheel” down the road, as well as the risk of repeating past mistakes. Different activities (including analysis, action plans and decisions) should be recorded properly and stored in a location where other professionals involved in the asset’s management can access the information in the future.

Conclusion

In this article, we reviewed the role of reliability engineering methodologies in asset performance management, and we proposed a flexible APM process for deploying different reliability tools and methods where they can be most effective. The proposed process is general enough to be easily adopted by different industries and can be used in conjunction with current reliability practices.

References

whose lifetimes are modeled with the Weibull distribution, each of which has the exact same MTBF. The fact that the MTBF of the three components is the same does not necessarily imply that the reliability at any given time will be the same. Figure 1 shows the reliability functions of three such components. Although the MTBF is the same for all three, the corresponding reliabilities at different times vary considerably. Therefore, it is clear that the use of a reliability requirement at a specific time (e.g., 95% at 1,000 hours) instead of simply an MTBF will be more descriptive of the expected life of a component.

Another example of an inadequate reliability requirement is the use of a point estimate with the absence of confidence bounds. Especially when setting requirements for suppliers, confidence bounds are crucial in order to ensure that the value claimed has been demonstrated properly. For example, consider a case where two vendors are evaluated in terms of the reliability of their components, and suppose that they both claim that their reliability is 95% at 1,000 hours. Given that information, one would expect that the decision should be made solely based on price because the reliabilities are the same. However, suppose that further investigation revealed that one vendor tested 100 components while the other tested only 5. Given that, it can be determined that the 90% lower confidence bound on reliability for the first vendor is 93%, while for the second vendor it is 78%. Thus, the basis for choosing the best vendor has changed. This simple example demonstrates that unless there is a lower confidence bound attached to the specification, there is no way to evaluate the validity of supplier claims and make valid comparisons.

Usage and Environmental Conditions

The core definition of reliability (the probability that the item will perform its intended function for a specific mission duration under specified conditions) suggests the need to clearly map out and understand the expected use conditions. Nevertheless, we have observed that many of the DFR challenges that organizations face are due to lack of consideration or poor understanding of usage and environmental factors.

The manner in which the product will be used in the hands of the customer should be given sufficient consideration in the design phase. Understanding what constitutes normal use or abuse can help with making the right design choices and selecting the right tests to simulate actual usage conditions during in-house testing. Technical directions in a user’s manual are, in most cases, not enough to protect a product from aggressive usage. Guidance such as “wait until the engine has warmed up to operate,” “switch from 4x4 to 2x4 when driving above 55 mph,” etc. may be frequently ignored in actual usage. If the tests do not account for aggressive usage, then the disconnect between in-house test reliability and field reliability is usually very high.

Usage can also be expressed in terms of understanding the proportion of customers who will reach a certain design life. For example, suppose a printer is designed to last five years, but it is also designed to last one million pages. Understanding the distribution of pages printed during five years can make a big difference in design decisions. Any reliability requirement is complete only when it has an associated percentile user. For example, a requirement to prove a certain level of printer component reliability for a 99th percentile user would mean proving that reliability for a specific number of pages printed.

Environmental conditions are also critical in making the right design choices to support reliability. Often products are tested in a very narrow range of environmental conditions, but they are used in a broader spectrum of conditions in the field. Using the same example of a printer, one can design a printer that will work without failures and paper jams in Arizona, but will fail to operate properly in Florida where the relative humidity is so high that it introduces new failure modes not observed in the tested environment. In this case, the paper in the trays curls from the high humidity environment and causes the printer to jam frequently. Up-front work needs to be done to clearly define the range of environmental conditions for which the product will operate, and testing needs to simulate various profiles of those environmental conditions in order to expose failure modes that would not show up in ambient conditions.

Temperature and humidity are only two of the major environmental conditions that can significantly affect product reliability. Depending on the specific application, solar load, water quality, rain, wind, snow, sand, dust, mud, hail, thermal cycling, voltage input stability and many other environmental conditions can be key factors that affect the product’s life. Major effort should be made up-front in the DFR process in...
order to identify realistic environmental conditions. The goal is to incorporate environmental concerns into the design early on, and also to be able to design tests that will reflect the actual environmental conditions to which the product will be exposed.

**Preparation Before Testing**

Reliability tests play an integral role in a DFR process because they provide the means to quantify reliability. In general, a lot of money, effort and resources can be saved through better preparation before reliability testing. For example, accelerated tests are often performed with a large number of stresses. This can result in very expensive tests or even unsuccessful tests that yield failure modes that are not expected to be seen in practice. However, if sufficient effort is spent in planning the test, the process will yield the same results in a much more efficient way. A best practice in this case would be to use Design of Experiments (DOE) methodologies to identify the most significant stresses that affect the life of the product. By performing small experiments to determine the few most important stresses, the overall cost of the test will be decreased significantly. Furthermore, the data collected from those experiments can also be used for planning the test so that the available samples are optimally allocated across the different stress levels.

**Execution and Analysis of Accelerated Tests**

Accelerated testing provides the benefit of uncovering failures in a short time for components that have very high life expectancy. However, it is important to ensure that the principles of accelerated testing and the assumptions of the statistical models used are not violated. When deciding on the levels of the stresses to be applied during the test, one must consider the design limits of the component. When the applied stress goes beyond those limits, then new failure modes that will not be seen in the field are introduced and the results of the test are not valid.

Besides engineering judgment, contour plots can be a useful tool in determining whether the component is failing the same way across all stress levels. For example, consider the contour plots shown in Figure 2, which represent data sets obtained at three different stress levels. The contour on the far left represents the highest stress, the contour in the middle represents the middle stress and the contour on the far right represents the lowest stress level. The Weibull distribution was used to analyze the data at each level. The assumption is that the component will show the same failure behavior across all stress levels and therefore the beta parameter remains the same. As shown in the figure, the beta parameter is significantly different for the data set obtained from the highest stress level at the 90% significance level, indicating that the failure behavior has changed at this stress level. Moreover, even if the stress levels are not beyond the design limits, it should be considered that the farther away the stress level is from usage conditions, the more error is introduced into the results of the analysis. In many cases, in an effort to minimize the duration and cost of a test, engineers fail to consider those principles, which results in tests that offer little or no value for reliability analysis.

Another area that requires careful attention is the analysis of the data obtained from the accelerated test. The most important part of the analysis, with the greatest effect on the results, is choosing the appropriate model to describe the life-stress relationship. There are a number of models that have been suggested to describe life-stress relationships, and the appropriateness of each model depends on the applied stress. For example, the Arrhenius model is commonly used when the stress is temperature, while the inverse power law model is often used when the stress is mechanical [2]. Therefore, when a practitioner chooses a model, he/she should carefully consider the applied stress and the physics of failure of the component.

A common characteristic of most of the available life-stress relationship models is that they are **monotonic**, which means that the life decreases as the stress increases. In practice, we have observed many cases where this assumption is violated. For example, in one such scenario, product life improved as temperature increased to a certain point; but once the upper limit of that particular temperature range was reached, a chemical reaction kicked in to reverse the trend and product life then began to decrease as temperature rose. This is illustrated in Figure 3 on page 13, where two different Arrhenius models were applied to the data. We can see that moving from the lowest stress level to the middle stress level, life is increasing when stress is increasing. On the other hand, moving from the middle stress level to the highest stress level, life is decreasing when stress is increasing. This type of life-stress relationship
Putting the reliability back into reliability centered maintenance™

RCM++ facilitates analysis, data management and reporting for Reliability Centered Maintenance (RCM) analysis.

- Supports the Equipment Selection, Failure Effect Categorization and Maintenance Task Selection logic from the major RCM standards and allows you to customize the logic to meet specific needs.
- Provides simulation-based calculations to compare maintenance strategies based on cost and average availability over the life of the equipment and to calculate the optimum interval for preventive maintenance.
- Provides a complete set of print-ready reports generated in Microsoft Word® or Excel®, a variety of pareto (bar), pie and matrix charts and a flexible query utility.
- Supports related analyses such as Control Plans, Design Verification Plans and Design Review Based on Failure Mode (DRBFM).
- Allows multiple users to work cooperatively on the analysis and provides numerous ways to leverage the lessons learned from previous analyses, including copy/paste, import/export, etc.

http://RCM.ReliaSoft.com

Xfmea facilitates analysis, data management and reporting for FMEA, FMECA and related analyses.

- Supports the major industry standards, such as SAE J1739, AIAG and MIL-STD-1629A, for all types of FMEA/FMECA. Provides extensive capabilities to customize the interface and reports.
- Supports Risk Priority Numbers (RPNs) and Criticality Analysis for risk assessment.
- Provides a complete set of print-ready reports generated in Microsoft Word® or Excel®, a variety of pareto (bar), pie and matrix charts and a flexible query utility.
- Supports related analyses such as Control Plans, Design Verification Plans and Design Review Based on Failure Mode (DRBFM).
- Allows multiple users to work cooperatively on the analysis and provides numerous ways to leverage the lessons learned from previous analyses, including copy/paste, import/export, etc.

http://Xfmea.ReliaSoft.com

Jump-start your FMEA or RCM initiatives

FMEA Accelerator® is your key to accessing an outstanding collection of FMEA templates for a wide variety of components — making it easy to search for and import selected data into your own analyses performed in ReliaSoft’s Xfmea or RCM++ software. The MRG Physical Asset FMEA Template Collection offers over 260 templates for components ranging from blowers, boilers and conveyors to pumps, tanks, valves and much more. Additional collections are planned for the future.

Continued from Page 11: “Avoiding Common Mistakes and Misapplications in Design for Reliability (DFR)”

Reliability demonstration tests are a common practice right before a product goes into mass production in order to assure that the reliability target has been met. The importance of these tests is that they provide a final validation of the redesigns and the reliability tests that took place during the design phase. Therefore, the proper application of those tests is critical in the DFR process before a product goes into production and out into the field where it is more costly to deal with reliability issues. However, missteps can take place both when planning the demonstration test and during the execution of these tests.

In terms of planning, the binomial equation can be an effective tool for reliability demonstration test design \( [4,5] \). With this approach, the analyst specifies a reliability goal at a given confidence level and the number of failures that are "allowed" during testing. Then he/she uses the model to compute the required number of units to be tested for a given test time, or the test time required for the given number of units. However, as we have observed in many cases, the design of such tests may be driven solely by the resource constraints of available time or samples without considering the statistical theory. As a result, the tests provide no statistical significance in terms of achieved reliability. In other words, time and money are spent without really proving that the reliability goals have been met, and the reliability engineer would have been better off not performing the demonstration test at all!

In terms of execution, another common misstep occurs when the engineers fail to reevaluate the test design after a failure occurs during a “zero failure test.” If the test has been designed as a "zero failure test," it means that no failures should be observed in the sample for the given test duration in order to demonstrate the specified reliability for the specified

Reliability Demonstration Tests

Understanding Failure Rate Behavior

One of the most important aspects of reliability engineering practice is to be able to characterize the failure rate behavior of a component or system. Specifically, DFR activities are typically used to 1) design out decreasing failure rate behavior at the start of the life of the product (often called infant mortality), 2) increase margins/robustness and reduce variation during the useful life and 3) extend wearout beyond the designed life (or institute preventive maintenance before wearout if it makes economic sense).

Using inappropriate models or assumptions can lead to erroneous conclusions about the failure rate behavior of a component or system. As mentioned previously in the discussion of defining appropriate reliability requirements, one of the most common missteps is the assumption of an exponential distribution as the underlying lifetime model for reliability data. The exponential distribution implies a constant failure rate and superimposes that behavior on the modeled data. As a result, the analyst misses the signals that can indicate infant mortality or wearout mechanisms (or a mix of these as subpopulations in the data). This very often leads to poor design decisions concerning the reliability behavior of products, inaccurate estimation of warranty costs and many surprises after the product is fielded.

We have frequently observed the following scenario when working with customers in a variety of industries: the design team requests component reliability information from the suppliers, and many of the suppliers provide a single estimate as MTBF/MTTF without associated confidence bounds. In most cases, these numbers are generated by testing units for a short time, so the parameters are estimated based on a lot of suspensions and very few failure points. At the same time, an exponential distribution is often assumed. This can create overly optimistic reliability estimates. If the same test were continued longer and the analysis performed with a flexible distribution such as a two-parameter Weibull, the same test would provide a more pessimistic estimation of reliability.

A similar situation occurs with accelerated data analysis when key parameters are superimposed instead of being calculated from data. A good example of this is the decision to superimpose the activation energy in an Arrhenius model. That value can drastically affect the acceleration factors assumed. As a result, the extrapolation back to use conditions can be adjusted easily to a wide range of values \( [3] \).
time. However, in practice, when the first failure occurs, engineers sometimes mistakenly recalculate the test time for a “one failure test.” Then when the second failure occurs, they recalculate the time for a “two failure test,” and so on. Of course, this practice usually leads to a situation where the engineer is essentially chasing his tail, with no useful results. Instead of spending valuable resources to try to force the original test plan to succeed, the engineers should either go back and reevaluate the test design from a reliability perspective or run the rest of the test units to failure and calculate the reliability using traditional life data analysis methods.

Effects of Manufacturing

Well-done DFR still needs to be supported by manufacturing reliability efforts to ensure that the inherent design reliability is not degraded or unstable. Manufacturing may introduce variations in material, processes, manufacturing sites, human operators, contamination, etc. [6]. A common mistake is to assume that the reliability of a unit produced out of the manufacturing line will automatically match the test results of the fine-tuned prototype units. In fact, Meeker and Escobar have identified differences in cleanliness and care, materials and parts, and highly trained technicians vs. factory workers [7].

Not paying attention to the effects of manufacturing on product reliability can result in units showing infant mortality, which is usually the result of misassembly, inappropriate transfer or storage, the line being unable to conform to designed specifications, or uncontrolled key product characteristics. The best approach is to identify and address manufacturing issues through activities such as Process FMEA (PFMEA), manufacturing control and screening/monitoring plans. Burn-in testing can be used to address infant mortality, but this is not the preferred choice because the ideal goal is to design out infant mortality [8, 9].

It is also important to note that variation in manufacturing is not resolved as soon as the first product out the door is reliable. Variation in terms of supplier material, processes, machinery, personnel skills and other factors can influence the reliability characteristics of the units produced. A common misstep is to assume that verifying the reliability of the products through a single demonstration test is adequate. Instead, a thorough DFR process examines the reliability characteristics of the produced units at regular intervals over time to understand what changed. The solution here is two-fold. It involves mostly quality control approaches (such as statistical process control for key characteristics that can influence product reliability), but it can also include “ongoing reliability tests.” These tests can also affect the impact of current product engineering changes on product reliability. For example, a firmware upgrade can cause unexpected interactions that can lead to altered reliability characteristics. This and similar issues can be identified through an ongoing reliability test initiative.

Warranty Data Analysis

Warranty data analysis is another key step in a DFR process, which helps to assure reliability monitoring throughout the product’s life cycle. DFR does not stop when the product ships. Instead, a warranty tracking and analysis process should be built into the plan in order to assure field reliability.

One seemingly trivial but very common misstep during this stage is failing to implement the infrastructure that allows the capture of time-to-failure data in the field. A simple Nevada chart warranty data analysis requires knowledge of when units were shipped and when they were returned in order to apply Weibull analysis methodologies. However, it is very common that failure time information is not available for the product due to lack of infrastructure, rush to market or overly complex supply chain processes. In such cases, warranty analysis either cannot be thoroughly conducted or the data set contains too much noise.

The next misstep during the warranty stage is to ignore “suspended” units (i.e., units that have not failed) when analyzing data from the field. But the suspension data is of as much value as the failure times, and ignoring it will lead to erroneous analysis results. Consider this example: a company has just launched its new product and started to track reliability-related failures in the field. Every month, 500 new products enter service. Table 1 shows the Nevada chart of returns during the first six months of service.

Table 1: Warranty return data (row = month in service, column = month returned)

<table>
<thead>
<tr>
<th></th>
<th>Jun - 10</th>
<th>Jul - 10</th>
<th>Aug - 10</th>
<th>Sep - 10</th>
<th>Oct - 10</th>
<th>Nov - 10</th>
</tr>
</thead>
<tbody>
<tr>
<td>May - 10</td>
<td>0</td>
<td>1</td>
<td>2</td>
<td>0</td>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td>Jun - 10</td>
<td>0</td>
<td>2</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>Jul - 10</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>2</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Aug - 10</td>
<td></td>
<td>2</td>
<td>2</td>
<td>0</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sep - 10</td>
<td></td>
<td></td>
<td>3</td>
<td>1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Oct - 10</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>2</td>
<td></td>
</tr>
</tbody>
</table>

This chart indicates, for example, that a total of five units were returned in August. Two of those units had been in service since May, two since June and one since July. In other words, one can read the Nevada chart diagonally in order to count the number of units that failed after a specific period of time in service. Table 2 shows the time-to-failure data compiled for reliability analysis.

Table 2: Time-to-failure data

<table>
<thead>
<tr>
<th>State</th>
<th>Quantity</th>
<th>Time (months)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Failed</td>
<td>8</td>
<td>1</td>
</tr>
<tr>
<td>Failed</td>
<td>7</td>
<td>2</td>
</tr>
<tr>
<td>Failed</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>Failed</td>
<td>3</td>
<td>4</td>
</tr>
<tr>
<td>Failed</td>
<td>1</td>
<td>5</td>
</tr>
<tr>
<td>Failed</td>
<td>2</td>
<td>6</td>
</tr>
</tbody>
</table>
Continued from Page 14: “Avoiding Common Mistakes and Misapplications in Design for Reliability (DFR)"

If the analyst uses maximum likelihood estimation (MLE) and fits a two-parameter Weibull distribution, the calculated parameters are $\beta = 1.6851$ and $\eta = 2.7986$ months. The prediction for the reliability at the warranty time of 36 months is almost zero.

However, the correct approach to predict reliability is to also consider all the suspended units as shown in Table 3.

Table 3: Data set with failures and suspensions

<table>
<thead>
<tr>
<th>State</th>
<th>Qty</th>
<th>Time (months)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Failed</td>
<td>8</td>
<td>1</td>
</tr>
<tr>
<td>Suspended</td>
<td>498</td>
<td>1</td>
</tr>
<tr>
<td>Failed</td>
<td>7</td>
<td>2</td>
</tr>
<tr>
<td>Suspended</td>
<td>496</td>
<td>2</td>
</tr>
<tr>
<td>Failed</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>Suspended</td>
<td>496</td>
<td>3</td>
</tr>
<tr>
<td>Failed</td>
<td>3</td>
<td>4</td>
</tr>
<tr>
<td>Suspended</td>
<td>496</td>
<td>4</td>
</tr>
<tr>
<td>Failed</td>
<td>1</td>
<td>5</td>
</tr>
<tr>
<td>Suspended</td>
<td>497</td>
<td>5</td>
</tr>
<tr>
<td>Failed</td>
<td>2</td>
<td>6</td>
</tr>
<tr>
<td>Suspended</td>
<td>494</td>
<td>6</td>
</tr>
</tbody>
</table>

With this data set, when the analyst again uses MLE and fits a two-parameter Weibull distribution, the calculated parameters are $\beta = 1.3621$ and $\eta = 130.3$ months. The prediction for the reliability at the warranty time of 36 months is now $R(36)=84\%$.

The previous example clearly illustrates the vast difference in reliability estimation during the warranty period when considering or ignoring suspensions, and suggests to always include suspensions for accurate warranty analysis. However, another common misstep is the extreme application of this rule – that is, considering suspensions when in reality there is no information at all on whether or not the units have survived. This is a common scenario in fielded systems analysis beyond warranty life. In this case, there is no reliable way to track if the unit is operating beyond the warranty time, but the analyst is assuming that the unit is still operating unless there is definite knowledge that it failed. Without a robust way to know the state of the fielded units, using the assumption that the units are still operating leads to overly optimistic reliability estimations.

As both of these examples illustrate, warranty analysis needs to rely on good data and true knowledge of the state of fielded units, which can be very challenging.

Concluding Remarks

In this article, we have outlined some special topics for consideration during the DFR process. Extra care and focus need to be used when deploying the DFR process so that these issues do not hinder the progress of aiming for, growing, achieving and sustaining high reliability. Although the list of caveats provided here is by no means comprehensive, the underlying idea is that some DFR activities require special attention for successful and meaningful execution. Otherwise, they become a check mark in a long list of activities but do not truly contribute to the reliability efforts. We hope that practitioners can benefit from this material and focus on improving the quality of key DFR activities in their organizations. With product development becoming more dynamic and complex every year, designing for reliability is becoming the only way to quickly meet reliability goals and the new extreme time-to-market requirements.

References


Learn more about DFR...

Design for Reliability is a very hot topic these days, and it can be a challenge to find a good starting point that will give you the foundation you need to start sifting through and exploring all of the available options. To address this need, ReliaSoft now offers a three-day training seminar entitled RS 560 - Fundamentals of Design for Reliability. For more information, please visit http://Seminars.ReliaSoft.com.
RGA®
Reliability growth and repairable system analysis

RGA was developed in cooperation with Dr. Larry Crow, the leading authority in the field of reliability growth analysis, as well as key development partners in government and industry. The software provides all the tools you need to plan your reliability growth strategy and analyze data from developmental tests. RGA also applies reliability growth models for fielded repairable system analysis, which provides optimum overhaul times and other results without the detailed data sets that normally would be required.

- Comprehensive platform for traditional reliability growth analysis using the Crow-AMSAA (NHPP), Duane, Gompertz, Modified Gompertz, Lloyd-Lipow or Logistic models.
- Exclusive support for innovative approaches that facilitate reliability growth projections, reliability growth program planning and multi-phase reliability growth analysis. Also offers an operational mission profile feature for creating balanced test plans and tracking the actual testing against the plan.
- A Design of Reliability Test (DRT) utility for repairable systems and a method for analyzing the system’s reliability behavior over time in order to calculate optimum overhaul times and other metrics of interest.

http://RGA.ReliaSoft.com

BlockSim®
The ultimate system visualization and analysis tool™

BlockSim provides a comprehensive platform for system analysis using the exact system reliability function or discrete event simulation. The software provides sophisticated and flexible capabilities to model systems using a Reliability Block Diagram (RBD) or Fault Tree Analysis (FTA) approach... or a combination of both!

- Supports all relevant RBD configurations and FTA gates/events, along with advanced capabilities for complex configurations, load sharing, standby redundancy, phases, duty cycles and more.
- Exact reliability results and plots based on the exact system reliability function (using an exclusive algorithm pioneered by ReliaSoft).
- Extensive simulation options for analysis of repairable systems with a variety of results and plots to support decision making, including uptime/downtime, availability, expected failures, spare parts requirements, optimum replacement interval, life cycle cost summaries and throughput estimations.
- Powerful features for determining the optimum reliability allocation strategy, identifying components that may require improvement and performing what-if analyses to evaluate different scenarios.

http://BlockSim.ReliaSoft.com
Accelerated Testing Data Analysis Without a Known Physical Failure Model

A common question from reliability engineers performing accelerated life testing data analysis is, “Which life-stress model should I choose?” A life-stress model should be chosen based on a specific failure mechanism, and sometimes a literature search on that mechanism will yield a mathematical relationship between life and stress. As an example, in the case of high cycle mechanical fatigue, the relationship between the applied stress and the number of cycles to failure, often called the S-N curve, is known to be in the form of an inverse power law life-stress model [1].

As technology evolves, however, it is becoming increasingly difficult to find an established relationship between life and stress for new failure mechanisms. If no model can be found, the most direct approach to determine the appropriate analysis model is to perform life tests at many different stress levels to empirically establish the mathematical form of the relationship. The drawback to this method is that it requires many tests and consequently can be very time-consuming and resource-intensive. This article uses a fictional example to present an alternative approach for choosing an accelerated testing data analysis model in the absence of an established physics-of-failure relationship between life and stress.

Introduction

The fictional XYZ Company has a highly reliable device that has been in the field for some time. Based on this success, XYZ has a potential new customer, ACME Corporation, who wants to use the device in a new application. Before ACME will purchase the device, the ACME design engineers want an assurance that the device will have sufficient reliability in the new environment. The engineers at XYZ suspect that testing the device under the new environmental conditions will not yield failures before ACME requires a reliability estimate, making it impossible to use traditional life data analysis to determine the reliability in the new environment. In addition, XYZ has only a limited number of test samples available. Therefore, the option to conduct a zero-failure reliability demonstration test is not feasible. The XYZ engineers conclude that the only way to provide ACME with the estimate of reliability they require is to perform accelerated tests and extrapolate the results to the new usage conditions.

Table 1 shows the time-to-failure data collected for three different combinations of temperature and relative humidity values. In addition, there is one set of field data available, which contains very few failures and many suspended data points. The devices in the field were operated at temperature and relative humidity values of 313K and 50%, respectively. A 1-parameter Weibull distribution was fitted to the field data using a beta (shape parameter) of 5 (based on the accelerated test data sets), and yielding an eta (scale parameter) of 129,000 hours at field conditions.

The failure mechanism that XYZ Company has seen in the field manifests itself when two events occur. First, high temperature causes decreased adhesion between layers of the material. Second, moisture enters the device via the void that was created by the decreased adhesion. It has also been observed that this failure mode will not occur at high temperature without moisture in the air, nor will it occur in moist air at low temperature. Thus, a two-stress model that takes into account both temperature and humidity must be used to accurately predict the failure of the device. (Note that the sequential nature of the failure mechanism cannot be considered in the analysis because it is not feasible to obtain information about the time at which temperature initiates a void in the material.)

The XYZ engineers do not know, based on physics-of-failure, the mathematical model that describes how the stresses affect the life of the device. Therefore, they decide to examine different two-stress models and choose the one that makes sense based on engineering knowledge and provides the best correlation with the results from the field data set. The specific models examined are the temperature-humidity, generalized Eyring and general log-linear models.

Temperature-Humidity Model

The first candidate model for analyzing the accelerated test data is the temperature-humidity model. The life-stress relationship for the temperature-humidity model is:

\[
L(T, RH) = Ae^{\left(\frac{b}{T} + \Phi RH\right)}
\]

where \(L\) is the life of the device, \(T\) is temperature, \(RH\) is relative humidity, and \(A\), \(b\) and \(\Phi\) are model parameters. This
Continued from Page 17: “Accelerated Testing Data Analysis Without a Known Physical Failure Model”

The model has no interaction term and therefore it assumes that the temperature and humidity stresses operate independently. Assuming a Weibull distribution, analysis of the accelerated testing data yields the parameters and 90% 2-sided confidence bounds on the parameters that are shown in Table 2.

Table 2: Calculated parameters for the temperature-humidity model

<table>
<thead>
<tr>
<th></th>
<th>Lower Bound</th>
<th>Median Estimate</th>
<th>Upper Bound</th>
</tr>
</thead>
<tbody>
<tr>
<td>Shape Parameter ((\beta))</td>
<td>5.89</td>
<td>7.73</td>
<td>10.12</td>
</tr>
<tr>
<td>A</td>
<td>5.79 E-13</td>
<td>6.26 E-12</td>
<td>6.77 E-11</td>
</tr>
<tr>
<td>(b)</td>
<td>637.24</td>
<td>719.41</td>
<td>811.57</td>
</tr>
<tr>
<td>(\phi)</td>
<td>7470.90</td>
<td>8082.57</td>
<td>8694.24</td>
</tr>
</tbody>
</table>

Figure 1 shows the effect of temperature on life, and Figure 2 shows the effect of humidity on life. As expected, increasing either of these stresses independently causes a decrease in life. However, Figure 3 shows a probability plot that superimposes the field data analysis against the analysis of the accelerated test data extrapolated to the use-level conditions (temperature = 313K and relative humidity = 50%). It can be seen that the temperature-humidity model predicts lifetimes that are much longer than observed in the field. For example, the B(10) life observed in the field is about 80,000 hours, while the B(10) life extrapolated to use conditions via the temperature-humidity model is around 1,400,000 hours. Therefore, XYZ Company concludes that there must be an interaction between the stresses and, therefore, the temperature-humidity model is not suitable for analysis.

Generalized Eyring Model

The second candidate model for analyzing the accelerated testing data is the generalized Eyring model. The life-stress relationship for the generalized Eyring model is:

\[
L(T, RH) = \frac{1}{T} e^{\left(\frac{A}{T} + \frac{1}{T} + C \cdot RH + D \cdot RH\right)}
\]

where \(L\) is the life of the device, \(T\) is temperature, \(RH\) is relative humidity, and \(A\), \(B\), \(C\) and \(D\) are model parameters. This model assumes that there is an interaction between temperature and humidity. However, because the generalized Eyring model has four parameters, there must be data from at least four different combinations of temperature and humidity in order to solve for all of the model parameters. XYZ Company tested at only three combinations of temperature and humidity levels, and there are no additional units available for testing. Therefore, the generalized Eyring model cannot be used to model the available test data.
General Log-Linear Model

The third candidate model for analyzing the accelerated testing data is the general log-linear (GLL) model. The life-stress relationship for the two-stress version of the general log-linear model is:

\[ L(X_1, X_2) = Ae^{(\alpha_0 + \alpha_1 X_1 + \alpha_2 X_2)} \]

where \( L \) is the life of the device, \( X_1 \) and \( X_2 \) are stresses, and \( \alpha_0, \alpha_1, \) and \( \alpha_2 \) are model parameters. This generalized model allows the engineers to choose a transformation that describes the behavior of each stress (exponential, Arrhenius or inverse power law). The engineers know that applying the general log-linear model with Arrhenius transformations for both stresses will yield the same results as the temperature-humidity model (shown on page 18). Therefore, they decide to try the model with an Arrhenius transformation for temperature and an inverse power law (IPL) transformation for humidity. The transformed general log-linear model is:

\[ L(T, RH) = Ae^{\left(\frac{\alpha_0 + \alpha_1}{T} + \alpha_2 \ln(RH)\right)} \]

where \( L \) is the life of the device, \( T \) is temperature, \( RH \) is relative humidity, and \( \alpha_0, \alpha_1, \) and \( \alpha_2 \) are model parameters. Once again assuming a Weibull distribution, analysis of the accelerated testing data yields the parameters and the 90% 2-sided confidence bounds on the parameters that are shown in Table 3.

Table 3: Calculated parameters for the general log-linear model for temperature/humidity data

<table>
<thead>
<tr>
<th></th>
<th>Shape Parameter (( \beta ))</th>
<th>( \alpha_0 )</th>
<th>( \alpha_1 )</th>
<th>( \alpha_2 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lower Bound</td>
<td>5.89</td>
<td>15.87</td>
<td>7470.90</td>
<td>-9.57</td>
</tr>
<tr>
<td>Median Estimate</td>
<td>7.73</td>
<td>20.37</td>
<td>8082.57</td>
<td>-8.48</td>
</tr>
<tr>
<td>Upper Bound</td>
<td>10.12</td>
<td>24.88</td>
<td>8694.24</td>
<td>-7.40</td>
</tr>
</tbody>
</table>

Table 4: Transformation of temperature and relative humidity to dew point

<table>
<thead>
<tr>
<th></th>
<th>Temperature (K)</th>
<th>Relative Humidity (%)</th>
<th>Dew Point (K)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Test Conditions</td>
<td>333</td>
<td>90</td>
<td>330.7</td>
</tr>
<tr>
<td></td>
<td>353</td>
<td>90</td>
<td>347.6</td>
</tr>
<tr>
<td></td>
<td>353</td>
<td>90</td>
<td>350.4</td>
</tr>
<tr>
<td>Use Conditions</td>
<td>313</td>
<td>50</td>
<td>300.6</td>
</tr>
</tbody>
</table>

The XYZ engineers decide to use the general log-linear model again to analyze the temperature/dew point data set. Based on their experience with the other models, they select an Arrhenius transformation for temperature and an IPL transformation for dew point. Therefore, the transformed general log-linear life stress model is:

\[ L(T, DP) = Ae^{\left(\frac{\alpha_0 + \alpha_1}{T} + \alpha_2 \ln(DP)\right)} \]

where \( L \) is the life of the device, \( T \) is temperature, \( DP \) is dew point, and \( \alpha_0, \alpha_1, \) and \( \alpha_2 \) are model parameters. Once again...
Is your organization faced with any of the following?

- Specifying the reliability of an item you are contracting to an outside vendor.
- Developing a reliability program plan that focuses on cost effective reliability tasks.
- Leveraging the “lessons learned” from historical data.
- Balancing deadlines associated with RMS tasks using an overburdened staff.
- Establishing “best-in-class” RMS practices without fully understanding the steps to reach this goal.
- Performing maintenance practices with limited resources while ensuring that requirements are not compromised.
- Quantifying the reliability of your product through effective accelerated life tests.
- Identifying the root cause of repeated warranty claims against your product.

Alion SRC consulting services address reliability, maintainability and supportability (RMS) challenges. Since 1968, Alion’s staff has provided integral support to commercial and defense customers to achieve their RMS goals. Our professionals provide expert support to improve your bottom line and meet customer needs.

Visit src.alionscience.com or call 888.722.8737 today.
Continued from Page 19: “Accelerated Testing Data Analysis Without a Known Physical Failure Model”

assuming a Weibull distribution, analysis of the accelerated testing data set yields the parameters and the 90% 2-sided confidence bounds on the parameters that are shown in Table 5.

Table 5: Calculated parameters for the general log-linear model for temperature/dew point data

<table>
<thead>
<tr>
<th>Shape Parameter (β)</th>
<th>α₀</th>
<th>α₁</th>
<th>α₂</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lower Bound</td>
<td>5.89</td>
<td>723.70</td>
<td>-3.95 E +4</td>
</tr>
<tr>
<td>Median Estimate</td>
<td>7.73</td>
<td>831.87</td>
<td>-3.43 E +4</td>
</tr>
<tr>
<td>Upper Bound</td>
<td>10.12</td>
<td>940.04</td>
<td>-2.90 E +4</td>
</tr>
</tbody>
</table>

Because the dew point is a function of both temperature and relative humidity, evaluating the effect of an increase in temperature or relative humidity on life must be performed using the acceleration factor. For the general log-linear analysis of the temperature/dew point data, the median life at the use-level condition (temperature = 313K, relative humidity = 50%, dew point = 300.6K) is found to be around 124,000 hours. Table 6 shows the acceleration factors for an increase in temperature while holding relative humidity constant, and also for an increase in relative humidity while holding temperature constant. As expected, the life decreases for these increased stress levels, leading to acceleration factors greater than 1.

Table 6: Acceleration factors and median life estimates

<table>
<thead>
<tr>
<th>Temperature (K)</th>
<th>Relative Humidity (%)</th>
<th>Dew Point (K)</th>
<th>Median Life (hours)</th>
<th>Acceleration Factor</th>
</tr>
</thead>
<tbody>
<tr>
<td>333</td>
<td>50</td>
<td>318.8</td>
<td>59,000</td>
<td>2.1</td>
</tr>
<tr>
<td>313</td>
<td>70</td>
<td>306.5</td>
<td>11,000</td>
<td>11.2</td>
</tr>
</tbody>
</table>

Figure 5 shows a probability plot that superimposes the field data analysis against the GLL analysis of the transformed temperature/dew point data set. It can be seen that the general log-linear model using an Arrhenius transformation for temperature and an IPL transformation for dew point predicts lifetimes that are very close to those observed in the field. Because the median lines are very close and the confidence bounds overlap for all values of unreliability (including the very low values that are of most interest to the engineers), XYZ Company concludes that this model adequately captures the interaction of temperature and relative humidity for the device. Based on their model, they are able to provide ACME Corporation with the requested reliability predictions for the device running under the new environmental conditions.

Conclusion

In an increasing number of real life testing scenarios, an established physical model is not available to relate applied stresses with the resulting life of a device. A systematic approach to determine a physics-of-failure model using test data alone is often not practical due to time or resource constraints, especially if interactions between the stresses are present. This article presented an approach to determine a life-stress model in which the stresses themselves were transformed to mimic the effect of the interaction between the stresses. Then, a flexible life-stress model (the general log-linear) was applied to analyze the transformed stresses. The model was validated against a set of field data to determine if it adequately captured the effects of the applied stresses on the life of the device.

For readers who are interested in more information about the underlying principles and theory of quantitative accelerated life testing data analysis, including more detailed information about the temperature-humidity, generalized Eyring and general log-linear models that were considered here, please consult the Accelerated Life Testing Analysis Reference [4].

References

DOE++ facilitates traditional Design of Experiments (DOE) techniques for studying the significant factors that affect a product or process in order to optimize test plans and improve designs. The software also expands upon standard methods to provide the proper analysis treatment for interval and censored data — a major breakthrough for reliability-related analyses!

Supported design types include:

**One Factor Designs**

- **Factorial Designs**
  - Two Level Full Factorial
  - Two Level Fractional Factorial
  - Plackett-Burman
  - General Full Factorial
  - Taguchi Orthogonal Array

- **Taguchi Robust Design**

**Response Surface Method Designs**

- Central Composite
- Box-Behnken

**Reliability DOE — Only in DOE++**

- One Factor Reliability Designs
- Two Level Full Factorial Reliability Designs
- Two Level Fractional Factorial Reliability Designs
- Plackett-Burman Reliability Designs

When actual product reliability data is not available, standards based reliability prediction may be used to evaluate design feasibility, compare design alternatives, identify potential failure areas, trade-off system design factors and track reliability improvement. ReliaSoft's Lambda Predict software facilitates reliability prediction analysis based on the major published standards, including MIL-HDBK-217, Bellcore/Telcordia and NSWC Mechanical.

- Makes it easy to build the system configuration from scratch or by importing data from Bill of Materials files, predefined part libraries or other external data sources.
- Generates a complete array of calculated results (pi factors, failure rates, MTBFs, etc.) along with graphical charts and customizable reports.
- Offers a full set of supporting tools, including reliability allocation, derating analysis and the ability to transfer and manage your data via flexible import/export or copy/paste.
- Provides exclusive access to PartLibraries.org, which allows you to search and import parts data from MIL-M-38510, EPRD-97 or NPRD-95 (free to all users) as well as more than 300,000 specific commercial electronic components (yearly subscription required).
For Your Information

Over the last four years, ReliaSoft has invested more in R&D (in terms of both effort and capital) than for all other versions and all other products combined to date. These efforts have been focused primarily on designing and delivering a new generation of ReliaSoft software tools built around a whole new paradigm and platform. The guiding principle of this monumental effort has been to both enhance the individuality, power and ease of use for each product in our portfolio, while also delivering seamless integration, data reuse and advanced "reliability knowledge management" capabilities at the enterprise level.

This multi-year project had to overcome the fundamental limitation of tool integration, namely that of sacrificing individual product power and flexibility for the sake of integration. To put it differently, the ultimate deliverable of our recent development efforts will be a suite of integrated products in which each individual product is the most accomplished soloist in its genre, while at the same time a vital member of a cohesive ensemble delivering unparalleled performance.

It has been a very long road, and while traversing this road we had to develop new methods, concepts and infrastructure. We also were challenged to rethink and streamline the way reliability engineering tasks and processes that have been virtually unchanged since the 60s and 70s should be adapted to take full advantage of today’s computer technology. As we near the end of this road (with completed products currently undergoing testing for a final release later this year), I wanted to be the first to publicly announce our upcoming Version 8 family of products built on the new "Synthesis Platform."

As we get closer to the planned release date, we will be sequentially unveiling some of these technologies and capabilities, as well as preparing preview versions of these products. While I can’t share more specifics with you in this column, I am sure that the first time you see the coherent integration, power and methodologies in these new releases, you will crack a smile a mile wide, knowing full well that a new era has arrived!

—Doug Ogden
VP Customer Services

Bulletin Board

Training Seminars
ReliaSoft offers an extensive curriculum of reliability training courses that provide thorough coverage of both the underlying principles and theory as well as the applicable software tools. Seminars are offered in both public and on-site venues. For course descriptions, registration and a calendar of upcoming public events, please visit http://Seminars.ReliaSoft.com.

Software
Acclaimed for their ease of use, analytical power and unparalleled technical support, ReliaSoft’s reliability engineering software tools facilitate a comprehensive set of modeling and analysis techniques. For detailed product information and free trial versions, please visit http://Software.ReliaSoft.com.

ReliaSoft’s Software Products

<table>
<thead>
<tr>
<th>Product</th>
<th>Version</th>
<th>Date</th>
<th>Description</th>
<th>Website</th>
</tr>
</thead>
<tbody>
<tr>
<td>Weibull++</td>
<td>7.5.10</td>
<td>8-Feb-11</td>
<td>Life Data Analysis</td>
<td><a href="http://Weibull.ReliaSoft.com">http://Weibull.ReliaSoft.com</a></td>
</tr>
<tr>
<td>ALTA</td>
<td>7.5.10</td>
<td>8-Feb-11</td>
<td>Accelerated Life Test Data Analysis</td>
<td><a href="http://ALTA.ReliaSoft.com">http://ALTA.ReliaSoft.com</a></td>
</tr>
<tr>
<td>DOE++</td>
<td>1.0.7</td>
<td>8-Feb-11</td>
<td>Experiment Design and Analysis</td>
<td><a href="http://DOE.ReliaSoft.com">http://DOE.ReliaSoft.com</a></td>
</tr>
<tr>
<td>RGA</td>
<td>7.6.1</td>
<td>24-Feb-11</td>
<td>Reliability Growth Analysis</td>
<td><a href="http://RGA.ReliaSoft.com">http://RGA.ReliaSoft.com</a></td>
</tr>
<tr>
<td>RCM++</td>
<td>5.1.1</td>
<td>3-Mar-11</td>
<td>Reliability Centered Maintenance</td>
<td><a href="http://RCM.ReliaSoft.com">http://RCM.ReliaSoft.com</a></td>
</tr>
<tr>
<td>MPC</td>
<td>3.0.16</td>
<td>12-Sep-08</td>
<td>MSG-3 Maintenance Program Creator</td>
<td><a href="http://MPC.ReliaSoft.com">http://MPC.ReliaSoft.com</a></td>
</tr>
<tr>
<td>RENO</td>
<td>1.0.11</td>
<td>5-Dec-08</td>
<td>Probabilistic Event and Risk Analysis</td>
<td><a href="http://RENO.ReliaSoft.com">http://RENO.ReliaSoft.com</a></td>
</tr>
<tr>
<td>XFRACAS</td>
<td>6.0.18</td>
<td>17-Feb-11</td>
<td>Web-based FRACAS</td>
<td><a href="http://XFRACAS.ReliaSoft.com">http://XFRACAS.ReliaSoft.com</a></td>
</tr>
</tbody>
</table>

Contact ReliaSoft’s Corporate Headquarters
Phone: +1.520.886.0410 or 1.888.886.0410 (toll free in USA/Canada)
Fax: +1.520.886.0399
E-mail: Sales@ReliaSoft.com or Support@ReliaSoft.com
For a complete directory, including regional office locations worldwide, please visit http://Directory.ReliaSoft.com.