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THESIS

ASSESSMENT OF EXTERNAL RELIABILITY DATA SOURCES AND RELIABILITY PREDICTIONS OF COMPLEX SYSTEMS IN EARLY SYSTEM DESIGN

by

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13. ABSTRACT (maximum 200 words)

Two common reliability prediction methods are the traditional method and physics of failure method. Each method requires accurate failure data in order to fully assess a system's durability. This is particularly important in early system design when historical design and relative failure rates are non-existent. Consequently, practitioners rely on the use of external reliability data sources such as MIL-HDBK-217F, especially when using the traditional reliability approach. Several other external reliability data sources are available to the practitioner, each with its own strengths and limitations. This thesis surveys the various external data sources industries use in reliability predictions and assesses the completeness of the reliability data sources. The thesis presents the inherent limitations of all external data sources along with further considerations on using the traditional reliability approach. Early system design offers practitioners a significant amount of decision-making flexibility. This thesis further analyzes both reliability approaches and addresses when it is appropriate for a practitioner to use either approach or a combination of the two approaches. The author develops a reliability decision framework to aid practitioners in selecting the reliability prediction approach appropriate for the system.

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ASSESSMENT OF EXTERNAL RELIABILITY DATA SOURCES AND RELIABILITY PREDICTIONS OF COMPLEX SYSTEMS IN EARLY SYSTEM DESIGN

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ABSTRACT

Two common reliability prediction methods are the traditional method and physics of failure method. Each method requires accurate failure data in order to fully assess a system's durability. This is particularly important in early system design when historical design and relative failure rates are non-existent. Consequently, practitioners rely on the use of external reliability data sources such as MIL-HDBK-217F, especially when using the traditional reliability approach. Several other external reliability data sources are available to the practitioner, each with its own strengths and limitations. This thesis surveys the various external data sources industries use in reliability predictions and assesses the completeness of the reliability data sources. The thesis presents the inherent limitations of all external data sources along with further considerations on using the traditional reliability approach. Early system design offers practitioners a significant amount of decision-making flexibility. This thesis further analyzes both reliability approaches and addresses when it is appropriate for a practitioner to use either approach or a combination of the two approaches. The author develops a reliability decision framework to aid practitioners in selecting the reliability prediction approach appropriate for the system.

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LIST OF ACRONYMS AND ABBREVIATIONS

APU	auxiliary power unit
CAI	critical application item
CCA	circuit card assembly
CSI	critical safety item
DGA	Délégation Générale pour l'Armement
DMSMS	diminishing manufacturing sources and material shortages
EPRD	electronics parts reliability data
ESS	environmental stress screening
FMD	failure mode mechanism distribution
FMECA	failure modes, effects, and criticality analysis
GSM	global system for mobile communication
HALT	highly accelerated life tests
HASA	highly accelerated stress audit
HASS	highly accelerated stress screen
IEEE	Institute of Electrical and Electronics Engineers
MTBF	mean time between failure
NC	non-critical
NPRD	non-electronic parts reliability data
NTT	Nippon Telegraph and Telephone
OEM	original equipment manufacturer
POF	physics of failure
RAC	reliability analysis center
RDF	reliability decision framework
SAE	Society of Automotive Engineers
STRIFE	stress plus life test

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EXECUTIVE SUMMARY

Reliability predictions are a methodology for the estimation of an item's ability to meet the operational capabilities of the system and the specified reliability requirements. System reliability estimations are performed early in the design process to aid the evaluation of the design in terms of system requirements and to provide a basis for continued reliability improvements (Blanchard and Fabrycky 2011). Reliability prediction methods can be categorized into two different approaches. These methods are the traditional reliability prediction approach and the physics of failure approach. The traditional reliability approach is commonly used and MIL-HDBK-217F is the most widely used source for predicting reliability of components (Varde 2010). All reliability prediction methods rely on three critical areas: failure data, statistical modeling of the failure data, and the system's reliability logic model. Failure data can be categorized into three types, field reliability data, test reliability data, and external data sources. Due to the limited information available to the practitioner in the early design phase, the traditional reliability approach is often constrained to using external data sources such as MIL-HDBK-217F.

An assessment of the various common external data sources was conducted to evaluate the completeness of the reliability data sources. The result found that all external data sources are inherently limited. All external data sources can be considered derivatives of MIL-HDBK-217F and are found to be tailored toward a specific industry. The major limitations of external data sources include: constant failure rates and stress factors, the test and/or field environments are not known, the failure data is for generic component types, which does not account for the part quality, and the failure data is generally outdated. As a result, the traditional reliability approach assesses one aspect of a failure and does not account for actual failure mechanisms.

The physics of failure approach assesses how a system fails, identifies the root causes of failures, and takes into consideration different failure mechanisms. As a result, the physics of failure approach leads to a more robust reliability prediction. The failure

mechanisms are modeled based on the expected operational life-stress profile of the system. The physics of failure models take into consideration the cumulative wear and stress on the system as opposed to the nature of independent failures in the traditional approach. The primary limitations of the physics of failure approach is the amount of time and additional costs required to assess the dominate failure mechanisms. Since the failure data specific to certain failure mechanisms are not readily available to the practitioner from suppliers or external data sources, the physics of failure approach requires the use of accelerated life tests. Accelerated life testing of the system is critical to receiving accurate failure rates pertaining to the identified failure mechanisms and determining the life-stress profile of the failure.

In the early system design process, the practitioner has great decision making flexibility in terms of which reliability approach would best serve the system's design. A reliability decision framework has been developed to assist the practitioner during this process. Iterative reliability assessments are crucial in the design process to improve the system's reliability. As a result, the reliability decision framework provides a focus on the reliability improvement and helps the practitioner in intelligently achieving the improvement. The practitioner should consider four factors in deciding which reliability prediction method is appropriate for his system in addition to the cost and timeframe factors. These factors are the availability of relevant historical failure data, the level of system complexity, the operational life requirement, and the criticality of the system. The reliability decision framework utilizes these factors to guide the practitioner in selecting an effective reliability approach for the system. The developed reliability decision framework presented in Figure 1, applies to the beginning of the preliminary design phase in the systems engineering process. The results further assist the practitioner in the allocation of system requirements.

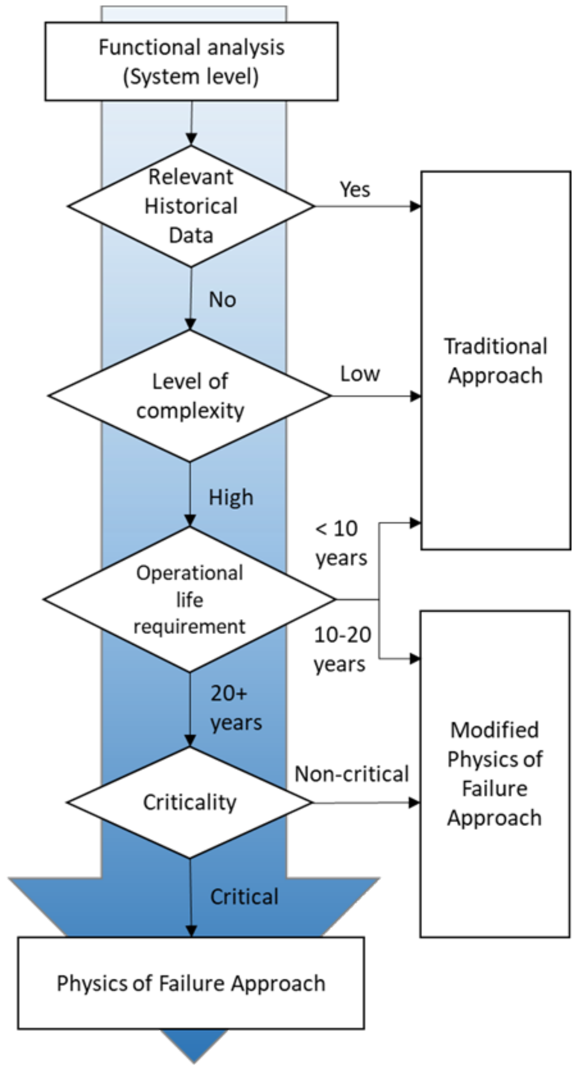

Figure 1. A Reliability Decision Framework

In general, a physics of failure approach will provide the practitioner with an understanding of the root causes of system failure. This approach is more intensive than the traditional approach and yields a more robust reliability prediction and system design. The trade-off is the need on accelerated life test to obtain failure data and to develop life-stress profiles for specific failure mechanisms. The accelerated life tests will naturally increase the time and cost for the program. The traditional approach is not as accurate as the physics of failure approach when using external data sources. The traditional reliability approach is better suited for use when accurate historical failure data is available to the practitioner. Data from historical life tests may also be used in the traditional approach if the environment and stressors for the tests are known and relevant.

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Blanchard, Benjamin S., and Wolter J. Fabrycky. 2011. *Systems Engineering and Analysis*, 5th ed. Saddle River, NJ: Pearson Education Inc.

Varde, P. V. 2010. “Physics-of-Failure Based Approach for Predicting Life and Reliability of Electronics Components.” *BARC Newsletter* Mar.-Apr. (313): 38–46.

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I. INTRODUCTION

Use of reliability predictions during early system design is a growing area of interest. Reliability predictions is a methodology for the estimation of an item's ability to meet the operational capabilities of the system and the specified reliability requirements. According to Blanchard and Fabrycky (2011), "A reliability prediction estimates the probability that an item will perform its required functions during the mission." System reliability estimations are performed early in the design process to aid the evaluation of the design in terms of system requirements and to provide a basis for continued reliability improvements (Blanchard and Fabrycky 2011). Reliability predictions can be categorized into two different methods. These methods are the traditional reliability prediction approach and the physics of failure approach.

All reliability prediction methods can be broken down into three key factors: failure data, statistical modeling, and the system's reliability logic model. Of these three factors, the failure data offers the greatest area of concern that can drive the variability in reliability predictions. Failure data can be collected through historical field data, accelerated life tests, or retrieved from external data sources. In early system design, practitioners are very limited in the amount of data they have available to them. Often, historical data is not available and test data is infeasible to obtain due to limited development costs and strict timeframes. As a result, it is common for practitioners to retrieve failure data from external reliability sources. As shown in Figure 1, field and external reliability data are prevalent to a traditional reliability approach. Due to the strong need of modeling various failure mechanisms, test data is more prevalent in a physics of failure approach. Chapter II surveys common external reliability data sources available to practitioners and provides an assessment on the completeness of the reliability data sources. Considerations for practitioners to use in early system design and a synthesis of the relationships among various reliability data sources are also provided in Chapter II.

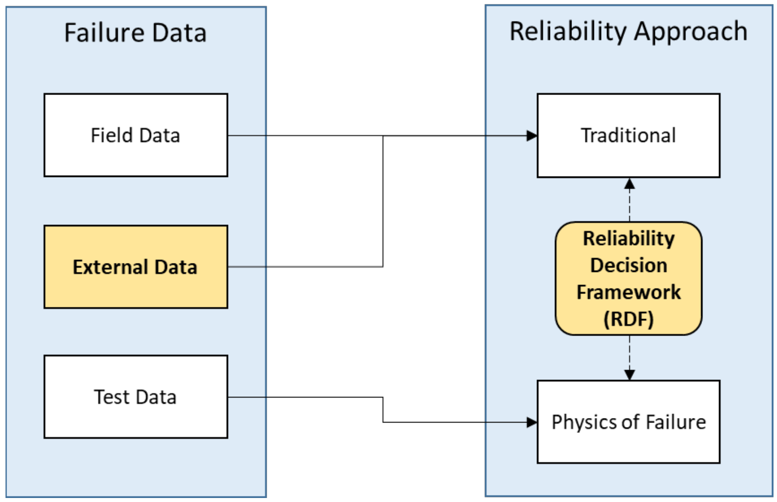

Figure 1. The Relationship between Failure Data and Reliability Approaches

The physics of failure approach seeks to understand the root causes of system failures. While this approach is not as common as the traditional approach, it is gaining popularity in the community as it addresses some of the major issues with the traditional approach. Chapter III provides an overview of the physics of failure reliability approach and how it relates to the traditional approach. In addition, Chapter III presents a reliability decision framework that addresses when it is appropriate for a practitioner to use a traditional or physics of failure approach.

This thesis intends to aid practitioners in performing system reliability predictions in the early stages of system design. The contributions of this thesis include a detailed assessment of common external reliability data sources, a synthesis of how various reliability data sources connect to each other, and a reliability decision framework for practitioners to utilize in early system design. These contributions address critical areas in the reliability prediction process that result in great variability in reliability estimations. As highlighted in Figure 1, the contributions specifically aid the practitioner in the decision-making process with regard to the use of reliability prediction approaches and the use of external data sources.

II. AN ASSESSMENT OF EXTERNAL RELIABILITY DATA SOURCES

A. INTRODUCTION

Reliability is the probability of a system adequately performing as intended without failure for a specified period of time under specified environmental conditions (Leemis 2009). Reliability predictions during early system design are a growing area of interest. Reliability predictions are a methodology for the estimation of an item's ability to meet the operational capabilities of the system and the specified reliability requirements. "A reliability prediction estimates the probability that an item will perform its required functions during the mission" (Blanchard and Fabrycky 2011). System reliability estimations are performed early in the design process to aid the evaluation of the design in terms of system requirements and to provide a basis for continued reliability improvements (Blanchard and Fabrycky 2011). There are different techniques and methods to determine the reliability of a system. Common reliability predictions rely on the use of failure data, a statistical model applied to the failure data, and a model of the system's reliability logic. Reliability predictions are known to be inaccurate. Based on the three areas of reliability predictions, the greatest cause of inaccurate predictions can be in the failure data. The model of the system's reliability logic is naturally tailored to the system, which is assumed to be an accurate representation of that system. The statistical model is applied to the failure data on which it is dependent. The failure data offers the greatest area of concern that can drive the variability in reliability predictions. The purpose of this paper is to survey the various reliability data sources industries use in their reliability predictions and to assess the completeness of those reliability data sources. The focus of the paper is on the reliability data sources used in the early system design stage to predict the reliability of the system. As such, this will not include internal company database data derived from testing the system and single use or one-shot devices, such as thermal batteries, unless in terms of a component within a system or the reparability and impact of repair on the system. The work in this paper can be applied to complex systems as the same methodology applies to both simple and complex systems.

(1) Summary of contributions

This research provides an assessment of common reliability data sources available to practitioners. This includes a summary of areas that practitioners should be wary of in assessing system reliability in early system design and a synthesis of how various reliability data sources connect to each other.

B. RELATED WORKS

A variety of existing work has limited focus on surveying reliability data sources. In general, this body of work has surveyed sources that focus on electronic components and reliability prediction methods.

Peter, Das, and Pecht (2015) provide a detailed review of MIL-HDBK-217 and its progeny and highlights areas of concern in the handbook and similar reliability prediction approaches. The study focused solely on electronic components and the reliability prediction methods presented in MIL-HDBK-217 and similar handbooks. The study did not discuss in much detail the reliability data presented in the data source.

Similarly, Pandian, Das, Li, Zio, and Pecht (2018) provide a detailed comparison of the common reliability prediction methods used in commercial and military avionics applications. The study is limited to electronic components used in avionic applications and an analysis on the reliability prediction methods presented in various common data sources.

Yu (1996) compares various reliability prediction methodologies, with the goal of defining a new reliability prediction method to evaluate computer and electronic systems. The focus is to develop a new reliability prediction methodology that minimizes the deficiencies of traditional methods. This includes reliability data to an extent but does not provide an assessment of data sources used to feed the prediction method.

The IEEE Standards Coordinating Committee developed a comprehensive guideline for selecting a reliability prediction method and documenting it properly (IEEE Standards Coordinating Committee 2003). As explained in Pecht, Das, and Ramakrishnan's study (2002), the IEEE guide is valuable to use as a framework for assessing reliability prediction methodologies and to understand the risks associated with the using the prediction method. The standard focuses on the compliance with IEEE standard 1413 and electronic systems. While the standard discusses the importance of having accurate and complete information and data for reliability predictions, the assessment of reliability data sources are not evaluated.

The field is focused on the reliability prediction techniques and methodologies used to predict a system's reliability accurately. While some works have identified external data sources, none have fully assessed and analyzed the data sources. The field discusses the importance of having good reliability data, but for the most part assumes that data is accurate. This chapter is relevant in early system design when the practitioner has great flexibility on system development and explores the external data sources in greater detail to aid the practitioner in deriving accurate reliability data to enhance the accuracy of reliability predictions.

C. METHODOLOGY

This section focuses first on defining relevant terms in reliability data sources. External reliability data sources are identified and summarized. The survey framework for the external reliability data sources are outlined and discussed followed by the assessment of the data sources.

There are various ways to obtain failure data and to model the system's reliability. Failure data can be categorized into field data, test data, and external reliability data sources. The use of different types of data alone can yield different results when predicting a system's reliability. These three terms are defined here.

Field reliability data is historical data collected from similar fielded systems operated in the same or similar environments. This utilizes previous experience from similar system designs and builds upon the knowledge and data gathered. To utilize previous field data, the system must be very similar in comparison to the previous system in terms of design complexity, technology maturity, item quality, operational and environmental stresses. These criteria limit the applicability of the field data primarily to systems derived from an older configuration. Even then, a framework to assess the usability of field reliability data from another system does not exist. When a new system exceeds the scope of the historical field data, the result can lead to very different experienced reliability. The design improvements of the newer configuration and the differences, if any, of the environmental stressors are factored into the reliability field data of the system.

Test reliability data is data collected through stress testing the system. Systems can be stress tested to develop a baseline reliability metric ensuring the system meets the operational, environmental, functional, and performance requirements. Test data can be used to narrow the critical focus areas in the design, outline a behavior map of the system, and identify any potential maintenance issues. Stress test data also provides a great understanding of the system's operational environment bounds and the issues experienced at the extremes of those environments. Test reliability data is collected through a variety of accelerated life tests such as environmental stress screening (ESS), burn-in, highly accelerated life tests (HALT), highly accelerated stress screen (HASS), stress plus life test (STRIFE), and highly accelerated stress audit (HASA) (McLean 2009). Accelerated life tests can assess the reliability of the system within a short period and improve the reliability of the system during the design and development phase.

External reliability data sources are a collection of empirical field failure rates for various types of components. The data is generally collected through a group or collection of companies and agencies, which have recorded the reliability of their components through either historical field data or test data. Various data sources exist for many common items and are generally used for system reliability predictions when historical data is not available or applicable and gathering test data is not feasible. Multiple external data sources exist for failure rate expectations.

Field and test reliability data are specific to a particular system, whereas external reliability data are more system-agnostics. In early design, a system has significant flexibility relative to its physical and functional architecture. In scenarios when a historical design is non-existent, reliability data is limited to only external data sources. This paper will survey and assess the several external data sources used in reliability engineering to demonstrate the inherent limitations and to present practitioners with considerations during early system design.

1. External Data Sources

External reliability data sources are identified and briefly explained in this section. This is to supplement and support an assessment on each data source. External reliability data sources provide valuable data for a practitioner to predict a system's reliability in which data is not readily available internally. Various organizations have developed their own data source applicable to their specific systems and industry. Table 1 provides a listing of the data sources that will be assessed throughout the paper.

Table 1. List of External Reliability Data Sources Surveyed in this Research

External Data Source	Application / (Country of Origin)	Latest Issue	Reliability Approach	Prediction Method
MIL-HDBK-217F (U.S. Air Force 1995)	Military/Commercial (U.S.)	1995	Traditional	Parts Count/Parts Stress Analysis
Bellcore/Telcordia SR-332 (Isograph n.d.)	Telecommunications (U.S.)	2006/2016	Traditional	Parts Count
CNET/RDF 2000 (Union technique de l'électricité 2000)	Telecommunications (France)	2000	Traditional	Parts Count/Parts Stress Analysis
NTT Procedure (Shiono, Arai, and Mutoh 2013)	Telecommunications (Japan)	1985	Physics of Failure	Parts Stress Analysis
SAE Reliability Prediction Method (Foucher et al. 2002)	Automotive (U.S.)	1987	Traditional	Parts Count
Siemens SN29500 (Jones and Hayes 1999)	Siemens Products (Germany)	2013	Traditional	Parts Count
GJB/Z 299C (Mou et al. 2013)	Military/aerospace (China)	2006	Traditional	Parts Stress Analysis
FIDES (FIDES Group 2009)	Commercial/Military (France) (mostly European industries)	2009	Physics of Failure	Parts Stress Analysis

External Data Source	Application / (Country of Origin)	Latest Issue	Reliability Approach	Prediction Method
RAC PRISM/RIAC 217Plus (O'Connor and Kleyner 2012)	Military/Commercial (U.S.)	2000/2015	Traditional	Parts Count/Parts Stress Analysis
IEC 62380/IEC 61709 (International Electrotechnical Commission 2011)	Telecommunications (France)	2006/2017	Traditional	Parts Count/Parts Stress Analysis
HRD-5 (Pandian et al. 2018)	Telecommunications (UK)	1994	Traditional	Parts Count
NPRD-2016 (Quanterion Solutions Inc. 2016b)	Military (U.S.)	2016	Traditional	Parts Count/Parts Stress Analysis
NSWC-98/LE1 (Naval Surface Warfare Center, Carderock Division 1998)	Military (U.S.)	1998	Traditional	Parts Stress Analysis
EPRD-2014 (Quanterion Solutions Inc. 2014)	Military (U.S.)	2014	Traditional	Parts Count/Parts Stress Analysis
FMD-2016 (Quanterion Solutions Inc. 2016a)	Military/Commercial Failure Modes (U.S.)	2016	Physics of Failure	Parts Stress Analysis

The most widely used external data source for failure rates of electronic components is MIL-HDBK-217F. Most of the other data sources are derivatives of the military handbook. The data provided by MIL-HDBK-217F is a constant base failure rate for each component and values for various stress factors being applied to those components. The stress factors include temperature, application, environment, quality, and various applicable electronic factors. The electronic factors include power rating, current rating, voltage stress, and matching network factors. The product of the base factors (i.e., pi factors) and the base failure rate provides the user with an estimated failure rate for the component. MIL-HDBK-217F provides two methods of reliability predictions, Part Stress Analysis and Parts Count. Part Stress Analysis is applicable during the late design phase in which most of the design is completed and a detailed parts list is available and the part stressors are known. It is also when the components or items of the system such as circuit card assemblies are designed. The Part Count methodology is applicable during the early design phase when determining part quantities, quality levels, and the applicable environment (U.S. Air Force 1995).

"Telcordia SR-332 was originally the Bell Laboratories, Bellcore standard for reliability prediction of commercial electronic components" (Isograph n.d.). The Telcordia SR-332 standard provides reliability predictions based on a parts count method using any combination of test data, field data, and parts count data. Telcordia SR-332 uses a Bayesian analysis to incorporate burn-in, field, and test data into its data source model.

CNET/RDF 2000 is a universal model for reliability prediction calculations for components, printed circuit boards, and equipment (Union technique de l'électricité 2000). RDF-2000 is primarily focused on the telecommunications industry. RDF-2000 provides field failure rates with various influencing factors operating in four different environments; weather protected ground stationary equipment (telecommunications equipment), non-weather protected stationary ground equipment (payphones GSM relays), airborne equipment, and non-stationary ground equipment. For a very few component families, RDF-2000 also provides life expectancy or end of life data. IEC TR 62380 builds upon the prediction methodologies outlined in RDF-2000 and provides updated failure rates and life expectancy for components and accounts for the effects of phased mission profiles and thermal cycling. IEC TR 62380 was eventually superseded by IEC 61709, which updates the guidance on the use of failure rate data for reliability predictions of electronic components and provides part stress models (International Electrotechnical Commission 2011).

Nippon Telegraph and Telephone (NTT) Procedure provides a failure rate prediction model based on field failure data collected and used in equipment reliability design (Shiono, Arai, and Mutoh 2013). The primary focus on the NTT procedure is the field failure data of semiconductor devices used in various telecommunications equipment and applies a physics of failure (POF)-based approach to reliability prediction.

SAE Reliability Prediction Method uses original equipment manufacturer (OEM) warranty and field repair data to develop a reliability prediction model for use in the automotive industry (Foucher et al. 2002). The field repair data is used to calculate the failure rates of individual components and subsequent systems. The SAE approach estimates the base failure rate for generic components which can be applied to other components of the same type based on the similarity of the physical characteristics of the component.

Siemens SN29500 is a Siemens AG standard for the reliability prediction of various electronic and electromechanical components. The standard provides expected values of failure rates for various electronic and electromechanical components (Jones and Hayes 1999).

PRISM was developed by the Reliability Analysis Center (RAC) and was released in 2000. It was based on MIL-HDBK-217F and was designed to overcome the limitations of the handbook after it was no longer being supported (O'Connor and Kleyner 2012). PRISM is a collection of reliability field and test data collected from military and commercial systems. In 2015, 217Plus was released to build upon the PRISM methodology. 217Plus increased the number of part type failure rate models and expanded the data to include additional electronic components.

GJB/Z 299C is the latest Chinese standard for the reliability prediction of electronic components. Similar to MIL-HDBK-217F, the GJB standard uses the part stress method to predict electronic component failure rates (Mou et al. 2013).

FIDES is a reliability methodology for electronic systems primarily using commercial-off-the-shelf items (FIDES Group 2009). The Délégation Générale pour l’Armement (DGA)–French Ministry of Defense and a consortium of aeronautical companies developed the FIDES method. The failure data contained within FIDES was collected from various companies throughout the aeronautical and defense industries (FIDES Group 2009). The FIDES reliability prediction methodology is based on a POF approach and takes into consideration the failures related to development, production, operation and maintenance processes. The failure rates are a collection of field data and over-stress test data.

HRD-5 is a British telecommunication standard that contains a collection of field and test failure rate data for various electronic components and circuit boards of British and French telecommunications equipment (Pandian et al. 2018).

The NSWC-98 is a U.S. Naval Surface Warfare Center handbook for the reliability prediction of mechanical equipment. "NSWC-98 provides a methodology for evaluating a design for reliability and maintainability that considers material properties, operating environment, and critical failure modes at the component level" (Naval Surface Warfare Center, Carderock Division 1998).

Non-electronic Parts Reliability Data (NPRD) and Electronics Parts Reliability Data (EPRD) are very similar. NPRD contains observed field failure rate data for various electrical, mechanical, electromechanical, and microwave parts and assemblies (Quanterion Solutions Inc. 2016b). EPRD shows the historically observed field failure rates for various electronic components and complements the prediction methods outlined in MIL-HDBK-217F (Quanterion Solutions Inc. 2014).

Failure Mode Mechanism Distribution (FMD) contains field failure mode and failure mechanism data on various electrical, mechanical, and electromechanical parts and assemblies. The FMD data was collected from military and commercial sources and is primarily used to support reliability analysis and assessments such as Failure Modes, Effects, and Criticality Analysis (FMECA) and fault tree analysis (Quanterion Solutions Inc. 2016a).

a. Data Sources

MIL-HDBK-217 was first developed in 1961 and since then other external reliability data sources have been created in its likeness (Gullo 2008). Most external reliability data sources can be viewed as derivatives of the MIL-HDBK-217F as most were modeled after the military handbook (Pandian et al. 2018). The creation of the various external data sources were needed to address some of the limitations in MIL-HDBK-217 and to provide relevant data on components common within their industry. Figure 2 shows a diagram of how these external data sources relate back to MIL-HDBK-217F. The external data sources are categorized by their relevant industry and their relation is reflected by either a dashed or solid line. The line, relationship, shows the reliability prediction methodology that is shared with the military handbook. A solid line represents a shared reliability prediction method; using either parts count or parts stress method. The dashed relationship shows a difference in prediction method, when the external data source takes on a more physics of failure approach. Independent of the reliability prediction method, all external data sources inherently share similar limitations as those in MIL-HDBK-217F. The assessment will further highlight these limitations.

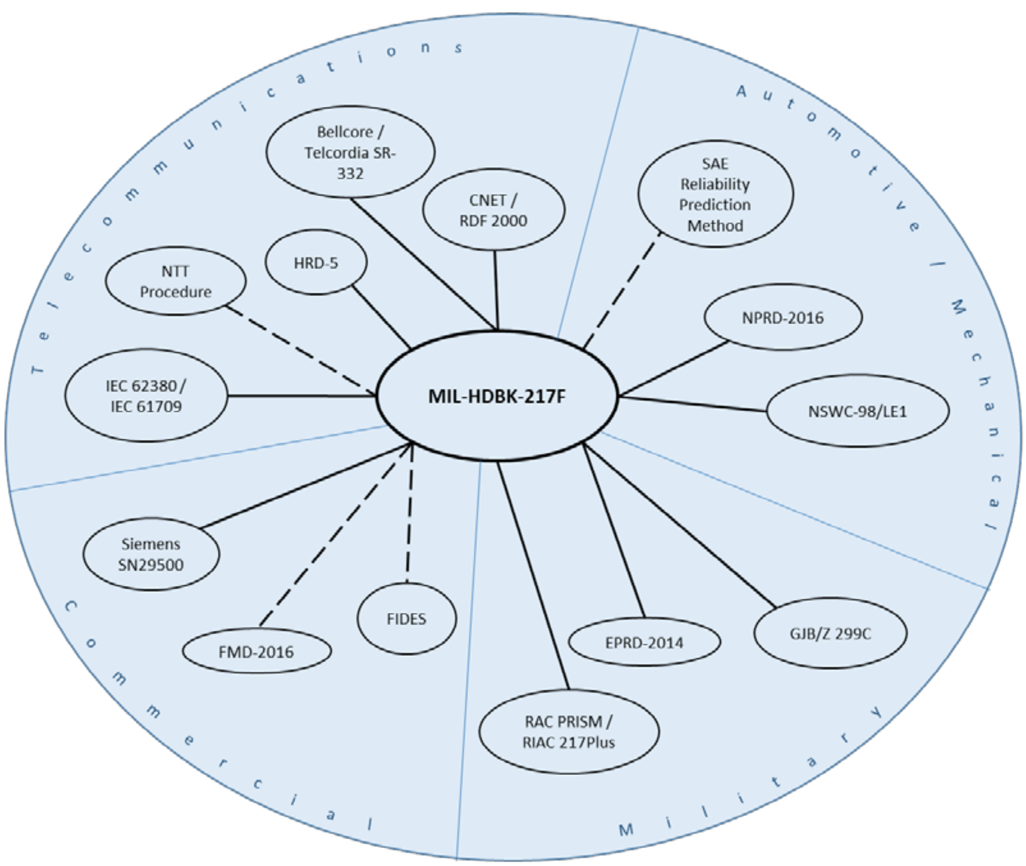

Figure 2. A Network of Reliability Data Sources

2. The Development of a Survey Framework for External Reliability Data Sources

A survey framework is developed in this section to assess each external reliability data source. The previously discussed literature is leveraged to discover the elements of reliability data sources that negatively contribute toward the systems' observed reliability within various industries. In addition, the metrics described in this paper are derived from the range of information presented within the data sources.

The elements of the survey framework are explained here. These elements include; completeness of data, age of data, and quality of data. The completeness of data can be characterized in three categories, data type, technology coverage, and data collection. The age of the data sources shows if the data was updated within the past five years and states the year in which the data source was last updated. Factors in assessing the quality of data are whether the environments are known, the part quality is known, whether the environment quality is known, and if the number of data points is known.

The total sets of metrics are used to evaluate each external data source and are designed to be independent from one another. The types of metrics used are categorical and are classified as either nominal, ordinal, or binary values. The following sections describe the elements and metrics used in greater detail.

a. Completeness of Data

The completeness of data analyzes the external data sources in terms of the type of component failure data represented and how the data was collected. This provides a representation of the robustness of the failure rate data expressed in each external data source.

The *data type* describes the type of data that was collected and published by the external data source. This metric is categorized as historical field data, test data, or both.

Technology coverage evaluates how extensive the component data is in terms of technology support. Technology includes the component type, the technology of the component, the component family, and package. This ordinal criterion ranges across extensive, moderate, and limited. This metric represents how extensive the data is on a particular component type and measures how well the component data was analyzed and portrayed in the data source. For instance, external data sources can provide data on components broken down into the types of family, the packaging used, and the technology type used (i.e., digital, analog, hybrid). An example is the technology coverage not addressing component options such as different interface types, material types, or packaging. In this scenario, the data source would be classified as having limited technology coverage. The coverage is assessed as moderate if it includes common options and extensive with the inclusion of uncommon options such as special plating, military temperature tolerances, ruggedized features.

Data collection method represents whether or not the data collection method is known as well as from what sources the data was collected from. The result is a binary assessment; either the data collection methodology is known or not known to the user of the external data source.

b. Age of Data

Given that technology advances over time, it is critical in any data source to remain current by incorporating technological advancements and improvements to part quality and performance. The study presented by Torresen and Lovland (2007) shows electronic replacement parts are needed within five years due to part obsolescence. As a result, the baseline measurement of an updated data source is set at five years. To assess the data source on relevance, each data source was measured on the date of its latest issue and if it was updated within the past five years.

c. Quality of Data

The *known environments* metric assesses if the data collected has also identified the environment and stressors the failure experienced. Different environmental stresses affect the failure rate differently. The more environments identified in the data source, the greater the robustness of the failure rate for that component. This metric is binary and measures if the environment is known or unknown. The environments are assessed as known if the data source has identified the type of data that was collected and provides the different failure rates for each environment.

The *quality of the environment* is another important factor in determining the quality of the data present in the data source. This is particularly important for test data as the test environments can be easily manipulated. The quality of the environment addresses whether the failure was experienced in a controlled environment with ideal conditions or experienced during exposure to operational field environments. The binary metric is measured as yes, the environmental quality is known or no, it is not known. The quality of the environment is known if the data source identifies how the item was tested or the conditions that the item was exposed to in the field.

The *part quality* assesses if the quality of the part was taken into consideration within the data source. Failure rates can correspond to the quality of the component. A high quality component may fail less often than an item of poor quality. This is when the quality level of the component would factor in and whether the data source identifies what level of quality of component best represents the data. The part quality is binary as yes (quality is known) or no (quality is unknown). The qualities of parts are known if it was specified within the data source or if different failure rates were identified for identical items from different manufacturers.

The number of *data points* collected for each component shows the confidence level of the failure rate. With more data samples comes a greater confidence in the collected data. This criteria measured in binary terms, evaluates whether the data points for each component is known or unknown.

3. The Assessment of External Reliability Data Sources

An assessment of external reliability data sources was conducted based on the survey framework previously discussed in the last section. The result of the assessment is provided in Table 2.

Table 2. External Data Source Assessment Results

Data Source	Completeness			Age		Quality			
	Data Type	Technology coverage*	Data collection method	Data updated within the last 5 years?	Latest Issue	Known Environments	Environment quality known	Part quality known	Data points known
MIL-HDBK-217F	Field data	Moderate	Unknown	No	1995	Yes	No	Yes	No
Bellcore/Telcordia SR-332	Field data	Moderate	Known	Yes	2016	Yes	No	Yes	No
CNET/RDF 2000	Field data	Moderate	Known	No	2000	Yes	No	No	No
NTT Procedure	Both	Limited	Unknown	No	1985	Yes	No	Yes	No
SAE Reliability Prediction Method	Field data	Limited	Unknown	No	1987	No	No	No	No
Siemens SN29500	Field data	Moderate	Unknown	Yes	2013	No	No	Yes	No
GJB/Z 299C	Field data	Moderate	Unknown	No	2006	Yes	No	Yes	No
FIDES	Both	Extensive	Known	No	2009	Yes	Yes	Yes	No
RAC PRISM/RIAC 217Plus	Field data	Moderate	Unknown	Yes	2000/2015	Yes	No	Yes	No
IEC 62380/IEC 61709	Field data	Moderate	Unknown	Yes	2006/2017	Yes	No	No	No
HRD-5	Both	Moderate	Unknown	No	1994	Yes	No	Yes	No
NPRD-2016	Field data	Moderate	Known	Yes	2016	Yes	No	Yes	Yes
NSWC-98/LE1	Both	Limited	Unknown	No	1998	Yes	No	No	No
EPRD-2014	Field data	Moderate	Known	Yes	2014	Yes	No	Yes	Yes
FMD-2016	Field data	Moderate	Known	Yes	2016	Yes	No	No	Yes

Some assumptions were made during the assessment of the external reliability data sources. These assumptions involved the technology coverage criteria, environments known and part quality known. For most external data sources, the items covered in the source are focused on the items used in the industry it serves. As such, not all technology options will be covered, but just those applicable to the industry. These data sources were given a ranking of moderate. In some circumstances, the environments were known; however, the environment factor list was not extensive. Instead, it focused on just those environments prevalent in the industry. RDF 2000 is an example of such a data source, in which only three or four levels of environments were identified. In these cases, the external data source was still evaluated as having identified the environments. While this is the approach used in this research, the user should be aware that the environmental factors listed may not be very extensive.

Most of the external data sources evaluated were originally created to fill in gaps to the data provided in MIL-HDBK-217F. Some of these data sources also focused solely on the items and environment relevant to the industry of which the data source was designed to cover. As such, no single external data source will contain all information on components in a particular system's architecture for a truly complex system. Most external data sources contain failure rates on electronic devices and would not have an extensive list on mechanical items.

A practitioner would use this research to understand the various external reliability data sources available to him, which external data source is optimal for his industry, and the limitations of each data source. Given that every system is unique, it becomes challenging to identify an ideal data source. The review presented in this paper suggests that one does not yet exist. However, if one were to be developed, it would contain the following characteristics: a combination of both test and operational field data, an extensive range of technology coverage, a clearly specified data collection method containing new failure rate data that is updated regularly. The environments and the quality of environments for each component are well defined. The failure rate data would consider the quality of the part and enough data points to represent a high confidence level.

D. CONCLUSION

The external reliability data sources were evaluated based on three main elements: the completeness, age, and quality of the data. In early system design, practitioners should carefully consider the elements of a data source and understand the data source inheritance.

There is no one external reliability data source that can be used for all applications and systems. External data sources should only be used in lieu of historical reliability field data observed from similar systems operating in similar environments. Similarly, reliability test data obtained from stress testing the system in expected environments can also be used. When reliability field data is unavailable and test data is not feasible to obtain, external data sources can be used. It is important, however, that the practitioner understand the applicability and the limitations of these data sources. Most external data sources have not been updated in the past five years and are outdated. Others only show data relevant to its end application and industry, and almost all external data sources suffer from the lack of quality within the environments and the data collected form industry.

E. FUTURE WORK

Reliability data sources are used early in the design phase to assist in the prediction of a system's reliability. Future works will include an assessment of reliability prediction methods to determine the elements that positively and negatively contribute towards accurate system reliability predictions.

III. SELECTING THE CORRECT RELIABILITY APPROACH IN EARLY SYSTEM DESIGN

A. INTRODUCTION

System reliability estimations are performed early in the design process to aid the evaluation of the design in terms of system requirements and to provide a basis for continued reliability improvements (Blanchard and Fabrycky 2011). Accurately predicting a system's reliability during early system design is a challenging task. The practitioner has limited resources to pull data from to formulate how reliable the system will perform once fielded. Reliability predictions typically rely on the use of failure data, a statistical model applied to the failure data, and a model of the system's reliability logic. The limiting factor in reliability predictions in most cases are the failure data available to the practitioner. It is vitally important for the practitioner to utilize the available failure data appropriately and efficiently.

The most common method to predict reliability to date has been the traditional reliability approach. The traditional approach utilizes the assumed constant failure rate to apply a statistical model to represent how system failures occur over time. In most cases, the statistical model is assumed as an exponential distribution. If a "goodness of fit" test is performed, the results often demonstrate that the exponential model is not valid (Leemis 2009). The results may lead to incorrect modeling of the system and the traditional reliability predictions are historically known to be inaccurate (Jones and Hayes 1999). An alternative to the traditional reliability approach is a physics of failure (POF) approach. "Physics of failure is the use of science to capture an understanding of failure mechanisms and evaluate useful life under actual operating conditions" (Schueller 2013).

In the early system design process, the practitioner has great decision making flexibility. A reliability decision framework is developed to assist the practitioner during this process. Iterative reliability assessments are crucial in the design process to improve the system's reliability. As a result, the reliability decision framework provides a focus on the reliability improvement and helps the practitioner in intelligently achieving the improvement. A significant amount of research exists on the benefits and limitations of each reliability approach; however, they do not address when it is appropriate for a practitioner to use the traditional or POF approach or if a combination of the two approaches can be performed. The reliability community seems to be split into using strictly traditional empirical approaches, POF-based approaches, or another unique internal reliability estimation method. This paper will explore both the traditional approach and the POF approach. An assessment of each approach is conducted to identify the key elements for a reliability decision framework. A reliability decision framework is presented that addresses when it is appropriate for a practitioner to use the traditional and POF reliability approach during early preliminary design phase.

B. BACKGROUND AND RELATED WORK

There are numerous works on comparing both the traditional and the POF reliability approaches. Most related works present the theory behind a POF approach in reliability predictions in relationship to the traditional approach (Jones and Hayes 1999; Matic and Sruk 2008; McLeish 2010; Pecht 1996; Aughenbaugh and Herrmann 2009). In particular, these explore how a POF-based approach can improve current traditional approaches, such as MIL-HDBK-217F methods, are discussed. Other general research has been done on reliability predictions (Schueller 2013; Varde 2010; Pecht and Gu 2009; Natarajan 2015). Very few publications exist that present a decision framework or aid practitioners in selecting an appropriate reliability approach. The most relevant related works evaluating reliability approaches are those by Matic and Sruk (2008), Pecht and Gu (2009), and Varde (2010). The related works by Barlow, Claroti, and Spizzichino (1993) and Aughenbaugh, and Herrmann (2009) are relevant to providing decision factors in reliability assessments, but lack a decision framework.

Matic and Sruk (2008) provides an outline of the classical approaches to reliability engineering and the POF approach. Their study discusses the advantages of the POF approach as it is compared to the classical approach. They noted a need for a probabilistic POF approach is explained due to the inevitable variations in processes contributing to failure occurrences.

Michael Pecht and Jie Gu (2009) present a POF based prognostics and health management approach for reliability predictions. An implementation procedure including a failure modes and effect analysis (FMEA) and data reduction is provided. Damage accumulation and an assessment of uncertainty is also presented along with a discussion of POF based prognostics applications. Their paper is limited to the assessment of a product's health, its degradation under normal operating conditions, and a procedure to predict the future state of the product's reliability using a FMEA.

Varde (2010) presents a POF approach for predicting reliability of electronic components. That article discusses the traditional reliability method and presents the POF approach. Varde primarily focuses on the POF approach, failure mechanisms, and POF models in regards to semiconductor devices.

Barlow, Claroti, and Spizzichino (1993) discuss the limiting of uncertainty involved with a system reliability analysis and prediction. The authors utilize Bayesian predictive approaches to increase the decision making of reliability problems (Barlow, Claroti, and Spizzichino 1993). The book focuses on the statistical techniques used in reliability analysis. Their book does not discuss the reliability prediction approaches in much detail and does not provide a decision framework for practitioners in selecting an approach.

Aughenbaugh and Herrmann (2009) discuss statistical approaches for modeling the uncertainty of new component's reliability. Their paper focuses on the decision practitioners make in choosing individual components for the system and the impact on the reliability of the system. In particular, they discuss whether to choose an existing component with known established reliability or to choose a new upgraded component containing unknown reliability. That paper does not discuss the reliability predictive approaches or the practitioner's decision in deciding between them for an early reliability assessment of the system.

The reliability prediction approaches discussed throughout this paper are presented objectively from the scope of early system design. This paper does not provide a best overall reliability prediction approach for all systems. Instead, the author discusses the factors that practitioners should consider when evaluating the different reliability approaches. In support of this, both approaches are presented and assessed. Common life-stress models and common failure mechanisms are provided for mechanical and electronic devices to further support a POF-based approach.

C. METHODOLOGY

The content described throughout this section outlines the basis for the Reliability Decision Framework (RDF). The relationship of the RDF and early system design is discussed in terms of the system engineering process. The RDF is presented and its methodology is explained. The outcomes of the RDF are discussed and the reliability prediction methods are analyzed.

The RDF aids the practitioner in choosing the appropriate reliability approach for their system early in the system functional analysis stage. As shown in Figure 3, the system functional analysis stage is defined here as the first stage in the preliminary design phase of the systems engineering process (Blanchard and Fabrycky 2011). The system functional analysis stage within the preliminary design phase is an extension of the system level functional analysis performed in the conceptual design phase. This stage extends the top-level functional analysis to its subsystems and lower-level assemblies. This methodology utilizes a top-down and bottom-up systems engineering approach to design. This approach is commonly used to trace the requirements between the system and subsystem levels. This implies an iterative process during early system design that ultimately results in an allocated baseline for the system at the conclusion of the preliminary design phase (Blanchard and Fabrycky 2011).

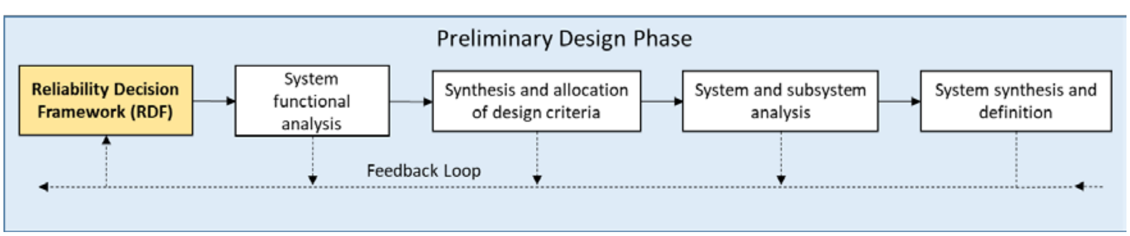

Figure 3. The Relationship of the RDF in the Preliminary Design Phase of the Systems Engineering Process

The RDF aids the practitioner during the system functional analysis stage when system operational functions, maintenance functions, and alternative functions and sub-functions are analyzed and defined. The results assist the practitioner in the allocation of performance factors, design factors, and effectiveness requirements. These are utilized in the subsequent stage of the Preliminary Design phase, synthesis, and allocation of design criteria. The RDF improves the practitioner's knowledge of the system's reliability and therefore enhances the decision making process throughout the design phase. As the system design process is an iterative process, so should be the reliability assessment process. The reliability assessment is again conducted in the detailed design phase in which individual components are selected for the system. The reliability can be further enhanced by the results of the prototype test and evaluation stage when accelerated life tests are performed on the system. This is indicated as the input to the feedback loop shown in Figure 3. The RDF conducted early during the preliminary design benefits the practitioner later in the design process when a bill of materials is developed.

The following section presents the RDF and explains it in relation to early system design. The results of the decision framework guides the practitioner to an appropriate reliability prediction approach. These prediction approaches are traditional, POF, and a modified POF approach. The traditional reliability prediction method commonly used throughout industry is presented as it relates to the RDF. The POF approach to system reliability prediction is discussed. The critical areas of the POF approach, common failure mechanisms and POF models, are discussed in addition to the modified POF approach, which can be adopted to suit the practitioner's needs.

1. Reliability Decision Framework

The RDF outlines factors that a practitioner should consider before choosing a reliability prediction approach appropriate to the system of interest. In practice, time and cost are generally constraints. The POF approach is more intensive in nature as compared to the traditional approach and will naturally result in requiring more time and cost to complete. This is indicated as an arrow on the decision framework flowchart in Figure 4. As the decision flows towards the POF approach, the cost and time increases as a greater importance is placed on the correct modeling and testing of the failure mechanisms in the late detailed design phase. Other than time and cost, other factors such as complexity, usable life or operational life, criticality, and reliability requirements are important. A flowchart on the RDF is presented in Figure 4.

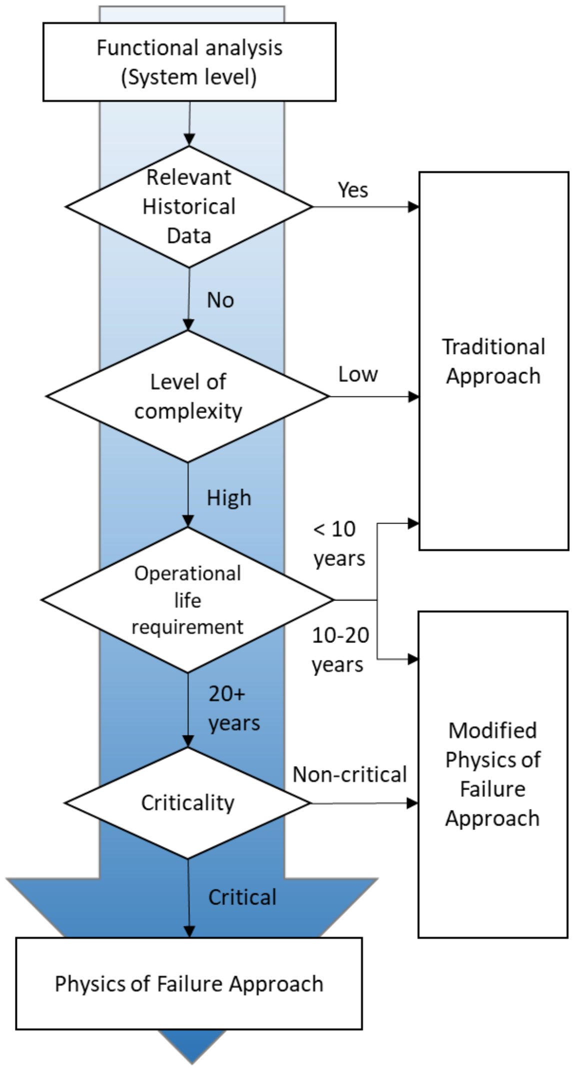

Figure 4. A Decision Flowchart of Reliability Predictions

a. Relevant Historical Data

The input to the RDF is the system level functional analysis generated during the conceptual design phase. In particular, the functional baseline, system architecture, and the top-level reliability requirement is desired. With this information, the practitioner can generate subsystem designs and allocate performance factors based on a flow down of the reliability requirements. During the system functional analysis stage in the preliminary design phase, the practitioner has great flexibility in the design of subsystems and assemblies to meet the higher-level reliability requirements of the system. A major factor in generating a subsystem design is the relevance of a previous similar design. If the system of interest is based on a similar system design or an older configuration, the practitioner will have historical failure rate data available. The relevant historical data can be either operational field data or relevant accelerated life test data previously obtained. The relevancy of the data is dependent on the similarity of the historical system and the system of interest in terms of 1) functionality, 2) architecture, and 3) operational environment. The historical failure data is determined to be relevant when the comparison yields similarities in all three criteria. If the historical failure data is available and relevant to the system of interest, then the traditional reliability approach becomes the most effective reliability prediction approach. Depending on the level of detail of the historical data, a more POF-based approach can also be used. To do so, the data must map failure rates based on specific failure mechanisms relevant to the system and its operational environment.

b. Level of Complexity

The level of complexity of the system dictates the intensity of a POF based reliability assessment. A system's complexity is difficult to quantify and is based on multiple factors including the number of components, subsystems, emergent behaviors and properties, and nonlinear relationships between components (BKCASE 2017). For the purposes of the RDF, the level of complexity is rated on a qualitative scale of 1–10, with ten being the maximum factor to represent the total number of system components in the thousands. A system with a level of complexity rating of six or greater represents a high level of complexity. A system with a high complexity level, will require additional man-hours to assess, analyze, and test the system for different dominate failure mechanisms.

c. Operational Life Requirement

The expected operational life of the system is driven by the requirements analysis. This factor dictates how robust the system needs to be to last in its intended lifecycle. If, for example, the system is expected to last roughly 50 years much like military systems, the use of a POF approach becomes more effective. This is because the POF approach analyzes multiple failure mechanisms of which can improve the robustness of the system's design and be used to enhance the system's overall reliability. In contrast, a system prone to technology refreshes much like those in consumer electronics will generally experience technological evolution over a shorter period, requiring frequent system redesigns. In this case, the traditional reliability approach becomes the most effective reliability prediction method because there is not a strong need to understand all failure mechanisms associated with the system. Since the expected operational life is less than 10 years, a thorough understanding of all failure mechanisms of the systems is not an efficient use of resources. For applying RDF, the operational life requirement was divided into three lengths of time. A low operational life is represented as a system expected to last 10 years or fewer. Within 10 years, a system has a high probability of requiring a redesign of circuit card assemblies due to component obsolescence (Torresen and Lovland 2007). An operational life of 10–20 years will generally require a partial redesign of the system and a complete redesign of the subsystems due to the obsolescence of technology (Singh and Sandborn 2006). Systems expected to operate for 20 years or greater will require a complete redesign due to diminishing manufacturing sources and material shortages (DMSMS), technology updates, performance increases, and component obsolescence (Singh and Sandborn 2006). While it is possible to extend the system's life cycle through mitigation of obsolescence during the sustainment phase, a practitioner can increase the design robustness of a system in the preliminary design phase to ensure the operational life requirements are satisfied. As such, the effective benefits for performing a POF reliability approach increases proportional to the increase in expected operational life of the system.

If the practitioner does not have relevant historical data, the level of complexity of the system is high, and the operational life requirement is greater than 10 years, then the reliability prediction becomes increasingly more important. At this point of the RDF, a

POF-based approach becomes more effective than just a pure traditional reliability approach. A POF approach can be modified using principles from both the traditional and POF methods. The modified POF approach is a customized approach to suit the practitioner's needs based on the information available. Some publications describing various modified reliability approaches exist (Thaduri 2013; Thaduri, Verma, and Kumar 2015; Yadav et al. 2003; Aughenbaugh and Herrmann 2009). These modified approaches take aspects of the traditional and POF approaches and specify the reliability assessment based on two primary factors: 1) the type of failure data available to the practitioner in terms of both quantity and quality, and 2) the physical architecture of the system.

d. Criticality

For a critical system application, the POF approach becomes crucial to increasing the system's survivability under varying operational stresses. This is particularly important in the aerospace, nuclear power, oil and gas, or healthcare industries in which system failures may lead to a catastrophic failure. The evaluation criteria used in the RDF for criticality are non-critical, mission critical, and safety critical. In military applications, these criticality classifications are designated as non-critical (NC), critical application item (CAI), and critical safety item (CSI), respectively (Office of the Under Secretary of Defense for Acquisition, Technology, and Logistics 2016). A failure of a non-critical system will not jeopardize the overall mission or render the application as un-operational. A failure in a mission critical system results in a significant decrease in performance, and the application will not be able to fulfill its primary purpose. Failures of safety critical systems are catastrophic failures of the application that renders the application as inoperable and may result in significant damage to the application, the loss of the application, or a loss of life (Bozzano and Villafiorita 2010). The RDF considers the mission critical and safety critical designations as a critical system classification. If the system contains critical characteristics whose failure, malfunction, or absence causes the application to be inoperable and creates an unacceptable risk to life, then the system is considered to be critical (Office of the Under Secretary of Defense for Acquisition, Technology, and Logistics 2016; Bozzano and Villafiorita 2010). A critical system in the RDF results in the use of a POF reliability approach. This is because the impact of a failure is significant and will require a thorough analysis of failure mechanisms to design a very robust system to mitigate catastrophic failures. In the RDF, a non-critical system results in the use of a modified POF approach. A non-critical system does not contain critical characteristics and, if the system fails, the application will continue to operate. A modified POF approach does not contain as thorough of an analysis on various failure mechanisms as the strict POF approach and uses principles of the traditional approach to utilize resources effectively.

As the decision flow gravitates toward the use of the POF approach, the costs and time become increasingly more important. The focus of the POF approach is initially on the dominate failure mechanisms of the system. As the system is revalidated through the detailed design phase, additional failure mechanisms are mitigated until a relatively high degree of confidence in meeting or exceeding the reliability requirements is achieved. As this revalidation cycle continues, the overall costs and time increases. It is vitally important in the POF approach to develop a solid, accelerated life test plan to address all of the dominate failures and reduce the number of additional tests.

2. Traditional Reliability Approach

Reliability predictions rely on three critical areas: failure data, statistical modeling of the failure data, and the system's reliability logic model. Failure data can be categorized into field reliability data, test reliability data, and external data sources. Due to the limited information provided to the practitioner in the early design stage, the traditional reliability approach is often constrained to using external data sources such as MIL-STD-217F.

The traditional reliability approach is commonly used and MIL-STD-217F is the most widely used source for predicting reliability of components (Varde 2010). The traditional reliability approach can be broken down into two methods, the Parts Count method and a Part Stress Analysis. Both methods are defined in MIL-STD-217F.

The Part Count method determines the Mean-Time-Between-Failure (MTBF) for each electronic device by taking the inverse of the sum of the failure rates for that generic component type (U.S. Air Force 1995). The constant failure rates are generally obtained from an external data source unless historical failure rates are known or the system has previously undergone an accelerated life test. The Part Count methodology is applicable to use because of having existing relevant, historical failure data in the RDF. Particularly when determining the part quantity and quality levels for subsystems to achieve the desired system reliability requirement.

A Part Stress Analysis takes the Part Count method a step further by applying additional stress factors. In the Part Stress method, a generic scaling stress factor is applied to the constant failure rate to determine a component's overall MTBF. The stress factor takes into account the reliability degradation due to various operational stressors such as power, duty cycle, and temperature. These stress factors are also generally obtained from external data sources when provided or estimated. The Part Stress Analysis is applicable in the RDF due to non-existing historical failure data. The Part Stress Analysis can be applied when the system complexity level is nominal or the operational life requirement of the system is short. The generic component types are identified later in the preliminary design phase and the part stressors are projected based on the intended operational environment of the system.

The primary advantages of the traditional reliability approach is the simplicity of the time to fail calculation and the speed in which the reliability of a system can be calculated. In addition, a practitioner given little information about the system can utilize industry external data sources to determine a rough reliability estimate on the system. The traditional reliability approach is a commonly used and accepted reliability prediction method (Pecht 1996). Multiple publications list the limitations of the traditional reliability approach. A brief summary of these limitations are presented here (Pecht 1996; McLeish 2010).

(1) The traditional approach provides an assessment on only one aspect of a failure. It does not include an assessment of different failure mechanisms or analyze how a component or system can fail (McLeish 2010).

(2) Reliability predictions in the traditional approach are based on constant failure rates. While this does simplify data collection and calculations, only the random failures are captured. As a result, the failure trends are typically

modeled as an exponential distribution and does not account for infant mortality and wear-out failures (Pecht 1996).

(3) The average failure rates provided by external data sources are for generic component types. There is no failure data for specific components (McLeish 2010).

(4) The test and environments for supplier derived failure rates are generally unknown. The failure rates that some suppliers may provide are in most cases, for ideal situations as it is in the supplier's best interest to promote high reliability metrics. The actual environment or testing method to collect this data is often unknown to the consumer (Pecht 1996).

(5) The traditional approach does not take into account actual failure mechanisms (Pecht 1996). The stress factors provided by the data sources are also generic and naturally limited.

(6) The stress factors the traditional approach uses are also constant. The stress factors are given by external data sources and are treated as a constant stress rate such as temperature. Other variable stress factors are not included in the prediction such as temperature cycling, humidity, shock, and vibration.

(7) The data generally provided by external data sources are outdated (Pecht 1996). Technology changes every so often and the data represented in the data sources are outdated as component types change, technology evolves, and advances in quality continues to improve. The last update to MIL-STD-217F, for instance, was in 1995 (Pecht 1996).

3. Physics of Failure Approach

Physics of failure is a science-based approach to determining the life of a product through an analysis of the failures. Physics of failure emphasizes the root cause of a failure, the identification of failure mechanisms, and a focused analysis of the failures. The POF approach provides the practitioner with a thorough understanding of the cause and effect of failures as well as the strength tolerance of materials and components that lead to a system failure. The strength of a component is measured by the amount of stress it can endure before failing.

In the POF approach, the operating environment must be properly defined. The environment can be defined through measurement or by customer requirements (Pecht 1996). By defining the operating environment, the practitioner can identify the potential stressors acting on the system. These stressors are modeled to determine the time to fail for the system. A detailed stress analysis is conducted based on the known stressors and the system. The stress analysis identifies the failure sites, modes, and failure mechanisms (Pecht 1996). The time to fail is calculated for each failure mechanism through modeling of the failure mechanism. A reliability assessment of the system during the preliminary design stage, aids the practitioner in identifying the system's weaknesses in both the failure sites and mechanisms that lead to the lowest time to fail for the system. These weaknesses can be addressed to improve the system's reliability and to enhance the robustness of the systems design. Later in the detail design phase, when a prototype of the system is developed, the use of accelerated life tests can further enhance the robustness of the system design. As the RDF leans towards a POF-based approach, an accelerated life test becomes imminent. Accelerated life tests are highly desired in the POF approach to verify the time to fail data for the failure mechanisms and in the identification of additional failure mechanisms that were not previously assessed. The critical areas of a POF-based approach is in the identification of potential failure mechanisms and the modeling of those failure mechanisms.

The POF approach assesses how a system fails, identifies the root causes of failures, and takes into consideration different failure mechanisms. This advantage alone leads to a more robust reliability prediction. The reliability assessment in the preliminary design phase focuses on the dominate failure mechanisms that drive a system failure. These dominate failure mechanisms serve the practitioner as areas of further reliability improvement. The failure mechanisms are modeled based on the expected operational life-stress profile of the system. This modeling does not assume a constant failure rate and can model different stages of a system's lifecycle such as the wear-out stage as opposed to just capturing the random failures. The models also take into consideration the cumulative wear and stress on the system.

The primary limitation of the POF approach is that it almost requires the use of accelerated life testing. Accelerated life testing of the system is critical to receiving accurate failure rates pertaining to the identified failure mechanisms and determining the life-stress profile of the failure. This detailed and specific failure data is generally not readily available to the practitioner from suppliers or external data sources. The POF approach inherently increases the accuracy and robustness of the reliability prediction at the expense of the length and cost associated with testing the system during the detail design phase.

The practitioner may also adapt a modified POF approach. This approach is best suited for a non-critical system applications and systems with an expected operational life requirement of 10–20 years as shown in the RDF. A modified POF approach take aspects of the traditional and POF approach. Two factors can influence the type of modified POF approach taken by the practitioner. The first factor is the type of failure data available to the practitioner in terms of both quantity and quality. The second factor is the projected physical architecture of the system. Based on these factors the practitioner can customize the POF approach to fit his needs. Publications exist on describing various modified reliability approaches (Thaduri 2013).

a. Common Failure Mechanisms

Failure mechanisms describe the failure that has occurred and the cause of the failure (O'Halloran, Stone, and Tumer 2012). Failure mechanisms are dependent on the system design and the types of components used. Presented here are some common failure mechanisms for electronic and mechanical devices. Collins provides a more complete failure mechanism taxonomy (Collins 1993). Uder, Stone, and Tumer (2004) provide an extension of Collin's taxonomy for electrical failure mechanisms.

Failure mechanisms can be categorized into three different types; manufacturing variation, overstress, and wear-out. Each category reflects a stage in the system's lifecycle. Manufacturing variation are the minor changes in production that yield early failures and represent infant mortality. Overstress failures mechanisms, such as those presented in Table 3, are the result of the stress exceeding the strength of the device (Natarajan 2015). Wear-out failure mechanisms are due to the accumulation of stress over time such as fatigue. The majority of mechanical failure mechanisms can be classified as wear-out.

Table 3. Common Failure Mechanisms for Electronic Devices

Device	Failure Mechanisms				
Integrated Circuits	Supply voltage and current	Input voltage and current	Power dissipation	Junction temperature	Operating temperature
Discrete Semiconductors	Dielectric breakdown	Junction breakdown voltages	Power dissipation	Hot carrier	Electro-migration
Resistors	Limiting dissipation	Power dissipation	Junction temperature	Operating temperature	
Capacitors	Voltage	Ripple current	Operating temperature		
Inductors and Transformers	Hot spot temperature	Voltage	Current	Power dissipation	Operating temperature
Connectors	Rated voltage	RF power rating	Rated current	Operating temperature	
Switches	Rated voltage	Rated current	Operating temperature		
Relays	Input power	Output power	Junction temperature	Operating temperature	
Fuses	Nominal current	Rated voltage	Breaking capacity	Operating temperature	
PCBs	Conductor temperature	Vibration resonance	Delamination	Shock fracture	Corrosion
Coaxial Cables	Bending diameter	Operating temperature			

ZVEI provides various common failure mechanisms specific to circuit card assemblies (CCA) (ZVEI Robustness Validation Working Group 2013). These failure mechanisms are categorized into four common sources: temperature, vibration/shock, humidity/moisture, contaminants and dust. These failure mechanisms produce circuit card assembly wear-out failures such as fatigue, delamination, creep, and corrosion (ZVEI Robustness Validation Working Group 2013).

Common failure mechanisms found in mechanical devices include, shear loading failure, instability failure, bending failure, compressive failure, tensile yield strength failure, fatigue, creep/rupture failure, stress concertation failure, material flaw, bearing failure, and metallurgical failure (Dhillon 2015; Safety and Reliability Society 2012).

b. Modeling

Once the potential failure mechanisms have been identified, it is important to apply the correct model to represent the failure and determine the time to fail for the failure mechanism. The POF or life stress models are life distributions that describe the time to failure of a system. These models are used to analyze the relationships between the causes of the failure (Leemis 2009). In the traditional reliability prediction approach, stress is treated as being independent of time, resulting in constant failure rates. The majority of complex systems, however, show stress levels vary with time (Anderson et al. 2004). Presented in this section are the common life stress models.

The *Arrhenius model* is a temperature dependent model widely used in the POF reliability approach. The model is used to predict the influence of steady-state temperature on failure rates for electronic devices (Lall 1996). The Arrhenius model by itself is limited as it factors temperature stress as a constant and does not factor in cyclic temperature, duty cycle, or on/off ratios (Lall 1996). Often, the Arrhenius model is combined with the inverse power law to yield a *temperature-non-thermal* relationship. This relationship models temperature with a second, non-thermal stressor such as vibration or voltage. This model shows the relationship of a non-thermal stressor on the system’s life, as temperature is remained constant and vice-versa (HBM Prenscia 2018). The *inverse power law model* is commonly used to model just non-thermal stresses (HBM Prenscia 2018).

The *Eyring Model* is similar to the Arrhenius model with the exception of variable stress instead of a constant stress. The Eyring model is often used for modeling the relationship between temperature and humidity.

The *cumulative-damage/exposure model* are appropriate for modeling step-stress profiles when the stress varies over time (Nelson 1990). The stress on the system is gradually increasing with each step representing the cumulative effect of the stress on the system. This model is also useful for measuring multiple different stresses acting on the system. Other multivariable stress models include the *general log-linear* and *proportional hazards* model. These models are used in cases when more than two different failure mechanisms are applied to the system as in most cases.

Multiple, fatigue life models exist for mechanical devices. The most common models are the Basquin and Coffin-Manson models. The *Basquin Model* is used for high-cycle fatigue and the *Coffin-Manson Model* is used for low-cycle fatigue. Often, both models are combined to represent both high and low cycling fatigue. The Coffin-Manson Model is also often used to model solder joint low-cycle fatigue. Similarly, the *Norris-Landzberg Model* modifies the Coffin-Manson to account for the effects of thermal cycling frequency and maximum temperature (Schenkelberg 2018).

Physics of failure models represent specific failure mechanisms acting on a component or system. Varde (2010) describes three models specific to degradation failure mechanisms for semiconductor devices. These models are Black's equation, anode hole injection, and hot carrier injection. *Black's equation* model shows the relationship between temperature and current density that leads to an electro-migration wear-out failure. The *anode hole injection* model represents the electric field across the dielectric as the temperature changes and models the dielectric breakdown. This model captures the degradation of gate dielectrics that leads to short circuits. The *hot carrier injection* models the hot carrier oxides degradation in semiconductor devices and the hot carrier injection in MOSFET devices (Varde 2010).

D. CASE STUDY

This section presents a case study to demonstrate how to apply the RDF and to articulate an example of the expected results. While this case study is presented for a real system, the results are only valid for better understanding the RDF methodology. Therefore, the results should not be used outside of this paper.

The system being used in this case study is a gas turbine auxiliary power unit (APU) on a military aircraft. This system was chosen because of the dynamic scenario it provides practitioners in early system design. As previously mentioned, an input to the method is a system functional analysis. Specifically, Figure 5 shows the information derived from a functional baseline, a functional architecture, and the top-level system reliability requirements that are results of the system level functional analysis conducted in the conceptual design phase. Using the functional baseline and architecture at the start of the preliminary design phase, the practitioner is extending the functional analysis to the subsystems and lower-level assemblies. The reliability requirement naturally becomes a flow down requirement for the design of the subsystems. During this stage, the practitioner has flexibility in allocating reliability requirements to elements of the subsystems and designing the subsystems to optimally meet or exceed the allocated reliability requirements.

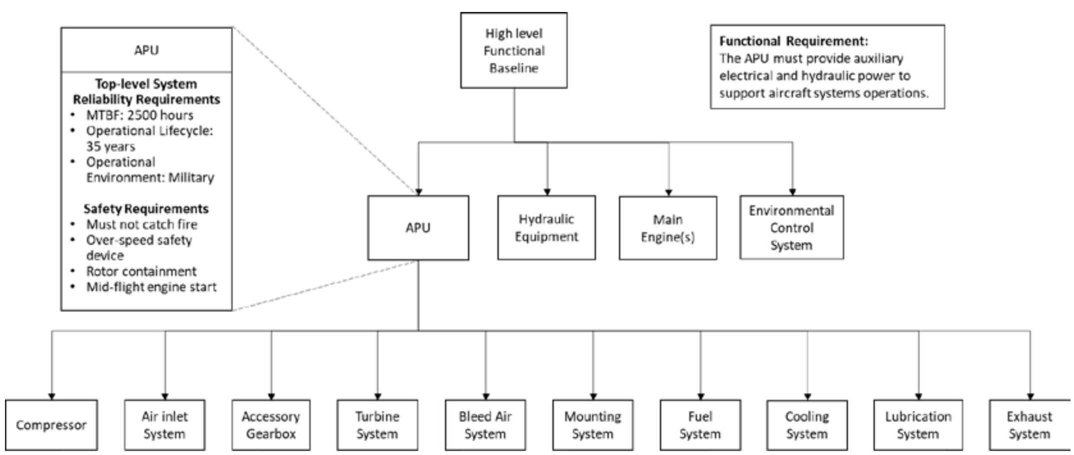

Figure 5. Relevant APU Information Retrieved from the Functional Analysis

A review of previously developed APU designs for the commercial industry show similarities in system functionality and architecture. The historical failure data collected by the commercial system is dependent on the environment and as the environment for the military application introduces different stressors, the historical data for the commercial system becomes less relevant to the military application. In the RDF, the historical data does not contain all three criteria of relevancy and therefore the practitioner does not have relevant historical data.

The level of system complexity is analyzed based on the number of subsystems, interfaces, and an estimation of components required for each subsystem. Applying an estimation factor of a thousand components per subsystem gives the system an estimated 10,000 components. This is equivalent to a complexity level of 10 in the RDF, constituting the system as having a high complexity level. The expected operational lifecycle for the APU is 35 years. At this point in the RDF, the traditional reliability approach is no longer a feasible option for the APU. Even though the criticality of the system is not specified in the system functional analysis, the system safety requirements are provided. The criticality of the system is estimated based on the functional requirement, interactions with external systems, safety requirements, and the end application of the APU. The APU provides electrical and hydraulic power to support aircraft systems. The aircraft systems the APU interfaces with are the hydraulic equipment, the main engines, and the environmental control system. The safety requirements are fire prevention, protection for over-speed, rotor containment, and mid-flight engine start. Based on these factors, the APU system is determined to be a mission critical system. Due to the functionality of the APU, the loss of the system in mid-flight will not result in the aircraft becoming inoperable or cause the loss of life. This eliminates the safety critical classification. The APU would be considered a non-critical system; however, the requirement of the APU starting an engine in mid-flight eliminates this classification as well. If the APU fails to start the engine in mid-flight or fails completely in flight, the successful operation of the aircraft is jeopardized. As a result, the RDF recommends the practitioner to perform a reliability assessment of the APU using a strict POF reliability approach.

E. DISCUSSION

By not using the RDF, the practitioner may have decided to use either a traditional or a modified POF approach. Performing a traditional approach for the APU will yield in a non-robust system due to the lack of reliability enhancements in system design and risks a reliability prediction that will not match the system's reliability once it is fielded.

In a scenario where ample historical data exists and is initially relevant, but the level of system complexity is high, the RDF will favor the traditional approach. The result is driven by the relevancy of the historical data. Of which is determined by the similarity of the historical system and the system of interest in terms of functionality, architecture, and operational environment. By meeting all three criteria and therefore determined relevant, the historical failure data becomes significantly more accurate to the system then failure data derived from external sources or through accelerated life tests. The results of a traditional approach utilizing the parts count method will yield a high confidence level due to the quality of the failure data. The system's complexity can be addressed by applying a traditional approach utilizing a parts stress methodology to the subsystems and lower assemblies. The result will earn the practitioner with additional knowledge of the system's reliability, which further enhances the decision making throughout the design phase.

The results of the system-level functional analysis generated in the conceptual design phase provides the practitioner with the necessary information to make a thoughtful decision on an appropriate reliability approach for the system. The RDF highlights the key factors in system design that contribute to an appropriate reliability approach. When used at the beginning of the preliminary design phase, the RDF aids the reliability allocation and assessment at the subsystem and component level. The reliability approach resulting from the RDF can be used in the refinement of the system and subsystem design. This further enhances the system's robustness throughout the rest of the iterative system design process. The APU case study provides a deeper understanding of the RDF methodology and validates the use of the RDF in early system design.

F. CONCLUSION

In early system design, relevant system failure data is the limiting factor in reliability predictions. Often practitioners are limited in collected historical failure data and data derived from accelerated life tests. The failure data generally provided by external data sources are very limiting and outdated. Traditional reliability prediction methods often rely on the use of external data sources in accurately predicting the reliability of a system. Many reliability predictions do not match experienced operational failures. The POF approach reduces the inaccuracy of reliability predictions by exploring the root causes of failures and defining failure rates for different failure mechanisms. The POF approach results in a more extensive reliability prediction but often requires failure data derived from accelerated life tests to determine the life-stress profile and properly model the failure mechanism over time. It is important for a practitioner to accurately assess and predict a system's reliability. Multiple publications exist weighing the benefits and limitations of each reliability predication approach. Few sources exist, however, that provide the practitioner guidance in determining when to use one approach over the other. The RDF identifies the key factors a practitioner should consider when selecting an approach. In systems exposed to multiple failure mechanisms and require a more robust design, a POF approach is the best in predicting and assessing the system's reliability. In scenarios when time and cost are extremely limited and those scenarios in which the system is not expected to last as long, the traditional approach will serve best as there is not a strong need to understand all failure mechanisms associated with the system. Although reliability is an iterative process throughout the design phases, the RDF is best applied in the early stage of the preliminary design phase when a system level functional analysis has been performed. In addition to assisting the selection of a reliability prediction method, the results of the RDF may further enhance the system design and the allocation of system requirements in the preliminary design phase.

G. FUTURE WORK

The reliability decision framework can be expanded on through the exploration and assessment of the varying types of modified POF approaches. An assessment of the modified methodologies is beneficial to the practitioner for specific types of devices and systems. In addition, most comparative studies lack data in quantifying the disparity of the different reliability approaches. A study simulating both reliability approaches for a system will help quantify the disparity in the different approaches. An additional study can be conducted comparing the predictive results with actual historical failures and failure mechanisms the system has experienced.

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IV. CONCLUSION

Accurate failure data and appropriate modeling of the failure data is vital in reliability predictions. Historical failure data for a similar systems operating in the same environment to the designed system is ideal as inputs to a reliability prediction. In early design, this not always an option for the practitioner. Test data obtained from life-stress tests such as accelerated life tests are a good alternative. The stress tests become even more important when using a physics of failure reliability approach. If accelerated life tests are an option to the practitioner, it is advised to perform a physics of failure approach and develop a throughout comprehensive accelerated test plan. An accelerated test plan will ensure the appropriate data for dominate failure mechanisms are captured and the tests are conducted efficiently. Applying the correct model to represent the data is equally as important in reliability predictions. This is best done through a goodness-of-fit test. The use of external reliability data sources should only be explored when no other options are available to the practitioner. Based on the assessment conducted in Chapter II, a single best external reliability data source does not exist. Each external data source varies from other sources. Many data sources are tailored to contain failure rate data relevant to the components and environments in a particular industry. All external data sources share the same inherent issues. These issues include average failure rates, undefined survey parameters for each component with unknown quality levels, and unknown environmental stresses. Practitioners should consider these factors when deciding on the appropriate external data to utilize in predictions. The unknown variables should be kept to a minimum to reduce the probability of an inaccurate reliability prediction.

The practitioner generally has two different approaches to predicting the reliability of a system, the traditional approach and the physics of failure approach. It is important to understand the advantages and limitations for both approaches. It is also equally as important to understand when it is appropriate to use each approach. Factors such as time and cost are significant in every program, but there additional factors to consider when choosing the appropriate approach. These factors include historical failure data, system complexity, projected operational life, demand, criticality, and reliability requirements.

Based on the scenario and the failure data available, the practitioner may inherently be limited to perform one approach over the other approach. In general, a physics of failure approach will provide the practitioner with an understanding of the root causes of system failure. This approach is more intensive than the traditional approach and will yield a more robust reliability prediction and system design. The trade-off is the need on accelerated life test to obtain failure data and to develop life-stress profiles for specific failure mechanisms. The accelerated life tests will naturally increase the time and cost for the program. The traditional approach is not as accurate as the physics of failure approach when using external data sources. The traditional reliability approach is better suited for use when accurate historical failure data is available to the practitioner. Data from historical life tests may also be used in the traditional approach if the environment and stressors for the tests are known and relevant.

V. FUTURE WORK

Most comparative studies lack data in quantifying the disparity of the different reliability prediction approaches. A study simulating both traditional and physics of failure approaches for a particular system will help quantify the disparity between the different prediction approaches. An additional comparative study can be conducted to assess the variable outcome of the prediction approaches, the models used for the prediction, actual historical failures, and the failure mechanisms the system has experienced. The results of which will further highlight the elements that positively and negatively contribute towards accurate system reliability predictions. The resulting elements will enhance the practitioner's ability to accurately predict the reliability of a system and support the system's design in meeting its intended reliability requirements. An experimental approach is desired to assess the outcomes of the reliability prediction methodology and the actual experienced system failure data. Further research into the varying types of modified reliability prediction methods can also be performed. Many modified methods use aspects of the physics of failure approach to compensate for the limitations in the traditional approach. An assessment of the modified methodologies may be beneficial to practitioners for specific types of devices and systems.

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