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Validation and Improvement of Reliability Methods for Air Force Building Systems

Patrick A. Deering

VALIDATION AND IMPROVEMENT OF RELIABILITY METHODS FOR AIR FORCE BUILDING SYSTEMS

THESIS

Patrick R. Deering, Capt, USAF

AFIT-ENV-16-M-143

DEPARTMENT OF THE AIR FORCE
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Patrick R. Deering, BS

Captain, USAF

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Abstract

The United States Air Force manages its civil infrastructure resource allocation via a two-dimensional risk model consisting of the consequence of failure and reliability. Air Force civil engineers currently use the BUILDER® Sustainment Management System to estimate and predict reliability at multiple levels within its civil infrastructure systems. Alley (2015) developed and validated a probabilistic model to calculate reliability at the system level. The probabilistic model was found to be a significant improvement over the currently employed BUILDER® model for four major building systems (electrical, HVAC, fire protection, and electrical). This research assessed the performance and accuracy of both the probabilistic and BUILDER® model, focusing primarily on HVAC systems.

This research used contingency analysis to assess the performance of each model for HVAC systems at six Air Force installations. Evaluating the contingency analysis results over the range of possible reliability thresholds, it was found that both the BUILDER® and probabilistic model produced inflated reliability calculations for HVAC systems. In light of these findings, this research employed a stochastic method, a Nonhomogenious Poisson Process (NHPP), in an attempt to produce accurate HVAC system reliability calculations. This effort ultimately concluded that the data did not fit a NHPP for the systems considered but posits that other stochastic process can provide more accurate reliability calculations when compared to the two models analyzed.

To my wife and daughter, thank you for your unwavering support and understanding through this journey. I wouldn't have made it without you.

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I would also like to thank the individuals who helped provide data and support to my research. Thank you to Mr. Art Uhlig, ACES/IWIMS program manager, for supporting numerous data pulls in an extremely timely manner. Also, thank you to Mr. Mike Grussing and Mr. Lance Marrano, US ARMY Engineer Research and Development Center Construction Engineering Research Laboratory, for their extensive knowledge in BUILDER™ and their willingness to sponsor this research.

Patrick R. Deering

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VALIDATION AND IMPROVEMENT OF RELIABILITY METHODS FOR AIR FORCE BUILDING SYSTEMS

I. Introduction

Background

In 2003, the United States Government Accountability Office (GAO) published a report highlighting the poor management of federal real property. The GAO went as far to designate federal real property management as a "high risk area" (Teicholz, Noferi, & Thomas, 2005). The findings of the 2003 report ultimately led to the publishing of Executive Order (EO) 13327, Federal Real Property Asset Management. The order required the implementation of a federal real property asset management program. The intent of the program was to focus on the efficient and economical use of real property assets. The EO also required each department within the executive branch to determine what assets they owned, what assets they needed, and what it costs to manage those assets (Teicholz et al., 2005). Each department was also responsible for developing and monitoring real property performance criteria.

Given the requirements defined in EO 13327, the Department of Defense (DoD) and subsequently the United States Air Force (USAF) initiated the implementation of asset management principles in 2007. Major General Del Eulberg, The Air Force Civil Engineer at the time, published a letter discussing the transition for USAF civil engineers into an asset management culture. General Eulberg defined asset management as the "systematic and integrated process to manage natural and built assets and their associated performance, risk, and expenditures over their life cycles to support…organizational goals" (Eulberg, 2007). General Eulberg's primary objective for Air Force asset management was to provide strategic direction by answering the similar questions highlighted in EO 13327: What assets does the USAF currently have? What assets does the USAF need? What are the gaps? And, how do we optimize those assets, from both a cost and performance standpoint?

To implement a program that answered these questions, the USAF published Air Force Policy Directive (AFPD) 32-10 *Installations and Facilities*. AFPD 32-10 directs the employment of a sustainable asset management approach centered on providing effective mission support at the lowest possible life-cycle cost (Office of the Secretary of the Air Force, 2010). The policy directive requires civil engineers to consider the return on investment and an asset's mission support capability when developing asset investment strategies. Additionally, engineers are required to determine how condition impacts the ability of an asset to adequately provide mission support. Engineers must also develop a process to monitor mission support through the use of performance indicators (Office of the Secretary of the Air Force, 2010). Although the directive outlines numerous requirements, it creates a central theme for Air Force civil engineering: engineers need to manage their assets in a way that effectively support the the Air Force's mission while minimizing asset life-cycle costs.

BUILDER®

AFPD 32-10 requires civil engineers to understand asset condition and monitor performance over the life cycle of an asset. Additionally, Gen Eulberg highlights the central objectives to implementing an asset management program as understanding what assets the USAF has in their inventory, the condition of those assets, the performance of those assets, and determining an optimal investment strategy.

In order to more effectively manage assets that provide effective support while minimizing asset life-cycle cost, the Office of the Secretary of Defense (OSD) mandated the Air Force to implement the use of BUILDER®. BUILDER® is a Sustainment Management System (SMS) developed by the United States Army Engineer Research and Development Center (ERDC) Construction Engineering Research Laboratory (CERL). CERL created BUILDER® to provide engineers an established, objective standard to quantify and communicate asset condition, risk, and mission readiness. In order to accomplish this, BUILDER® provided a standardized framework encompassing five areas: determining asset inventory, quantifying asset Condition Indices (CIs), predicting future CIs, generating work plans, and analyzing investment courses of action (COAs) (United States ARMY Corps of Engineers (USACE), 2015a). Of these five areas the Air Force is primarily utilizing BUILDER® to determine asset inventory, quantify asset CIs, and predict future CIs. Thus, the system allows engineers to track assets in their current portfolio and assess asset life-cycle performance.

The Air Force uses CI to measure life-cycle performance. Chapter II will explain the calculation of CIs at the various level within an asset's hierarchy. However, the basic principle of the BUILDER® model uses CI and replacement costs at lower levels of the system to calculate a CI at the system level. It is important to note CI and reliability are thought to be "proportionally similar" (Grussing, Uzarski, & Marrano, 2006). That is to say that a system having a CI of 50 is assumed to have an approximate reliability of 50 percent. Thus, CI is used to approximate an asset's reliability, and subsequently it's probability of failure

Probabilistic Assessment of Failure

In an attempt to improve the BUILDER® CI model, Alley (2015) proposes an alternate model for calculating the probability of failure at the system level within the BUILDER® hierarchy. In contrast to the use of replacements cost, Alley calculates probability of failure at higher levels through the use of fault trees with fuzzy logic and importance weighting.

Alley (2015), validates her model through the use of work order (WO) data contained in the Interim Work Information Management System (IWIMS) database. This validation equates a WO coded as Emergency (E) or Urgent (U) to a failed state as these actions are not planned or preventive in nature, but reactive and corrective to a failed system. Alley uses contingency analysis to both compare the models to one another and determine which model possessed more predictive capability for system level failures. When comparing the two models to one another, Alley determined that both models found similar results in only 10 out of 46 component-sections analyzed. Leading to the conclusion that each model differs in their ability to calculate system level probability of failure. Subsequently, Alley analyzed each model's ability to predict system level failure. Still using contingency analysis, Alley states that the BUILDER® model possessed little to no predictive ability, while the alternate model was able to predict probability of failure with a statistical significance of 0.12 (Alley, 2015).

Problem Statement

The United States Air Force is concerned with providing assets that effectively support the mission while simultaneously minimizing life cycle costs. Air Force engineers currently employ the BUILDER® Sustainment Management System to track civil infrastructure asset condition indices. Engineers use these indices as a proportional measure of asset reliability and likelihood of failure (Air Force Civil Engineer Center (AFCEC), 2015). The models discussed above focus on providing an accurate estimation of civil infrastructure reliability. This research aims to further improve these reliability calculations by assessing the performance and accuracy of both models. In doing so, this research focuses primarily on investigating underlying assumptions associated with each model. Specifically, both models use a reliability threshold of 37 percent as a representation of a system level failure. Additionally, Alley assumes a Weibull distribution and parameters to quantify the probability of failure at the component-section level of the probabilistic model. Lastly, the original validation performed by Alley assessed the models at only a single Air Force installation. By addressing these concerns, the objective of this research is to further improve civil system reliability estimation for Air Force civil engineers.

Research Objectives and Investigative Questions

This research investigates the BUILDER® and probabilistic model in order to more accurately predict the probability of failure at a building's system level. In order to accomplish this, this research will focus on reducing the underlying model assumptions and perform further model validation and statistical analysis. This research will accomplish these objectives by answering the following questions:

1. What assumptions associated with the original research effort can be reduced or eliminated through data collection and analysis?

    a) Is the assumption that a reliability threshold of 37 valid for the systems analyzed? If not, does the model indicate a reliability threshold for these systems?

    b) Can probabilistic distributions and associated parameters be estimated for system components?

2. After further model validation, do the models still present statistical significance for predicting the probability of failure at the system level?

3. After further model validation, do the models accurately predict the probability of failure at the system level?

4. Can alternative methods be used to assess system reliability for Air Force civil infrastructure systems?

Overview

This document follows a traditional five chapter thesis format. Chapter I provides the context for this research and the research objectives and question. Chapter II provides a literature review of topics relevant to this research. Chapter III provides the methodology of the research, specifically discussing methods for assessing the performance and accuracy of both the Probabilistic Assessment of Failure (PoF) and System Condition Index (SCI) models. Chapter IV discusses the data and data collection process and discloses the results of the study. Finally, Chapter V will present discussion of these results, conclusions for Air Force asset management, and recommendations for follow on research.

II. Literature Review

Chapter Overview

This literature review presents topics pertinent to this research effort. In order to lay the foundational understanding of assessing failure and reliability of building systems, this review begins with an understanding of systems. It subsequently introduces the technical civil infrastructure elements and further details how these elements comprise civil engineering systems. This discussion specifically highlights architectural, or building, systems as an area of focus. Next, this literature review explains reliability with respect to civil infrastructure systems and further explains how performance is linked to reliability. Additionally, this review introduces how United States Air Force Civil Engineers assess reliability through the sustainment management system BUILDER®. Finally, the chapter closes with an explanation of the model under consideration, the Probabilistic Assessment of Failure (PoF) Model (Alley, 2015).

Systems Thinking

For ease of transition through the chapter, and prior to explaining what compromises a system, this review will introduce systems thinking. Systems thinking is a tool for understanding or mentally visualizing systems. Originally, technology and technological development focused primarily on the technical artifact. In contrast to this, systems thinking requires a holistic approach to understanding how all components within a system interact and work together (Blanchard & Fabrycky, 2011; De Weck, Roos, & Magee, 2011; Labi, 2014). The next two paragraphs introduce the concepts of "level of abstraction" and "viewing angle" as tools for holistic understanding of systems.

Blanchard and Fabrycky (2011) discuss the utility of a "top-down" approach to systems thinking. In this approach, systems are decomposed in a hierarchical nature. De Weck et al. (2011) discuss the same approach, but build on it by adding that a person can and should change their "level of abstraction" when using a top-down approach. Level of abstraction defines at what level of detail a person is analyzing the system. For example, if viewing a system through a microscope, the zoom on the microscope represents the level of abstraction. Zooming out, the system is possibly seen as a large system with multiple sub-systems. Zooming in, system thinking allows for a more detailed view limiting the view to a single system or single component therein.

De Weck et al. (2011) also introduces the concept of changing "viewing angles" in systems thinking. Using the microscope example, if the zoom is the level of abstraction, the viewing angle can be thought of as the lens from which the system is "viewed". In systems thinking, one lens might represent the energy input and output into a system, another might represent the economic input and output, and yet another might represent the functional output of a system (De Weck et al., 2011). The intent of thinking about systems through multiple lenses is to incorporate a multidisciplinary understanding of the system (Blanchard & Fabrycky, 2011; De Weck et al., 2011). By doing this, one gains a broad but detailed understanding of the systems.

Systems thinking provides a way to think about a system from a holistic perspective. But to what end? The intent is to provide a framework for holistic understanding of a system in order to more effectively manage a system. The next few sections will introduce the characteristics of a system in generic terms and then introduce civil infrastructure systems. The intent is for the reader to understand the complex nature of systems, specifically civil systems, and comprehend the need for systems thinking in order to effectively manage those systems.

Attributes of Systems

Almost everything in our world is a part of a system and the quantity and types of systems are numerous. Examples of a few types of systems are natural, like the earth's tectonic plates, social, such as the communities in which we live, and technical, like a countries electrical system. But what comprises a system? Due to the complexity of answering this question with respect to the numerous types of systems, this review will narrow its focus to technical systems. Therefore, when using the word system, note that this review discusses technical systems only.

Systems are largely the result of technology and technological advancement. Traditionally, the focus of technology was on singular a technical device, or technical artifact (Joerges, 1988). Hughes (1987) describes an artifact as a physical or non-physical functioning invention. Emphasizing the words function and singular, a technical artifact is a single invention designed to perform a desired function (De Weck et al., 2011). As the world's population grew and humans continued to shape the world in which they lived, technical artifacts became prevalent and interconnected (De Weck et al., 2011). These interconnections are what gave birth to the concept of systems.

The general understanding of a system is defined as a collection of components interacting to meet a desired goal (De Weck et al., 2011; Hughes, 1987; Labi, 2014). This definition implies at least three requirements of a system: components, interactions, and a purpose. Labi (2014) incorporates these three requirements of a system and also includes individual component roles, governing rules and procedures, system structure, system boundary, and surrounding environment. De Weck et al. (2011) further expands the requirements for systems by concluding that systems are dynamic and change over time. Hughes (1987) adds that human interaction plays a crucial role in the creation and feedback loop of the system. Additionally, systems require resources in order to achieve the specified system objective. Given the commonalities that appear when defining a system, the attributes of a system include: objective, resources, rules and procedures, components and their roles, component interactions, system structure, system boundary, surrounding environment, dynamic, human interaction. Understanding general systems concepts will aid in the understanding of civil systems in addition to the BUILDER® and PoF model discussed later, therefore Table 1 and Table 2 further explain the common system attributes listed above.

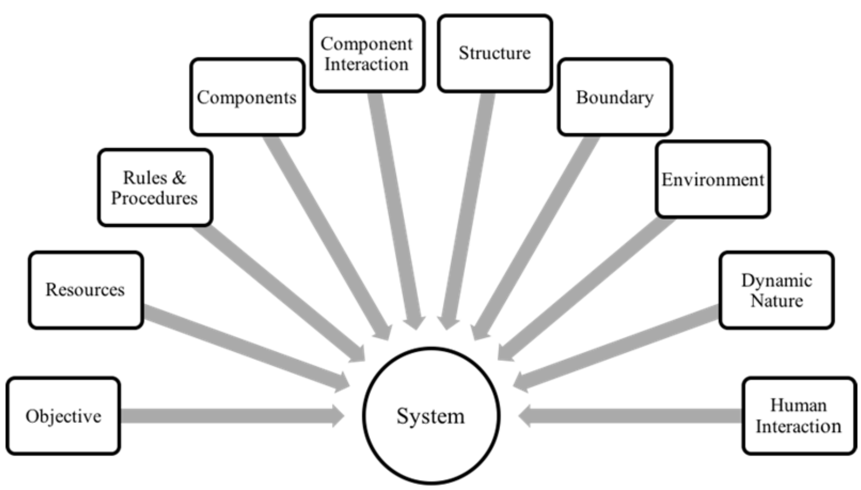


Figure 1: System Attributes

Table 1: System Attributes

Objective
Systems and their components are the product of human intervention and are constructed or procured for a purpose (De Weck et al., 2011). In an organizational context, the system's purpose is often aligned with the objectives of the organization or system owner (Labi, 2014). Sage and Armstrong (2000) classify systems into three functional objective categories: service-oriented, product-oriented, and process-oriented. De Weck et al. (2011) expands on the process of systems. System processes are divided into five categories of objectives: transform, transport, store, exchange, and control.
Resources
A system requires resources to perform its intended function (Hughes, 1987). Resources can come in the form of energy, material, finances, labor, time, etc. Thus, system output is the product of all of its resource input. System components can also receive input and produce output. The output of one component may become the input of another. These input/output linkages help define component interactions (Hughes, 1987).
Components
Components are the foundation on which the system is constructed (De Weck et al., 2011). Components can be physical or non-physical. A physical component might be a transformer in an electrical distribution system while a non-physical component might be a regulatory law under which the transformer or distribution system must operate (Hughes, 1987). Similar to the overall system objective, each component performs a specific function within the system and requires resources in order to aid in achieving the system objective.
Component Interactions
Component interactions transform a collection of individual components into an interrelated system with an overarching objective. To achieve this objective, components trade inputs and outputs with one another (Labi, 2014). This trading of inputs and outputs is component interaction. These interactions can be both positive and negative in nature and become more complex as thy system grows (Joerges, 1988). Identifying which components interact and the nature of their interaction defines the system structure (Hughes, 1987).
System Structure
Systems are often decomposed into some sort of structure (hierarchical, distributed, network, etc.). The purpose for decomposing systems into a structure is to better understand the individual components and how they interact with other components in the system (De Weck et al., 2011; Labi, 2014; Sage & Armstrong, 2000). De Weck et al. (2011) posit that engineering systems require at least 4 levels of decomposition to aid in comprehending the component interactions. They also argue that the need for decomposed structuring rests on the human brains capacity for processing information.

Table 2: System Attributes Continued

System Boundary
The system boundary is meant to delineate elements or components that are internal to the system from those that are external to the system (Labi, 2014). De Weck et al. (2011) offer two ways of understanding the system boundary. First, the space comprised of elements in direct control of the system owners. Second, the space that includes elements that may be directly or indirectly affected by the system. The latter being the more comprehensive captures all interactions of a system and accounts for externalities. Understanding the system boundary provides a clear line of delineation between all the components that comprise a system and the system's external environment.
Surrounding Environment
The surrounding environment is defined as the space outside the system boundary, this includes elements that are complimentary to the system (Labi, 2014). Hughes (1987) further explains "complimentary to the system" elements external to the system that have a "one-way relationship" with the system. The system may either influence the environment or be influenced by the environment. However, elements in the environment are not treated as system components because there is no interaction with system components (Hughes, 1987).
Dynamic
Systems are not static as they change with time (De Weck et al., 2011; Labi, 2014; Sage & Armstrong, 2000). Changes in state or condition can be understood as either discrete or continuous (De Weck et al., 2011). In addition to conditional changes over time, systems also evolve and grow. As technology advances systems advance and change. Sometimes subsystems or components can change at different rates than other parts of the system, increasing the complexity of understanding the system (Blanchard & Fabrycky, 2011)
Rules and Procedures
Simply stated, these are the governing procedures that determine how the system can be operated (Labi, 2014). Rules and procedures provide the physical and regulatory context in which the system may operate.
Human Interaction
Human interaction plays a major part in systems. Systems are constructed or procured by humans to perform some function. The system exists solely as a result of human intervention (De Weck et al., 2011). Humans are also responsible for maintaining, evolving, and operating systems. Additionally, humans perform the important role of completing the feedback loop for system performance and are the link between assessing system performance against system goals and correcting system errors (Hughes, 1987).

Civil Infrastructure Systems

This review has now presented information with respect to systems in general. Because this research focuses solely on civil infrastructure systems, it is important for this review to introduce the major civil systems and explain how the generic systems information presented above is applicable when discussing civil infrastructure systems.

Labi (2014) highlights nine major technical areas within civil engineering: structural, transportation, hydraulic, environmental, geotechnical, construction, geomatic, civil materials, and architectural. Grigg et al. (2001) highlights two additional technical areas: emergency management and systems engineering. These technical areas represent areas of focus and technical expertise with civil engineering. In a similar fashion to the evolution from technical artifacts to systems, some of the technical areas identified by Labi (2014) and Grigg et al. (2001) now form the major civil systems seen today. These systems are highly interactive with each other (Little, 2002), as depicted in Figure 2, and are often comprised of multiple sub-systems (Labi, 2014). Given their interactive and complex nature, it is necessary to view civil infrastructure as systems. Little (2002) identifies four major civil systems: transportation, energy (electrical power, oil, and natural gas), water, and telecommunications systems. Grigg et al. (2001) and Labi (2014) identify additional civil systems: geotechnical, structural, environmental and architectural systems.

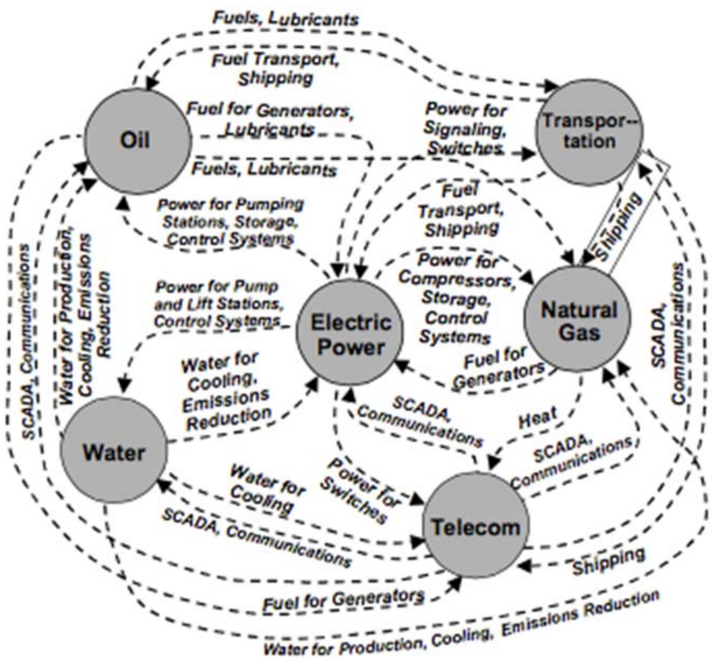


Figure 2: Civil Infrastructure Systems (Little, 2002)

Aside from the fact that literature identifies the majority of civil technical areas as civil systems, literature also shows that the composition of civil systems is in agreement with traditional systems literature. Just as all systems are comprised of multiple components working together to perform a desired objective, civil systems have the same composition. For example, bridges or other structures are composed of multiple structural elements. These elements have a specific arrangement and specific individual functions; i.e. support in tension, support in compression, spanning, or cantilevering. Each member's individual function coupled with the relationship with other members determine the overall system structure and its ability to perform the desired objective (Ambrose, 1967). Bridges and structures also age with time and require maintenance, which is performed and governed by some human entity. Revisiting the requirements to be called a system, this simple example illustrates the concepts of system components, interactions, system and component objectives, structure, dynamic nature, rules and procedures, and human interaction (De Weck et al., 2011; Hughes, 1987; Labi, 2014; Sage & Armstrong, 2000). Additionally, applying De Weck's (2011) concept of level of abstraction, one can "zoom" away from this bridge and see it as a component within a larger transportation system. The bridge as a system has its own physical boundary and surrounding environment, satisfying the last two requirements for classification as a system (De Weck et al., 2011; Hughes, 1987; Labi, 2014).

Although the above example is simplistic, it displays the transformation from thinking about physical structures as civil artifacts to components within civil system, or as civil systems themselves. Once engineers think about civil infrastructure as civil systems, they can begin to apply the systems thinking concepts outlined by De Weck et al. (2011). Applying these concepts will aid engineers and infrastructure managers in the design and management of civil infrastructure systems.

Labi (2014) categorizes the majority, if not all, of civil infrastructure into their individual systems. Kandiah and Rao (2008) discuss the evolution of civil water infrastructure from artifacts into systems and then into complex interdependent systems. Heller (2001) also discusses the interdependencies in many civil systems and identifies power generation and distribution systems, transportation systems, and telecommunication systems as complex and adaptive systems. Lastly, and arguably most applicable to this research, is the introduction of building or architectural systems (Labi, 2014; Piper, 2004; Rush, 1986). These systems are the built infrastructure, or facilities, in which society lives and operates. While architectural systems are systems in their own right, they are more accurately described as a system with multiple sub-systems. The following section provides further understanding of architectural system composition.

Architectural (Building) Systems

The primary focus of this research is to understand reliability of certain systems within architectural systems. Therefore, it is necessary to understand what different systems make up Architectural systems. Architectural systems are described as the built infrastructure in which society lives and works. These buildings can be simple structures comprised of only two or three systems or can be a very complex with many sub-systems. Rush (1986) classifies four distinct systems within the architectural system framework: building envelope, structural, mechanical, and interior systems. Bachman (2003) replaces the mechanical system classification with service systems and introduces the exterior site as a system. Benggeli (2003) and Piper (2004) follow similar system characterization, however both decompose mechanical systems into the common systems in this category: heating ventilation air conditioning (HVAC), fire protection, electrical, plumbing, and conveyance systems separately. The following sections offer a brief explanation of the five major systems that comprise architectural systems.

Structural.

The structural system in a building consists of any members that are responsible for maintaining static equilibrium from static or dynamic loading (Bachman, 2003; Rush, 1986). Components of a structural system are load bearing walls, columns, beams, foundations, and the like.

Envelope.

The envelope system is responsible for limiting the interaction of the interior systems and the building's external environment. The envelope primarily consists of walls, fenestrations (windows and doors), roofs, and insulation (Bachman, 2003; Sadineni, Madala, & Boehm, 2011).

Interior.

One can think of interior systems as anything visible from the inside a building. These include partitions and their coverings, floor coverings, ceilings, interior fenestrations, and fixtures. The interior system is typically interdependent with the envelope system (Binggeli, 2003; Piper, 2004; Rush, 1986).

Services.

The services systems provide services to the facility or occupants within the facility. The major systems found in this category are: HVAC, power distribution, water distribution, and waste. These systems are responsible for regulating heat transfer, safely distributing electricity and lighting, providing potable water, and removing waste from a building, respectively. This category also includes conveyance systems responsible for transporting people and products within a building (i.e. elevators and escalators). Lastly, services systems include life safety systems such as fire protection, security and control systems (Bachman, 2003; Rush, 1986).

Site.

The site consists of any natural or constructed elements that are part of, but external to, the building system. Elements such as vegetation, landscaping, sidewalks, parking areas, and drainage compose the site system (Bachman, 2003; Piper, 2004).

A building may contain all or only a few of these described systems. Backman (2003), Binggeli (2003), Piper (2004), and Rush (1986) all highlight the hierarchical nature of their relationship to the building system as a whole. In a similar fashion, each system is comprised of numerous components arranged in the same hierarchical structure; and these components work together to achieve the overall system objective. Just as system components work together, each system works toward the building system objective, often in an integrated nature. Rush (1986) highlights five levels of system integration: remote, touching, connected, meshed, and unified. Remote systems share no connection, physical or otherwise. Touching indicates contact between two systems without permanent attachment while connected systems are permanently attached. Meshed systems occupy the same space but may or may not be connected. Finally, unified systems are integrated to the point that the separate systems are no longer distinct from one another (Rush, 1986). The level of integration will vary from building system, however it is arguable that the majority of building systems are at a minimum touching or meshed.

With numerous possible combinations of systems and many possible levels of integration within architectural systems, it is easy to see that architectural systems are complex. Engineers and facility managers must use concepts described in systems thinking to visualize and understand how these systems work and interact with the intent to more effectively manage these systems. The following sections explain how understanding reliability, failure, and performance are used to manage complex architectural systems.

Reliability

The content presented when explaining systems and civil engineering systems highlights that systems have some inherent purpose or objective. Systems are constructed to achieve something and all systems are susceptible to failing to meet their objectives. Reliability is the the measurement of how likely a system is to meet its objectives. Ang and Tang (1984) discuss the importance of understanding the the reliability of a civil system throughout its lifetime. Understanding a system's reliability allows engineers to better design and manage the system. Equation 2 presents reliability is the mathematical compliment of the probability of failure. Basic definitions state that reliability is the ability of a system to perform a desired function, however, a critical component of reliability in civil systems is understanding its relationship with uncertainty (Ang & Tang, 1984; Labi, 2014; Singh, Jain, & Tyagi, 2007).

$$P_f(t) = P(T \leq t) \tag{1}$$

$$R(t) = 1 - P(T \leq t) = P(T > t) \tag{2}$$

Literature on reliability in civil infrastructure shows that reliability evaluation has changed over the years as engineers seek to quantify the level of uncertainty in civil systems. Traditionally, reliability was assessed through deterministic means (Ang & Tang, 1984; Singh et al., 2007). In a deterministic analysis, engineers quantified the capacity of the system or components therein. Engineers would then quantify the "worst case" load combination. Given certain factors of safety, if the system capacity was greater then the worst case load the system was deemed reliable (Singh et al., 2007). The primary weakness of this assessment technique is the failure to include uncertainty.

In contrast, a probabilistic analysis of reliability attempts to understand the uncertainty associated with both loads and system capacity. Probabilistic methods quantify the different load and capacity possibilities and their respective probabilities. From there, system reliability becomes the probability that the system capacity is greater than the load placed on the system. Figure 3, depicts this relationship. The overlap of the two probability distributions represents the probability of failure. The remaining area under the strength density function, $\bar{S}$, represents the overall system reliability (Ang & Tang, 1984; Labi, 2014; Singh et al., 2007).

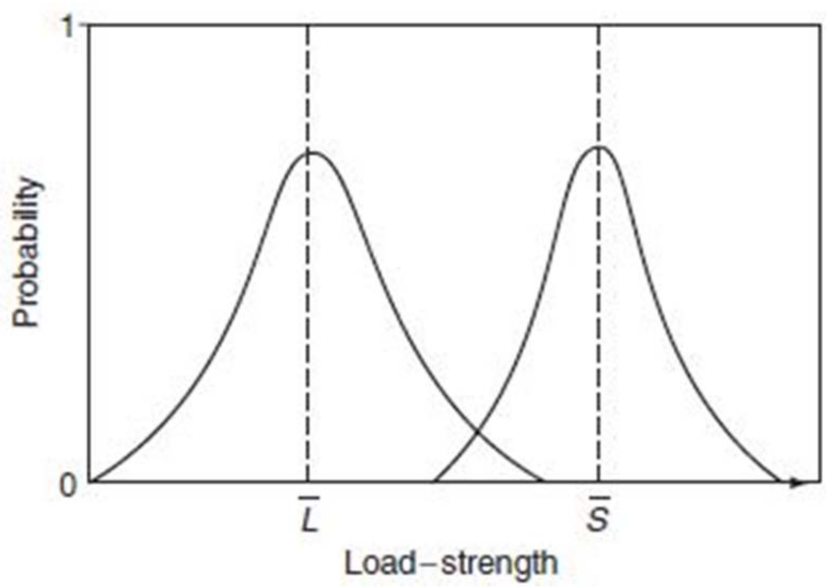


Figure 3: Load-Strength Reliability ("Introduction to Reliability Engineering," 2015)

It is also important to note that assessing reliability of system can vary depending on the operational requirements, operating environment and the individual assessing reliability (Dummer & Winton, R.C., 1986; Labi, 2014). More specifically, Labi (2014) discusses how system reliability is dependent upon the criterion being assessed. For example, the reliability of a concrete column with respect to compressive strengths will be different than reliability for shear cracking or corrosion. Therefore reliability assessments must be paired with a performance criterion or failure modes. To indicate this, a new equation for reliability is presented with a subscript "c" in equation 3 to represent reliability in terms of a specific criterion (Labi, 2014).

$$R_c(t) = 1 - P(T \leq t) = P(T > t) \tag{3}$$

Reliability as a Performance Measurement

Stating that an asset has failed typically indicates that the asset is no longer performing the desired function at some desired specification. Performance with respect to infrastructure is defined as "the accomplishment of a task set for the system or its parts by the society that builds, operates, or uses that infrastructure" (National Research Council, 1996, p. 33). This definition implies that infrastructure is built to meet societal or organizational objectives. These needs and objectives can range in complexity and vary greatly (National Research Council, 1996). Additionally, large organizations typically contain numerous stakeholders with varying positions, needs, and individual objectives.

Performance indicators that meet the broad objectives of numerous stakeholders are lumped into multiple categories. The National Research Council (1996) outlines three major categories: effectiveness, reliability, and financial performance. Similarly, Levy et al. (2010) identify three categories associated with infrastructure performance: financial, physical, and functional. These different categorizations effectively cover an assets financial performance, capability to perform its intended function, and reliability with respect to performing its intended function. Therefore, large organizations can use reliability as a performance measure when trying to evaluate the objectives of numerous stakeholders.

Air Force Infrastructure Performance Measurement

To improve Infrastructure Asset Management within the Air Force, civil engineers have identified ten metrics and key performance indicators (KPIs) for assessment. These indicators focus primarily on financial performance with respect to the amount of resources required to maintain a facility or system. The primary focus of these indicators is measuring cost of preventive maintenance (PM), corrective maintenance (CM), labor hours and work responsiveness (United States Air Force, 2015). However, data against these KPIs are not frequently captured for Air Force facilities therefore cannot provide a comprehensive understanding of asset performance. In an attempt to quantify asset performance, the Air Force has implemented the use of BUILDER® and currently collects physical condition data on a five year cycle. With the adoption of BUILDER®, engineers have attempted to equate annual condition indices to a proportional measure of asset reliability, as discussed in Grussing et al. (2006).

Literature shows that reliability can be used to assess asset performance (Lavy et al., 2010; National Research Council, 1996). With the implementation of BUILDER®, the Air Force has begun to assess the performance of civil infrastructure via asset condition and use asset condition as a proxy measure of reliability. As with any performance objective, an organization must determine the desirable range before performance assessment can begin. With respect to asset condition, the Air Force has accepted the minimum threshold for condition at a CI = 37, consistent with the terminal value for failure defined in BUILDER® (Grussing, M. N., 2015). The Air Force is now prepared to use calculated CIs to assess asset performance and prioritize resource allocations for civil infrastructure.

It is worth noting that KPIs and CI appear to focus primarily on the financial aspects associated with an asset. The KPIs outlined in the AF CE Operations Engineering Playbook (United States Air Force, 2015) focus primarily on an assets financial performance while condition indices attempt to connect asset condition to reliability. However, condition is better suited to capture an asset's degradation and quantify the financial requirement required to return an asset to near perfect condition. What remains to be shown is if asset condition is truly an accurate proxy measure for asset reliability.

BUILDER®

BUILDER® is a Sustainment Management System (SMS) developed by the United States Army Corps of Engineers. A primary function of this system is to track asset inventory and monitor asset condition. BUILDER® also provides asset managers with the ability to configure standards, policies, prioritizations and funding to generate work (United States ARMY Corps of Engineers (USACE), 2015c). Because these secondary functions are outside the scope of this research, these topics will not be discussed and this literature review will focus primarily on asset condition assessment and Condition Index calculations.

BUILDER® Hierarchy.

BUILDER® permits asset managers to construct a comprehensive asset portfolio where they can analyze life-cycle performance at various levels of infrastructure systems. BUILDER® uses the UNIFORMAT II (U2) format to compose the hierarchy associated with infrastructure assets(U.S. Army ERDC/CERL, 2007a). The hierarchy begins with the creation of sites, or geographical regions. Each site is populated with one or more "buildings", which represent individual facilities in the portfolio. BUILDER® allows for further decomposition from the building level to the system, component, component-section, and sub-component levels. A depiction of this relationship is displayed in Figure 4. Users may select from 12 systems when using BUILDER®(U.S. Army ERDC/CERL, 2007a), as seen in Table 3. Not all systems are present in every facility and a facility may only possess one of each type of system.

Decomposing systems requires the identification of individual components. Each system possesses a standard list of components that data managers must select from to populate the system. Continuing down the facility hierarchy, BUILDER® manages data and calculates foundational condition indices at the component-section level (U.S. Army ERDC/CERL, 2007a). While component-sections can be broken down into sub-components for condition information purposes, decomposition of assets primarily stops at the component-section level.

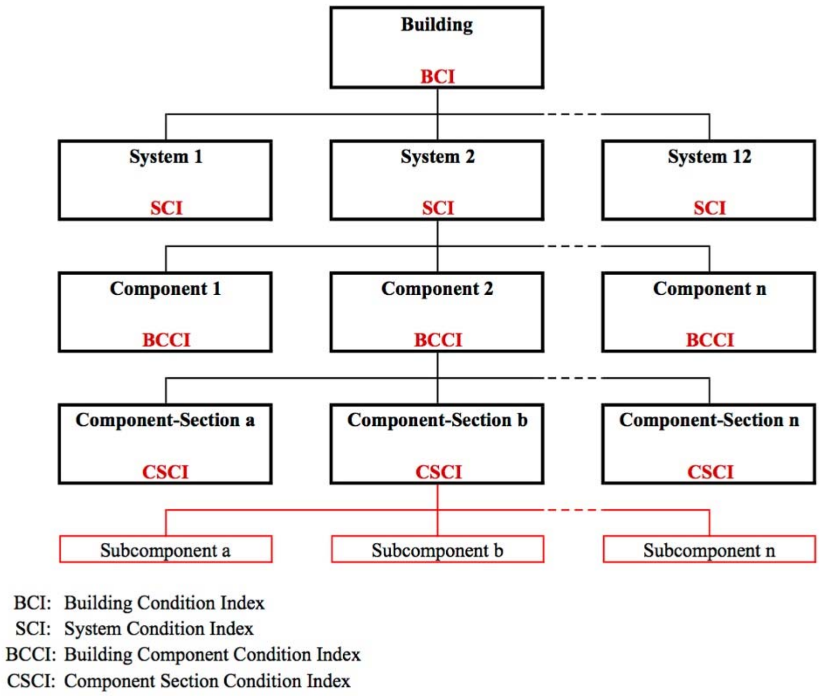


Figure 4: Building Hierarchy (Uzarski & Grussing, 2006)

Table 3: Building Systems (U.S. Army ERDC/CERL, 2007b)

BUILDER®	UNIFORMAT II	
Conveying	A10 Foundations	D50 Electrical
Electrical	A20 Basement Construction	E10 Equipment
Exterior Circulation	B10 Superstructure	E20 Furnishings
Exterior Closure	B20 Exterior Enclosure	F10 Special Construction
Fire Suppression	B30 Roofing	
HVAC	C10 Interior Construction	
Interior Construction	C20 Staircases	
Plumbing	C30 interior Finishes	
Roofing	D10 Conveying	
Site	D20 Plumbing	
Specialties	D30 HVAC	
Structural	D40 Fire Protection	

Data Input: BUILDER® Surveys.

The foundation of asset life-cycle analysis is the data collected and input into BUILDER®. Once data managers have established the necessary hierarchy for an asset down to the component-section level, associated data is then put into the system. Condition data is collected from two types of surveys: direct rating and distress based surveys. Distressed based surveys are an in-depth process that identifies the type, quantity, and severity of distress for a particular sub-component (Uzarski & Grussing, 2006). BUILDER® uses this distress data to calculate a deduct value and an associated subcomponent condition index (CI). BUILDER® then calculates component-section CIs (CSCI) by weighting individual subcomponent CIs (U.S. Army ERDC/CERL, 2007a).

As a note, both survey types contain some subjectivity because neither is intended to be a detailed engineering analysis. However, direct rating surveys are less qualitative and consequently more subjective. Direct rating surveys assign a rating of Green, Amber, or Red to a given component-section. These ratings represent a sliding scale of serviceability loss due to degradation. Green represents the positive end of the spectrum implying minor, if any, serviceability loss while Red represents a serious loss of serviceability. Amber represents the stages between Green and Red, and indicates that some serviceability loss is present and further analysis, or a distressed based survey, is warranted (Uzarski & Grussing, 2006). Each rating can also be assigned a (+) or (-) value, therefore a direct rating survey results in a component-section receiving one of nine possible ratings as seen in Table 4. Similar to distress based surveys, BUILDER® uses the results of the direct rating survey to calculate a component-section deduct value and subsequent CSCI.

Once condition data is input against a component-section and BUILDER® calculates a CSCI, higher-level CIs can then be calculated. BUILDER® calculates a particular level CI using the average of the lower level CI weighted by its cost of replacement (U.S. Army ERDC/CERL, 2007a). Equations 4-6 depict this process starting at the component-section level and terminating at the building level where BCCI is the building-component CI, SCI is the system component CI, and BCI is the building CI.

$$BCI = \frac{\sum(SCI \ x \ Individual \ System \ CRV)}{\sum System \ CRV} \tag{4}$$

$$SCI = \frac{\sum(BCCI \ x \ Individual \ Component \ CRV)}{\sum Component \ CRV} \tag{5}$$

$$BCCI = \frac{\sum(CSCI \ x \ Individual \ Section \ CRV)}{\sum Section \ CRV} \tag{6}$$

Data Output: Condition Index.

BUILDER® uses survey data to calculate a Component-Section Condition Index (CSCI) for each component and uses the roll-up process depicted in equations 4-6 to calculate higher-level CI values. Condition Index is a numeric value from 0-100 that is equated to being proportionate with reliability (Grussing et al., 2006), and subsequently the probability of failure for a given system or component therein. A CI of 100 represents a perfectly reliable asset displaying no aspects of failure. Perfect reliability is typically only found at time zero (time of installation) for a given component. A decrease in CI, ultimately terminating at a CI of 0, represents the decrease in ability of an asset to perform its intended function (Grussing et al., 2006). The current CI failure threshold is represented by CI values less than or equal to 37, representing an unacceptable loss of asset functional ability (Grussing et al., 2006).

Table 4: Direct Survey Rating Criteria (United States ARMY Corps of Engineers (USACE), 2015b; Uzarski & Grussing, 2006)

Rating		Rating Definition
100	Green (+)	Entire component-section is free of observable or known distress
99-93	Green	No component-section serviceability or reliability reduction. Some, but not all, non-critical subcomponents may suffer from slight degradation or few critical subcomponents may suffer from slight degradation
92-86	Green (-)	Slight or no component-section serviceability or reliability reduction. Some, but not all, non-critical subcomponents may suffer from slight degradation or more than one critical subcomponents may suffer from slight degradation
85-75	Amber (+)	Component-section serviceability or reliability is degraded, but adequate. A very few, critical subcomponents may suffer from moderate deterioration with perhaps a few non-critical subcomponents suffering from severe deterioration.
74-65	Amber	Component-section serviceability or reliability is definitely impaired. Some, but not a majority, critical subcomponents may suffer from moderate deterioration with perhaps a few non-critical subcomponents suffering from severe deterioration.
64-56	Amber (-)	Component-section has significant serviceability or reliability loss. Most subcomponents may suffer from moderate degradation or a few critical subcomponents may suffer from severe degradation.
55-37	Red (+)	Significant serviceability or reliability reduction in component-section. A majority of subcomponents are severely degraded and others may have varying degrees of degradation.
36-11	Red	Sever serviceability or reliability reduction to the component-section such that it is barely able to perform. Most subcomponents are severely degraded.
10-0	Red (-)	Overall component-section degradation is total. Few, if any, subcomponents salvageable. Complete loss of component-section serviceably.

In addition to providing current CI values, BUILDER® possesses the capability to forecast condition trends over the life cycle of an asset. This forecasting capability aids asset managers with the ability to estimate an asset's condition at a future date and plan reinvestment strategies. BUILDER® uses a Weibull cumulative probability distribution function, Equation 7, to calculate CI at future time, t

$$CI(t) = a \times e^{-\left(\frac{t}{\beta}\right)^{\alpha}} \tag{7}$$

where a is the initial steady state component-section index with possible values ranging from 0 to 100, β is the service life adjustment factor (scale parameter), and α is the deterioration factor (shape parameter).

BUILDER® defines β as the service life adjustment factor. The traditional Weibull nomenclature defines β as the equations scale parameter. Increasing this factor will increase the scale, or range, of the CI curve. BUILDER® defines α as the deterioration factor. More specifically, Weibull defines α as the shape or slope parameter. α directly defines the slope at which the curve deteriorates. Increases in α indicate and increases slope or rate of deterioration.

Equation 7 represents the CI distribution for a given component-section. At time of installation, distribution parameters are estimated using industry standard or the manufacturer supplied service life. However, factors such as the environment and maintenance rates can cause an assets actual performance to differ from the projected CI curve. Once a component-section has survey data populated against it, BUILDER® uses this data and a regression model to minimize the sum of squares residual errors to best fit a new CI curve (Grussing et al., 2006). The model also uses weights for each data point collected, assigning and increasing weights based on the certainty of the information (i.e. estimated versus actual), the type of inspection, how recent the data is, and the change in CI from the last inspection. This data and regression model ultimately best fit a new curve and with updated β and α parameters.

Probabilistic Assessment of Failure

In a previous study of the BUILDER® model, Alley (2015) proposes an alternate model for computing the probability of failure at the system level. In contrast to the use of replacement costs, Alley uses fault trees with fuzzy logic combined with importance weighting to calculate the probability of failure at the component-section level. She then uses the same method to calculate the probability of failure at higher levels. Basic fault trees use AND and OR operators to calculate statistical probabilities. These basic probability equations can be found in Equations 8 and 9 (Alley, 2015).

$$P_f(A \text{ AND } B) = P_f(A \cap B) = P_f(A) \times P_f(B) \tag{8}$$

$$P_f(\text{A OR B}) = P_f(A \cup B) = P_f(A) + (B) - P_f(A) \times P_f(B) \tag{9}$$

Fault trees with fuzzy logic use Order Weighted Averages (OWA) to adjust the degree to which an operator represents an OR or an AND gate. That is to say, OWA replaces traditional OR and AND gates with a new operator that lies somewhere between a true OR or AND gate. OWA uses a weight vector, W, and a probability vector, B. These two vectors are multiplied together to calculate a scalar, ORAND operator (Alley, 2015). This methodology uses the ORAND operator to calculate the probability of failure at time, t, for a given component and system.

Equation 10 calculates the probability vector, *B*, for a given component-section. This equation represents a Weibull cumulative probability distribution, where *A* is an asset's initial condition index at time of installation. CI_f is the condition index threshold for failure, set at $CI_f = 37$. *t*, is time in years represented as a percentage of the assets expected service life. β is the Weibull scale parameter, and α is the Weibull shape parameter. In the construction of this model, Alley assumes a $\beta = 1$ and an α of 2.64 (Alley, 2015).

$$P_f = 1 - \left[A \times \left[\frac{1}{CI_f} \right]^{-\left(\frac{t}{\beta}\right)^{\alpha}} \right] \tag{10}$$

The weight vector, *W,* for each component and component-section is determined using their respective importance indicators. As previously stated, these vectors are then multiplied together to compute a scalar, component level, ORAND operator. This process is repeated once more to compute the probability of failure at the system level. While this communicates a cursory explanation of how the probabilistic model uses OWA, Chapter III will provide a detailed explanation of these calculations.

After constructing the PoF model, Alley validates the model through work order (WO) data contained in the Interim Work Information Management System (IWIMS) database. Alley collects failure data founded on the assumption that a WO coded with work order indicator (WOIND) J and type of service (TYPESVS) of emergency (E) or urgent (U) combined with a title indicating system level failure point toward a system failure as these actions are not planned or preventive in nature, but reactive and corrective to a failed system (Alley, 2015). Examples of WOs meeting these criteria in the Electrical and HVAC systems are shown in Table 5.

Once the failed systems are identified, Alley extracts facility data from BUILDER® to determine the average component-section age. The average age extracted from BUIDER® is then input into Equation 10 to calculate the probability of failure associated with that particular component-section. Each component-section probability of failure represents a single value in the *B* vector. Alley then uses OWA and sub-component importance, the *W* vector, to "roll" the probability of failure up to the component level. The OWA method is repeated until the model computes a system level probability of failure. This probability is then compared to the System Condition Index (SCI) calculated by BUILDER® (Alley, 2015).

Table 5: Work Order Failure Examples (Alley, 2015)

Electrical System				
FAC#	WOTITLE	DATE	TYPESVS	WOIND
525	POWER LOSS	141114	U	J
763	NO POWER	140923	E	J
1544	EMERGENCY LIGHTS/ NO POWER	140127	U	J
1639	NO POWER	141014	U	J
5500	NO POWER	141006	U	J
6510	POWER OUTAGE	140423	E	J
7011	LOSS OF POWER	131230	E	J
8500	LOST ELECTRICAL POWER	140703	U	J
HVAC System				
FAC#	WOTITLE	DATE	TYPESVS	WOIND
7011	A/C NOT WORKING	140312	U	J
7015	A/C UNIT STOPPED WORKING	140825	E	J
7025	HVAC IS DOWN	140818	E	J
8195	HVAC UNIT DOWN	141110	E	J
8500	REPAIR A/C UNITS INOP	140916	U	J
10130	HVAC NOT WORKING	130925	U	J
10660	HVAC NOT WORKING	140206	U	J
12000	REPAIR INOP. HVAC	140728	U	J

Once values using the Probabilistic Assessment of Failure model are calculated and SCI values extracted from BUILDER®, Alley uses contingency analysis to both compare the models to one another and determine which model possesses more predictive capability. To do this, Alley creates two population samples. The first population sample, categorized as the failed sample, is created using the previously mentioned assumption of failure associated with IWIMS work orders. Facilities with WOs meeting the requirements for system failure are placed in the failed sample, size *n*. A second, non-failed population consists of any remaining facilities not meeting the prerequisites for failure. From this non-failed population, Alley selects a random sample of size *n* (Alley, 2015).

With a failed and non-failed sample, Alley determined that both models predicted similar results in 10 out of 46 component-sections analyzed. Each model is also analyzed to determine its predictive capability of system level failure. Figure 5 and Figure 6 display the results of the contingency analysis for each model. Still using contingency analysis, Alley found that the BUILDER® model possessed little to no predictive ability while her model was able to accurately predict probability of failure with a statistical significance of 0.12 (Alley, 2015).

	Observed	Fail	No Fail	Row Total
Truth	Fail	6	17	23
	No Fail	2	21	23
	Column Total	8	38	46
Test		**ChiSquare**		**Prob>ChiSq**
Likelihood Ratio		2.515		0.1128
Pearson		2.421		0.1197

Figure 5: PoF vs Truth Contingency Analysis (Alley, 2015)

	Observed	Fail	No Fail	Row Total
Truth	Fail	2	21	23
	No Fail	2	21	23
	Column Total	4	42	46
Test		**ChiSquare**		**Prob>ChiSq**
Likelihood Ratio		0.000		1.000
Pearson		0.000		1.000

Figure 6: SCI vs Truth Contingency Analysis (Alley, 2015)

Summary

This chapter presented a literature review of topics relevant to this research. The chapter provided an overview of systems literature, civil infrastructure systems and architectural systems. Additionally, system reliability was presented and how it relates to failure and performance. Finally, this chapter presented both the BUILDER® SCI model and the Probabilistic Assessment of Failure model. The following chapter will further detail the methodology of the Probabilistic Assessment of Failure model and explain additional methodology associated with this research.

III. Methodology

Chapter Overview

This chapter presents the methodology associated with this research. The chapter begins by explaining the calculations behind the Probabilistic Assessment of Failure (PoF) model developed by Alley (2015). Next, this chapter presents the method for assessing the both the PoF and BUILDER® model performance through the use of the Fisher's Exact Test and Odds Ratios. The chapter concludes by presenting the method for assessing the accuracy of both models through a comparison of reliability calculated via a Nonhomogeneous Poisson Process (NHPP) Availability Growth Model (AGM).

Probabilistic Assessment of Failure (PoF) Model

Fault Trees with Fuzzy Logic

Traditional fault trees calculate the probability of events via traditional AND and OR gates. The AND gate requires that all basic events in a Fault Tree occur before a higher-level event occurs. In contrast, the OR gate requires only one basic event occur in order to trigger a higher-level event. Ross (1996) discusses the restrictive nature of boolean style gates and proposes that basic events truly lie somewhere between a true AND gate and a true OR gate. Ross proposes the use of Ordered Weighted Averaging to construct logic gates that are not entirely AND or OR in nature (Ross, 1996).

Ordered Weighted Averaging (OWA)

Ordered Weighted Averaging (OWA) has it roots in multi-criteria decision analysis. Modelers used the process to determine to what degree a proposed alternative, *X,* satisfied a desired criteria (Yager, 1988). In the context of this research, OWA in conjunction with fault trees will determine to what extent, or the likelihood, a system will fail. This research will validate the results using a determined "failed" state as defined by Alley (2015).

In conjunction with Fault Trees, this research uses OWA to calculate an aggregate operator that lies somewhere between a true AND gate and true OR gate. When referring to the aggregate operator, this research uses the term ORAND operator. The ORAND operator requires the construction of two vectors. The first of which is a weighting vector, W, where $w_i \in (0,1)$ and $\sum W_i = 1$. The second vector, B, is the ordered argument vector representing failure probabilities for each component or component-section, depending on what level in the system hierarchy the vector represents. Where $b_i \in [0,1]$ and all b_i are ordered in descending order.

$$W_i = [w_1 \quad w_2 \quad w_3] \tag{11}$$

$$B_i = \begin{bmatrix} b_1 \\ b_2 \\ b_3 \end{bmatrix} \tag{12}$$

Yager (1988) emphasizes that the B vector must be ordered when applying OWA. OWA differs from simple weighted averaging in that weights are not associated with particular attributes but with respect to an ordered position (Yager, 1988). In other words, W_i is associated with the i^{th} largest argument in the B vector.

Weighted Average	Ordered Weighted Average Where B is ordered in descending order
$$G(a_1, \dots, a_n) = \sum_{j=1}^{n} w_j a_j$$	$$F(B) = WB = [w_1, \dots, w_n] \begin{bmatrix} b_1 \\ \vdots \\ b_n \end{bmatrix}$$

Figure 7: Weighted Average vs. OWA

After populating the *W* and *B* vectors, this method computes the ORAND operator by multiplying the two vectors together. Letting *F(B)* be a resulting ORAND operator, the following example illustrates the ORAND calculation. Given the *W* vector, this example will calculate *F(0.6, 1.0, 0.7)*.

$$W = \begin{bmatrix} 0.3 \\ 0.4 \\ 0.3 \end{bmatrix} \qquad B = \begin{bmatrix} 1.0 \\ 0.7 \\ 0.6 \end{bmatrix} \qquad F(B) = W'B = [0.3, 0.4, 0.3] \begin{bmatrix} 1.0 \\ 0.7 \\ 0.6 \end{bmatrix}$$

$$F(B) = (0.3)(1.0) + (0.4)(0.7) + (0.3)(0.6) = 0.76$$

Figure 8: Example of ORAND operator calculation

This operator combines 30% of a pure *or* gate (the maximum basic event of 1.0), 30% of a pure *and* gate (the minimum basic event of 0.6) and 40% from the intermediate valued basic event (0.7). This calculated ORAND operator of 0.76 hows the nature of the logic gate lies between the maximum basic event (1.0) and minimal basic event (0.6).

The Weight Vector, W

This research will construct the *W* vector using two sets of weights contained in BUILDER®. At the component-section level of the building hierarchy, Figure 4, this research uses an average subcomponent importance weight to populate component-section W vector. At the component level, each component's Component Criticality Index (CCI) populates the W vector. The Construction and Engineering Research Laboratory (CERL) developed the subcomponent importance weights and CCI. The importance weights represent each component-section's cost and importance in relation to its associated component while the CCI quantifies the same relationship between the component and the system (United States ARMY Corps of Engineers (USACE), 2015b). Because all values of W must be between 0 and 1, all weights and CCIs will be standardized when populating the W vector.

Because Ordered Weighted Averaging orders the argument vector, the order in which the weights are placed in the weight vector can effect the scalar ORAND operator produced by the cross product of the two vectors. However, neither Yager (1988) nor Ross (1996) prescribe a method for the populating the W vector prior to ordering the B vector. In order to provide a consistent method for populating the W vector, this research populates both the W vector and B vector in ascending order based on the numerical component-section indicator given in BUILDER™. After which the B vector is ordered consistent with the method described by Yager (1988) while the W maintains its initial ordering. This method for populating the W vector is consistent with the method used to develop the PoF model (Alley, 2015).

The Argument Vector, B

This research uses equation to calculate the probability vector, B, for a given component-section. This equation represents a Weibull cumulative probability distribution:

$$P_f = 1 - \left[A \times \left[\frac{1}{CI_f}\right]^{-\left(\frac{t}{\beta}\right)^{\alpha}} \right] \tag{13}$$

where A is an asset's initial condition index at time of installation, assumed to be 100. CI_f is the condition index threshold for failure, set at $CI_f = 37$. β is the Weibull scale parameter, and α is the Weibull shape parameter. The PoF model assumes a $\beta = 1$ and an α of 2.64 (Alley, 2015). The time in years, t, is represented as a percentage of the asset's expected service life. This research calculates t by taking the component-sections average age and dividing by the expected service life.

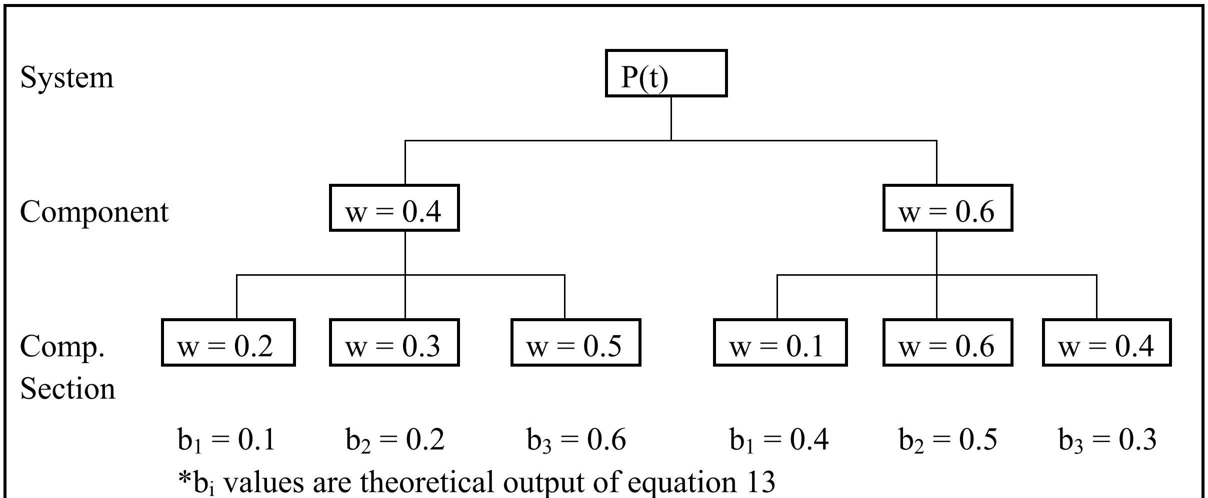
Equation 13 calculates the probability of failure for each component-section in a system, representing the individual values, b_i, in the argument vector. These values range from 0.00 to 1.00, satisfying the requirement that $b_i \in [0,1]$. In accordance with the OWA, this method orders all b_i values to form the completed B vector. Figure 9 displays a pictorial and mathematical representation for calculating the probability of failure, *P(t)*, and reliability, *R(t)*, for a simple system using the PoF model.

Model Validation: Performance Assessment

Two-Way Contingency Analysis

This research employs the use of two-way contingency analysis to assess each model's performance. Contingency analysis provides the ability to test for independence between two categorical variables (McClave, Benson, & Sincich, 2014). In this research, the categorical variables are the truth state and the model's predicted state. Both the truth state and model predicted state consist of a failed and non-failed sample, thus providing the necessary groupings for a two-way analysis. To populate the failed sample, this research considers a system failed if for a given year of analysis if it has a work order (WO) indicating a system level failure, as described in Chapter II. To populate the non-failed sample, this research randomly selected a representative sample from the remaining system population. For continuity in methodology, the non-failed sample size will match the failed population size. These two failed and non-failed samples represent the truth state.

After placing systems in their respective populations within the truth state, this research cross-references their corresponding facility number with BUILDER® to determine the age and service life of each component-section in the system. Given the age and service life, the OWA method calculates a probability of failure for that system. Using the prescribed failure threshold of SCI = 37, this research is now able to assign systems to the failed or non-failed population within the model predicted state. Remembering that SCI of 37 is a threshold for reliability, the probability of failure, *P(f)*, calculated by the OWA method is subtracted from 1 to calculate the reliability of the system, *R(t)*. Table 6 summarizes the criteria for each categorical state population. The annotations provided in Table 6 correspond to the population size depicted in the two-way table in Figure 10. The sample size for the entire test, $n = n_{tf} + n_{tn} = n_{mf} + n_{mn}$.



Example Calculations:

Component-Section Level

$W_1 = (0.2, 0.3, 0.5)$

$B_1 = (0.6, 0.2, 0.1)$

$F(B_1) = W_1 \times B_1$

$= (0.2*0.6+0.3*0.2+0.5*0.1)$

$F(B_1) = 0.68$

$W_2 = (0.1, 0.6, 0.4)$

$B_2 = (0.5, 0.4, 0.3)$

$F(B_2) = W_2 \times B_2$

$= (0.1*0.5+0.6*0.4+0.4*0.3)$

$F(B_2) = 0.41$

Component Level

$W_3 = (0.4, 0.6)$

$B_3 = (0.68, 0.41)$

$P(t) = W_3 \times B_3 = (0.4*0.68 + 0.6*0.41)$

$P(t) = 0.518$ $R(t) = 1-P(t) = 1-0.518 = 0.482$

Figure 9: PoF Model Example Calculation

Table 6: Contingency Analysis Population Criteria

State: Population	Criteria	Annotation
Truth: Failed	A system having a work order indicating system level failure. Direct schedule work with type of service indicator emergency (E) or urgent (U).	n_{tf}
Truth: Non-failed	Any system not having a work order indicating a system level failure.	n_{tn}
Model: Failed	Any system with a reliability, $R(t) \leq 0.37$	n_{mf}
Model: Non-failed	Any system with a reliability, $R(t) > 0.37$	n_{mn}

		Model Predicted State		
		Failed	Not Failed	
Truth State	Failed	True Pos	False Neg	n_{tf}
	Not Failed	False Pos	True Neg	n_{tn}
		n_{mf}	n_{mn}	n

Figure 10: Example Two-Way Table

Figure 10 introduces four terms when defining the agreement or disagreement between the truth state and model predicted state: true positive, true negative, false positive, and false negative. To ensure understanding of these terms, this research defines each as follows. True positive is when both the truth state and model state agree on the failed nature of a system. True negative is when the truth state and model state agree on the non-failed state of a system. A false positive exists when the model predicts failure, but in fact the truth state declares a non-failed system. A false negative exists when the model predicts a non-failed system, but in fact the truth state declares a failure.

Hypothesis Testing

As stated above, two-way tables test for independence between two categorical variables (McClave et al., 2014). This research identifies the two categorical variables as the truth state and the model predicted state, displayed in Figure 10. This research uses two-way tables and their associated hypothesis testing method to address model performance. The null hypothesis, H_0, is that these two variables are independent. The corresponding alternate hypothesis, H_a, is that the two variables are dependent. Figure 11 below displays the general form for hypothesis testing with two-way table analysis. This research will utilize the Fisher's Exact Test as the resulting test statistic with a corresponding significance level, $\alpha = 0.10$. Therefore, this research will consider any Fisher's Exact Test p-value < 0.10 statistically significant.

H_o = The two classifications are independent
H_a = The two classifications are dependent
Test statistic = Fisher's Exact Test, p-value
Rejection Region = α > p-value

Figure 11: Two-Way Table Analysis: Fisher's Exact Test for Independence (adapted from McClave et al., 2014)

Fisher's Exact Test

Fisher's Exact Test is a probability test that calculates the exact probability of receiving a specific outcome of a two-way table. This test appropriately replaces a chi-squared or other approximation test statistics when expected individual cell counts in a two-way table are low: less than five (McClave et al., 2014) or less then ten (Shasha & Wilson, 2011). This research will utilize the more conservative threshold provided and use the Fisher's Exact Test when cell counts are lower then five. Using a table similar to Figure 10, Figure 12 shows an example of a two-way table with low expected values, indicated by bold text. These expected values are less then five, thus suitable for Fisher's Exact Test.

		Model Predicted State		
		Failed	Not Failed	
Truth State	Failed	TP	FP	n_{tf}
	Not Failed	FN	TN	n_{tn}
		n_{mf}	n_{mn}	n

		Model Predicted State		
		Failed	Not Failed	
Truth State	Failed	3 **2**	1 **2**	4
	Not Failed	2 **3**	4 **3**	6
		5	5	10

Figure 12: Example Two-Way Table

Fisher's Exact Test provides an exact probability, or p-value, associated with a specific table. Referencing the upper portion of Figure 12, equation 14 provides the p-value calculation for a specific two-way table.

$$\frac{(TP+FP)!(FN+TN)!(TP+FN)!(FP+TN)!}{TP!FN!FP!TN!n!} \tag{14}$$

For the specific table displayed in Figure 12, equation 14 calculates the p-value as follows:

$$\frac{(3+1)!(2+4)!(3+2)!(2+3)!}{2!2!3!3!10!} = {}^{10}/_{42} = 0.2381 \tag{15}$$

This example calculates a p-value of 0.2381 for the specific table displayed in Figure 12. To calculate the Fisher's Exact Test p-value, this method first finds the resulting p-values for all combinations of a two-way table that have the same column and row totals as the observed table in Figure 12. This method then sums the p-value of all two-way tables labeled “more extreme” then the observed table. The Fisher’s Exact method labels a table “more extreme” if the table has a p-value less than or equal to the observed table (Shasha & Wilson, 2011). Figure 13 provides an example of calculating a p-value with the Fisher’s Exact methodology using Figure 12 as the observed table.

Matrix			Probability Calculation	Probability
0	4	4	(0+4)!(5+1)!(0+5)!(4+1)! / 0!4!5!1!10!	0.02381
5	1	6	=1/42	
1 correct, 9 incorrect				
1	3	4	(1+3)!(4+2)!(1+4)!(3+2)! / 1!3!4!2!10!	0.2381
4	2	6	=10/42	
3 correct, 7 incorrect				
2	2	4	(2+2)!(3+3)!(2+3)!(2+3)! / 2!2!3!3!10!	0.4762
3	3	6	=20/42	
5 correct, 5 incorrect				
3	1	4	(3+1)!(2+4)!(3+2)!(1+4)! / 3!1!2!4!10!	0.2381
2	4	6	=10/42	
7 correct, 3 incorrect (observed table from Figure 12)				
4	0	4	(4+0)!(1+5)!(4+1)!(0+5)! / 4!0!1!5!10!	0.0238
1	5	6	=10/42	
9 correct, 1 incorrect				
Fisher's Exact p-value			= 0.2381+0.2381+0.0238+0.0238	0.5238

Figure 13: Example of Fisher's Exact p-value Calculation

For the example displayed in Figure 13, the resulting Fisher’s Exact Test p-value for the table in Figure 12 is p = 0.5238. Because contingency analysis tests for independence between two categorical variables, this p-value indicates the dependence between the truth state and the model predicted state has ~52.4% probability being the result of random chance. This high p-value would require this research to not reject the null-hypothesis and maintain that truth state and model predictive state are independent of one another.

Odds Ratios

The p-value calculated by Fisher's Exact Test enables this research to determine the presence of a relationship between the truth state and model predictive state. However, this value fails to communicate the magnitude and nature (i.e. positive or negative) of that relationship. The odds ratio allows for the determination of the magnitude and nature of the relationship. This method calculates the odds ratio (OR) using equation 16 (Glas, Lijmer, Prins, Bonsel, & Bossuyt, 2003).

$$OR = \frac{TP}{FN} \Big/ \frac{FP}{TN} \tag{16}$$

An OR value can range from 0 to infinity. Values greater than 1.0 indicate a positive relationship between the truth and model state. Higher OR values indicate a stronger positive relationship and signify stronger model predictive capability. Values of 1.0 indicate no relationship between the truth state and the model predictive state. OR values equal to 1.0 are typically accompanied by p-values of 1.0, both values equaling 1.0 indicate complete independence (i.e. no relationship) between the two states. OR values less than 1.0 indicate a negative relationship between the truth and model state (Glas et al., 2003). Therefore, when assessing the overall performance of the model, this research looks to obtain statistically significant p-values accompanied by OR values greater than 1.0.

Model Validation: Accuracy Assessment

In addition to assessing each models performance through the use of contingency analysis, this research also assesses each model's ability to accurately calculate system reliability. This method calculates system level reliability using a counting process known as the Nonhomogeneous Poisson Process and Availability Growth modeling.

Counting Processes

Counting processes are useful when considering repairable systems, sub-systems, or components. Given a system put into operation at time $t = 0$, its k^{th} failure occurs at time S_k. Given a failure, the system is restored to a functioning state allowing it to operate until the next failure. Therefore, over its lifetime, a system will have a sequence of failure time $S_1, S_2, S_3, \ldots S_k$. Additionally, T_k represents the time between failure k-1 and failure k. T_k is known as the failure interarrival time, or time between failures (Høland & Rausand, 1994).

The random variable of interest in a counting process, $N(t)$, is the number of failures in the time interval (0,t]. This process is considered a counting process if $N(t)$ satisfies the following (Høland & Rausand, 1994):

1. $N(t) \geq 0$
2. $N(t)$ is an integer
3. If $s < t$ then $N(s) \leq N(t)$
4. For s < t, [$N(t)$-$N(s)$] equals the number of failures in the interval (s, t]

Nonhomogeneous Poisson Process

When considering a counting process, the interarrival times are important as they determine which kind of counting process is appropriate for calculating system reliability (Høland & Rausand, 1994). Due to the nature of system failure interarrival times, this research will use a Nonhomogeneous Poisson Process (NHPP). NHPP assumes interarrival times are neither independent nor identically distributed. For clarification, an assumption of independence requires that the number of failure events in interval (t-1, t] is not influenced by failures in a previous interval. Further, an assumption of identical distribution requires that the number of failure events in interval (t-1, t] depends only on the length of the interval and not the interval's distance from t_0 (Høland & Rausand, 1994). This research assumes that the systems considered have failure times that are neither independent nor identically distributed. Failure events in interval (t-1, t] are influenced by previous failures and the number of failures in interval (t-1, t] do depend on the length of the interval's distance from t_0. Negating the assumptions of independence and identical distribution is consistent with the assumption that the systems analyzed in this research are minimally repaired. In other words, maintenance strategies restore failed systems to an operational state as quickly as possible by replacing only the failed component(s) and not the entire system. Høland and Rausand (1994) label this strategy "as bad as old", compared to a renewal process where a system is restored to "as good as new" after each failure.

Renewal Process	
Independent Increments Identically Distributed	"as good as new" repair strategy
Nonhomogeneous Poisson Process	
Non Independent Increments Non Identically Distributed	"as bad as old" repair strategy

Figure 14: Counting Process Assumptions

Because the NHPP has interarrival times that vary with time, the typical Poisson arrival rate, λ, is replaced by a cumulative intensity function *M(t),* a function of the Rate of Occurrence of Failure (ROCOF) function, *m(t)* (Høland & Rausand, 1994). Equation 17 shows the relationship between *M(t)* and the ROCOF function, *m(t)*. Common forms of the ROCOF function in a NHPP process are the exponential failure rate model, the linear failure rate model, and the power law failure rate model (Atwood, 1992).

$$M(t) = \int_0^t m(t)dt \tag{17}$$

Because this research focuses on repairable systems, typical calculations for reliability are not suitable, as they typically do not consider events beyond an initial failure. Høland and Rausand (1994) introduce Availability as a more appropriate measure for assessing the probability that a repairable system will be in a functioning state at time *t.* Given that the system has the following state variable:

$$\mathrm{X(t)} = \begin{cases} \text{1 if component is functioning at time t} \\ \text{0 if component is under repair at time t} \end{cases}$$

Equation *18* calculates the availability, or probability that the system is functioning, at time *t*

$$A(t) = P(X(t) = 1) = \frac{MTBF}{MTBF+MTTR} \tag{18}$$

where MTBF is the mean time between failure and MTTR is the mean time to repair.

This research will model MTBF and MTTR using the Rate of Occurrence of Failure function, *m(t)*. As previously mentioned, there are three common forms of the ROCOF function with respect to NHPPs. This research will assess the fit of the power-law model in conjunction with Availability Growth Modeling.

Availability Growth Modeling

Availability Growth Modeling (AGM) assesses system performance based on the probability that a system will be in a functional state at a given time. When used with repairable systems, it is appropriate to assess the MTTF and MTTR using a ROCOF function (Bluvban & Porotsky, 2011). This research will assess the fit of the power-law ROCOF function. The power-law function intensity function, *m(t),* has the form

$$m(t) = \lambda \beta t^{\beta - 1} \tag{19}$$

with model parameters λ and β (Department of Defense, 1981). This research will assess the fit of the power-law intensity function via a visual test known as Duane plotting and a parametric goodness of fit test as outlined in Military Handbook 189 (Department of Defense, 1981).

Reliability analysts use Duane Plotting to assess fit and determine parameter estimates for a power-law intensity function. This research will use Duane plotting primarily to assess fit. Duane plots plot cumulative MTBF versus actual failure times on a log-log scale. For example, if the k^{th} failure occurs at time t_k, Duane plots plot t_k/k versus t_k for all observed failures. If the data follow a power-law intensity function, the plot should display a linear trend (NIST/SEMATECH, 2012). Figure 15 displays an example of a simple Duane Plot. The positive slope indicates an increase in the MTBF, signifying an improving system.

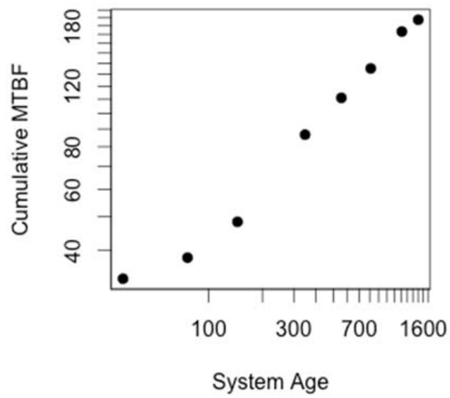


Figure 15: Example Duane Plot (Adapted from NIST/SEMATECH, 2012)

This research will utilize the procedures to estimate parameters and goodness of fit for a power-law intensity function for time terminated testing, as outlined in Military Handbook 189. Time terminated testing procedures assume that the data analyzed is from systems which are terminated at a predetermined time or are currently in operation and data is available through some time (Department of Defense, 1981). The latter of which describes the systems analyzed in this research. To determine the parameters of equation 19, this research uses maximum likelihood estimates $\hat{\beta}$ and $\hat{\lambda}$

$$\hat{\beta} = \frac{N}{N ln T - \sum_{i=1}^{N} ln X_i} \tag{20}$$

$$\hat{\lambda} = N/T^{\hat{\beta}} \tag{21}$$

where N is the total number of failures, T is the total time on test for the system of interest, and X_i is the failure time of the i^{th} failure (Department of Defense, 1981).

For systems with small sample sizes, this research utilizes an unbiased estimator $\bar{\beta}$ to replace $\hat{\beta}$.

$$\bar{\beta} = \frac{N-1}{N}\hat{\beta} \tag{22}$$

Given the maximum likelihood estimates, this research will determine the goodness of fit through the use of the Cramer-von Mises statistic. The null hypothesis associated with this test statistic is that a NHPP with intensity function

$$m(t) = \lambda\beta t^{\beta-1} \tag{23}$$

accurately describes the reliability growth of a given system. The goodness of fit statistic is

$$C_M^2 = \frac{1}{12M} + \sum_{i=1}^{M}\left[\left(\frac{X_i}{T}\right)^{\overline{\beta}} - \frac{2i-1}{2M}\right]^2 \tag{24}$$

where *M* is equal to *N* for time terminated testing. The null hypothesis is rejected if the statistic exceeds the for the critical value at a significance of 0.10 (Department of Defense, 1981). If the research determines that a Nonhomogeneous Poisson Process appropriately represents the data, the MTBF at time, *t*, is simply the inverse of *m(t)*.

$$MTBF(t) = m(t)^{-1} = \left[\lambda\beta t^{\beta-1}\right]^{-1} \tag{25}$$

Calculating Availability

This research assumes both failure data and repair data follow a NHPP and will use the Duane plotting method and goodness of fit testing to determine distribution parameters. With goodness of fit requirements satisfied and parameters fit to the data, this research calculates the availability of system with equation 26. Time, *t*, is the system's age in 2015, the year from which the data was pulled.

$$A(t) = \frac{MTBF}{MTBF+MTTR} \tag{26}$$

Accuracy Assessment: Paired Difference

After populating the failed sample and non-failed sample, as described earlier and in Alley (2015), and calculating both the system reliability (PoF model) and system availability (Availability Growth Model), this research focuses on assessing the accuracy of the PoF as compared to the Availability Growth Model through paired differences.

Paired difference experiments allow for the comparison of two populations to determine if their means differ. This method compares population means by comparing the differences between experimental units (McClave et al., 2014). In the case of this research the experimental units are the PoF model and Availability Growth Model output for a given system.

Paired difference experiments use hypothesis-testing procedures similar to those explained previously. This research will use a large sample, two-tailed test to determine if the two models are comparable. Figure 16 displays hypothesis-testing criteria for this test. This research will use a significance level, α, of 0.10 and a $D_0 = 0$. Using $D_0 = 0$ signifies a null hypothesis, H_0, stating that the two population means are equal. If the results fail to reject the null hypothesis, the model is in agreement with the AGM and thus an accurate estimate of system reliability.

Two-tailed test

H_o: $\mu_0 = D_0$

H_a: $\mu_0 \neq D_0$

Test statistic: $z = \frac{\bar{d}-D_0}{\sigma_d/\sqrt{n_d}} \approx \frac{\bar{d}-D_0}{s_d/\sqrt{n_d}}$

Rejection Region: $|z| > z_{\alpha/2}$ $\alpha = 0.10$

Confidence Interval

$$\bar{d} \pm z_{\alpha/2}\frac{\sigma_d}{\sqrt{n_d}} \approx \bar{d} \pm z_{\alpha/2}\frac{s_d}{\sqrt{n_d}}$$

Figure 16: Paired Difference Test of Hypothesis for $\mu_d = (\mu_1 - \mu_2)$ (Adapted from McClave et al., 2014)

Summary

This chapter presented the methodology associated with this research. First by explaining the calculations behind the Probabilistic Assessment of Failure (PoF) model developed by Alley (2015). Second, by presenting the method for assessing the performance of both the PoF and BUILDER® models through the use of the Fisher's Exact Test and Odds Ratios. Lastly, by presenting a method for assessing both models accuracy through comparison of a Nonhomogeneous Poisson Process (NHPP) Availability Growth Model. Through these accuracy and performance assessments, this research will determine the validity of both the PoF and BUILDER® model to calculate reliability at the system level.

IV. Analysis and Results

Chapter Overview

This chapter presents the results of this research effort. First, the chapter presents the results associated with the performance of both the Probabilistic Assessment of Failure (PoF) and the BUILDER® SCI models through contingency analysis and the use of odds ratios. This segment of analysis utilized a Shiny application and system attribute data to determine what type of systems, and at what reliability threshold each model displays significant agreement with the truth state. By doing so, this research focused on improving the predictive capability both models. Next, this research attempts to compare the output of both models with that of an accepted method in reliability analysis. Utilizing a Nonhomogeneous Poisson Process (NHPP) method, this research attempts to develop a system Availability Growth Model (AGM) for 40 HVAC systems in order to compare the output with that of the PoF and SCI models. Each major sections of this chapter presents information regarding the data used in the research, the results of the analysis, and relevant discussion with respect to the results.

Model Performance Assessment

This section presents the data, results, and discussion associated with the performance of both the PoF model and the SCI model. This research assessed the performance of each model in four major building systems (heating ventilation and cooling (HVAC), electrical, fire protection, and plumbing) through the use of contingency analysis. The research ultimately narrows its scope to focus primarily on the performance of both models with respect to HVAC systems.

Failure Data

This research collected work order (WO) data from calendar year 2014 for six Air Force Installations: Barksdale AFB, Cannon AFB, Davis Monthan AFB, Keesler AFB, Patrick AFB, and Scott AFB. This research used a definition of failure which elicited failure data from the USAF's Interim Work Information Management System (IWIMS). Table 7 presents examples of work orders indicating system level failures used for this research. If a facility had at least one WO indicating failure for a given system during 2014, that system was placed into the failed population for the year of analysis.

Table 7: Example Work Orders Indicating System Level Failure

WOTITLE	**WOIND**	**TYPESVC**	**WONR**	**FACIDNR**
HVAC System Failures				
HEATER INOP FOR BAYS 1 AND 2	J	U	Y6486	04809
NO HEAT TO BLDG	J	U	Y6729	00220
A/C INOP IN HALF THE BLDG	J	E	Y6816	00078
A/C INOP FOR BLDG	J	U	Y8345	02301
Electrical System Failures				
HALF THE BUILDING HAS NO POWER	J	U	Y9066	04701
NO POWER TO BUILDING.	J	U	Y9859	07318
POWER OUT IN WHOLE BLDG	J	U	Z1048	05230
NO POWER	J	U	Z1061	07000
Fire Protection System Failures				
FIRE ALARM IN TROUBLE, ISO DOC	J	U	Y9706	00129
FIRE ALARM IN TROULBE	J	U	Z0427	00183
FIRE ALARM SYSTEM, STILL IN FI	J	E	Z0675	04876
FIRE ALARM INOP	J	U	Z3226	00410
Plumbing System Failures				
NO WATER IN BUILDING.	J	U	Y7782	00130
LOW WATER PRESSURE	J	E	Z0915	02350
WATER CUT OFF IN BLDG	J	U	Z1743	00096
NO WATER	J	E	Z2717	75046

BUILDER® Data

After this research determined the failures for a given system, BUILDER® data was necessary to calculate the average age of each component-section. Component-section data was obtained from BUILDER® by cross referencing the facility ID number (FACIDNR) associated with each failure WO. Because the contingency analysis explained in Chapter III required both a failed and non-failed sample, this research populated a non-failed sample via random sampling from the remaining facilities in each installation's BUILDER® inventory. For continuity of method with Alley (2015), this research populated the non-failed sample to equal the size of the failed sample for each system. This research then obtained component-section data for the non-failed sample to determine the average component-section age.

As a note, this research selected the six bases for analysis based on the quality of their BUILDER® inventory data. However, BUILDER did not contain inventory data for some facilities. If a non-failed system was not in the inventory data, this research randomly chose an additional system to take its place. If a failed system was not in the inventory data, the failed data point was omitted thus reducing both the failed and non-failed samples by the number of omitted data points.

Table 8 displays the number of failures per system per base for 2014. It also annotates the number of systems omitted due to lack of facility inventory data in BUILDER® and total failed sample size per system.

Table 8: Model Performance Assessment Data Summary

Installation	HVAC	Plumbing	Electrical	Fire	
Barksdale	49	4	14	2	Failed
	12	*1*	*5*	*2*	*Omitted*
Cannon	89	10	11	4	
	8	*2*	*2*	*3*	
Davis Monthan	74	4	18	5	
	11	*1*	*6*	*3*	
Keesler	29	3	13	7	
	4	*3*	*4*	*0*	
Patrick	88	2	16	57	
	7	*0*	*7*	*37*	
Scott	88	5	16	2	
	25	*1*	*5*	*0*	
Total Failed	417	28	88	77	
Total Omitted	67	8	29	45	
Failed Population Total	**350**	**20**	**59**	**32**	

Because this research narrowed its focus to HVAC systems and collected additional HVAC system data, it was able to ensure the randomly selected non-failed systems were a representative random sample. The research ensured the non-failed sample was representative with respect to age and size of the facility supported by the HVAC system. Table 9 displays the breakdown of the non-failed HVAC sample compared to that of the non-failed HVAC population. The “bins” used to ensure a representative sample were based on the 10% quantiles of the population with respect to the two attributes. Because the same level of analysis performed on the HVAC systems was not accomplished for electrical, fire protection, and plumbing systems, attribute data was not available to ensure a representative sample for these systems.

Table 9: HVAC Sample Representation

Facility Size (sq ft)			**Facility Year**		
Population Quantiles (sq ft)	**Population**	**Sample**	**Population Quantiles (year)**	**Population**	**Sample**
560	10.0%	10.5%	1951	10.4%	11.6%
1,515	9.9%	10.5%	1958	9.6%	10.8%
2,805	10.0%	11.6%	1968	10.9%	9.3%
4,551	10.0%	9.3%	1977	9.1%	10.5%
6,360	10.3%	10.5%	1986	10.4%	11.0%
9,825	9.8%	10.2%	1991	8.6%	7.3%
15,832	10.0%	11.6%	1996	11.6%	12.2%
25,598	10.0%	11.0%	2000	10.0%	9.3%
45,184	10.0%	6.4%	2006	10.2%	9.3%
275,900	9.9%	8.4%	2014	9.1%	8.7%

Table 9 displays the proportion of the population and sample that fall between the 10% quantiles. As expected, the population proportions are fairly close to 10% in each quantile. With respect to both attributes, Table 9 displays that the sample shows some deviation from the population proportions. To determine if the sample is representative, this research used a t-test to compare the mean population and sample proportions. The t-test employed a null hypothesis of "the true difference in means is equal to zero" at a statistical significance of 0.10. For both facility size and facility year, the t-test failed to reject the null hypothesis with p-values of 0.98 for both tests. Based on these results, this research concludes that there is no difference in mean proportions for both facility size and facility year; and deems the sample used a random representative sample.

Calculations Using PoF Model

After computing the average age for each component-section, this research used equation 27 to calculate each component-sections probability of failure. After which the system level probability of failure was computed using the structure dictated by the PoF model. Due to the large nature of the data set, this research utilized the statistical programming software R to compute the system level probabilities of failure for the four major systems at the six installations. Appendix A displays the calculation results for each installation and Appendix B displays the R code used to compute the system level probability of failures.

$$P_f = 1 - \left[\mathrm{A} \times \left[\frac{1}{CI_f} \right]^{-\left(\frac{t}{\beta}\right)^{\alpha}} \right] \tag{27}$$

Contingency Analysis

From the results displayed in Appendix A, this research was able perform a contingency analysis for each system. The original PoF model validation assumed that a reliability threshold of 37 was the threshold for system failure. This research focuses on determining the performance of each model by determining at what threshold the model displays statistically significant results. This research defines statistical significance as a contingency analysis having a Fisher's Exact p-value less than or equal to 0.10. This p-value indicates a statistically significant relationship between the PoF models output and the truth state. The level indicates that there is less than a ten percent probability that a relationship between the two states is due to random chance. This research also employs an odds ratio to determine the magnitude and direction of the relationship; any odds ration greater than 1.0 indicates a positive relationship. Therefore, this research defines "good model performance" as a contingency analysis having a p-value less than 0.10 combined with an odds ratio greater than or equal to 1.0. Appendix C displays the R code used to calculate and plot p-values and odds ratios over all possible threshold values.

PoF Performance Results: Fire, Plumbing, and Electrical systems

Figure 17 through 20 display the output of the model performance calculations for the four major systems under consideration. The data presented is from all six installations introduced above. A horizontal dashed line is included in each figure to annotate the statistical significance requirement of 0.10. Beginning with Figure 17, the PoF model does not display good performance within the electrical system. However, there are areas of positive relationship between PoF model output and the truth state but not at the statistical significance expected for this research.

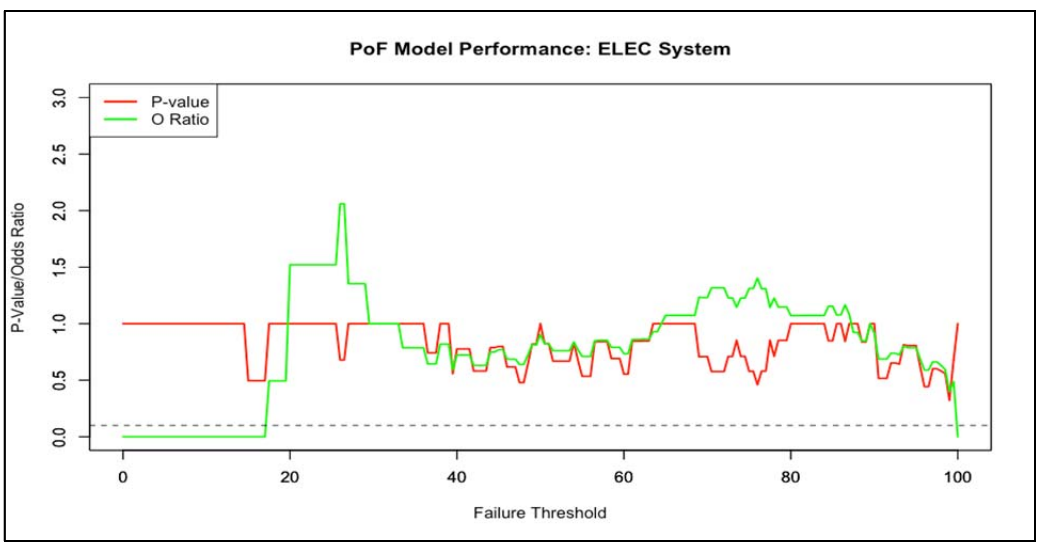


Figure 17: Electrical System PoF Model Performance

Figure 18 displays the results for PoF model performance with respect to the fire protection system. Unlike the electrical system, the PoF displays good performance at a failure threshold of 49, with a p-value of 0.06 and odds ratio of 4.29. This indicates agreement between the model predictive state and the truth state when the reliability threshold is set at 49. This signifies that infrastructure managers should expect to see fire protection system failures when a system receives a reliability estimate at or below 49, as calculated by the PoF model.

Figure 19 displays the results for the PoF model with respect to the plumbing system. The PoF begins to demonstrate a positive relationship at approximately a reliability of 70 and approaches statistical significance at reliability thresholds of 77 and 84. However, the model falls slightly short with p-values of 0.20 and 0.11 respectively. The PoF model does not obtain good performance until a reliability threshold of 95 with a p-value of 0.07 and odds ratio of 5.74. While not statistically significant until a threshold of 95, the PoF model does demonstrate some performance at lower reliabilities and suggest a failure threshold for the plumbing systems may reside in the 70-85 range.

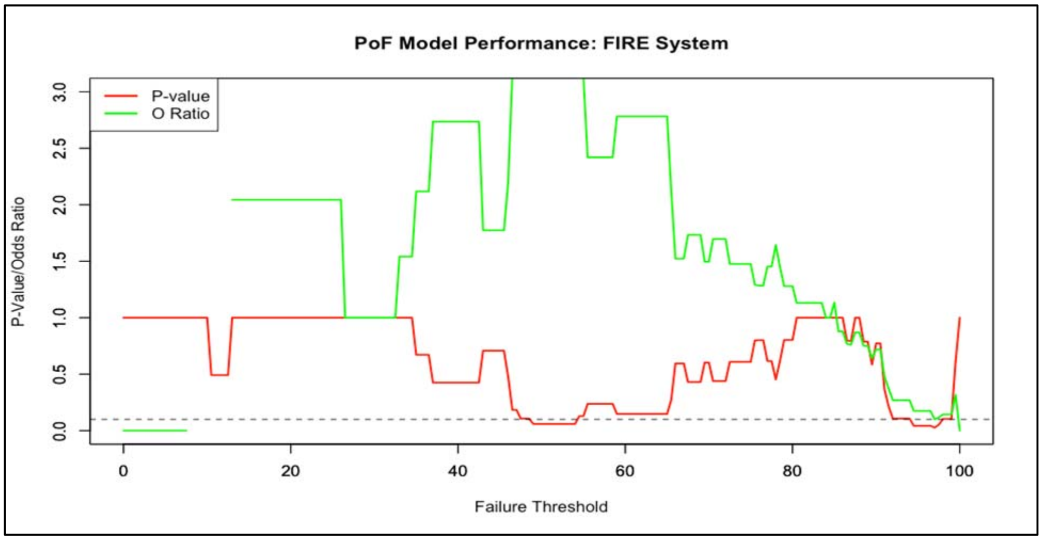


Figure 18: Fire Protection System PoF Model Performance

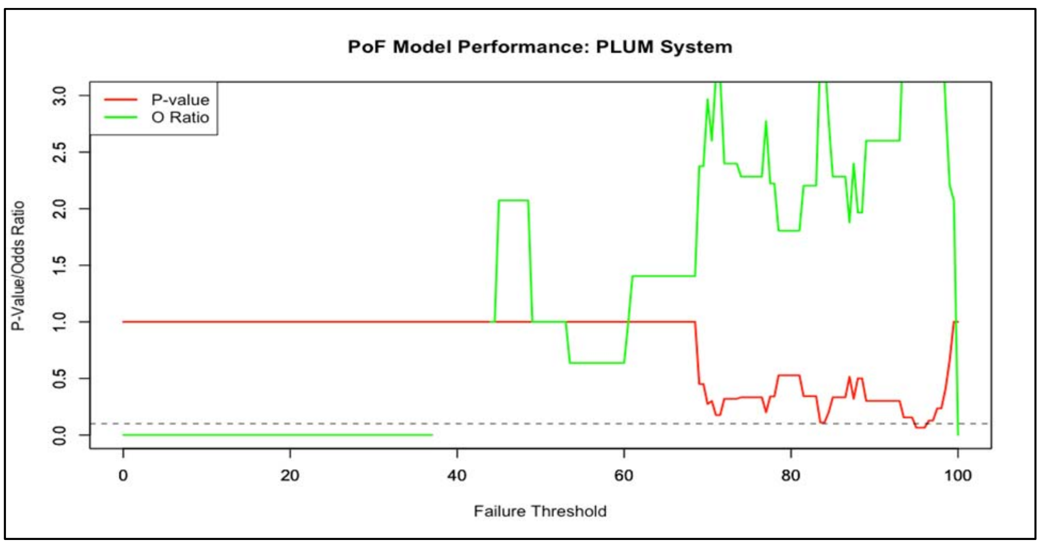


Figure 19: Plumbing System PoF Model Performance

Figure 20 presents the results for PoF model performance with respect to the HVAC system. This figure differs from the previous three in that the model does not display a positive relationship at any reliability threshold. The model attains an odds ratio of 1.0 near a reliability of 90, however the odds ratio never goes above 1.0. Because

PoF model output displays some level of positive relationship with the truth state with the three previous systems and no positive relationship with the HVAC system, this research continued by focusing solely on the HVAC system.

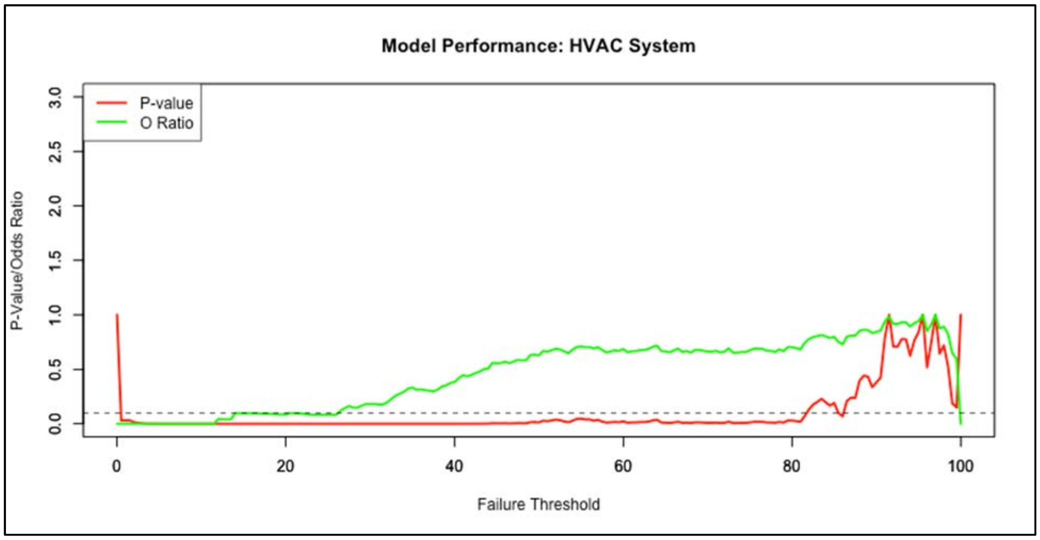


Figure 20: HVAC System Model Performance

SCI Model Performance Results: Fire, Plumbing, and Electrical systems

Similar to the analysis of the PoF model, this research began analyzing the SCI mode with a basic analysis of the fire protection, electrical and plumbing systems. The results of that analysis are displayed in figures 21-23. Figure 21 displays the performance of the SCI model when considering electrical systems. The figure shows no area of positive agreement between the model predictive state and truth state. Figure 22 displays the performance of the SCI model for fire protection systems. The figure displays areas of positive agreement between reliability thresholds of 8-25 and near 65. When analyzing the contingency tables for these thresholds, this research suggests 65 as a more suitable threshold. While not statistically significant with a p-value of 0.59 and odds ratio of 1.52, a threshold of 65 displays greater positive detection to false detection when analyzing the contingency table. Figure 23 displays positive agreement for the plumbing system at reliability thresholds of 88 and 92. Although not statistically significant, when analyzing the contingency tables for these values this research suggests 88 as a more suitable threshold. Having a p-value of 0.32 and an odds ratio 2.39 of, the contingency table for a threshold of 88 displayed more positive detections then false and a balance between false positives and false negatives.

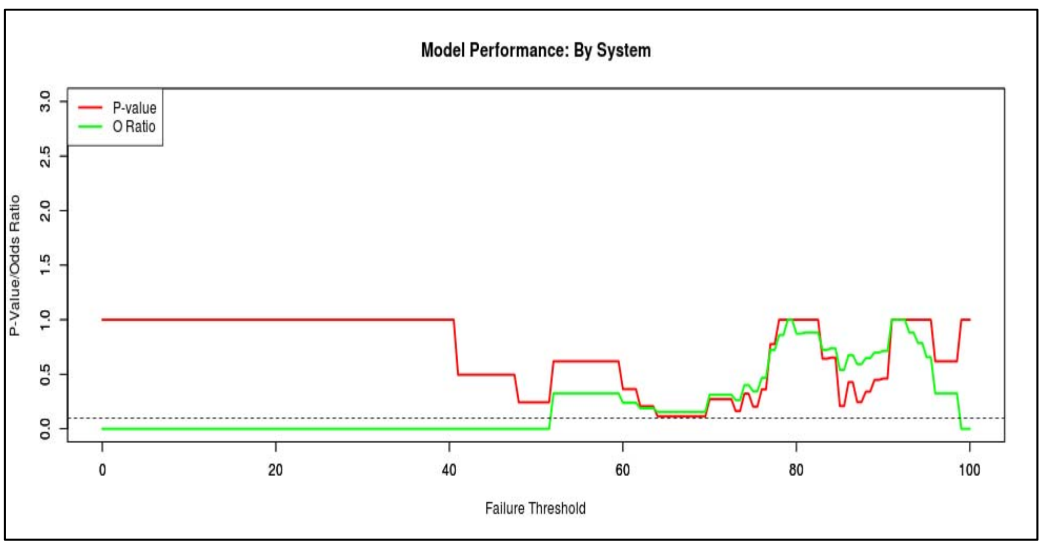


Figure 21: Electrical system SCI Model performance

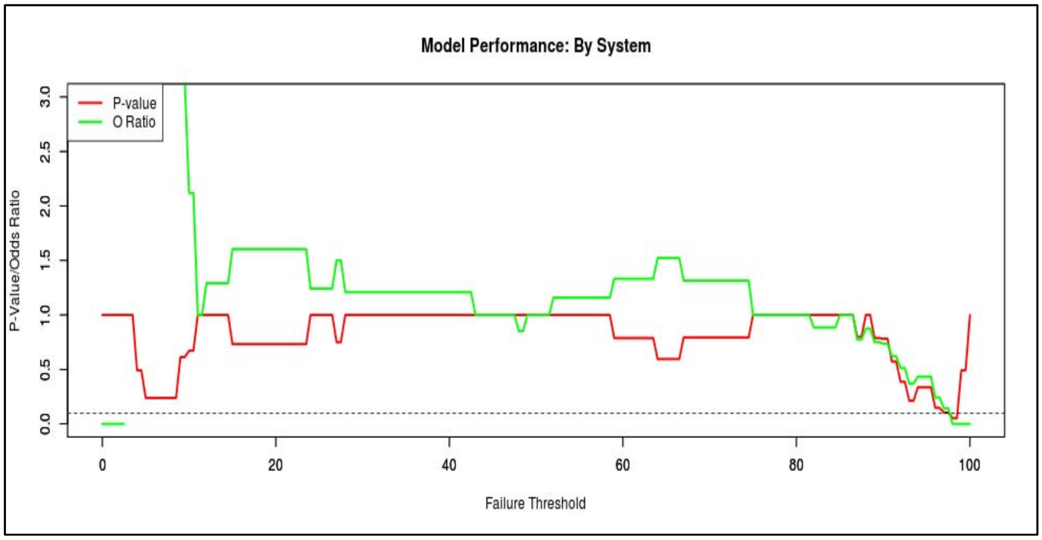


Figure 22: Fire Protection system SCI Model performance

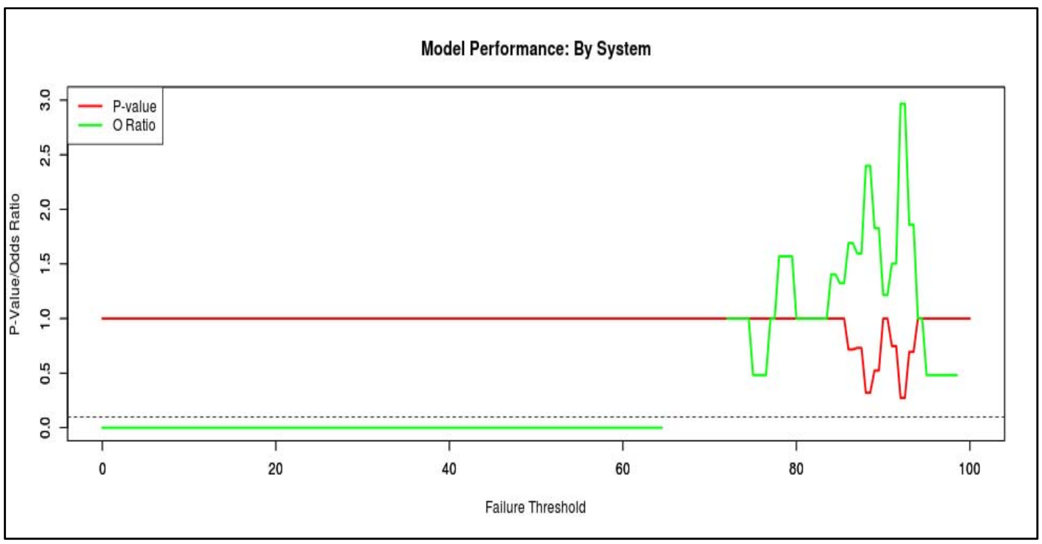


Figure 23: Plumbing system SCI Model performance

Model Performance Assessment: HVAC system analysis

In an attempt to have a greater impact on the reliability analysis for Air Force civil infrastructure and generate greater understanding of each model's performance with respect to a single system, this research limited further analysis solely to HVAC systems. In doing so, this research obtained HVAC system attribute data to determine if the PoF and SCI models performed better with different types and sizes of HVAC systems.

In order to further the analysis, this research determined different attributes associated with each system. The following attributes were obtained from BUILDER® for each HVAC system: number of floors in the facility, square footage of the facility, system age, facility age, and number of unique component-sections in the systems. This research attempted to use a measure of the systems size (total tonnage) as an attribute for analysis. This attribute was ultimately eliminated due to insufficient data on system tonnage within BUILDER®.

This research created and utilized a Shiny© application to manipulate the type and range of the above attributes to asses each model's performance. For example, a system attribute of facility square footage can be selected and HVAC systems supporting facilities larger than 15,000 square feet can be assessed. The Shiny© application developed for this research is available at https://prdhd7.shinyapps.io/Deering-16-M-143/#1. The application is interactive and users may select and change system attributes for analysis.

PoF Model Results: HVAC systems

Figures 24 through 35 display the results of assessing PoF performance against different facility attributes. Figure 24 displays the PoF model performance when analyzing facilities that are 15,000 sq-ft to 25,000 sq-ft. While not at the statistical significance desired, the model begins to show agreement with the truth state at a reliability threshold near 40. This particular example shows how accounting for other system features can increase the predictive capability of the PoF model. Figure 25 displays the resulting contingency table, p-value, and odds ratio for a reliability threshold of 40.

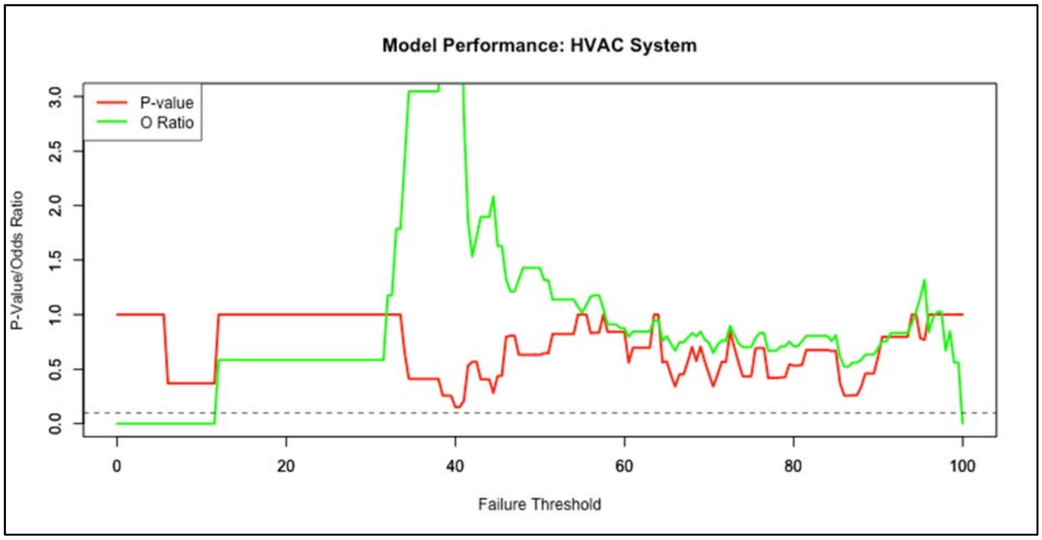


Figure 24: HVAC PoF Model (15K-25K Sq Ft)

		PoF Predicted State				
		Failed	Not Failed			
Truth State	Failed	8	67	75	CI_f =	40
	Not Failed	1	43	44	p-value =	0.151
		9	110	119	odds ratio =	5.082

Figure 25: HVAC PoF Model (CI_f = 40, 15K-25K Sq Ft)

The analysis continued by increasing the range of facility square footage to all facilities greater than 15,000 sq ft. Figure 26 displays the results for the PoF model for these facilities indicating good performance at a reliability threshold of 35. Figure 27 displays the resulting contingency table, p-value, and odds ratio for a reliability threshold of 35. The model displays statistically significant results with an odds ratio of infinity.

An odds ratio of infinity is a result of the contingency table having a zero count in the "false positive" cell. While this result satisfies the requirements for statistically significant agreement between the PoF model predicted state and truth state, the contingency table in Figure 27 shows large count of "false negatives". This displays the PoF model leaves a substantial amount of failures left undetected.

One could reasonably assume that larger facilities have larger HVAC systems; and large HVAC systems will likely have more unique component-sections. Therefore, this research examined if the PoF model displayed any performance when limited to larger number of unique component-sections.

Figure 28 displays PoF model results for systems with seven or more unique component-sections. Although the model does not display good performance at any reliability threshold it does display positive agreement at a threshold of 35, similar to that of larger facilities (≥ 15,000 sq ft).

This research also assessed model performance with respect to the number of floors in a facility. Figure 30 displays the PoF model performance for facilities with 3 or more stories. The model begins to display a positive relationship near a reliability threshold of 70 and continues to display this relationship through a reliability of 99. In this range, the model displays the best performance at a reliability threshold of 77.5, displayed in Figure 31. While this result is not consistent with a reliability threshold of 35 displayed in Figures 26-29, it does suggest that a reliability threshold exists at 77.5. The merit with this threshold is the increased recognition of true failures. While a threshold of 77.5 does not eliminate false positives or false negatives, the ratio of false detections to positive detections is substantially improved.

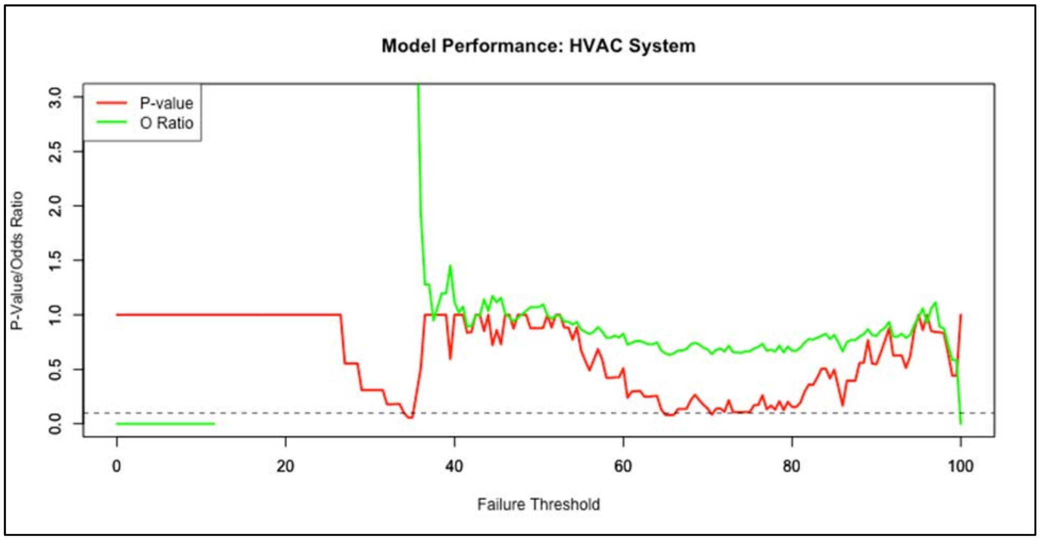


Figure 26: HVAC PoF Model (≥ 15K Sq Ft)

		PoF Predicted State				
		Failed	Not Failed			
Truth State	Failed	8	196	204	CI_f =	35
	Not Failed	0	96	96	p-value =	0.058
		8	292	300	odds ratio =	Infinity

Figure 27: HVAC PoF Model (CI_f = 35, ≥ 15K Sq Ft)

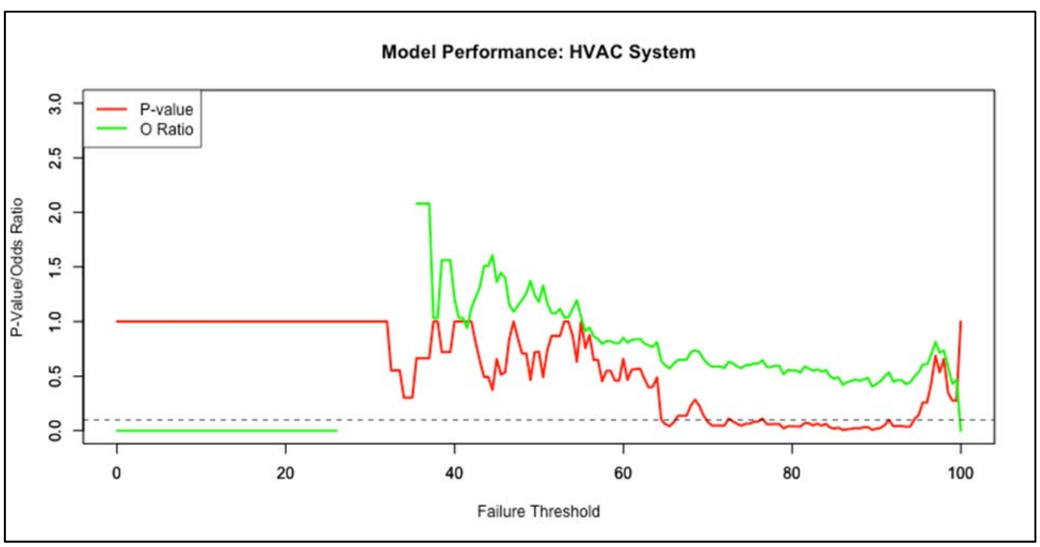


Figure 28: HVAC PoF Model (≥ 7 component-sections)

		PoF Predicted State		
		Failed	Not Failed	
Truth State	Failed	4	163	167
	Not Failed	0	86	86
		4	249	253

CI_f = 35
p-value = 0.302
odds ratio = Infinity

Figure 29: HVAC PoF Model (CIf = 35, ≥ 7 component-sections)

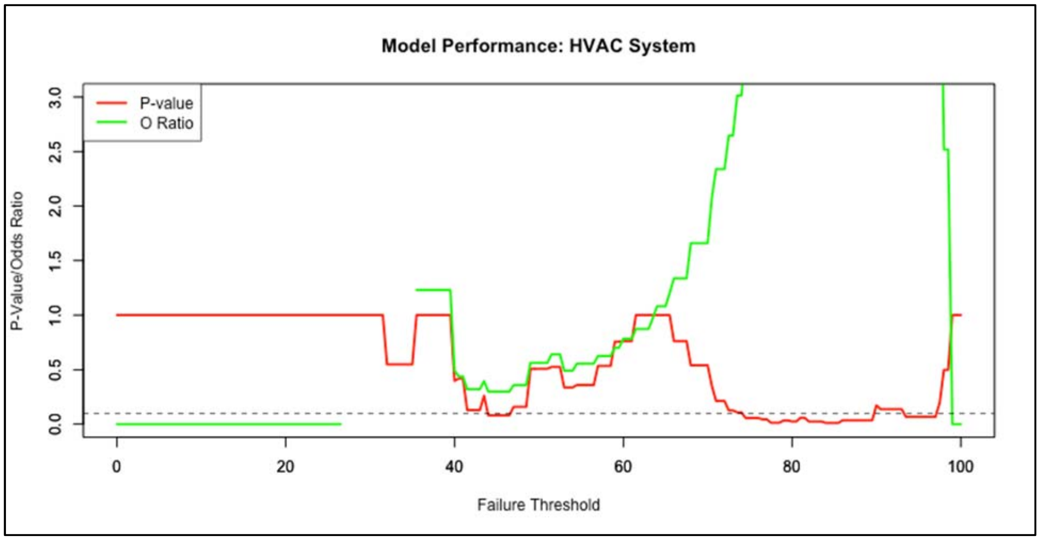


Figure 30: HVAC PoF Model (3-9 Floors)

		PoF Predicted State		
		Failed	Not Failed	
Truth State	Failed	31	6	37
	Not Failed	7	8	15
		38	14	52

CI_f = 77.5
p-value = 0.013
odds ratio = 5.695

Figure 31: HVAC PoF Model (CIf = 77.5, ≥ 3 stories)

Aside from indicators of facility size, this research also assessed the PoF model against age based attributes. When analyzing against facility age, this research found no ranges in which the PoF model displayed good performance. However, the PoF model displayed good performance when analyzed against system age and segregated into two ranges: 0-9 years and ≥ 9 years. Figure 32 and Figure 33 display the PoF model performance for systems with an average age greater than or equal to nine years. The model displays good performance at a reliability threshold of 92.5. Figure 33 displays the contingency table for this scenario highlighting a large proportion of true positives and false positives. Figure 34 displays the PoF model performance for systems with an average age of 0-9 years. Interestingly the model displays a reliability threshold of 91.5 for this range, similar to that of systems nine years and older. In contrast to the older systems, the contingency table for this scenario displays large proportion of true detections to false detections which is not the case for scenario with the systems greater than 9 years old.

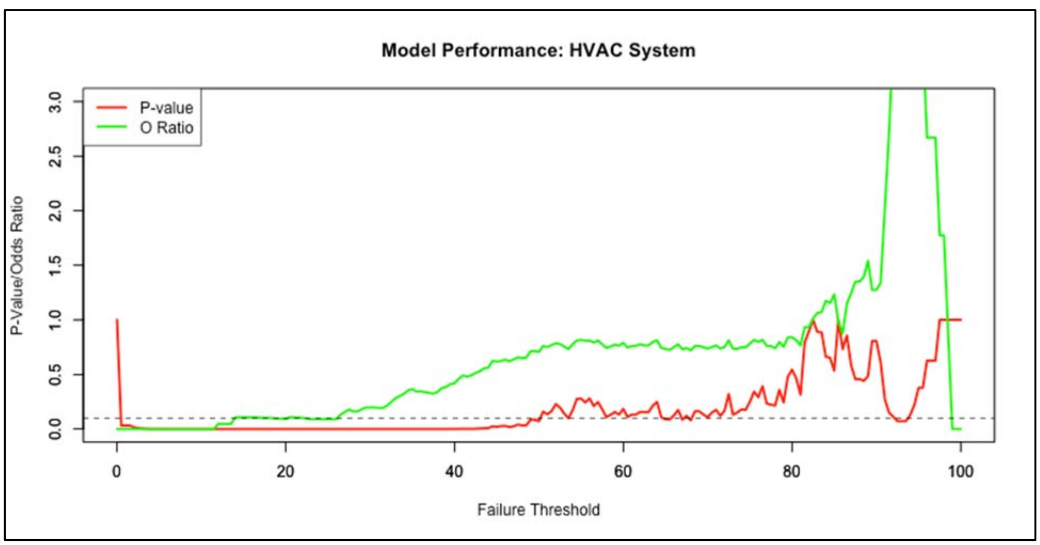


Figure 32: HVAC PoF Model (System age ≥ 9 years)

		PoF Predicted State				
		Failed	Not Failed			
Truth State	Failed	238	1	239	CI_f =	92.5
	Not Failed	263	7	270	p-value =	0.072
		401	8	409	odds ratio =	6.316

Figure 33: HVAC PoF Model (CI_f = 92.5, System age ≥ 9 years)

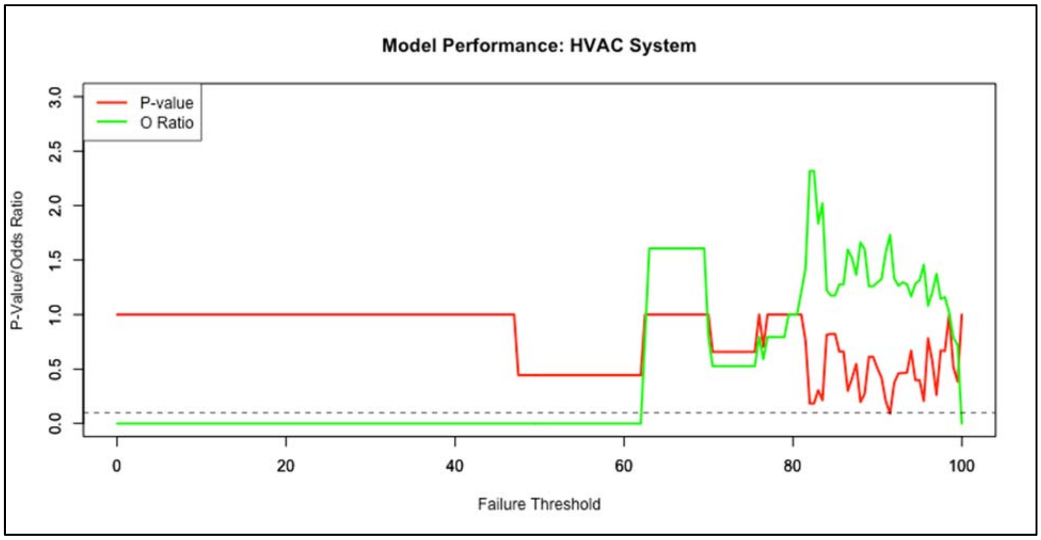


Figure 34: HVAC PoF Model (System age 0-9 yrs)

		PoF Predicted State				
		Failed	Not Failed			
Truth State	Failed	39	76	115	CI_f =	91.5
	Not Failed	21	71	92	p-value =	0.091
		60	147	207	odds ratio =	1.730

Figure 35: HVAC PoF Model (CIf = 91.5, System age 0-9 yrs)

In addition to PoF model assessment using HVAC system attribute data, this research also analyzed the models performance with respect to installation. By doing so, this research could determine if the model displayed differences in reliability thresholds based on the installation under consideration. This research used the HVAC systems analyzed above to perform this analysis.

Table 10 displays the results of the installation level analysis. All six installations displayed areas of positive agreement between the model predictive state and the truth state. However, the model did not display areas of statistically significant agreement when considering installation. Additionally, the majority of possible reliability thresholds identified do not appear suitable due to the large number of false detections. This research ultimately concluded that installation was not a variable that contributed to the significance of the PoF model's performance.

Table 10: PoF Model performance for HVAC systems by installation

	CI_f	P-value	Odds ratio	Suitability
Barksdale				
>7 Component Sections	53	0.27	2.81	Large number of false negatives
Cannon				
Sq ft > 15K	65	0.13	2.98	Large number of false negatives
System Age 0-9 yrs	95.5	0.23	2.28	Large number of false negatives
Davis Monthan				
System Age 0-9 yrs	91.5	0.22	4.22	Large number of false negatives
System Age > 9 yrs	92	0.12	Inf	Large number of false positives
Keesler				
Sq ft > 15K	51	0.12	4.20	Large number of false negatives
>7 Component Sections	51	0.24	2.80	Greater positive detections to false
System Age > 9 yrs	51	0.31	2.24	Large number of false negatives
Patrick				
System Age 0-9 yrs	91.5	0.21	2.10	Greater positive detections to false
System Age > 9 yrs	82	0.33	2.27	Large number of false positives
Scott				
System Age > 9 yrs	83	0.57	1.61	Large number of false positives

PoF Model Performance Summary

Overall the PoF model showed sporadic performance in agreement with the truth state and model output at reliability thresholds of 35, 77.5, 91.5, and 92.5. Among these thresholds, this research noted a reliability of 35, similar to that of the current 37. However, this threshold resulted in a substantial amount of false negatives. Reliabilities of 77.5 and 91.5 stand out as more likely thresholds. While each scenario has both false negatives and false positive detections, the number of positive detections is greater than the number false detections, indicating better model performance. However, reliability thresholds of 77.5 and 91.5 are fairly high, suggesting the PoF model may be over estimating HVAC system reliability.

SCI Model Performance: HVAC systems

Figure 36 displays the performance for the SCI model for facilities greater than 12,000 square feet. The model achieves good performance at a SCI threshold of 55 with a p-value of 0.064 and odds ratio of 4.013. The associated contingency table in Figure 37 displays the results and indicates a similar to trend to that of the PoF model; the model predicts a large number false negatives.

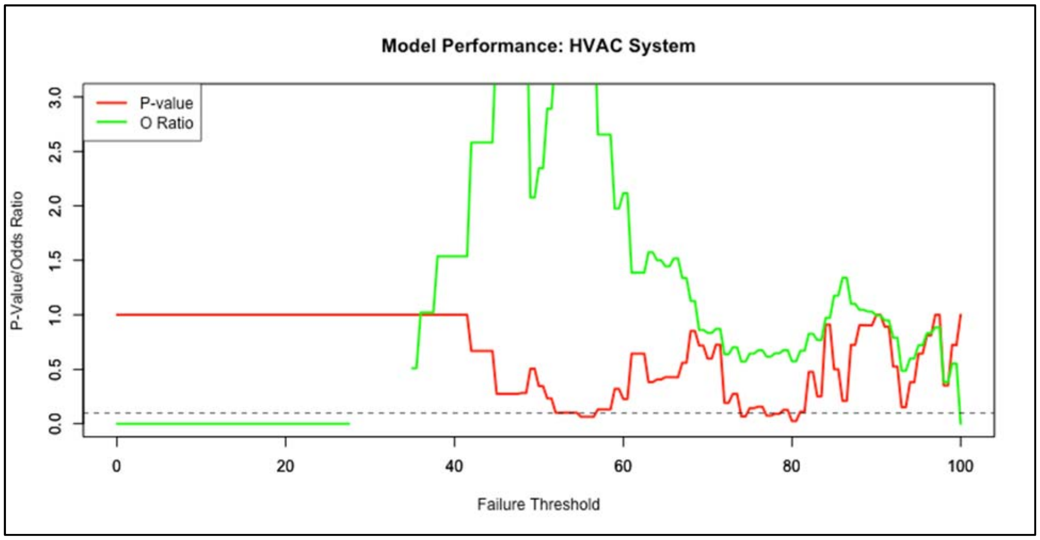


Figure 36: HVAC SCI Model (≥ 12K Sq Ft)

		SCI Predicted State				
		Failed	Not Failed			
Truth State	Failed	15	218	233	CI_f =	55
	Not Failed	2	117	119	p-value =	0.064
		17	335	352	odds ratio =	4.013

Figure 37: HVAC SCI Model (CI_f = 55, ≥ 12K sq ft)

Figure 38 displays the performance of the SCI model with respect to 7 or more unique component-sections. For these facilities, the model displays statistically significant results at a reliability threshold of 66 and a possible SCI threshold of 55. Figure 39 and 40 display the contingency tables for these two thresholds which indicates, again, a trend of numerous false negative predictions. Due to the nature of displaying two possible reliability thresholds, this indicates the possibility of a true SCI threshold residing somewhere within the 55-66 range.

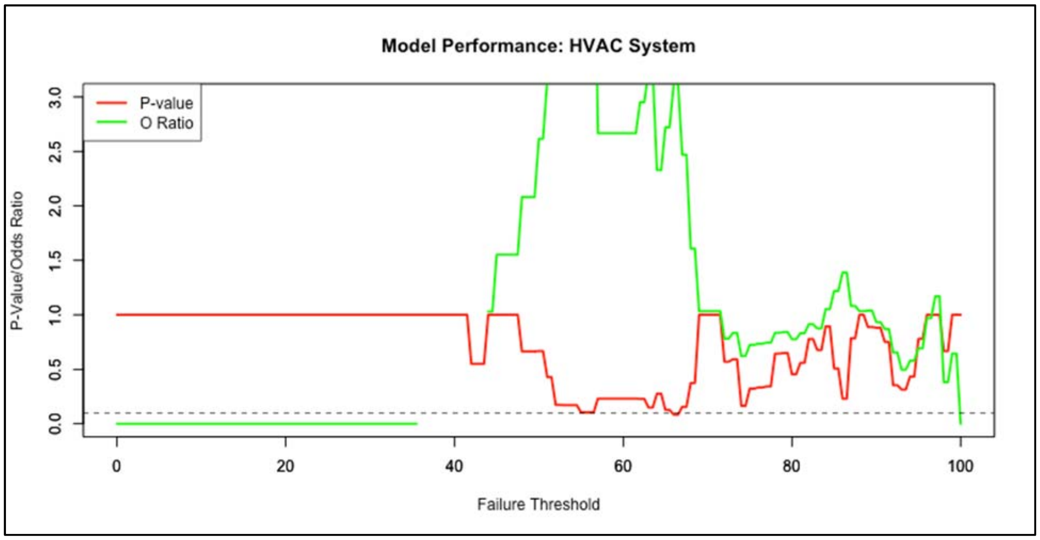


Figure 38: HVAC SCI Model (≥ 7 component-sections)

		SCI Predicted State				
		Failed	Not Failed			
Truth State	Failed	17	150	167	CI_f =	66
	Not Failed	3	83	86	p-value =	0.084
		11	242	253	odds ratio =	3.124

Figure 39: HVAC SCI Model (CI_f = 66, ≥ 7 component-sections)

		SCI Predicted State				
		Failed	Not Failed			
Truth State	Failed	10	157	167	CI_f =	55
	Not Failed	1	85	86	p-value =	0.104
		11	242	253	odds ratio =	5.388

Figure 40: HVAC SCI Model(CI_f = 55, ≥ 7 component-sections)

When considering age related attributes, the SCI model displays fairly consistent results when segregating both facility age and system age. With respect to facility age, the model displays a high level of agreement over ages 0-40 years and statistically significant agreement at ages 20-40 years old. Figure 41 and Figure 43 display the results for these scenarios, indicating a reliability threshold of 86. With respect to system age, the model displays agreement over a range from 0-20 years, 20-40 years, and 0-40 years. In each scenario the model indicates a reliability threshold at or near 86. Figure 45 and Figure 47 display the results for the 0-20 years and 20-40 years scenarios. In both scenarios, false positive and false negative detections are present; however, the model presents a greater number of positive detections than false detections. This finding suggests that an SCI score of 86 is more appropriate than previously discussed thresholds.

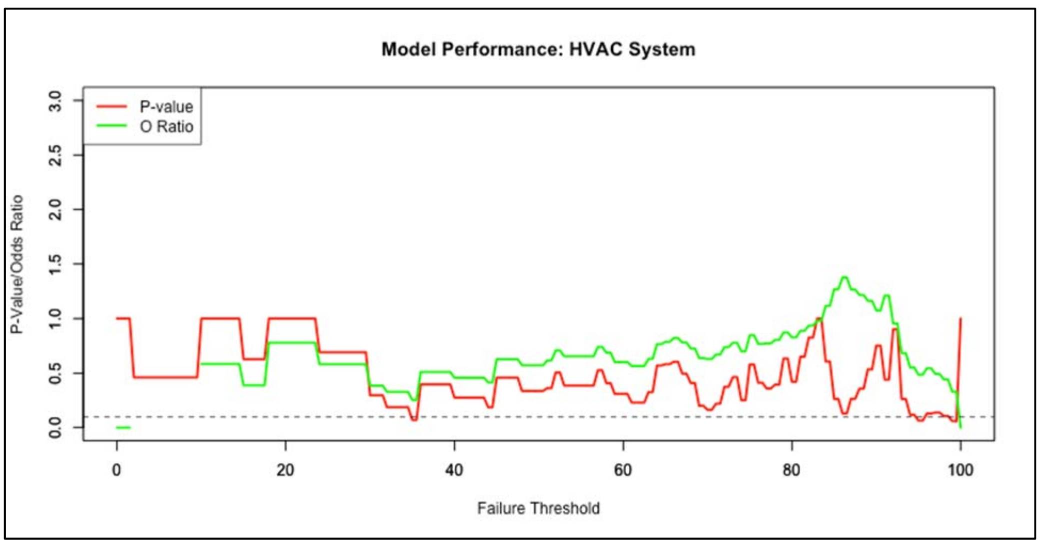


Figure 41: HVAC SCI Model (Facility age 0-40 years)

		SCI Predicted State				
		Failed	Not Failed			
Truth State	Failed	100	82	182	CI_f =	86
	Not Failed	100	113	213	p-value =	0.130
		200	195	395	odds ratio =	1.376

Figure 42: HVAC SCI Model(CI_f = 86, Facility age 0-40 years)

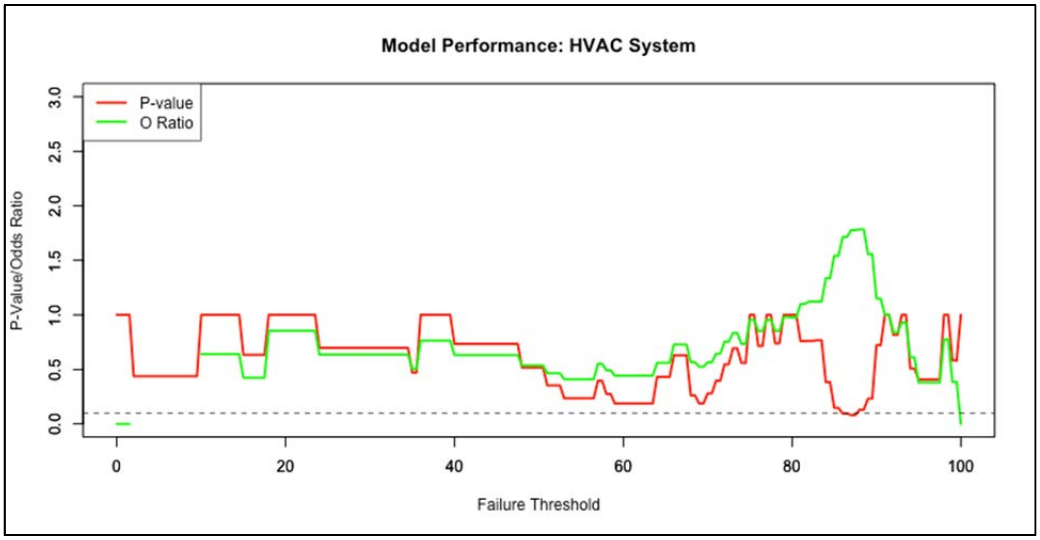


Figure 43: HVAC SCI Model (Facility age 20-40 years)

		SCI Predicted State				
		Failed	Not Failed			
Truth State	Failed	60	24	84	CI_f =	86
	Not Failed	64	44	108	p-value =	0.095
		124	68	192	odds ratio =	1.714

Figure 44: HVAC SCI Model(CI_f = 86, Facility age 20-40 years)

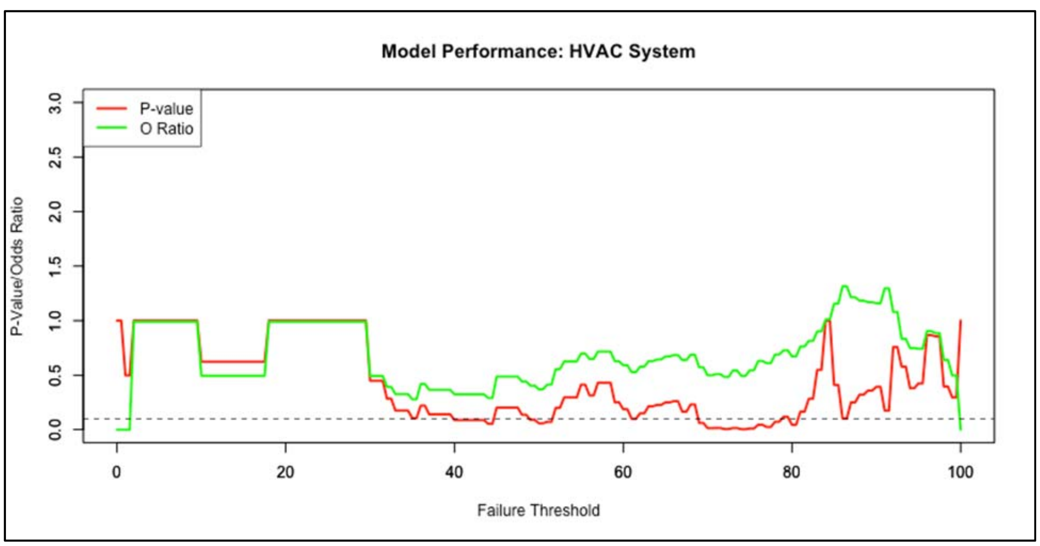


Figure 45: HVAC SCI Model (System age 0-20 years)

		SCI Predicted State				
		Failed	Not Failed			
Truth State	Failed	161	140	301	CI_f =	86
	Not Failed	139	159	298	p-value =	0.102
		300	299	599	odds ratio =	1.314

Figure 46: HVAC SCI Model(CI_f = 86, System age 0-20 years)

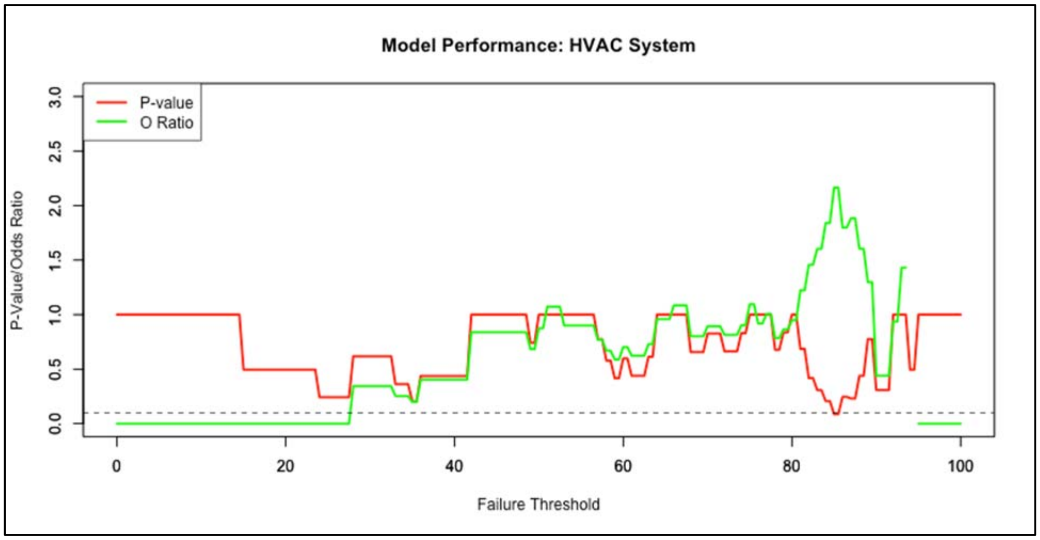


Figure 47: HVAC SCI Model (System age 20-40 years)

		SCI Predicted State				
		Failed	Not Failed			
Truth State	Failed	36	11	47	CI_f =	86
	Not Failed	30	20	50	p-value =	0.087
		66	31	97	odds ratio =	2.164

Figure 48: HVAC SCI Model(CI_f = 86, System age 20-40 years)

Lastly, Figure 49 displays the SCI model performance for all facilities considered. The model shows good performance again at a reliability threshold of 86 with a p-value and odds ratio of 0.09 and 1.30, respectively, and the associated contingency table is displayed in Figure 50. The contingency table displays a high number of false positives and false negatives; however, the model attains more positive detections than false detections. The statistical significance at this threshold indicates that for a majority of the 700 HVAC systems considered, Air Force civil engineers are assigning SCIs of up to 86 for systems that soon after fail.

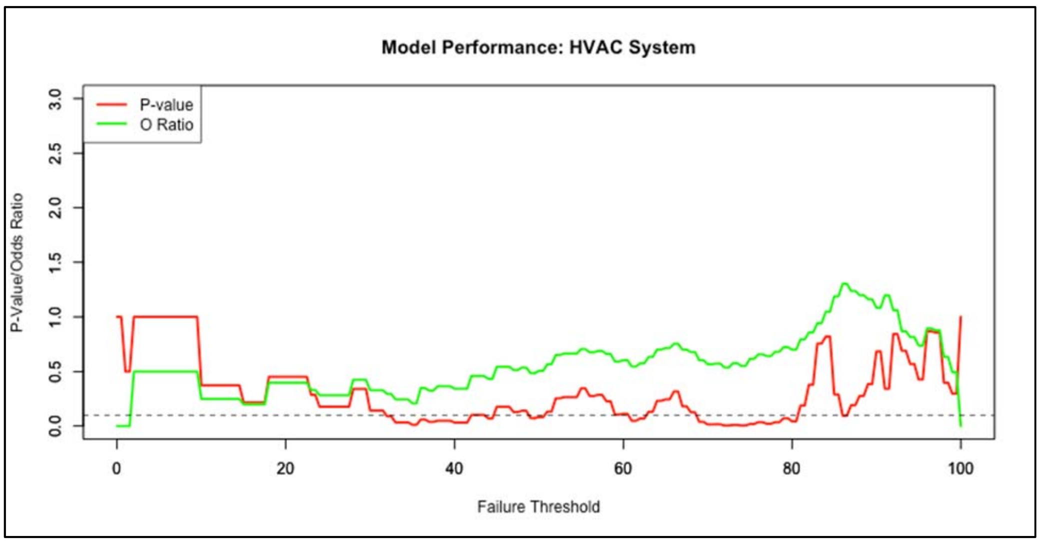


Figure 49: HVAC SCI Model

		SCI Predicted State				
		Failed	Not Failed			
Truth State	Failed	201	149	350	CI_f =	86
	Not Failed	178	172	350	p-value =	0.095
		379	321	700	odds ratio =	1.303

Figure 50: HVAC SCI Model (CI_f = 86)

In addition to analyzing the SCI model against system attributes, this research sought to understand the performance of the model when considering systems at individual installations. Table X displays the results for the SCI model for HVAC systems at each installation. Five out of the six installations displayed areas of positive agreement. Three of which (Davis Monthan AFB, Keesler AFB, and Patrick AFB) displayed statistically significant agreement at or near 86, the reliability threshold noted when considering all systems in Figure 49. Additionally, the systems at these installations showed relatively consistent performance when considering multiple system attributes.

Cannon AFB and Scott AFB displayed consistent agreement across multiple attributes, but at substantially different reliability thresholds. Cannon AFB displayed statistically significant agreement at a threshold of 91 while Scott AFB displayed statistically significant agreement at a threshold of 71. This suggests that the installation under consideration can have an effect on the appropriate reliability threshold for a system.

Table 11: SCI Model performance for HVAC systems by installation

	CI_f	P-value	Odds ratio	Suitability
Cannon				
All Facilities	91	0.10	1.95	Greater positive detections to false
Fac Age 20-40 yrs	91	0.11	Inf	Large number of false positives
Syst Age 0-20 yrs	91	0.02	2.37	Greater positive detections to false
Davis Monthan				
All Facilities	86	0.12	1.92	Greater positive detections to false
Fac Age 20-40 yrs	86	0.09	2.96	Greater positive detections to false
Keesler				
All Facilities	85	0.04	3.91	Greater positive detections to false
>7 Component Section	86	0.06	5.15	Greater positive detections to false
Fac Age 0-40 yrs	86	0.02	6.92	Greater positive detections to false
Syst Age 0-20 yrs	85	0.02	5.98	Greater positive detections to false
Patrick				
Sq Ft > 14.6K	89	0.06	4.17	Greater positive detections to false
Syst Age 0-20 yrs	85	0.11	1.72	Greater positive detections to false
Scott				
Sq Ft > 2.6K	71	0.05	2.81	Greater positive detections to false
>7 Component Section	67	0.07	6.19	Large number of false negatives
Syst Age 0-20 yrs	71	0.04	4.06	Greater positive detections to false

SCI Model Performance Summary

The SCI model displayed statistically significant agreement with the truth state at reliability thresholds of 55, 66, and 86. When analyzing the contingency tables at thresholds of 55 and 66, the model predicted numerous false negatives indicating these may not be accurate threshold values. However, the model consistently shows statistical agreement with the truth state at a reliability threshold of 86. When analyzed at 86, the model consistently presented more positive detections than false detections suggesting 86 as more accurate reliability threshold. Similar to the PoF model, a threshold this high indicates the SCI model is likely overestimating HVAC system reliability. Additionally, the results of Table 11 suggest the installation under consideration may have an impact as to what reliability threshold is appropriate for a system.

Model Accuracy Assessment

This section will present the data, results, and discussion associated with assessing the accuracy of the PoF and SCI models via a Non-homogeneous Poisson Process in conjunction with the Availability Growth Model.

Failure Data

This research utilized two data sets when analyzing the PoF model accuracy. In the first stage of this analysis this research used HVAC failure data from the six previously mentioned Air Force installations. This research captured HVAC system failures via IWIMS work orders from calendar year 2013 and 2014.

Table 12 displays the total number of failures per year, per installation. The following results will show that this data set was deemed unsuitable thus requiring a second data set. The second data comprised solely of HVAC failures from Cannon Air Force Base, dating back to 1995. The primary intent for developing a new data sat was to collect HVAC failures over a system's lifetime in contrast to only a 2 year period. Therefore, due to the IWIMS data dating back to 1995, facilities constructed prior to this year were not considered. This research randomly selected 30 facilities constructed on or after 1995. In order to capture additional "older" facilities that could offer more lifetime data, the sample was ultimately increased to 33 systems. Appendix D displays the failure data collected for these facilities.

Table 12: PoF Model Accuracy Assessment Data Summary

Installation	2013	2014	Total
Barksdale	99	62	161
Cannon	71	181	252
Davis Monthan	84	113	197
Keesler	44	31	75
Patrick	140	251	391
Scott	125	230	355
Total	**563**	**868**	**1431**

Results

The initial assessment for determining if the data fit a nonhomogeneous process was a visual check using Duane plots. The system under consideration likely followed a NHPP with a power-law intensity function if the cumulative mean time between failure (MTBF) versus failure time displayed a linear tend. This research began this portion of analysis by assessing the Duane plots of the data presented in Table 12. Figure 51 presents the plot for this data set and displays a mostly linear trend from 0-7000 days (0-19 years), at which the cumulative MTBF sharply increases into a secondary linear trend. This research concluded that the shift in trend was likely due to truncated failure data. Truncation occurs when observations outside a particular range are not known (Meeker & Escobar, 1998). In this case, truncation occurred because failure events outside of 2013 and 2014 were not know. This research noticed similar trends in all six installations. Appendix E displays similar plots to Figure 51 for all six installations individually.

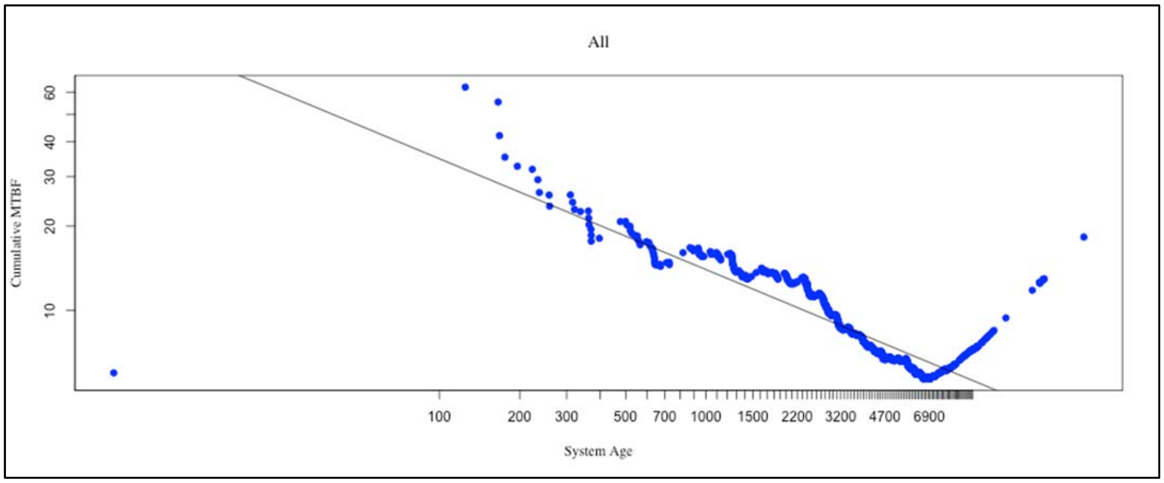


Figure 51: HVAC Duane plot for all installations (CY13/14 failures)

To overcome the perceived issues with truncated failure data, this research adjusted failure times by counting the time to failure from the beginning of the window in which data was collected. In other words, Figure 51 displays failure times counted from when a system was placed into operation while Figure 52 displays data with failure times counted from January 1, 2013. This correction resulted in a plot that displayed s somewhat linear trend. This research assesses the goodness of fit via the Cramer-von Mises test statistic. Table 13 displays the results, highlighting that the resulting test statistic is well above the critical value at a significance level of 0.10, thus rejecting the null hypothesis that data fit a NHPP with power-law intensity function. This research obtained critical values for the Cramer-von Mises test statistic from Military Handbook 189 (Department of Defense, 1981).

Table 13: Goodness of Fit results for truncation adjusted HVAC data

N	$\hat{\beta}$	$\hat{\lambda}$	C_M^2	C_M^2 crit
1423	1.6124	0.0344	4.201	0.173
4.20 > 0.17, reject H_o of NHPP power-law intensity				

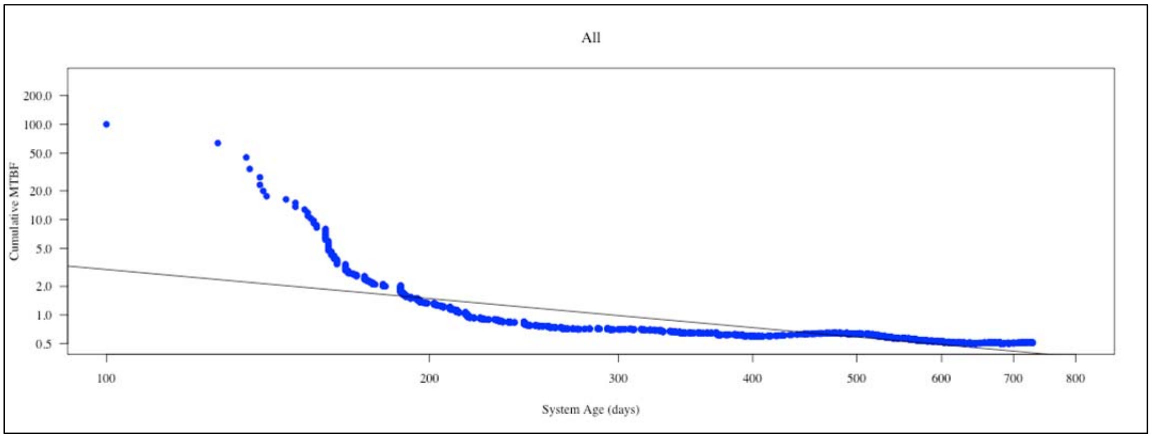


Figure 52: HVAC Duane plot for all installations (CY13/14 failures adjusted for truncation)

Due to the inability to develop an availability growth model with the data presented above, this research limited its focus to HVAC systems at Cannon Air Force base in an effort to collect system lifetime failure data. The data used for this portion of analysis is presented in Appendix D. Beginning with visual assessment of the Duane plots, figures 53-54 present 12 of the 33 systems analyzed. These figures help summarize the visual assessment and are used to describe the general theme for how the systems considered visually fit the NHPP. Appendix F displays Duane plots for all 33 facilities.

Of the 40 systems analyzed, Figure 53 presents six plots for the HVAC systems that displayed a good linear trend. However, only four of the six systems in this figure pass the Cramer-von Mises goodness of fit test, displayed in Table 14. Of the six plots, five display deteriorating systems while the HVAC system in building 00208 displays a positive trend at roughly 600 days, indicating an improving system.

Figure 54 displays additional facilities that show changes in trend from a deteriorating system to an improving system. In this analysis, seven total systems displayed trend changes (00208, 01155, 01159, 01161, 02134, 02206, and 04081). This research referenced BUILDER® inventory data to determine if possible component-section replacement efforts could account for the system improvement and ultimately found no information to suggest this. If there were data to suggest component-section replacement affected the MTBF, this research could have assessed the systems fit to a NHPP after the replacements were made. However due to the lack of data to suggest the change in trend was the cause of a replacement effort, this research could not reasonably exclude data prior to trend change. Overall, of these seven systems only three (00208, 02134 and 04081) pass the Cramer-von Mises test statistic suggesting that the remaining four systems do not follow a NHPP.

Appendix F displays the remainder of the Duane plots for the systems analyzed by this research. The majority of these plots either display no linear trend or comprise of only 2-3 data points, thus making it difficult to make a declaration as to the visual fit of the system. Table 14 displays the parameters and goodness of fit results for all 40 systems analyzed. Of the 40 systems only 20 pass the Cramer-von Mises test statistic satisfying the null hypothesis that the HVAC systems analyzed fit a NHPP. Due to this low level of agreement, this research concludes that fitting HVAC systems to a NHPP with power-law intensity is not effective for estimating the MTBF, thus could not accurately calculate a measure of system reliability via this method.

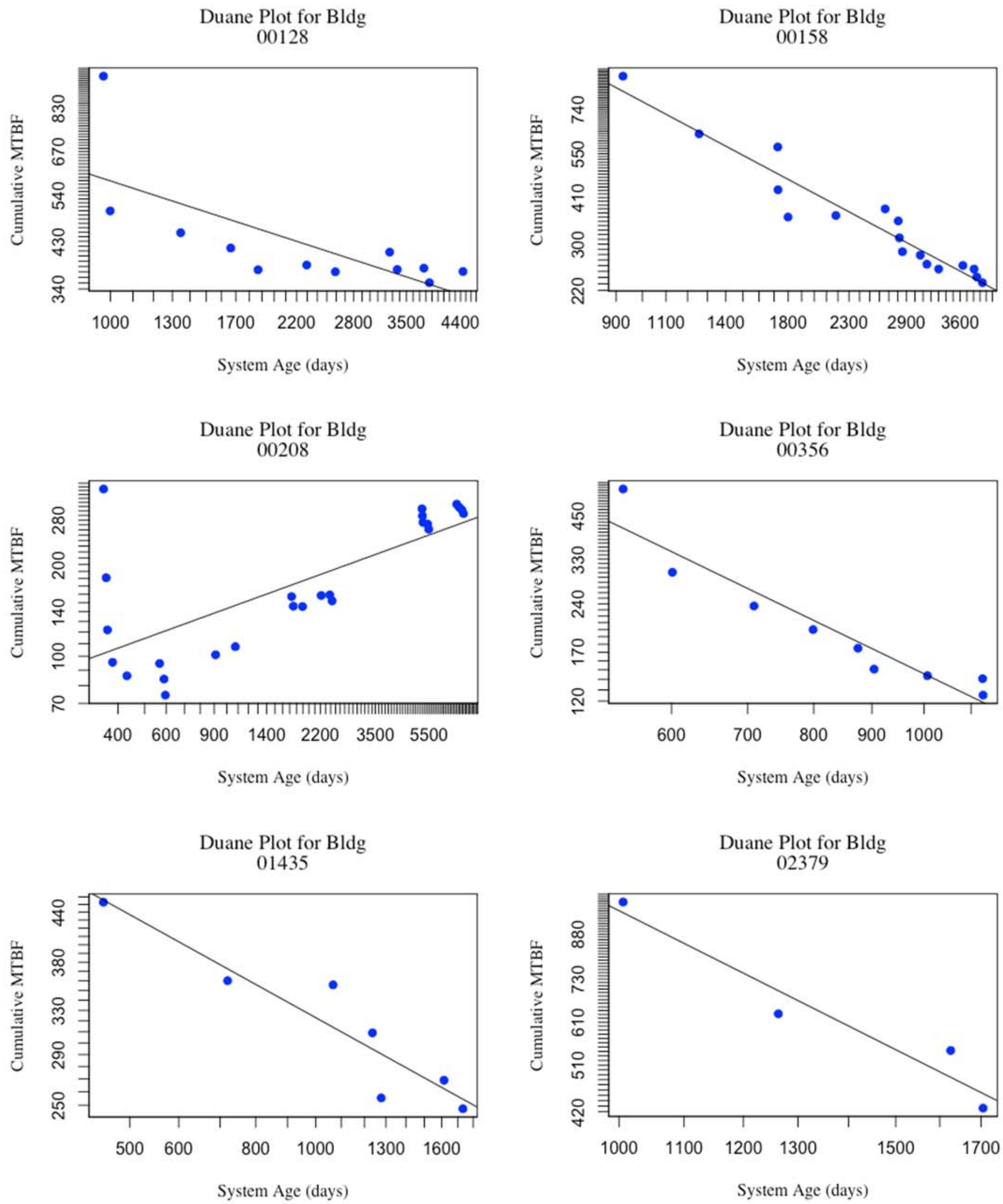


Figure 53: Duane plots displaying good fit

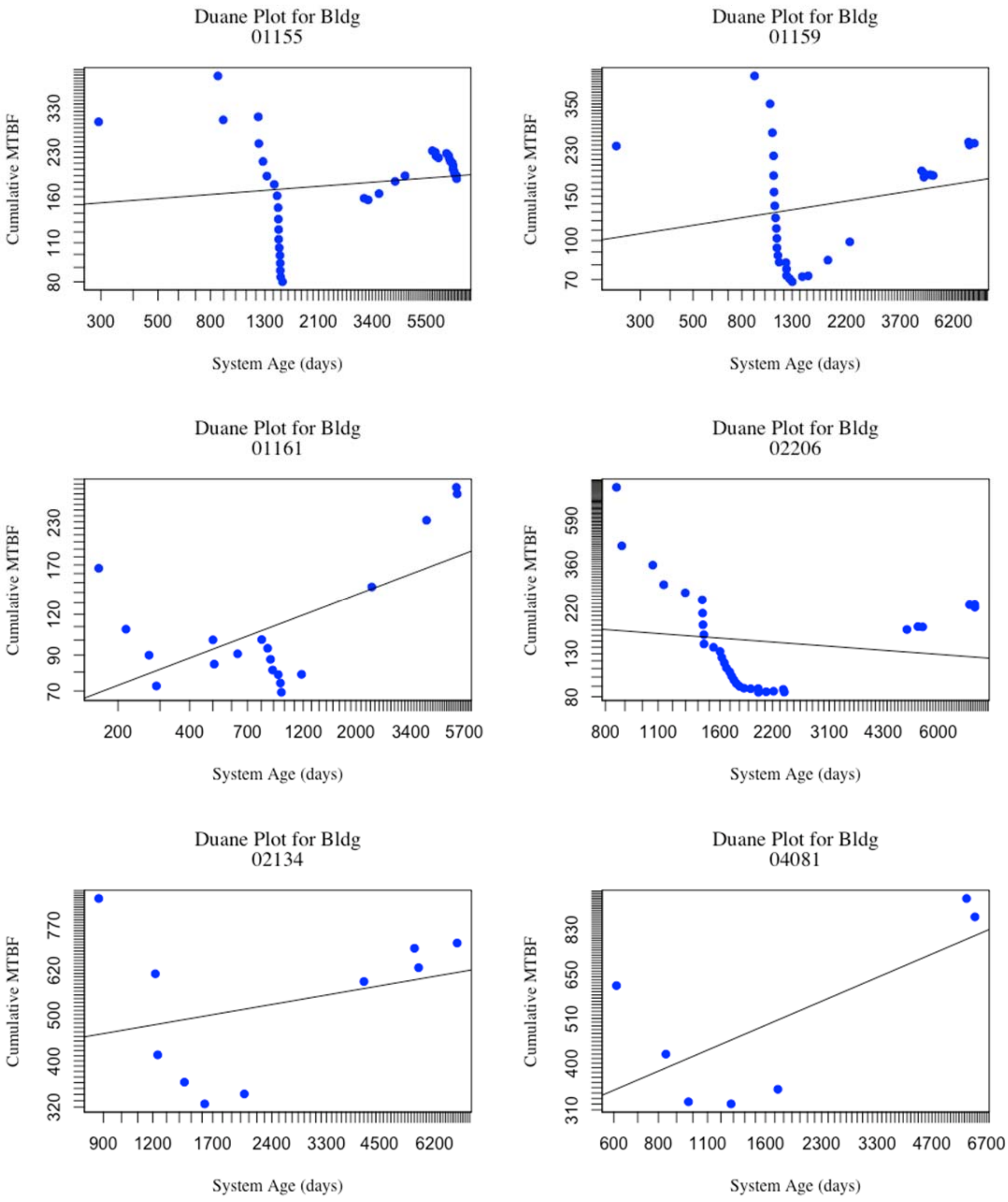


Figure 54: Duane plots displaying changing trends

Table 14: Parameter and Goodness of Fit Results

Bldg	System Age	N(t)	$\hat{\beta}$	$\bar{\beta}$	$\hat{\lambda}$	C_M^2	C_M^2 cr	MTBF(t)
128	13	12	1.417	1.299	7.82E-05	0.033	0.169	268.278
158	12	17	1.916	1.804	1.94E-06	0.048	0.171	128.849
724	5	13	1.417	1.308	3.60E-04	0.060	0.169	89.184
575	11	7	2.084	1.786	2.39E-07	0.061	0.165	262.762
300	17	16	1.939	1.818	7.52E-07	0.061	0.171	194.156
2370	6	3	2.272	1.515	9.39E-08	0.071	0.155	294.492
777	3	2	1.917	0.959	4.22E-06	0.086	0.162	237.946
2371	4	3	3.599	2.400	1.98E-11	0.089	0.155	118.308
1435	5	7	2.299	1.971	2.83E-07	0.089	0.165	102.058
4609	2	2	1.251	0.626	7.50E-04	0.095	0.162	218.762
2134	20	10	0.911	0.820	3.10E-03	0.105	0.167	781.339
4605	4	6	1.324	1.103	4.60E-04	0.107	0.162	160.858
848	3	5	1.735	1.388	3.66E-05	0.113	0.160	105.209
2220	12	2	2.306	1.153	8.80E-09	0.122	0.162	909.937
4081	18	7	0.754	0.646	9.45E-03	0.136	0.165	1209.951
4607	3	5	2.890	2.312	1.39E-08	0.136	0.160	63.153
234	4	2	2.088	1.044	6.53E-07	0.137	0.162	305.903
4606	3	6	1.741	1.451	4.22E-05	0.147	0.162	87.370
2320	19	5	0.905	0.724	1.72E-03	0.147	0.160	1492.994
208	21	25	0.689	0.661	5.37E-02	0.162	0.172	434.557
4624	3	11	1.807	1.643	4.92E-05	0.170	0.169	45.907
850	9	3	1.819	1.212	1.34E-06	0.186	0.154	568.615
251	20	2	0.578	0.289	1.19E-02	0.188	0.162	6157.626
2379	5	4	5.512	4.134	7.57E-18	0.219	0.155	74.499
1275	2	3	2.450	1.633	5.87E-07	0.221	0.154	74.492
4623	2	6	4.003	3.336	6.53E-11	0.359	0.162	22.793
4619	2	4	5.880	4.410	3.16E-16	0.384	0.155	23.277
4620	2	5	5.816	4.653	5.93E-16	0.385	0.160	18.828
1161	17	19	0.516	0.488	2.14E-01	0.425	0.171	614.809
356	19	9	0.477	0.424	1.34E-01	0.618	0.167	1572.643
1155	20	39	1.043	1.016	3.75E-03	0.629	0.172	174.994
1159	20	31	0.703	0.681	6.06E-02	0.832	0.172	326.508
355	18	20	0.446	0.424	4.02E-01	0.988	0.171	716.364
2206	21	34	0.767	0.744	3.64E-02	1.197	0.172	287.061
278	5	1	* Only a single failure for the given system. Parameter estimation/goodness of fit not computed.					
307	6	1						
1825	6	1						
4082	18	1						
173	6	1						
1824	6	1						

Summary

This chapter presented results and analysis associated with the performance of the Probability of Failure (PoF) model and the BUILDER® SCI model. Some findings associated with the two models indicate that different systems may possess different reliability thresholds. Additionally, the analysis shows that both models present a high number of false negatives when assessed for statistical significance via contingency analysis. Initially, this research attempted to utilize an accepted method for calculating reliability for repairable systems as a means to determine the accuracy of both models. However, given amount of false negatives this research attempted to present an Availability Growth Model using the Nonhomogeneous Poisson Process (NHPP) as an alternate to the PoF and SCI model. Ultimately the research concluded that a NHPP model was not effective for assessing HVAC systems and was unable to construct an Availability Growth Model.

V. Discussion and Conclusion

Chapter Overview

This chapter provides a discussion of the results of this research and answers the research questions presented in Chapter I. The chapter then discusses limitations associated with the research effort. Further, this chapter places the findings within the context of infrastructure asset management within the Air Force. Lastly, this chapter presents recommendations for future research efforts.

Discussion

The PoF Model

When considering the PoF model, there is evidence to suggest that different systems have different reliability thresholds. As displayed in Figure 19 the model prediction for the plumbing system shows statistically significant agreement between the truth state and the model results at a reliability range of 70-85. Additionally, Figure 18 displays the same agreement for the fire protection system at a threshold of 50. These results suggest that a single reliability threshold of 37 may not be applicable for all systems. If using the PoF model to predict failure, infrastructure managers should expect to see system failures for plumbing systems when the system has a calculated reliability between 70-85. Similarly, infrastructure managers should expect to see system failures for fire protection at calculated reliability of 50. Unfortunately, this research can not make any assertions with respect to an appropriate reliability threshold for the electrical system based on the PoF model. Figure 17 displays the performance of the PoF model with respect to the electrical system. While there are areas where the model prediction does begin to show agreement with the truth state, it is not at the statistical significance necessary for this research. At best, the PoF model displays a statistical significance of 0.5 for the electrical system. Indicating the dependence between the model state and truth state is roughly the equivalent of a coin toss.

When analyzing the PoF model with respect to HVAC systems, the model displays no agreement with the truth state when considering small to medium-sized facilities. However, the model does display agreement with the truth state at reliability thresholds of 35 and 77 when assessed against larger facilities (i.e. ≥ 15,000 square feet, ≥ 7 component-sections, ≥ 3 stories). The model also displays agreement at thresholds of 91.5 and 92.5 when assessed against system age. However, because of the large number of false detections associated with thresholds of 35 and 92.5, this research deems 77 and 91.5 as more likely reliability threshold for the PoF model. This indicates that infrastructure managers should expect to see system failures when systems in larger facilities and systems in facilities 0-9 years old have calculated reliabilities of 77 and 91.5 respectively.

Overall, the agreement of the PoF model with the truth state is sporadic and displays a large number of false negative when assessed at lower thresholds. The combination of the significant agreement at thresholds of 77 and 91.5 and the numerous false negative detections at lower thresholds lead this research to conclude that the PoF model is overestimating HVAC system reliability. This research proposes three possible reasons for this: the Ordered Weighted Averaging method is not an appropriate method for "rolling-up" system reliability, the weights used to construct the model are incorrect, and the assumption made for selecting a distribution and parameters for these distributions result in overestimated component reliability. This research believes the latter of the three is most likely. The PoF model uses an assumption of a "70-30" Weibull distribution for the component-sections. This assumption parameterizes the distributions to have only a 30% reliability drop over the first 70% of the component-section's life. This would account for somewhat aged component-sections retaining a fairly high reliability, resulting in a higher system level reliability. Unfortunately, Air Force civil engineers are not currently collecting failure data at the detail necessary to fit failure distributions at the component-section level.

The SCI Model

Shifting attention to the SCI model performance with respect to HVAC systems, the SCI consistently displays statistically significant agreement with the truth state at a reliability threshold of 86. This is well above the current reliability threshold of 37. When analyzed in a similar fashion to the PoF model, the SCI model also displays agreement at a threshold of 55 for larger facilities. However, at this threshold the model displays a large proportion of false negatives. The numerous false negatives combined with statistically significant agreement at 86 lead to the conclusion that the SCI model is also overestimating system reliability. This research proposes two possible reasons for this: the "roll up" model using Current Replacement Value (CRV) is an inappropriate method for calculating higher reliabilities or the component-section condition assessment process is not accurate. This research believes it is likely a combination of the two.

In system reliability analysis, the system failure probability is a function of the system structure and system component reliability (Meeker & Escobar, 1998). Reliability block diagrams (RBDs) and fault trees are often used to quantify the relationships between system components in order to accurately model the system structure (Labi, 2014; Meeker & Escobar, 1998). The SCI roll-up method is purely a cost model and does not quantify the relationships and interactions of lower level components and component-sections to the overall system. Additionally, the majority of condition assessments completed by Air Force civil engineers are direct rating assessments. While these assessments decrease the time and resources required to assess condition, they are inherently more subjective and may be unintentionally reporting an inflated component-section condition. This may lead to inaccurate measurements of lower level component reliability. This research concludes that these two issues combined contribute to the overestimating of the SCI model.

Shiny© Application and Data Analysis

This research completed the above assessments of the PoF and SCI model through the use of Shiny©, a web application for R statistical software. Constructed and customized specifically for this research effort, the Shiny© application allowed for the creation and manipulation of system attribute filters in order to determine if the models performed differently given a specific attribute. The application also allowed for the adjustment of attribute values. For instance, this research noted no agreement between the PoF model and truth state for HVAC systems over the entire range of facility sizes. However, when limited to facilities ≥ 15,000 square feet, the model displayed statistically significant agreement. Using attribute data, this research developed attribute "filters" for facility size, facility age, system age, number of floors, and number of unique component-sections. The capability to select and manipulate attribute data and receive graphical output was instrumental to the analysis in this research.

A fundamental benefit of Shiny© is that it pairs the data analytics and tools of R statistical software with a customizable, user friendly graphical user interface. Users can decide what data to bring in and how to analyze it. The output of the application is also customizable and can be tailored to meet the needs of the user. Given a problem of interest, a data set, and an idea of how to obtain information from that data, users can perform instantaneous data analysis that meets their specific need. Proving its utility in reliability analysis in this research, a Shiny© application could be tailored to meet the needs of almost any data analysis or data presentation needs.

Alternative Reliability Model

Finally, this research attempted to employ an alternative method of measuring reliability with the intention of assessing the accuracy of both the PoF and SCI model output. While the method did not prove effective for the systems analyzed, this research believes future efforts should focus on modeling system reliability via a stochastic process using failure data. This research shows that both the PoF and SCI model overestimate HVAC system level reliability and cannot accurately assess the probability of a system being in a failed state.

System Reliability Theory, as discussed by Høyland and Rausand (1994), presents statistical models to calculate system reliability using failure data. One such model is the Markov process which estimates the probability of a system being in a particular state by modeling the transitions from state to state (Høland & Rausand, 1994). In a Markov process, the assumption is that all transitions follow an exponential distribution (Meeker & Escobar, 1998). This research achieved preliminary reliability calculations using a finite state Semi-Markov process (SMP) as discussed by Warr (n.d.). SMPs relax the exponential transition state assumption, allowing modelers to assess the fit of other distributions. Because of the preliminary nature of these results, this research did not present them in Chapter IV. Readers may view an overview of the SMP method and preliminary results in Appendix G.

Review of Research Questions

The primary purpose of reliability analysis is to provide information for use in decision making. The decision application can vary from risk and safety analysis, maintenance and operation analysis, to engineering design (Høland & Rausand, 1994). Alley (2015) developed the PoF model in an attempt to improve the SCI model and improve the decision making capability of Air Force civil engineers with respect to Infrastructure Asset Management. This research attempted to validate and improve the PoF model by answering the following questions:

1. *What assumptions associated with the original research effort can be reduced or eliminated through data collection and analysis?*

    a. *Is the assumption that a reliability threshold of 37 valid for the systems analyzed? If not, does the model indicate a reliability threshold for these systems?*

Of the systems analyzed with the PoF model, HVAC systems displayed possible reliability thresholds at 77 and 91.5. With the combination of these large values and numerous false negative detections, this research posits that the PoF model may be overestimating HVAC system reliability. However, PoF model did suggest that different systems have different reliability thresholds. The results suggest the plumbing system and fire protection system have reliability thresholds of 70 and 50 respectively based on the statistically significant agreement between the failed state model predictive state.

This indicates that system failures should be noticed when a system has calculated reliability at or near their respective threshold.

Additionally, when analyzing the SCI model, this research suggests that using a reliability threshold of 37 for HVAC systems is not appropriate for the current model configuration. With its current configuration, the SCI model displays a reliability threshold of 86 for all HVAC systems based on the statistically significant agreement between the failed state and model predictive state. Similar to thresholds discussed above, system failures should be noticed when a system has calculated reliability at or near this threshold.

b. Can probabilistic distributions and associated parameters be estimated for system components?

Yes, understanding component probabilistic distributions along with system structure is a general requirement for understanding system reliability (Meeker & Escobar, 1998). The aircraft, automotive, electronic, and many other sectors collect multiple levels of failure data to improve the reliability of their systems or products.

Unfortunately, the Air Force does not currently collect data at the level of detail necessary to obtain failure data below the system level. The Air Force currently collects condition data at the component-section level as a means to estimate the reliability of those component-sections. If the Air Force desires to more accurately assess reliability using stochastic processes, it must collect more detailed component-section data.

2. *After further model validation, does the model still present statistical significance for predicting the probability of failure at the system level?*

Yes, both the PoF and SCI model output present statistical significant agreement with the truth state. However, statistical significance alone does not indicate sound model performance. Both models display signs of overestimating system reliability.

3. *After further model validation, does the model accurately predict the probability of failure at the system level?*

Although this research was unable to precisely assess the accuracy of the PoF and SCI model via comparison to a stochastic model, it is able to make some declarations about the accuracy of the models. Both models predicted a large number of false negatives and show signs of overestimating, leading this research to conclude that each model is producing inaccurate results for some systems.

4. *Can alternative methods be used to assess system reliability for Air Force civil infrastructure systems?*

Yes. The use of availability as a measure for reliability for repairable systems remains a viable method as annotated by reliability literature (Høland & Rausand, 1994; Limnios, 2011; Meeker & Escobar, 1998). Additionally, Labi (2014) and Meeker and Escobar (1998) discuss the use of system structure diagrams combined with component reliability calculations as a method for calculating system reliability. While the development of an Availability Growth Model using a Nonhomogeneous Poisson Process was not an effective method for the systems considered in this research, this research achieved preliminary results using a finite state Semi Markov Process (SMP). The SMP method could be employed with reliability methods discussed in the literature to calculate system reliability for Air Force civil infrastructure systems.

Research Limitations

This research focused on providing an objective assessment of current and available methods for calculating the reliability of Air Force civil infrastructure systems. As with any research effort, it is important to consider the results presented in conjunction with the limitations of the research. This section focuses on limitations associated with method selection, data, and applicability of results.

With respect to the method selected, the Nonhomogeneous Poisson Process (NHPP) required an assumption that the systems under consideration received "as bad as old" maintenance when a failure was observed. Prior to data analysis, this research deemed this assumption valid with respect to the maintenance strategy for the systems considered. After analyzing the data, this assumption appeared to lose its validity as repair actions were noted to improve the performance of some systems. While a limitation of this research, highlighting that this assumption and the NHPP process are not effective for analyzing HVAC systems eliminates a method of analysis and narrows the focus of future research.

With respect to the data selected, this research aspired to obtain objective, representative data. Considering failure data, the Air Force does not actively collect system failure data but, however, does collect civil infrastructure repair work order (WO) data. Based on indicators in the WO data, this research made assumptions as to which WOs represented a system level failure. The research focused on being as objective as possible when identifying failures, however some subjectivity is present when determining which WOs indicated a system level failure. Developing an objective way to identify and quantify system failure in Air Force civil infrastructure is offered as a focus for future research. Having access to such data will only improve efforts to understand civil infrastructure reliability.

Shifting focus to obtaining representative data, based on the detail of data collected, this research was not able to determine if the non-failed samples for the electrical, fire protection, and plumbing systems were a representation of the non-failed population. This presents a limitation when applying the results of the analysis for those systems.

Lastly, the intent of this research was to improve the understanding of reliability for civil systems across the population of the Air Force infrastructure. A limitation associated with this research was the availability of BUILDER® data. BUILDER® inventory data was fundamental to this research. This research selected installations for data collection based on the quality and availability of their BUILDER® inventory data. The result of this selection was a sample of installations in hot and humid and hot and dry climates and thus the results are more applicable to systems in these environments. To improve the applicability of these results, a more representative sample of installations should be selected.

Implications for Air Force Asset Management

Air Force civil engineers currently utilize the BUILDER® model to assess risk associated with the Air Forces civil infrastructure and prioritize resources according the assessed risk. The fundamental elements of risk are: identifying a possible hazard, understanding the consequences of the hazard, and understanding the likelihood of the hazard (Ezell, Farr, & Wiese, 2000; Kaplan & Garrick, 1981; Singh et al., 2007).

Remembering that reliability is the mathematical compliment of the probability of failure, BUILDER® quantifies the probability of failure in the Air Force Asset Management risk model (Air Force Civil Engineer Center (AFCEC), 2015).

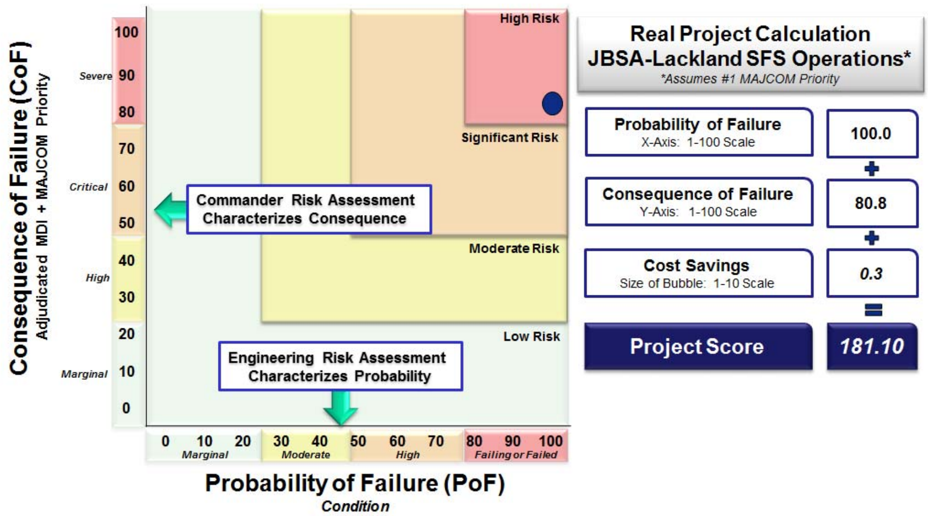


Figure 55: Air Force Risk Model Example (Air Force Civil Engineer Center (AFCEC), 2015)

Unfortunately, this research concludes that the BUILDER® model may not be providing an accurate assessment of the probability of failure at the system level. Air Force civil engineers are directed to manage their assets in a way that effectively support the Air Force mission and minimize asset life cycle cost (Office of the Secretary of the Air Force, 2010). The achievement of these two directives relies heavily on being able to accurately quantify the probability of failure for a given asset. Air Force civil engineers cannot understand how effectively an asset is supporting the mission if they cannot accurately quantify reliability. Additionally, Air Force civil engineers cannot effectively manage life-cycle spending if the model used to allocate resources relies on an inaccurate reliability calculation. Given their current asset management methods, asset reliability calculation is something Air Force civil engineers cannot afford to get wrong.

In order to improve the accuracy of Air Force civil engineer reliability analysis, this research believes Air Force civil engineers need to establish and quantify the relationship between the BUILDER® condition indices and asset failure. Traditional reliability analysis focuses on preventing failures (Høland & Rausand, 1994). The first step to preventing a failure is to identify it and then seek to understand how and why it occurred; after which, reliability analysts can assess the effectiveness of improvement efforts and provide reliability calculations based on the failure data collected. Air Force civil engineers are not collecting failure data at the detail necessary to make accurate reliability calculations. Collecting more detailed failure data would allow engineers to do two things: (1) understand the relationship between asset condition and asset failure and (2) use the data to construct more accurate stochastic based reliability models. The discussion of failure data and stochastic based reliability models lends as a useful transition to recommendations for future research.

Recommendations for Future Research

This section will present topics for future research in civil infrastructure reliability. While not an exhaustive list, this research regards data and methods as important focus areas for improving system reliability calculations for Air Force civil infrastructure. This section discusses the use of failure mode and effects analysis as possible way to improve failure data and understating. Additionally, this section introduces finite state Semi Markov Processes as an alternative method for calculating repairable system reliability.

Failure Data

How would Air Force civil engineers begin to understand failure and collect failure data? One approach is failure mode and effects analysis (FMEA). FMEA was one the first organized techniques for failure analysis and serves as a basis for quantitative reliability and availability analysis (Høland & Rausand, 1994). FMEA is a detailed analysis that reliability analysts can use at the system, subsystem, or component levels to identify the modes (or events) which cause an asset's functional failure. This level of analysis could prove a daunting task as a single asset can have numerous failure modes (Moubray, 1997). However, Moubray (1997) argues that daily maintenance is managed at the failure mode level. That is to say, that work orders logged into the interim work order management system (IWIMS) are the result of a failure mode. To begin collecting data against these failure modes requires only working through the FMEA process. Having access to the detailed data that would result from a FMEA would greatly enhance the accuracy of Air Force civil engineer reliability analysis. For an introduction and detailed overview of the FMEA process, see Høland and Rausand (1994) and Moubray (1997) respectively.

Stochastic Reliability Models

The second phase of this research attempted to construct a stochastic reliability model using a NHPP. The NHPP method did not prove effective to the systems analyzed. However, this research posits that assessing reliability via a stochastic process will yield the most accurate reliability calculations for Air Force civil systems. This research began preliminary reliability analysis using a finite state Semi-Markov process (SMP). This method used data to model inter arrival times between failures and calculate reliability estimates using an algorithm developed by Freels and Warr (2015). Appendix G provides a methodological overview and preliminary results. Based on the initial success of the SMP method, this research believes that further analysis is warranted to assess its applicability in Air Force civil engineering reliability analysis.

Conclusions

Air Force civil engineers are focused on providing civil infrastructure that both effectively supports the Air Force mission and provides service at the lowest life cycle cost. With emphasis on effective mission support, Air Force civil engineers have implemented a measure of reliability through BUILDER® to monitor and predict infrastructure performance. The intent of this research was to validate reliability models currently used and available to Air Force civil engineers and further the field of reliability analysis with respect to repairable civil infrastructure systems. Ultimately focusing on HVAC systems, this research determined that both the PoF and SCI models frequently over estimate system reliability, resulting in a larger proportion of false negative detections. This result suggests that Air Force civil engineers cannot accurately asses the reliability and performance of some systems. This impairs their ability to effectively manage civil infrastructure that provides effective mission support at the lowest life cycle cost.

In an attempt to improve reliability calculations for repairable civil systems, this research proposed the use of an Availability Growth Model using a Nonhomogeneous

Poisson Process (NHPP). However, the NHPP method proved ineffective for modeling HVAC systems. Nevertheless, this research recommends exploration of other stochastic methods to assess civil system reliability. There are numerous methods available in reliability analysis. Given the right application, these methods have the potential to improve reliability calculations for Air Force civil engineers and help them more effectively manage their civil infrastructure assets.

Appendix A. PoF Model Calculation Output

Barksdale AFB

HVAC Failed				HVAC Non-Failed			
Fac Nmbr	SCI	R(t)	Pf(t)	Fac Nmbr	SCI	R(t)	Pf(t)
1955	81	0.420	0.580	3435	93	0.806	0.194
2914	75	0.634	0.366	3722	72	0.564	0.436
2945	83	0.481	0.519	3725	87	0.843	0.157
3433	85	0.487	0.513	3800	92	0.700	0.300
3578	93	0.786	0.214	4030	85	0.280	0.720
3723	90	0.998	0.002	4168	74	0.467	0.533
4145	78	0.642	0.358	4173	49	0.362	0.638
4161	95	0.946	0.054	4186	80	0.578	0.422
4221	51	0.120	0.880	4359	88	0.354	0.646
4223	85	0.579	0.421	4543	72	0.788	0.212
4351	78	0.836	0.164	4549	87	0.886	0.114
4560	36	0.661	0.339	4631	86	0.705	0.295
4565	92	0.615	0.385	5755	92	0.590	0.410
4714	76	0.704	0.296	5821	23	0.000	1.000
5141	86	0.522	0.478	5821	86	0.763	0.237
5155	87	0.944	0.056	5822	86	0.720	0.280
5441	84	0.879	0.121	6064	48	0.569	0.431
5650	84	0.504	0.496	6200	93	0.842	0.158
5999	93	0.510	0.490	6249	69	0.567	0.433
6067	85	0.419	0.581	6442	93	0.306	0.694
6225	93	0.847	0.153	6626	78	0.600	0.400
6238	91	0.913	0.087	6803	93	0.619	0.381
6402	92	0.899	0.101	6803	55	0.573	0.427
6412	95	0.520	0.480	6824	61	0.215	0.785
6413	90	0.854	0.146	6824	89	0.652	0.348
6603	93	0.949	0.051	6825	84	0.529	0.471
6604	94	0.442	0.558	682	90	0.572	0.428
6809	88	0.863	0.137	6830	88	0.633	0.367
6815	93	0.737	0.263	6836	90	0.817	0.183
6819	91	0.539	0.461	7236	90	0.344	0.656
7251	96	0.793	0.207	7243	98	0.986	0.014
7282	84	0.635	0.365	7274	50	0.464	0.536
7305	91	0.676	0.324	7280	51	0.349	0.651
7306	92	0.725	0.275	7297	90	0.546	0.454
7332	94	0.428	0.572	7574	92	0.734	0.266
7700	86	0.628	0.372	7625	87	0.503	0.497
7710	83	0.407	0.593	18383	86	0.437	0.563

Electric Failed				Electric Non-Failed			
Fac Nmbr	SCI	R(t)	Pf(t)	Fac Nmbr	SCI	R(t)	Pf(t)
2914	81	0.620	0.380	1080	94	0.955	0.045
2945	77	0.446	0.554	3435	92	1.000	0.000
3900	94	0.757	0.243	6215	90	0.765	0.235
5546	94	1.000	0.000	6809	90	0.855	0.145
6067	85	0.646	0.354	6810	62	0.149	0.851
6628	88	0.778	0.222	6830	48	0.268	0.732
7236	90	0.536	0.464	6836	87	0.783	0.217
7306	90	0.704	0.296	7332	64	0.471	0.529
7445	94	0.778	0.222	7411	10	0.084	0.916

Fire Protection Failed				Fire Protection Non-Failed			
Fac Nmbr	SCI	R(t)	Pf(t)	Fac Nmbr	SCI	R(t)	Pf(t)
* Facility Data not available for failed systems							

Plumbing Failed				Plumbing Non-Failed			
Fac Nmbr	SCI	R(t)	Pf(t)	Fac Nmbr	SCI	R(t)	Pf(t)
4565	92	0.688	0.312	5155	91	0.990	0.010
2914	78	0.698	0.302	6604	93	0.773	0.227
4631	91	0.831	0.169	5224	89	0.879	0.121

Cannon AFB

HVAC Failed				HVAC Non-Failed			
Fac Nmbr	SCI	R(t)	Pf(t)	Fac Nmbr	SCI	R(t)	Pf(t)
1	85	0.3300	0.6700	9	77	0.6785	0.3215
22	82	0.4559	0.5441	10	77	0.7035	0.2965
54	87	0.3426	0.6574	74	89	0.5433	0.4567
58	85	0.7979	0.2021	75	87	0.4332	0.5668
60	76	0.9664	0.0336	78	87	0.9789	0.0211
70	83	0.4867	0.5133	79	66	0.1663	0.8337
76	83	0.5862	0.4138	106	86	0.2275	0.7725
77	78	0.6181	0.3819	109	80	0.4578	0.5422
102	86	0.8191	0.1809	124	90	0.5643	0.4357
119	85	0.5620	0.4380	125	83	0.6848	0.3152
122	85	0.4107	0.5893	128	88	0.9002	0.0998
123	84	0.6477	0.3523	135	83	0.6544	0.3456
126	81	0.5406	0.4594	173	93	0.9573	0.0427
130	86	0.4450	0.5550	174	93	0.9659	0.0341
133	86	0.5068	0.4932	192	93	0.7758	0.2242
150	86	0.9071	0.0929	204	82	0.6903	0.3097
155	91	0.7918	0.2082	206	87	0.6765	0.3235
158	85	0.8335	0.1665	209	84	0.0891	0.9109
160	86	0.8140	0.1860	212	86	0.4195	0.5805
164	84	0.4768	0.5232	214	85	0.5943	0.4057
186	83	0.9375	0.0625	215	86	0.8068	0.1932
190	84	0.5627	0.4373	226	86	0.2001	0.7999
194	91	0.6270	0.3730	229	92	0.9153	0.0847
195	93	0.9170	0.0830	230	100	0.9987	0.0013
196	91	0.6249	0.3751	250	92	0.9951	0.0049
197	84	0.4243	0.5757	251	85	0.5472	0.4528
198	75	0.7784	0.2216	252	72	0.6135	0.3865
199	86	0.3759	0.6241	253	93	0.6026	0.3974
208	90	0.9608	0.0392	269	93	0.9921	0.0079
216	88	0.4974	0.5026	307	93	0.9875	0.0125
219	85	0.2936	0.7064	317	93	0.9747	0.0253
234	86	0.9982	0.0018	326	90	0.7104	0.2896
300	86	0.6835	0.3165	337	79	0.1393	0.8607
335	74	0.3570	0.6430	356	86	0.6880	0.3120
379	88	0.3484	0.6516	368	67	0.7269	0.2731
444	91	0.6593	0.3407	370	93	0.9963	0.0037
550	86	0.4323	0.5677	374	56	0.6785	0.3215
555	85	0.7626	0.2374	375	88	0.3234	0.6766

HVAC Failed				HVAC Non-Failed			
Fac Nmbr	SCI	R(t)	Pf(t)	Fac Nmbr	SCI	R(t)	Pf(t)
593	87	0.9542	0.0458	442	77	0.0000	1.0000
620	89	0.9511	0.0489	494	86	0.4609	0.5391
622	86	0.9897	0.0103	575	74	0.8792	0.1208
680	77	0.5383	0.4617	600	84	0.3997	0.6003
684	84	0.7920	0.2080	622	86	0.9879	0.0121
724	97	0.9975	0.0025	624	83	0.2922	0.7078
777	100	0.9998	0.0002	626	78	0.6510	0.3490
780	80	0.8880	0.1120	728	88	0.4908	0.5092
785	88	0.4440	0.5560	772	81	0.6407	0.3593
790	85	0.8075	0.1925	799	49	0.1882	0.8118
850	92	0.9542	0.0458	1202	85	0.4115	0.5885
1111	83	0.4903	0.5097	1265	100	0.9995	0.0005
1155	84	0.7740	0.2260	1398	86	0.0550	0.9450
1156	89	0.6342	0.3658	1825	93	0.9820	0.0180
1159	87	0.9046	0.0954	1898	86	0.0460	0.9540
1161	86	0.7995	0.2005	2112	83	0.1094	0.8906
1208	86	0.4737	0.5263	2123	83	0.4080	0.5920
1225	91	0.9874	0.0126	2207	86	0.0550	0.9450
1254	86	0.3960	0.6040	2209	100	0.9977	0.0023
1275	100	1.0000	0.0000	2214	86	0.2240	0.7760
1404	77	0.3245	0.6755	2220	76	0.8525	0.1475
1435	99	0.9959	0.0041	2280	67	0.0004	0.9996
1812	81	0.5859	0.4141	2302	82	0.6316	0.3684
1816	86	0.4987	0.5013	2304	85	0.0892	0.9108
1818	86	0.5548	0.4452	2306	94	0.9977	0.0023
1819	87	0.6042	0.3958	2311	92	0.9153	0.0847
1820	85	0.6193	0.3807	2315	84	0.5709	0.4291
1824	93	0.9859	0.0141	2332	84	0.0001	0.9999
1900	81	0.5657	0.4343	2347	93	0.9921	0.0079
2110	86	0.1354	0.8646	2348	93	0.9859	0.0141
2132	86	0.5014	0.4986	2349	97	0.9956	0.0044
2206	83	0.4354	0.5646	2371	92	0.9977	0.0023
2320	81	0.5234	0.4766	2372	90	0.9908	0.0092
2328	96	0.9910	0.0090	2380	100	1.0000	0.0000
2370	89	0.9803	0.0197	3107	86	0.0177	0.9823
2379	93	0.9989	0.0011	3252	93	0.9859	0.0141
4081	90	0.3295	0.6705	4082	90	0.5188	0.4812
4605	93	0.9980	0.0020	4083	94	0.0321	0.9679
4606	97	0.9997	0.0003	4619	100	1.0000	0.0000
4607	100	0.9995	0.0005	4620	98	1.0000	0.0000

HVAC Failed				HVAC Non-Failed			
Fac Nmbr	SCI	R(t)	Pf(t)	Fac Nmbr	SCI	R(t)	Pf(t)
4609	100	1.0000	0.0000	355	84	0.7699	0.2301
4623	100	1.0000	0.0000	2300	78	0.5243	0.4757
4624	100	0.9997	0.0003	2318	76	0.5201	0.4799

Electric Failed				Electric Non-Failed			
Fac Nmbr	SCI	R(t)	Pf(t)	Fac Nmbr	SCI	R(t)	Pf(t)
196	92	0.6063	0.3937	103	93	0.9867	0.0133
444	92	0.5687	0.4313	122	92	0.3613	0.6387
679	91	0.3976	0.6024	197	93	0.3911	0.6089
680	77	0.1705	0.8295	214	93	0.7336	0.2664
772	87	0.8551	0.1449	326	94	0.5147	0.4853
1275	100	1.0000	0.0000	356	92	0.5972	0.4028
2209	99	0.9317	0.0683	374	93	0.2932	0.7068
2300	86	0.4820	0.5180	1156	86	0.7755	0.2245
2379	93	0.9940	0.0060	2220	92	0.9003	0.0997

Fire Protection Failed				Fire Protection Non-Failed			
Fac Nmbr	SCI	R(t)	Pf(t)	Fac Nmbr	SCI	R(t)	Pf(t)
4081	100	0.9999	0.0001	10	83	0.9416	0.0584

Plumbing Failed				Plumbing Non-Failed			
Fac Nmbr	SCI	R(t)	Pf(t)	Fac Nmbr	SCI	R(t)	Pf(t)
126	77	0.8340	0.1660	102	94	0.984	0.016
130	94	0.9316	0.0684	123	90	0.700	0.300
684	92	0.6856	0.3144	124	87	0.735	0.265
785	86	0.8741	0.1259	206	91	0.973	0.027
799	89	0.7018	0.2982	356	94	0.783	0.217
850	92	0.9470	0.0530	371	94	0.996	0.004
1435	99	0.9948	0.0052	442	92	0.992	0.008
2328	99	0.9982	0.0018	4607	100	1.000	0.000

Davis Monthan AFB

HVAC Failed				HVAC Non-Failed			
Fac Nmbr	SCI	R(t)	Pf(t)	Fac Nmbr	SCI	R(t)	Pf(t)
63	78	0.4037	0.5963	38	95	0.3582	0.6418
70	75	0.8243	0.1757	73	40	0.5633	0.4367
74	79	0.8058	0.1942	79	76	0.2001	0.7999
75	66	0.7209	0.2791	129	61	0.5599	0.4401
96	78	0.4710	0.5290	137	95	0.4757	0.5243
113	66	0.2639	0.7361	142	73	0.3542	0.6458
211	84	0.1370	0.8630	165	71	0.9964	0.0036
220	89	0.8617	0.1383	171	95	0.9720	0.0280
265	93	0.9936	0.0064	173	84	0.9594	0.0406
304	95	0.8525	0.1475	182	90	0.0000	1.0000
306	64	0.4899	0.5101	184	95	0.2294	0.7706
404	99	0.9594	0.0406	186	10	0.6785	0.3215
415	100	0.9996	0.0004	208	61	0.4998	0.5002
1226	98	0.9859	0.0141	253	87	0.9170	0.0830
1246	73	0.9397	0.0603	254	87	0.9170	0.0830
1358	75	0.4188	0.5812	269	85	0.9831	0.0169
1440	85	0.7831	0.2169	1446	88	0.8525	0.1475
1444	78	0.9977	0.0023	1712	89	0.6980	0.3020
1550	82	0.8892	0.1108	1740	93	0.8064	0.1936
1619	86	0.9122	0.0878	2300	74	0.5090	0.4910
1630	78	0.6630	0.3370	2356	99	0.9814	0.0186
1631	90	0.8378	0.1622	2402	87	0.9568	0.0432
1632	88	0.8827	0.1173	2520	94	0.2023	0.7977
2301	79	0.8174	0.1826	2555	94	0.9410	0.0590
2505	79	0.5651	0.4349	4065	72	0.7038	0.2962
2525	77	0.6103	0.3897	4153	70	0.5750	0.4250
2550	75	0.4082	0.5918	4201	65	0.6573	0.3427
2612	84	0.8612	0.1388	4455	74	0.8228	0.1772
2614	73	0.7206	0.2794	4531	69	0.4455	0.5545
3205	42	0.3844	0.6156	4555	89	0.6682	0.3318
3208	66	0.5377	0.4623	4710	78	0.6918	0.3082
3219	63	0.4347	0.5653	4713	78	0.7086	0.2914
3500	86	0.9302	0.0698	4750	95	0.5536	0.4464
3501	28	0.2655	0.7345	4818	70	0.6917	0.3083
4211	76	0.6354	0.3646	4819	37	0.2646	0.7354
4224	52	0.5861	0.4139	4853	87	0.6146	0.3854
4300	64	0.5146	0.4854	5010	68	0.7313	0.2687
4400	84	0.9698	0.0302	5111	59	0.3569	0.6431

HVAC Failed				HVAC Non-Failed			
Fac Nmbr	SCI	R(t)	Pf(t)	Fac Nmbr	SCI	R(t)	Pf(t)
4413	72	0.7704	0.2296	5126	77	0.4190	0.5810
4414	76	0.5364	0.4636	5251	77	0.4570	0.5430
4701	100	0.9073	0.0927	5258	89	0.4247	0.5753
4800	81	0.8770	0.1230	5301	59	0.2001	0.7999
4809	82	0.8617	0.1383	5303	93	0.7696	0.2304
4815	79	0.4663	0.5337	5314	58	0.1960	0.8040
4820	70	0.3204	0.6796	5315	60	0.5007	0.4993
4824	80	0.8128	0.1872	5405	70	0.9594	0.0406
4826	86	0.4024	0.5976	5423	64	0.5850	0.4150
4832	94	0.9972	0.0028	5434	59	0.6678	0.3322
4838	93	0.9899	0.0101	7230	78	0.3295	0.6705
4859	86	0.9415	0.0585	7236	10	0.0705	0.9295
4885	96	0.9994	0.0006	7323	82	0.9030	0.0970
4889	99	1.0000	0.0000	7328	69	0.6227	0.3773
5129	68	0.6844	0.3156	7391	87	0.9302	0.0698
5247	87	0.8797	0.1203	7405	89	0.4510	0.5490
5256	73	0.7048	0.2952	7406	89	0.6621	0.3379
5420	82	0.8893	0.1107	7410	70	0.8525	0.1475
5500	84	0.9822	0.0178	7421	70	0.9153	0.0847
5600	92	0.9646	0.0354	7427	95	0.6785	0.3215
5607	82	0.9070	0.0930	7431	85	0.4081	0.5919
6000	77	0.7529	0.2471	7454	90	0.6585	0.3415
6006	90	0.9757	0.0243	7455	69	0.7269	0.2731
7439	80	0.6001	0.3999	7513	67	0.6452	0.3548
7514	76	0.5845	0.4155	7830	90	0.9594	0.0406

Electric Failed				Electric Non-Failed			
Fac Nmbr	SCI	R(t)	Pf(t)	Fac Nmbr	SCI	R(t)	Pf(t)
12	91	0.4974	0.5026	290	60	0.6240	0.3760
184	95	0.7481	0.2519	1447	73	0.4586	0.5414
188	95	0.6864	0.3136	2352	90	0.9046	0.0954
220	90	0.8916	0.1084	2353	90	0.9046	0.0954
1632	78	0.5607	0.4393	5607	75	0.5103	0.4897
2521	94	0.4351	0.5649	7104	96	0.6923	0.3077
4413	76	0.6930	0.3070	7109	95	0.3946	0.6054
4701	92	0.4890	0.5110	7333	93	0.8746	0.1254
4707	91	0.6885	0.3115	7432	86	0.5422	0.4578
4800	91	0.3796	0.6204	7433	95	0.8525	0.1475
5230	86	0.9192	0.0808	7440	90	0.5677	0.4323
5430	83	0.2588	0.7412	7506	92	0.4490	0.5510

Fire Protection Failed				Fire Protection Non-Failed			
Fac Nmbr	SCI	R(t)	Pf(t)	Fac Nmbr	SCI	R(t)	Pf(t)
129	64	0.3686	0.6314	5111	48	0.2600	0.7400
183	78	0.8376	0.1624	5010	11	0.6563	0.3437

Plumbing Failed				Plumbing Non-Failed			
Fac Nmbr	SCI	R(t)	Pf(t)	Fac Nmbr	SCI	R(t)	Pf(t)
130	65	0.6076	0.3924	7232	95	0.8466	0.1534
2350	84	0.8897	0.1103	4820	75	0.8678	0.1322
96	87	0.7686	0.2314	5420	72	0.5310	0.4690

Keesler AFB

HVAC Failed				HVAC Non-Failed			
Fac Nmbr	SCI	R(t)	Pf(t)	Fac Nmbr	SCI	R(t)	Pf(t)
404	98	0.9893	0.0107	222	91	0.7335	0.2665
470	92	0.6529	0.3471	233	83	0.6329	0.3671
1203	85	0.5644	0.4356	237	93	0.9981	0.0019
1906	92	0.8255	0.1745	414	84	0.3942	0.6058
2004	36	0.4679	0.5321	417	97	0.9352	0.0648
2306	100	0.9968	0.0032	2818	87	0.6482	0.3518
2505	72	0.6800	0.3200	2901	90	0.4636	0.5364
2801	62	0.8135	0.1865	3101	87	0.8575	0.1425
2804	93	0.7230	0.2770	3518	98	0.9864	0.0136
2816	92	0.3847	0.6153	3823	91	0.6349	0.3651
2902	89	0.3931	0.6069	3945	92	0.7622	0.2378
3501	83	0.6300	0.3700	4002	84	0.6020	0.3980
3903	80	0.2747	0.7253	4204	89	0.7792	0.2208
4106	91	0.7848	0.2152	4213	92	0.8918	0.1082
4263	84	0.9090	0.0910	4281	94	0.9397	0.0603
4266	84	0.8698	0.1302	4309	90	0.5626	0.4374
4301	84	0.5011	0.4989	4330	72	0.6480	0.3520
4605	84	0.4509	0.5491	4408	97	0.9877	0.0123
4707	82	0.9588	0.0412	4609	99	0.9859	0.0141
5745	92	0.8421	0.1579	5025	98	0.9739	0.0261
5904	92	0.6820	0.3180	6902	76	0.5504	0.4496
6950	45	0.6781	0.3219	6903	57	0.3701	0.6299
7320	51	0.7065	0.2935	7408	89	0.3519	0.6481
7701	92	0.5041	0.4959	7409	86	0.5122	0.4878
7704	79	0.3352	0.6648	7712	91	0.6911	0.3089

Electric Failed				Electric Non-Failed			
Fac Nmbr	SCI	R(t)	Pf(t)	Fac Nmbr	SCI	R(t)	Pf(t)
1101	90	0.9950	0.0050	308	93	0.7980	0.2020
3501	79	0.5626	0.4374	1203	84	0.5465	0.4535
4106	93	0.7653	0.2347	2004	83	0.7734	0.2266
4221	99	0.9833	0.0167	4213	93	0.8749	0.1251
4301	74	0.1981	0.8019	4225	99	0.9840	0.0160
4329	93	0.5126	0.4874	4266	93	0.8402	0.1598
6734	84	0.9684	0.0316	4331	83	0.9156	0.0844
6965	90	0.8531	0.1469	5904	83	0.8653	0.1347
7315	90	0.8140	0.1860	2902	80	0.7611	0.2389

Fire Protection Failed				Fire Protection Non-Failed			
Fac Nmbr	SCI	R(t)	Pf(t)	Fac Nmbr	SCI	R(t)	Pf(t)
1101	52	0.8466	0.1534	1704	24	0.4291	0.5709
1201	87	1.0000	0.0000	4004	87	0.5533	0.4467
1510	94	0.9674	0.0326	4213	87	0.8830	0.1170
3101	5	0.6725	0.3275	4247	92	0.8652	0.1348
4410	76	0.4598	0.5402	4278	93	0.8909	0.1091
4432	4	0.7003	0.2997	4408	97	0.9957	0.0043
7404	80	0.4611	0.5389	6732	96	0.9113	0.0887

Plumbing Failed				Plumbing Non-Failed			
Fac Nmbr	SCI	R(t)	Pf(t)	Fac Nmbr	SCI	R(t)	Pf(t)
*Facility data not available for failed systems							

Patrick AFB

HVAC Failed				HVAC Non-Failed			
Fac Nmbr	SCI	R(t)	Pf(t)	Fac Nmbr	SCI	R(t)	Pf(t)
6	90	0.3868	0.6132	204	81	0.9807	0.0193
206	81	0.9722	0.0278	205	81	0.9773	0.0227
253	92	0.9354	0.0646	236	92	0.9404	0.0596
265	76	0.6790	0.3210	255	87	0.7129	0.2871
308	85	0.8123	0.1877	264	90	0.4785	0.5215
312	83	0.9078	0.0922	335	89	0.6033	0.3967
313	87	0.7830	0.2170	345	92	0.6663	0.3337
319	18	0.2000	0.8000	401	86	0.4498	0.5502
350	82	0.5550	0.4450	432	88	0.5878	0.4122
352	85	0.7936	0.2064	505	90	0.9770	0.0230
402	92	0.8314	0.1686	511	78	0.8515	0.1485
404	81	0.3442	0.6558	513	91	0.4709	0.5291
415	84	0.8607	0.1393	521	92	0.8657	0.1343
423	82	0.7331	0.2669	523	86	0.7551	0.2449
424	83	0.6928	0.3072	530	83	0.6754	0.3246
425	82	0.4021	0.5979	534	91	0.7254	0.2746
431	90	0.6381	0.3619	535	93	0.5023	0.4977
502	68	0.3964	0.6036	537	83	0.5759	0.4241
533	92	0.3901	0.6099	561	68	0.0254	0.9746
543	91	0.9996	0.0004	606	53	0.1817	0.8183
545	83	0.5488	0.4512	657	92	0.9594	0.0406
546	83	0.5152	0.4848	673	84	0.4819	0.5181
550	78	0.7468	0.2532	676	87	0.7628	0.2372
556	83	0.9275	0.0725	689	89	0.9901	0.0099
559	91	0.7598	0.2402	692	92	0.9397	0.0603
560	83	0.5408	0.4592	700	93	0.7725	0.2275
577	92	0.9837	0.0163	708	80	0.0550	0.9450
629	91	0.9421	0.0579	818	81	0.7725	0.2275
654	84	1.0000	0.0000	912	88	0.5230	0.4770
671	87	0.8093	0.1907	917	93	0.8525	0.1475
681	91	0.9048	0.0952	953	91	0.9859	0.0141
698	45	0.5948	0.4052	957	91	0.9893	0.0107
702	87	0.7036	0.2964	960	92	0.8862	0.1138
710	82	0.8755	0.1245	1343	90	0.8371	0.1629
720	83	0.7725	0.2275	1365	90	0.7181	0.2819
721	93	0.8145	0.1855	1366	91	0.9272	0.0728
722	90	0.6451	0.3549	1371	80	0.6415	0.3585
732	89	0.9002	0.0998	1374	44	0.6415	0.3585

HVAC Failed				HVAC Non-Failed			
Fac Nmbr	SCI	R(t)	Pf(t)	Fac Nmbr	SCI	R(t)	Pf(t)
750	53	0.8113	0.1887	1376	88	0.9977	0.0023
751	92	0.8882	0.1118	1388	91	0.9595	0.0405
810	81	0.7532	0.2468	1390	82	0.3683	0.6317
820	82	0.7317	0.2683	1392	93	0.7269	0.2731
821	85	0.7161	0.2839	1399	92	0.6785	0.3215
822	87	0.4594	0.5406	1433	80	0.0321	0.9679
910	85	0.9138	0.0862	1435	84	0.1370	0.8630
935	91	0.9773	0.0227	1440	93	0.1370	0.8630
938	93	0.8195	0.1805	1475	82	0.8297	0.1703
945	84	0.4078	0.5922	1493	92	0.8023	0.1977
961	83	0.5539	0.4461	1498	90	0.2784	0.7216
967	91	0.8993	0.1007	1373	92	0.9594	0.0406
969	91	0.6925	0.3075	1432	84	0.1370	0.8630
978	92	0.8862	0.1138	610	32	0.1370	0.8630
981	84	0.6836	0.3164	699	92	0.9397	0.0603
984	79	0.6306	0.3694	306	88	0.8147	0.1853
985	92	0.7632	0.2368	925	91	0.4984	0.5016
986	88	0.9612	0.0388	1437	93	0.1370	0.8630
988	79	0.5039	0.4961	997	91	0.9734	0.0266
989	81	0.5447	0.4553	679	30	0.4337	0.5663
991	87	0.6953	0.3047	884	1	0.5760	0.4240
992	91	0.9934	0.0066	1372	87	0.7855	0.2145
993	82	0.7695	0.2305	605	68	0.2784	0.7216
994	91	0.8699	0.1301	503	70	0.3964	0.6036
996	99	0.9872	0.0128	691	33	0.2242	0.7758
998	83	0.8432	0.1568	1502	92	0.8862	0.1138
1000	97	0.9696	0.0304	1060	92	0.6028	0.3972
1317	89	0.7402	0.2598	9001	92	0.9747	0.0253
1319	92	0.9364	0.0636	891	78	0.5309	0.4691
1337	92	0.9594	0.0406	653	93	0.9193	0.0807
1350	86	0.6486	0.3514	1401	66	0.0550	0.9450
1358	91	0.9934	0.0066	266	83	0.8862	0.1138
1364	81	0.5437	0.4563	3650	82	0.9397	0.0603
1368	93	0.9198	0.0802	990	33	0.5425	0.4575
1369	88	0.7155	0.2845	1361	30	0.8377	0.1623
1379	100	0.9996	0.0004	647	91	0.6438	0.3562
1391	90	0.7140	0.2860	882	92	0.8862	0.1138
1402	93	0.8755	0.1245	407	84	0.5760	0.4240
1500	92	0.8830	0.1170	453	79	0.9996	0.0004
3656	73	0.9059	0.0941	337	87	0.6667	0.3333

HVAC Failed				HVAC Non-Failed			
Fac Nmbr	SCI	R(t)	Pf(t)	Fac Nmbr	SCI	R(t)	Pf(t)
3659	84	0.7308	0.2692	1470	87	0.0387	0.9613
5101	75	0.8177	0.1823	408	92	0.8527	0.1473
5105	81	0.8110	0.1890	819	91	0.7725	0.2275

Electric Failed				Electric Non-Failed			
Fac Nmbr	SCI	R(t)	Pf(t)	Fac Nmbr	SCI	R(t)	Pf(t)
550	93	0.9913	0.0087	264	94	0.9773	0.0227
661	93	1.0000	0.0000	556	92	0.9260	0.0740
692	92	0.9397	0.0603	561	85	0.7827	0.2173
750	70	0.8941	0.1059	605	85	0.8116	0.1884
821	93	0.8437	0.1563	606	91	0.9994	0.0006
822	89	0.8416	0.1584	635	85	0.9352	0.0648
989	92	0.6433	0.3567	676	85	0.9594	0.0406
1475	86	0.7363	0.2637	708	94	0.8525	0.1475
3656	91	0.9863	0.0137	721	85	0.7725	0.2275

Fire Protection Failed				Fire Protection Non-Failed			
Fac Nmbr	SCI	R(t)	Pf(t)	Fac Nmbr	SCI	R(t)	Pf(t)
306	99	0.8980	0.1020	29	75	0.8533	0.1467
313	44	0.0790	0.9210	236	9	0.6540	0.3460
350	96	0.9743	0.0257	251	96	0.6551	0.3449
352	99	0.9951	0.0049	308	98	0.8980	0.1020
502	10	0.6540	0.3460	311	67	0.9055	0.0945
503	83	0.4618	0.5382	345	82	0.5411	0.4589
545	3	0.1008	0.8992	415	78	0.8638	0.1362
698	88	0.8749	0.1251	511	43	0.7538	0.2462
750	89	0.4867	0.5133	522	44	0.7559	0.2441
810	49	0.7552	0.2448	533	28	0.6540	0.3460
821	99	0.9939	0.0061	546	11	0.1254	0.8746
822	97	0.8963	0.1037	561	89	0.9651	0.0349
967	59	0.7671	0.2329	624	91	0.7204	0.2796
985	15	0.4731	0.5269	629	75	0.6930	0.3070
986	12	0.3253	0.6747	630	76	0.9161	0.0839
996	90	0.5856	0.4144	632	89	0.7821	0.2179
1000	100	0.9906	0.0094	651	87	0.8376	0.1624
1319	98	0.9791	0.0209	671	88	0.8537	0.1463
1391	27	0.3470	0.6530	672	90	0.8376	0.1624

Fire Protection Failed				Fire Protection Non-Failed			
Fac Nmbr	SCI	R(t)	Pf(t)	Fac Nmbr	SCI	R(t)	Pf(t)
1433	88	0.8698	0.1302	980	80	0.9069	0.0931

Plumbing Failed				Plumbing Non-Failed			
Fac Nmbr	SCI	R(t)	Pf(t)	Fac Nmbr	SCI	R(t)	Pf(t)
986	88	0.8109	0.1891	533	92	0.9608	0.0392
439	85	0.4468	0.5532	530	85	0.4393	0.5607

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HVAC Failed				HVAC Non-Failed			
Fac Nmbr	SCI	R(t)	Pf(t)	Fac Nmbr	SCI	R(t)	Pf(t)
3	65	0.5981	0.4019	5	92	0.6973	0.3027
8	92	0.9694	0.0306	6	73	0.6256	0.3744
10	95	0.9412	0.0588	44	15	0.3955	0.6045
40	52	0.7009	0.2991	54	83	0.7356	0.2644
43	86	0.6923	0.3077	150	83	0.8981	0.1019
50	67	0.6600	0.3400	352	92	0.8499	0.1501
52	87	0.9127	0.0873	386	72	0.7286	0.2714
56	90	0.8415	0.1585	464	92	0.8358	0.1642
57	84	0.7377	0.2623	468	93	0.9397	0.0603
60	93	0.7469	0.2531	513	87	0.3863	0.6137
61	93	0.6648	0.3352	514	80	0.5324	0.4676
382	91	0.9953	0.0047	516	93	0.6432	0.3568
433	84	0.5972	0.4028	517	72	0.6012	0.3988
450	91	0.4473	0.5527	528	92	0.8588	0.1412
460	93	0.7058	0.2942	531	93	0.7836	0.2164
470	96	0.9784	0.0216	549	88	0.6957	0.3043
506	87	0.9995	0.0005	742	85	0.6402	0.3598
548	87	0.8225	0.1775	750	84	0.5275	0.4725
555	93	0.5007	0.4993	755	91	0.9801	0.0199
700	82	0.4329	0.5671	859	92	0.7868	0.2132
861	48	0.2650	0.7350	1089	99	0.9951	0.0049
864	93	0.8724	0.1276	1191	93	0.6705	0.3295
868	57	0.4866	0.5134	1420	75	0.9575	0.0425
1192	83	0.7175	0.2825	1425	98	0.9859	0.0141
1422	82	0.8215	0.1785	1426	82	0.9575	0.0425
1423	98	0.9994	0.0006	1427	98	0.9859	0.0141
1424	83	0.9575	0.0425	1428	82	0.9575	0.0425
1441	92	0.5452	0.4548	1430	84	0.7407	0.2593
1510	60	0.2899	0.7101	1443	78	0.7407	0.2593
1513	38	0.3197	0.6803	1515	92	0.9738	0.0262
1521	89	0.9995	0.0005	1529	83	0.5383	0.4617
1533	93	0.4629	0.5371	1530	79	0.4108	0.5892
1560	94	0.8645	0.1355	1534	91	0.8909	0.1091
1600	42	0.6588	0.3412	1575	68	0.4586	0.5414
1620	78	0.6881	0.3119	1601	35	0.0869	0.9131
1650	93	0.9261	0.0739	1907	72	0.7040	0.2960
1670	85	0.4995	0.5005	1980	77	0.5491	0.4509
1700	88	0.6753	0.3247	1981	77	0.9193	0.0807

HVAC Failed				HVAC Non-Failed			
Fac Nmbr	SCI	R(t)	Pf(t)	Fac Nmbr	SCI	R(t)	Pf(t)
1800	72	0.9693	0.0307	3272	38	0.2053	0.7947
1805	71	0.7097	0.2903	3284	93	0.9200	0.0800
1807	86	0.9831	0.0169	3285	65	0.6759	0.3241
1820	95	0.8169	0.1831	3292	47	0.0200	0.9800
1830	65	0.5688	0.4312	3300	99	0.8408	0.1592
1850	91	0.9772	0.0228	3301	24	0.1204	0.8796
1900	92	0.7408	0.2592	3307	0	0.0000	1.0000
1906	64	0.8494	0.1506	3600	93	0.5080	0.4920
1930	77	0.7233	0.2767	3651	89	0.6404	0.3596
1934	50	0.3278	0.6722	3652	84	0.7120	0.2880
1940	93	0.8130	0.1870	3677	92	0.5505	0.4495
1948	78	0.8276	0.1724	3901	87	0.8400	0.1600
1961	78	0.7903	0.2097	4010	67	0.7668	0.2332
1981	78	0.9193	0.0807	4020	82	0.8327	0.1673
1987	70	0.7845	0.2155	4022	78	0.8073	0.1927
1989	55	0.6061	0.3939	4024	92	0.9107	0.0893
3189	63	0.4559	0.5441	4030	93	0.8702	0.1298
3192	93	0.6700	0.3300	4032	92	0.8834	0.1166
3650	86	0.6596	0.3404	4036	93	0.9457	0.0543
3689	2	0.4420	0.5580	5000	79	0.7977	0.2023
3900	84	0.6994	0.3006	5008	78	0.7983	0.2017
4001	87	0.8621	0.1379	5022	80	0.7742	0.2258
4560	93	0.6348	0.3652	5046	91	0.6483	0.3517
4780	93	0.7703	0.2297	5048	77	0.9805	0.0195
5713	90	0.9237	0.0763	5498	35	0.6356	0.3644

Electric Failed				Electric Non-Failed			
Fac Nmbr	SCI	R(t)	Pf(t)	Fac Nmbr	SCI	R(t)	Pf(t)
40	92	0.9942	0.0058	382	92	0.9918	0.0082
352	93	0.7820	0.2180	460	92	0.8837	0.1163
57	92	0.6346	0.3654	861	81	0.4736	0.5264
433	88	0.6069	0.3931	1510	88	0.7604	0.2396
533	52	0.1993	0.8007	1620	93	0.7226	0.2774
859	92	0.7601	0.2399	1807	87	0.9856	0.0144
1515	93	0.9783	0.0217	1900	90	0.3332	0.6668
1521	91	0.9189	0.0811	3284	93	0.8994	0.1006
1530	86	0.8633	0.1367	3289	41	0.4172	0.5828
4001	94	0.4716	0.5284	3650	94	0.5033	0.4967
4024	93	0.9299	0.0701	3900	87	0.5800	0.4200

Fire Protection Failed				Fire Protection Non-Failed			
Fac Nmbr	SCI	R(t)	Pf(t)	Fac Nmbr	SCI	R(t)	Pf(t)
506	85	0.9939	0.0061	750	10	0.7856	0.2144
1948	93	0.7784	0.2216	861	93	0.8045	0.1955

Plumbing Failed				Plumbing Non-Failed			
Fac Nmbr	SCI	R(t)	Pf(t)	Fac Nmbr	SCI	R(t)	Pf(t)
3	92	0.3730	0.6270	1191	90	0.8425	0.1575
1575	91	0.6043	0.3957	1807	93	0.9899	0.0101
1700	88	0.7060	0.2940	1900	89	0.4852	0.5148
3900	91	0.7360	0.2640	3189	80	0.7158	0.2842

Note: SCI values were not calculated via the PoF model. SCI values were pulled from BUILDER® for CY14.

Appendix B. R code for Probabilistic Assessment of Failure (PoF) model

The below code represents the Ordered Weighted Average method to construct the Probabilistic Assessment of Failure (PoF) model. This research created an R function for the four major systems considered. Once created, a user needs only to input the component-section average age.

Plumbing System (D20)

```
D20 = function(bldg,
        d211,d212,d213,d214,d215,d216,d217,d219,
        d221,d222,d223,d224,d225,d229,
        d231,d232,d233,d234,d235,d239,
        d241,d242,d243,d244,d249,
        d291,d292,d293,d294,d295,d299) {
#Year of Data Being Pulled
  yr =
#Put into component vectors
  i.21 = c(d211,d212,d213,d214,d215,d216,d217,d219)
  i.22 = c(d221,d222,d223,d224,d225,d229)
  i.23 = c(d231,d232,d233,d234,d235,d239)
  i.24 = c(d241,d242,d243,d244,d249)
  i.29 = c(d291,d292,d293,d294,d295,d299)
#Return Logic Weight vectors
  lg.21 = (as.logical(i.21))
  lg.22 = (as.logical(i.22))
  lg.23 = (as.logical(i.23))
  lg.24 = (as.logical(i.24))
  lg.29 = (as.logical(i.29))
#Assign C-S Weights
  w1.21 = c(.6375,.4067,.6500,.5375,1.0,1.0,.4933,1.0)
  w1.22 = c(.3030,1.0,1.0,1.0,1.0,1.0)
  w1.23 = c(.4114,1.0,1.0,1.0,1.0,.4750)
  w1.24 = c(1.0,.5475,.9014,1.0,1.0)
  w1.29 = c(.4360,1.0,1.0,1.0,1.0,.5083)
#Standardize the C-S Weight cs
  w.21 = w1.21*lg.21
  w.22 = w1.22*lg.22
  w.23 = w1.23*lg.23
```

```
 w.24 = w1.24*lg.24
 w.29 = w1.29*lg.29

 w.21 = w.21[w.21 != 0 ]
 w.22 = w.22[w.22 != 0 ]
 w.23 = w.23[w.23 != 0 ]
 w.24 = w.24[w.24 != 0 ]
 w.29 = w.29[w.29 != 0 ]

 w.21 = w.21/sum(w.21)
 w.22 = w.22/sum(w.22)
 w.23 = w.23/sum(w.23)
 w.24 = w.24/sum(w.24)
 w.29 = w.29/sum(w.29)
#Assign Service Lives
 l.21 = c(25,25,25,25,25,10,25,15)
 l.22 = c(50,25,25,25,25,8)
 l.23 = c(50,25,25,25,25,100)
 l.24 = c(25,25,25,25,25)
 l.29 = c(15,25,25,25,25,25)
#Calculate t as a percentage of service life
 t.21 = ((yr-i.21)/l.21)*lg.21
 t.22 = ((yr-i.22)/l.22)*lg.22
 t.23 = ((yr-i.23)/l.23)*lg.23
 t.24 = ((yr-i.24)/l.24)*lg.24
 t.29 = ((yr-i.29)/l.29)*lg.29
#Calculate PoF vector
 pof.21 = c(); pof.22=c();pof.23=c();pof.24=c();pof.25=c();pof.26=c();pof.27=c();pof.29=c(
);
 b = 1
 a = 2.64
 CI_t = .37
 for(i in 1:length(t.21)){
  pof = 1-(1/CI_t)^(-(t.21[i]/b)^a)
  pof.21[i] = pof
 }
 for(i in 1:length(t.22)){
  pof = 1-(1/CI_t)^(-(t.22[i]/b)^a)
  pof.22[i] = pof
 }
 for(i in 1:length(t.23)){
  pof = 1-(1/CI_t)^(-(t.23[i]/b)^a)
  pof.23[i] = pof
```

```
  }
  for(i in 1:length(t.24)){
    pof = 1-(1/CI_t)^(-(t.24[i]/b)^a)
    pof.24[i] = pof
  }
  for(i in 1:length(t.29)){
    pof = 1-(1/CI_t)^(-(t.29[i]/b)^a)
    pof.29[i] = pof
  }
#Sort PoF Vector
  pof.21 = sort(pof.21, decreasing = T)
  pof.22 = sort(pof.22, decreasing = T)
  pof.23 = sort(pof.23, decreasing = T)
  pof.24 = sort(pof.24, decreasing = T)
  pof.29 = sort(pof.29, decreasing = T)
#Assign CII Weights
  if (sum(pof.21) == 0){c.21 = 0}else {c.21 = .4472}
  if (sum(pof.22) == 0){c.22 = 0}else {c.22 = .5419}
  if (sum(pof.23) == 0){c.23 = 0}else {c.23 = .6279}
  if (sum(pof.24) == 0){c.24 = 0}else {c.24 = .5216}
  if (sum(pof.29) == 0){c.29 = 0}else {c.29 = .3025}
#Standardize CII Weights
  sys.wt.2 = c(c.21,c.22,c.23,c.24,c.29)
  sys.wt.2 = sys.wt.2[sys.wt.2 != 0 ]
  sys.wt.2 = (sys.wt.2/(sum(sys.wt.2)))
#Remove zeroes from PoF vectors
  pof.21 = pof.21[pof.21 != 0 ]
  pof.22 = pof.22[pof.22 != 0 ]
  pof.23 = pof.23[pof.23 != 0 ]
  pof.24 = pof.24[pof.24 != 0 ]
  pof.29 = pof.29[pof.29 != 0 ]
#Compute Compontent Level ORAND Operators
  pofc.21 = crossprod(pof.21,w.21)
  pofc.22 = crossprod(pof.22,w.22)
  pofc.23 = crossprod(pof.23,w.23)
  pofc.24 = crossprod(pof.24,w.24)
  pofc.29 = crossprod(pof.29,w.29)
  comp.op.2 = c(pofc.21,pofc.22,pofc.23,pofc.24,pofc.29)
#Sort the Component level vector
  comp.op.2 = comp.op.2[comp.op.2 != 0 ]
  comp.op.2 = sort(comp.op.2, decreasing = T)
#Calculate System PoF
sys.pof.fail.2 = crossprod(sys.wt.2,comp.op.2)
```

```
sys.pof.fail.2
}
```

HVAC System (D30)

```
D30 = function(bldg,
            d311,d312,d313,d314,d315,d316,d317,d319,
            d321,d322,d323,d324,d325,d329,
            d331,d332,d339,
            d341,d342,d343,d344,d345,d346,d347,d348,d349,
            d351,d352,d353,d354,d355,d356,d359,
            d361,d362,d363,d364,d365,d369,
            d371,d372,d373,d379,
            d391,d392,d399) {
 yr =
 #Put ages into component vectors
 i.31 = c(d311,d312,d313,d314,d315,d316,d317,d319)
 i.32 = c(d321,d322,d323,d324,d325,d329)
 i.33 = c(d331,d332,d339)
 i.34 = c(d341,d342,d343,d344,d345,d346,d347,d348,d349)
 i.35 = c(d351,d352,d353,d354,d355,d356,d359)
 i.36 = c(d361,d362,d363,d364,d365,d369)
 i.37 = c(d371,d372,d373,d379)
 i.39 = c(d391,d392,d399)
 #Return Logic vectors
 lg.31 = (as.logical(i.31))
 lg.32 = (as.logical(i.32))
 lg.33 = (as.logical(i.33))
 lg.34 = (as.logical(i.34))
 lg.35 = (as.logical(i.35))
 lg.36 = (as.logical(i.36))
 lg.37 = (as.logical(i.37))
 lg.39 = (as.logical(i.39))
 #Assign C-S Weights
 w1.31 = c(1.0,0.2,1.0,1.0,1.0,1.0,1.0,1.0)
 w1.32 = c(1.0,0.5265,.4247,.648,1.0,1.0)
 w1.33 = c(1.0,1.0,0.09)
 w1.34 = c(.31,.436,1.0,1.0,.2186,1.0,1.0,1.0,.1775)
 w1.35 = c(1,1,1,.2640,.2725,1,.2718)
 w1.36 = c(1,.5650,.5650,1,1,.4325)
 w1.37 = c(1,1,1,1)
 w1.39 = c(1,1,.2344)
```

```
#Standardize the C-S Weight cs
 w.31 = w1.31*lg.31
 w.32 = w1.32*lg.32
 w.33 = w1.33*lg.33
 w.34 = w1.34*lg.34
 w.35 = w1.35*lg.35
 w.36 = w1.36*lg.36
 w.37 = w1.37*lg.37
 w.39 = w1.39*lg.39

 w.31 = w.31[w.31 != 0 ]
 w.32 = w.32[w.32 != 0 ]
 w.33 = w.33[w.33 != 0 ]
 w.34 = w.34[w.34 != 0 ]
 w.35 = w.35[w.35 != 0 ]
 w.36 = w.36[w.36 != 0 ]
 w.37 = w.37[w.37 != 0 ]
 w.39 = w.39[w.39 != 0 ]

 w.31 = w.31/sum(w.31)
 w.32 = w.32/sum(w.32)
 w.33 = w.33/sum(w.33)
 w.34 = w.34/sum(w.34)
 w.35 = w.35/sum(w.35)
 w.36 = w.36/sum(w.36)
 w.37 = w.37/sum(w.37)
 w.39 = w.39/sum(w.39)
 #Assign Service Lives vectors
 l.31 = c(20,50,20,20,25,20,20,20)
 l.32 = c(30,15,25,20,20,20)
 l.33 = c(20,20,15)
 l.34 = c(20,30,20,20,30,20,10,15,30)
 l.35 = c(20,25,15,30,25,20,25)
 l.36 = c(20,10,10,25,20,10)
 l.37 = c(20,20,20,20)
 l.39 = c(20,20,20)
 #Calculate t as a percentage of service life
 t.31 = ((yr-i.31)/l.31)*lg.31
 t.32 = ((yr-i.32)/l.32)*lg.32
 t.33 = ((yr-i.33)/l.33)*lg.33
 t.34 = ((yr-i.34)/l.34)*lg.34
 t.35 = ((yr-i.35)/l.35)*lg.35
 t.36 = ((yr-i.36)/l.36)*lg.36
```

```
  t.37 = ((yr-i.37)/l.37)*lg.37
  t.39 = ((yr-i.39)/l.39)*lg.39
#Calculate PoF vector
pof.31 = c(); pof.32=c();pof.33=c();pof.34=c();pof.35=c();pof.36=c();pof.37=c();pof.39=c();
b = 1
a = 2.64
CI_t = .37
for(i in 1:length(t.31)){
  pof = 1-(1/CI_t)^(-(t.31[i]/b)^a)
  pof.31[i] = pof
}
for(i in 1:length(t.32)){
  pof = 1-(1/CI_t)^(-(t.32[i]/b)^a)
  pof.32[i] = pof
}
for(i in 1:length(t.33)){
  pof = 1-(1/CI_t)^(-(t.33[i]/b)^a)
  pof.33[i] = pof
}
for(i in 1:length(t.34)){
  pof = 1-(1/CI_t)^(-(t.34[i]/b)^a)
  pof.34[i] = pof
}
for(i in 1:length(t.35)){
  pof = 1-(1/CI_t)^(-(t.35[i]/b)^a)
  pof.35[i] = pof
}
for(i in 1:length(t.36)){
  pof = 1-(1/CI_t)^(-(t.36[i]/b)^a)
  pof.36[i] = pof
}
for(i in 1:length(t.37)){
  pof = 1-(1/CI_t)^(-(t.37[i]/b)^a)
  pof.37[i] = pof
}
for(i in 1:length(t.39)){
  pof = 1-(1/CI_t)^(-(t.39[i]/b)^a)
  pof.39[i] = pof
}
#Sort PoF Vector
pof.31 = sort(pof.31, decreasing = T)
pof.32 = sort(pof.32, decreasing = T)
pof.33 = sort(pof.33, decreasing = T)
```

```
pof.34 = sort(pof.34, decreasing = T)
pof.35 = sort(pof.35, decreasing = T)
pof.36 = sort(pof.36, decreasing = T)
pof.37 = sort(pof.37, decreasing = T)
pof.39 = sort(pof.39, decreasing = T)
#Assign CII Weights
if (sum(pof.31) == 0){c.31 = 0} else {c.31 = .3163}
if (sum(pof.32) == 0){c.32 = 0} else {c.32 = .6363}
if (sum(pof.33) == 0){c.33 = 0} else {c.33 = .5755}
if (sum(pof.34) == 0){c.34 = 0} else {c.34 = .4835}
if (sum(pof.35) == 0){c.35 = 0} else {c.35 = .5836}
if (sum(pof.36) == 0){c.36 = 0} else {c.36 = .5014}
if (sum(pof.37) == 0){c.37 = 0} else {c.37 = .5168}
if (sum(pof.39) == 0){c.39 = 0} else {c.39 = .3239}
sys.wt = c(c.31,c.32,c.33,c.34,c.35,c.36,c.37,c.39)
sys.wt = sys.wt[sys.wt != 0 ]
sys.wt = (sys.wt/(sum(sys.wt)))
#Remove zeroes from PoF vectors
pof.31 = pof.31[pof.31 != 0 ]
pof.32 = pof.32[pof.32 != 0 ]
pof.33 = pof.33[pof.33 != 0 ]
pof.34 = pof.34[pof.34 != 0 ]
pof.35 = pof.35[pof.35 != 0 ]
pof.36 = pof.36[pof.36 != 0 ]
pof.37 = pof.37[pof.37 != 0 ]
pof.39 = pof.39[pof.39 != 0 ]
# Compute Compontent Level ORAND Operators
pofc.31 = crossprod(pof.31,w.31)
pofc.32 = crossprod(pof.32,w.32)
pofc.33 = crossprod(pof.33,w.33)
pofc.34 = crossprod(pof.34,w.34)
pofc.35 = crossprod(pof.35,w.35)
pofc.36 = crossprod(pof.36,w.36)
pofc.37 = crossprod(pof.37,w.37)
pofc.39 = crossprod(pof.39,w.39)
comp.op = c(pofc.31,pofc.32,pofc.33,pofc.34,pofc.35,pofc.36,pofc.37,pofc.39)
#Sort the Component level vector
comp.op = comp.op[comp.op != 0 ]
comp.op = sort(comp.op, decreasing = T)
#Calculate System PoF
sys.pof.fail = crossprod(sys.wt,comp.op)
sys.pof.fail
}
```

Fire Protection System (D40)

```
D40 = function(bldg,
            d411,d412,
            d421,d422,
            d431,
            d441,d442,
            d451,
            d491,d492,d494,d494,d499) {
#Year of Data Being Pulled
 yr =
#Put into component vectors
 i.41 = c(d411,d412)
 i.42 = c(d411,d412)
 i.43 = c(d431)
 i.44 = c(d441,d442)
 i.45 = c(d451)
 i.49 = c(d491,d492,d493,d494,d499)
#Return Logic Weight vectors
 lg.41 = (as.logical(i.41))
 lg.42 = (as.logical(i.42))
 lg.43 = (as.logical(i.43))
 lg.44 = (as.logical(i.44))
 lg.45 = (as.logical(i.45))
 lg.49 = (as.logical(i.49))
#Assign C-S Weights
 w1.41 = c(1.0,0.3613)
 w1.42 = c(1.0,1.0)
 w1.43 = c(.2114)
 w1.44 = c(.3150,.3150)
 w1.45 = c(1.0)
 w1.49 = c(.4700,1.0,1.0,.4700,1.0)
#Standardize the C-S Weight cs
 w.41 = w1.41*lg.41
 w.42 = w1.42*lg.42
 w.43 = w1.43*lg.43
 w.44 = w1.44*lg.44
 w.45 = w1.45*lg.45
 w.49 = w1.49*lg.49

 w.41 = w.41[w.41 != 0 ]
 w.42 = w.42[w.42 != 0 ]
```

```
 w.43 = w.43[w.43 != 0 ]
 w.44 = w.44[w.44 != 0 ]
 w.45 = w.45[w.45 != 0 ]
 w.49 = w.49[w.49 != 0 ]

 w.41 = w.41/sum(w.41)
 w.42 = w.42/sum(w.42)
 w.43 = w.43/sum(w.43)
 w.44 = w.44/sum(w.44)
 w.45 = w.45/sum(w.45)
 w.49 = w.49/sum(w.49)
#Assign Service Lives #Working#
 l.41 = c(20,20)
 l.42 = c(20,20)
 l.43 = c(20)
 l.44 = c(50,23)
 l.45 = c(20)
 l.49 = c(25,20,20,25,20)
#Calculate t as a percentage of service life
 t.41 = ((yr-i.41)/l.41)*lg.41
 t.42 = ((yr-i.42)/l.42)*lg.42
 t.43 = ((yr-i.43)/l.43)*lg.43
 t.44 = ((yr-i.44)/l.44)*lg.44
 t.45 = ((yr-i.45)/l.45)*lg.45
 t.49 = ((yr-i.49)/l.49)*lg.49
#Calculate PoF vector
 pof.41 = c(); pof.42=c();pof.43=c();pof.44=c();pof.45=c();pof.49=c();
 b = 1
 a = 2.64
 CI_t = .37
 for(i in 1:length(t.41)){
  pof = 1-(1/CI_t)^(-(t.41[i]/b)^a)
  pof.41[i] = pof
 }
 for(i in 1:length(t.42)){
  pof = 1-(1/CI_t)^(-(t.42[i]/b)^a)
  pof.42[i] = pof
 }
 for(i in 1:length(t.43)){
  pof = 1-(1/CI_t)^(-(t.43[i]/b)^a)
  pof.43[i] = pof
 }
 for(i in 1:length(t.44)){
```

```
    pof = 1-(1/CI_t)^(-(t.44[i]/b)^a)
    pof.44[i] = pof
  }
  for(i in 1:length(t.45)){
    pof = 1-(1/CI_t)^(-(t.45[i]/b)^a)
    pof.45[i] = pof
  }
  for(i in 1:length(t.49)){
    pof = 1-(1/CI_t)^(-(t.49[i]/b)^a)
    pof.49[i] = pof
  }
  #Sort PoF Vector
  pof.41 = sort(pof.41, decreasing = T)
  pof.42 = sort(pof.42, decreasing = T)
  pof.43 = sort(pof.43, decreasing = T)
  pof.44 = sort(pof.44, decreasing = T)
  pof.45 = sort(pof.45, decreasing = T)
  pof.49 = sort(pof.49, decreasing = T)
#Assign CII Weights
  if (sum(pof.41) == 0){c.41 = 0}else {c.41 = .3070 }
  if (sum(pof.42) == 0){c.42 = 0}else {c.42 = .3460}
  if (sum(pof.43) == 0){c.43 = 0}else {c.43 = .3425}
  if (sum(pof.44) == 0){c.44 = 0}else {c.44 = .2680}
  if (sum(pof.45) == 0){c.45 = 0}else {c.45 = .3190}
  if (sum(pof.49) == 0){c.49 = 0}else {c.49 = .2680}
#Standardize CII Weights
  sys.wt.4 = c(c.41,c.42,c.43,c.44,c.45,c.49)
  sys.wt.4 = sys.wt.4[sys.wt.4 != 0 ]
  sys.wt = (sys.wt.4/(sum(sys.wt.4)))
#Remove zeroes from PoF vectors
  pof.41 = pof.41[pof.41 != 0 ]
  pof.42 = pof.42[pof.42 != 0 ]
  pof.43 = pof.43[pof.43 != 0 ]
  pof.44 = pof.44[pof.44 != 0 ]
  pof.45 = pof.45[pof.45 != 0 ]
  pof.49 = pof.49[pof.49 != 0 ]
# Compute Compontent Level ORAND Operators
  pofc.41 = crossprod(pof.41,w.41)
  pofc.42 = crossprod(pof.42,w.42)
  pofc.43 = crossprod(pof.43,w.43)
  pofc.44 = crossprod(pof.44,w.44)
  pofc.45 = crossprod(pof.45,w.45)
  pofc.49 = crossprod(pof.49,w.49)
```

```
 comp.op.4 = c(pofc.41,pofc.42,pofc.43,pofc.44,pofc.45,pofc.49)
#Sort the Component level vector
 comp.op.4 = comp.op.4[comp.op.4 != 0 ]
 comp.op.4 = sort(comp.op.4, decreasing = T)
#Calculate System PoF
sys.pof.fail.4 = crossprod(sys.wt.4,comp.op.4)
sys.pof.fail.4
}
```

Electrical System (D50)

```
D50 = function(bldg,
        d511,d512,d513,d514,d515,d516,d519,
        d521,d522,d529,
        d531,d532,d533,d534,d535,d536,d537,d539,
        d591,d592,d593,d594,d595,d596,d599){
#Year of Data Being Pulled
 yr =
#Put into component vectors
 i.51 = c(d511,d512,d513,d514,d515,d516,d519)
 i.52 = c(d521,d522,d529)
 i.53 = c(d531,d532,d533,d534,d535,d536,d537,d539)
 i.59 = c(d591,d592,d593,d594,d595,d596,d599)
#Return Logic Weight vectors
 lg.51 = (as.logical(i.51))
 lg.52 = (as.logical(i.52))
 lg.53 = (as.logical(i.53))
 lg.59 = (as.logical(i.59))
#Assign C-S Weights
 w1.51 = c(1.0,1.0,.4850,1.0,1.0,.3840,1.0)
 w1.52 = c(.2357,.3014,.4300)
 w1.53 = c(1.0,1.0,.3500,1.0,1.0,1.0,1.0,.3700)
 w1.59 = c(1.0,1.0,.5250,.6100,1.0,1.0,.4225)

#Standardize the C-S Weight cs
 w.51 = w1.51*lg.51
 w.52 = w1.52*lg.52
 w.53 = w1.53*lg.53
 w.59 = w1.59*lg.59

 w.51 = w.51[w.51 != 0]
 w.52 = w.52[w.52 != 0]
```

```
 w.53 = w.53[w.53 != 0]
 w.59 = w.59[w.59 != 0]

 w.51 = w.51/sum(w.51)
 w.52 = w.52/sum(w.52)
 w.53 = w.53/sum(w.53)
 w.59 = w.59/sum(w.59)
#Assign Service Lives #Working#
 l.51 = c(20,20,30,50,50,40,25)
 l.52 = c(60,20,15)
 l.53 = c(20,20,15,20,20,20,20,15)
 l.59 = c(20,20,50,50,20,20,18)
#Calculate t as a percentage of service life
 t.51 = ((yr-i.51)/l.51)*lg.51
 t.52 = ((yr-i.52)/l.52)*lg.52
 t.53 = ((yr-i.53)/l.53)*lg.53
 t.59 = ((yr-i.59)/l.59)*lg.59
#Calculate PoF vector
 pof.51 = c(); pof.52=c();pof.53=c();pof.59=c();
 b = 1
 a = 2.64
 CI_t = .37
 for(i in 1:length(t.51)){
  pof = 1-(1/CI_t)^(-(t.51[i]/b)^a)
  pof.51[i] = pof
 }
 for(i in 1:length(t.52)){
  pof = 1-(1/CI_t)^(-(t.52[i]/b)^a)
  pof.52[i] = pof
 }
 for(i in 1:length(t.53)){
  pof = 1-(1/CI_t)^(-(t.53[i]/b)^a)
  pof.53[i] = pof
 }
 for(i in 1:length(t.59)){
  pof = 1-(1/CI_t)^(-(t.59[i]/b)^a)
  pof.59[i] = pof
 }
#Sort PoF Vector
 pof.51 = sort(pof.51, decreasing = T)
 pof.52 = sort(pof.52, decreasing = T)
 pof.53 = sort(pof.53, decreasing = T)
 pof.59 = sort(pof.59, decreasing = T)
```

```
#Assign CII Weights
 if (sum(pof.51) == 0){c.51 = 0}else {c.51 = .6091}
 if (sum(pof.52) == 0){c.52 = 0}else {c.52 = .6708}
 if (sum(pof.53) == 0){c.53 = 0}else {c.53 = .3362}
 if (sum(pof.59) == 0){c.59 = 0}else {c.59 = .3826}
#Standardize CII Weights
 sys.wt.5 = c(c.51,c.52,c.53,c.59)
 sys.wt.5 = sys.wt.5[sys.wt.5 != 0 ]
 sys.wt.5 = (sys.wt.5/(sum(sys.wt.5)))
#Remove zeroes from PoF vectors
 pof.51 = pof.51[pof.51 != 0 ]
 pof.52 = pof.52[pof.52 != 0 ]
 pof.53 = pof.53[pof.53 != 0 ]
 pof.59 = pof.59[pof.59 != 0 ]
#Compute Compontent Level ORAND Operators
 pofc.51 = crossprod(pof.51,w.51)
 pofc.52 = crossprod(pof.52,w.52)
 pofc.53 = crossprod(pof.53,w.53)
 pofc.59 = crossprod(pof.59,w.59)
 comp.op.5 = c(pofc.51,pofc.52,pofc.53,pofc.59)
#Sort the Component level vector
 comp.op.5 = comp.op.5[comp.op.5 != 0 ]
 comp.op.5 = sort(comp.op.5, decreasing = T)
#Calculate System PoF
sys.pof.fail.5 = crossprod(sys.wt.5,comp.op.5)
sys.pof.fail.5
}
```

With the above functions created, this research was able to import tables of component-section average ages and calculate the probability of failure for each system. The system probability of failure was then output as a seperate data file via the code below. The "SystOWA" package called in line two of the below code is the package created with the code above for the four major systems.

```
library(XLConnect)
library(SystOWA)
#The data file pulled in needs to be a table of component-section average ages.  This will
produce a results workbook for each bases failed and non-failed data set
data = loadWorkbook("/Users/deeringpatrick/Documents/AFIT/1. Thesis/Model Validati
```

```
on/Data Files/Raw Data/Cannon_NoFail.xls")

HVAC = readWorksheet(data, sheet = "HVAC")
ELEC = readWorksheet(data, sheet = "ELEC")
FIRE = readWorksheet(data, sheet = "FIRE")
PLUMB = readWorksheet(data, sheet = "PLUMB")

output = matrix(nrow = nrow(HVAC), ncol = 4, byrow = T )
output2 = matrix(nrow = nrow(PLUMB), ncol = 4, byrow = T)
output3 = matrix(nrow = nrow(ELEC), ncol = 4, byrow = T)
output4 = matrix(nrow = nrow(FIRE), ncol = 4, byrow = T)

for(i in 1:nrow(HVAC)){
 SCI = HVAC[i,1]
 bldg = HVAC[i,2];
 d311=HVAC[i,3];d312=HVAC[i,4];d313=HVAC[i,5];d314=HVAC[i,6];d315=HVAC[i,7];d31
6=HVAC[i,8];d317=HVAC[i,9];d319=HVAC[i,10];
 d321=HVAC[i,11];d322=HVAC[i,12];d323=HVAC[i,13];d324=HVAC[i,14];d325=HVAC[i,15
];d329=HVAC[i,16];
 d331=HVAC[i,17];d332=HVAC[i,18];d339=HVAC[i,19];
 d341=HVAC[i,20];d342=HVAC[i,21];d343=HVAC[i,22];d344=HVAC[i,23];d345=HVAC[i,24
];d346=HVAC[i,25];d347=HVAC[i,26];d348=HVAC[i,27];d349=HVAC[i,28];
 d351=HVAC[i,29];d352=HVAC[i,30];d353=HVAC[i,31];d354=HVAC[i,32];d355=HVAC[i,33
];d356=HVAC[i,34];d359=HVAC[i,35];
 d361=HVAC[i,36];d362=HVAC[i,37];d363=HVAC[i,38];d364=HVAC[i,39];d365=HVAC[i,40
];d369=HVAC[i,41];
 d371=HVAC[i,42];d372=HVAC[i,43];d373=HVAC[i,44];d379=HVAC[i,45];
 d391=HVAC[i,46];d392=HVAC[i,47];d399=HVAC[i,48]
 sys.pof.fail.h = D30(bldg,d311,d312,d313,d314,d315,d316,d317,d319,d321,d322,d323,
d324,d325,d329,d331,d332,d339,d341,d342,d343,d344,d345,d346,d347,d348,d349,d35
1,d352,d353,d354,d355,d356,d359,d361,d362,d363,d364,d365,d369,d371,d372,d373,d
379,d391,d392,d399)
output[i,]= c(bldg,as.numeric(SCI),as.numeric(1-sys.pof.fail.h),as.numeric(sys.pof.fail.h))
}

rm(list=setdiff(ls(), c("data","output","output2","output3","output4","FIRE","HVAC","PL
UMB","ELEC")))

for(i in 1:nrow(PLUMB)){
 SCI=PLUMB[i,1];bldg=PLUMB[i,2];
 d211=PLUMB[i,3];d212=PLUMB[i,4];d213=PLUMB[i,5];d214=PLUMB[i,6];d215=PLUMB[
i,7];d216=PLUMB[i,8];d217=PLUMB[i,9];d219=PLUMB[i,10];
 d221=PLUMB[i,11];d222=PLUMB[i,12];d223=PLUMB[i,13];d224=PLUMB[i,14];d225=PL
```

```
UMB[i,15];d229=PLUMB[i,16];
 d231=PLUMB[i,17];d232=PLUMB[i,18];d233=PLUMB[i,19];d234=PLUMB[i,20];d235=PL
UMB[i,21];d239=PLUMB[i,22];
 d241=PLUMB[i,23];d242=PLUMB[i,24];d243=PLUMB[i,25];d244=PLUMB[i,26];d249=PL
UMB[i,27];
 d291=PLUMB[i,28];d292=PLUMB[i,29];d293=PLUMB[i,30];d294=PLUMB[i,31];d295=PL
UMB[i,31];d299=PLUMB[i,32]
 sys.pof.fail.p = D20(bldg,d211,d212,d213,d214,d215,d216,d217,d219,d221,d222,d223,
d224,d225,d229,d231,d232,d233,d234,d235,d239,d241,d242,d243,d244,d249,d291,d29
2,d293,d294,d295,d299)
 output2[i,]= c(bldg,as.numeric(SCI),as.numeric(1-sys.pof.fail.p),as.numeric(sys.pof.fail.
p))
}

rm(list=setdiff(ls(), c("data","output","output2","output3","output4","FIRE","HVAC","PL
UMB","ELEC")))


for(i in 1:nrow(ELEC)){
 SCI=ELEC[i,1];bldg=ELEC[i,2];
 d511=ELEC[i,3];d512=ELEC[i,4];d513=ELEC[i,5];d514=ELEC[i,6];d515=ELEC[i,7];d516=EL
EC[i,8];d519=ELEC[i,9];
 d521=ELEC[i,10];d522=ELEC[i,11];d529=ELEC[i,12];
 d531=ELEC[i,13];d532=ELEC[i,14];d533=ELEC[i,15];d534=ELEC[i,16];d535=ELEC[i,17];d5
36=ELEC[i,18];d537=ELEC[i,19];d539=ELEC[i,20];
 d591=ELEC[i,21];d592=ELEC[i,22];d593=ELEC[i,23];d594=ELEC[i,24];d595=ELEC[i,25];d5
96=ELEC[i,26];d599=ELEC[i,27];
 sys.pof.fail.e = D50(bldg,d511,d512,d513,d514,d515,d516,d519,d521,d522,d529,d531,
d532,d533,d534,d535,d536,d537,d539,d591,d592,d593,d594,d595,d596,d599)
 output3[i,]= c(bldg,as.numeric(SCI),as.numeric(1-sys.pof.fail.e),as.numeric(sys.pof.fail.
e))
}

rm(list=setdiff(ls(), c("data","output","output2","output3","output4","FIRE","HVAC","PL
UMB","ELEC")))

for(i in 1:nrow(FIRE)){
 SCI=FIRE[i,1];bldg=FIRE[i,2];
 d411=FIRE[i,3];d412=FIRE[i,4];
 d421=FIRE[i,5];d422=FIRE[i,6];
 d431=FIRE[i,7];
 d441=FIRE[i,8];d442=FIRE[i,9];
 d451=FIRE[i,10];
```

```
  d491=FIRE[i,11];d492=FIRE[i,12];d493=FIRE[i,13];d494=FIRE[i,14];d499=FIRE[i,15];
  sys.pof.fail.f = D40(bldg,d411,d412,d421,d422,d431,d441,d442,d451,d491,d492,d493,
d494,d499)
  output4[i,]= c(bldg,as.numeric(SCI),as.numeric(1-sys.pof.fail.f),as.numeric(sys.pof.fail.f
))
}

rm(list=setdiff(ls(), c("data","output","output2","output3","output4","FIRE","HVAC","PL
UMB","ELEC")))

wb = loadWorkbook("Cannon_NoFail_Pull2.xls", create = T)
createSheet(wb, name = "HVAC")
writeWorksheet(wb, output, sheet = "HVAC")
createSheet(wb, name = "PLUMB")
writeWorksheet(wb, output2, sheet = "PLUMB")
createSheet(wb, name = "FIRE")
writeWorksheet(wb, output4, sheet = "FIRE")
createSheet(wb, name = "ELEC")
writeWorksheet(wb, output3, sheet = "ELEC")
saveWorkbook(wb)
```

Appendix C. R code for contingency analysis and plot output

The below code used the output from the code presented in Appendix B to perform a contingency analysis and plot the associated p values and odds ratios for a given system over all possible values of a reliability threshold.

```
library(XLConnect)
data = loadWorkbook("/Users/deeringpatrick/Documents/AFIT/1. Thesis/Model Validati
on/Data Files/Results Data/Threshold Data Files/Consolidated Results_By System.xlsx")

HVAC.Fail = readWorksheet(data, sheet = "Fail", startRow = 97, endRow = 446, startCol
= 4, endCol = 4, header = FALSE)
PLUMB.Fail = readWorksheet(data, sheet = "Fail", startRow = 447, endRow = 466, startC
ol = 4, endCol =4, header = FALSE)
FIRE.Fail = readWorksheet(data, sheet = "Fail", startRow = 61, endRow = 96, startCol = 4
, endCol = 4, header = FALSE)
ELEC.Fail = readWorksheet(data, sheet = "Fail", startRow = 2, endRow = 60, startCol = 4,
endCol =4, header = FALSE)


HVAC.NoFail = readWorksheet(data, sheet = "NoFail", startRow = 97, endRow = 446, sta
rtCol = 4, endCol = 4, header = FALSE)
PLUMB.NoFail = readWorksheet(data, sheet = "NoFail", startRow = 447, endRow = 466,
startCol = 4, endCol =4, header = FALSE)
FIRE.NoFail = readWorksheet(data, sheet = "NoFail", startRow = 61, endRow = 96, startC
ol = 4, endCol = 4, header = FALSE)
ELEC.NoFail = readWorksheet(data, sheet = "NoFail", startRow = 2, endRow = 60, startC
ol = 4, endCol =4, header = FALSE)

output = NULL
x = 0

for(a in 0:200){
FF = sum(HVAC.Fail<=x)
FN = sum(HVAC.Fail>x)
NF = sum(HVAC.NoFail<=x)
NN = sum(HVAC.NoFail>x)

c.test = matrix(c(FF,NF,FN,NN), nrow = 2, ncol = 2, byrow = F)
```

```
f.test = fisher.test(c.test)

p.val = f.test$p.value
o.ratio = f.test$estimate
output = rbind(output, data.frame(x, p.val, o.ratio))
x = x+0.5
rm("FF","FN","NF","NN","c.test","f.test","p.val","o.ratio")
}

output2 = NULL
x2 = 0

for(a in 0:200){
 FF = sum(PLUMB.Fail<=x2)
 FN = sum(PLUMB.Fail>x2)
 NF = sum(PLUMB.NoFail<=x2)
 NN = sum(PLUMB.NoFail>x2)

 c.test2 = matrix(c(FF,NF,FN,NN), nrow = 2, ncol = 2, byrow = F)

 f.test2 = fisher.test(c.test2)

 p.val2 = f.test2$p.value
 o.ratio2 = f.test2$estimate
 output2 = rbind(output2, data.frame(x2, p.val2, o.ratio2))
 x2 = x2+0.5
 rm("FF","FN","NF","NN","c.test2","f.test2","p.val2","o.ratio2")
}

output3 = NULL
x3 = 0

for(a in 0:200){
 FF = sum(FIRE.Fail<=x3)
 FN = sum(FIRE.Fail>x3)
 NF = sum(FIRE.NoFail<=x3)
 NN = sum(FIRE.NoFail>x3)

 c.test3 = matrix(c(FF,NF,FN,NN), nrow = 2, ncol = 2, byrow = F)

 f.test3 = fisher.test(c.test3)

 p.val3 = f.test3$p.value
```

```
 o.ratio3 = f.test3$estimate
 output3 = rbind(output3, data.frame(x3, p.val3, o.ratio3))
 x3 = x3+0.5
 rm("FF","FN","NF","NN","c.test3","f.test3","p.val3","o.ratio3")
}

output4 = NULL
x4 = 0

for(a in 0:200){
 FF = sum(ELEC.Fail<=x4)
 FN = sum(ELEC.Fail>x4)
 NF = sum(ELEC.NoFail<=x4)
 NN = sum(ELEC.NoFail>x4)

 c.test4 = matrix(c(FF,NF,FN,NN), nrow = 2, ncol = 2, byrow = F)

 f.test4 = fisher.test(c.test4)

 p.val4 = f.test4$p.value
 o.ratio4 = f.test4$estimate
 output4 = rbind(output4, data.frame(x4, p.val4, o.ratio4))
 x4 = x4+0.5
 rm("FF","FN","NF","NN","c.test4","f.test4","p.val4","o.ratio4")
}

plot(output4$x4,output4$p.val4, type = "l", col="red", xlab = "", ylab = "", ylim = c(0,2))
par(new=TRUE)
plot(output4$x4,output4$o.ratio4, type = "l", col = "green", xlab = "", ylab = "",ylim = c(0
,2))
title(main = "PoF Model Performance: ELEC System", ylab = "P-Value/Odds Ratio", xlab =
"Failure Threshold")

plot(output3$x3,output3$p.val3, type = "l", col="red", xlab = "", ylab = "", ylim = c(0,3))
par(new=TRUE)
plot(output3$x3,output3$o.ratio3, type = "l", col = "green", xlab = "", ylab = "",ylim = c(0
,3))
title(main = "PoF Model Performance: FIRE System", ylab = "P-Value/Odds Ratio", xlab =
"Failure Threshold")

plot(output2$x2,output2$p.val2, type = "l", col="red", xlab = "", ylab = "", ylim = c(0,3))
par(new=TRUE)
plot(output2$x2,output2$o.ratio2, type = "l", col = "green", xlab = "", ylab = "",ylim = c(0
```

```
,3))
title(main = "PoF Model Performance: PLUM System", ylab = "P-Value/Odds Ratio", xlab
= "Failure Threshold")

plot(output$x,output$p.val, type = "l", col="red", xlab = "", ylab = "", ylim = c(0,2))
par(new=TRUE)
plot(output$x,output$o.ratio, type = "l", col = "green", xlab = "", ylab = "",ylim = c(0,2))
title(main = "PoF Model Performance: HVAC System", ylab = "P-Value/Odds Ratio", xlab
= "Failure Threshold")

    ```
```
```

Appendix D. Cannon AFB HVAC failure data

The data collected for this potion of the research required system lifetime failure data. IWIMS data was only available from 1995-2015. Therefore, this research did not consider failure data for facilities constructed prior to 1995. Of the 175 HVAC systems in the BUILDER® inventory for Cannon AFB, 58 were commissioned on or after 1995. Of those 58 systems, this research found data in IWIMS for 40 of them. The data presented below displays the data for those 40 systems.

Building Number	Time to Failure	Time Between Failures	System Age (yrs)	Failure Number
00128	971	971	13	1
00128	999	28	13	2
00128	1346	347	13	3
00128	1664	318	13	4
00128	1868	204	13	5
00128	2295	427	13	6
00128	2590	295	13	7
00128	3261	671	13	8
00128	3367	106	13	9
00128	3767	400	13	10
00128	3856	89	13	11
00128	4446	590	13	12
00158	925	925	12	1
00158	1257	332	12	2
00158	1726	469	12	3
00158	1728	2	12	4
00158	1799	71	12	5
00158	2182	383	12	6
00158	2661	479	12	7
00158	2805	144	12	8
00158	2818	13	12	9
00158	2853	35	12	10
00158	3066	213	12	11
00158	3148	82	12	12
00158	3301	153	12	13
00158	3640	339	12	14

Building Number	Time to Failure	Time Between Failures	System Age (yrs)	Failure Number
00158	3808	168	12	15
00158	3850	42	12	16
00158	3939	89	12	17
00173	3987	3987	6	1
00208	354	354	21	1
00208	362	8	21	2
00208	366	4	21	3
00208	382	16	21	4
00208	431	49	21	5
00208	568	137	21	6
00208	589	21	21	7
00208	596	7	21	8
00208	910	314	21	9
00208	1075	165	21	10
00208	1727	652	21	11
00208	1752	25	21	12
00208	1893	141	21	13
00208	2216	323	21	14
00208	2384	168	21	15
00208	2430	46	21	16
00208	5182	2752	21	17
00208	5203	21	21	18
00208	5226	23	21	19
00208	5434	208	21	20
00208	5486	52	21	21
00208	6946	1460	21	22
00208	7093	147	21	23
00208	7255	162	21	24
00208	7352	97	21	25
00234	719	719	4	1
00234	871	152	4	2
00251	1253	1253	20	1
00251	1270	17	20	2
00278	897	897	5	1
00300	913	913	17	1
00300	1321	408	17	2
00300	2377	1056	17	3
00300	2460	83	17	4
00300	3552	1092	17	5
00300	3860	308	17	6
00300	3910	50	17	7

Building Number	Time to Failure	Time Between Failures	System Age (yrs)	Failure Number
00300	4003	93	17	8
00300	4161	158	17	9
00300	4196	35	17	10
00300	4910	714	17	11
00300	5310	400	17	12
00300	5614	304	17	13
00300	5744	130	17	14
00300	5850	106	17	15
00300	6003	153	17	16
00307	2056	2056	6	1
00355	155	155	18	1
00355	355	200	18	2
00355	361	6	18	3
00355	523	162	18	4
00355	525	2	18	5
00355	544	19	18	6
00355	546	2	18	7
00355	557	11	18	8
00355	567	10	18	9
00355	574	7	18	10
00355	585	11	18	11
00355	592	7	18	12
00355	733	141	18	13
00355	762	29	18	14
00355	916	154	18	15
00355	981	65	18	16
00355	1075	94	18	17
00355	1419	344	18	18
00355	1660	241	18	19
00355	3255	1595	18	20
00356	544	544	19	1
00356	601	57	19	2
00356	709	108	19	3
00356	799	90	19	4
00356	875	76	19	5
00356	904	29	19	6
00356	1007	103	19	7
00356	1126	119	19	8
00356	1127	1	19	9
00575	1481	1481	11	1
00575	1857	376	11	2

Building Number	Time to Failure	Time Between Failures	System Age (yrs)	Failure Number
00575	2082	225	11	3
00575	2158	76	11	4
00575	3078	920	11	5
00575	3117	39	11	6
00575	3560	443	11	7
00724	150	150	5	1
00724	338	188	5	2
00724	367	29	5	3
00724	716	349	5	4
00724	884	168	5	5
00724	888	4	5	6
00724	996	108	5	7
00724	1040	44	5	8
00724	1104	64	5	9
00724	1412	308	5	10
00724	1473	61	5	11
00724	1488	15	5	12
00724	1770	282	5	13
00777	370	370	3	1
00777	793	423	3	2
00848	258	258	3	1
00848	489	231	3	2
00848	636	147	3	3
00848	658	22	3	4
00848	671	13	3	5
00850	709	709	9	1
00850	2818	2109	9	2
00850	2872	54	9	3
01155	294	294	20	1
01155	854	560	20	2
01155	896	42	20	3
01155	1225	329	20	4
01155	1232	7	20	5
01155	1278	46	20	6
01155	1324	46	20	7
01155	1414	90	20	8
01155	1450	36	20	9
01155	1463	13	20	10
01155	1466	3	20	11
01155	1470	4	20	12
01155	1471	1	20	13

Building Number	Time to Failure	Time Between Failures	System Age (yrs)	Failure Number
01155	1478	7	20	14
01155	1488	10	20	15
01155	1491	3	20	16
01155	1492	1	20	17
01155	1498	6	20	18
01155	1522	24	20	19
01155	3158	1636	20	20
01155	3272	114	20	21
01155	3607	335	20	22
01155	4167	560	20	23
01155	4551	384	20	24
01155	5810	1259	20	25
01155	5971	161	20	26
01155	6008	37	20	27
01155	6143	135	20	28
01155	6597	454	20	29
01155	6713	116	20	30
01155	6764	51	20	31
01155	6825	61	20	32
01155	6948	123	20	33
01155	6993	45	20	34
01155	6996	3	20	35
01155	7063	67	20	36
01155	7098	35	20	37
01155	7210	112	20	38
01155	7218	8	20	39
01159	238	238	20	1
01159	905	667	20	2
01159	1051	146	20	3
01159	1075	24	20	4
01159	1087	12	20	5
01159	1088	1	20	6
01159	1092	4	20	7
01159	1100	8	20	8
01159	1108	8	20	9
01159	1117	9	20	10
01159	1122	5	20	11
01159	1123	1	20	12
01159	1134	11	20	13
01159	1148	14	20	14
01159	1225	77	20	15

Building Number	Time to Failure	Time Between Failures	System Age (yrs)	Failure Number
01159	1232	7	20	16
01159	1233	1	20	17
01159	1269	36	20	18
01159	1302	33	20	19
01159	1436	134	20	20
01159	1519	83	20	21
01159	1838	319	20	22
01159	2271	433	20	23
01159	4547	2276	20	24
01159	4643	96	20	25
01159	4650	7	20	26
01159	4938	288	20	27
01159	5082	144	20	28
01159	7158	2076	20	29
01159	7210	52	20	30
01159	7564	354	20	31
01161	166	166	17	1
01161	216	50	17	2
01161	270	54	17	3
01161	290	20	17	4
01161	501	211	17	5
01161	507	6	17	6
01161	636	129	17	7
01161	803	167	17	8
01161	850	47	17	9
01161	874	24	17	10
01161	892	18	17	11
01161	942	50	17	12
01161	962	20	17	13
01161	971	9	17	14
01161	1180	209	17	15
01161	2329	1149	17	16
01161	3953	1624	17	17
01161	5274	1321	17	18
01161	5316	42	17	19
01275	176	176	2	1
01275	523	347	2	2
01275	524	1	2	3
01435	453	453	5	1
01435	720	267	5	2
01435	1067	347	5	3

Building Number	Time to Failure	Time Between Failures	System Age (yrs)	Failure Number
01435	1236	169	5	4
01435	1277	41	5	5
01435	1614	337	5	6
01435	1732	118	5	7
01824	1721	1721	6	1
01825	1949	1949	6	1
02134	876	876	20	1
02134	1218	342	20	2
02134	1235	17	20	3
02134	1443	208	20	4
02134	1624	181	20	5
02134	2045	421	20	6
02134	4106	2061	20	7
02134	5510	1404	20	8
02134	5645	135	20	9
02134	7065	1420	20	10
02206	855	855	21	1
02206	883	28	21	2
02206	1065	182	21	3
02206	1138	73	21	4
02206	1297	159	21	5
02206	1437	140	21	6
02206	1440	3	21	7
02206	1443	3	21	8
02206	1451	8	21	9
02206	1452	1	21	10
02206	1538	86	21	11
02206	1600	62	21	12
02206	1618	18	21	13
02206	1642	24	21	14
02206	1663	21	21	15
02206	1696	33	21	16
02206	1717	21	21	17
02206	1740	23	21	18
02206	1766	26	21	19
02206	1800	34	21	20
02206	1850	50	21	21
02206	1927	77	21	22
02206	2017	90	21	23
02206	2019	2	21	24
02206	2115	96	21	25

Building Number	Time to Failure	Time Between Failures	System Age (yrs)	Failure Number
02206	2213	98	21	26
02206	2347	134	21	27
02206	2361	14	21	28
02206	4960	2599	21	29
02206	5302	342	21	30
02206	5456	154	21	31
02206	7247	1791	21	32
02206	7477	230	21	33
02206	7484	7	21	34
02220	1748	1748	12	1
02220	4235	2487	12	2
02320	1070	1070	19	1
02320	1077	7	19	2
02320	1218	141	19	3
02320	6095	4877	19	4
02320	6524	429	19	5
02370	993	993	6	1
02370	1330	337	6	2
02370	1636	306	6	3
02371	736	736	4	3
02371	1101	365	4	1
02371	1118	17	4	2
02379	1006	1006	5	1
02379	1263	257	5	2
02379	1626	363	5	3
02379	1705	79	5	4
04081	610	610	18	1
04081	840	230	18	2
04081	972	132	18	3
04081	1281	309	18	4
04081	1734	453	18	5
04081	5881	4147	18	6
04081	6208	327	18	7
04082	543	543	18	1
04605	136	136	4	1
04605	351	215	4	2
04605	824	473	4	3
04605	1038	214	4	4
04605	1046	8	4	5
04605	1094	48	4	6
04606	316	316	3	2

Building Number	Time to Failure	Time Between Failures	System Age (yrs)	Failure Number
04606	477	161	3	3
04606	520	43	3	4
04606	538	18	3	5
04606	598	60	3	6
04606	729	131	3	1
04607	499	499	3	4
04607	566	67	3	5
04607	728	162	3	1
04607	736	8	3	2
04607	741	5	3	3
04609	125	125	2	1
04609	485	360	2	2
04619	371	371	2	1
04619	387	16	2	2
04619	540	153	2	3
04619	587	47	2	4
04620	387	387	2	1
04620	400	13	2	2
04620	418	18	2	3
04620	552	134	2	4
04620	583	31	2	5
04623	362	362	2	1
04623	364	2	2	2
04623	372	8	2	3
04623	376	4	2	4
04623	561	185	2	5
04623	582	21	2	6
04624	223	223	3	1
04624	234	11	3	2
04624	237	3	3	3
04624	527	290	3	4
04624	615	88	3	5
04624	622	7	3	6
04624	636	14	3	7
04624	639	3	3	8
04624	876	237	3	9
04624	919	43	3	10
04624	1017	98	3	11

Appendix E. Duane Plots by Installation

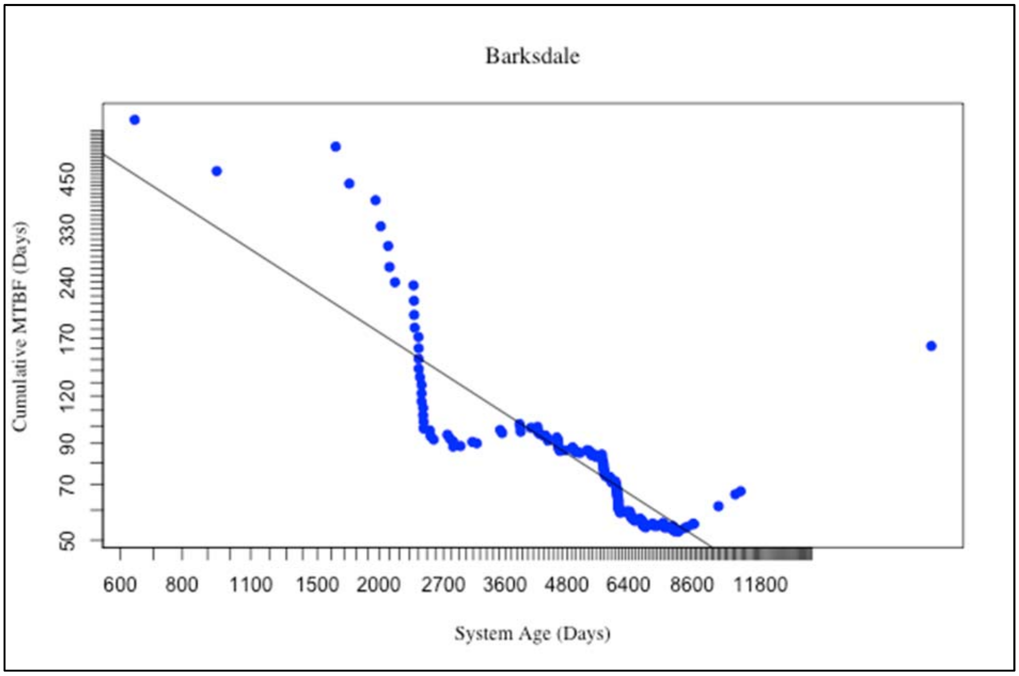


Figure E-1: Barksdale AFB HVAC Duane Plot

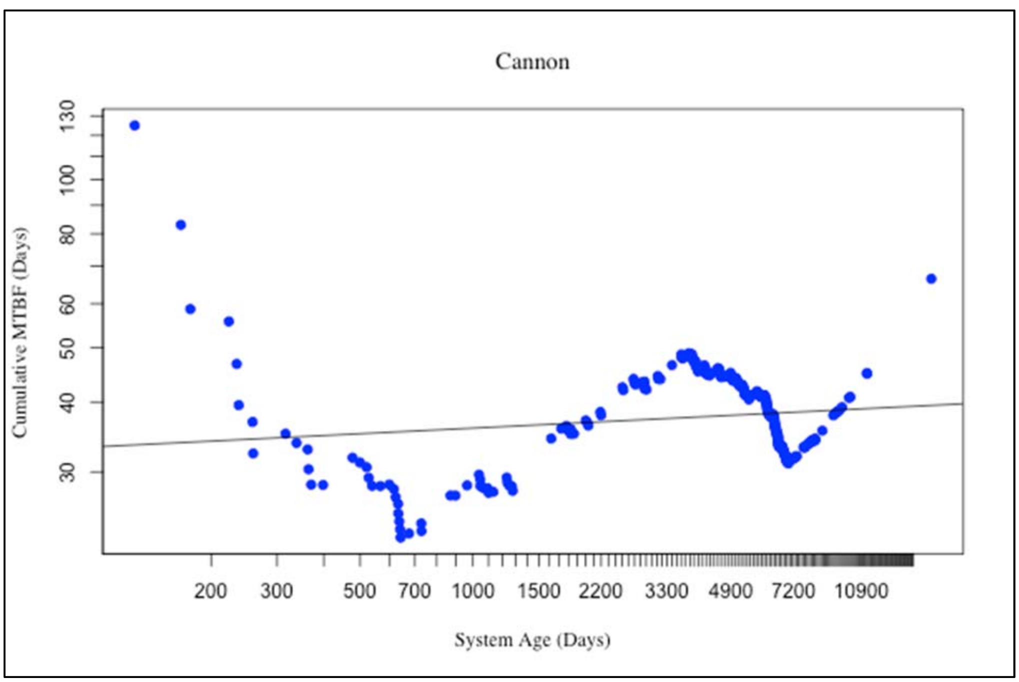


Figure E-2: Cannon AFB HVAC Duane Plot

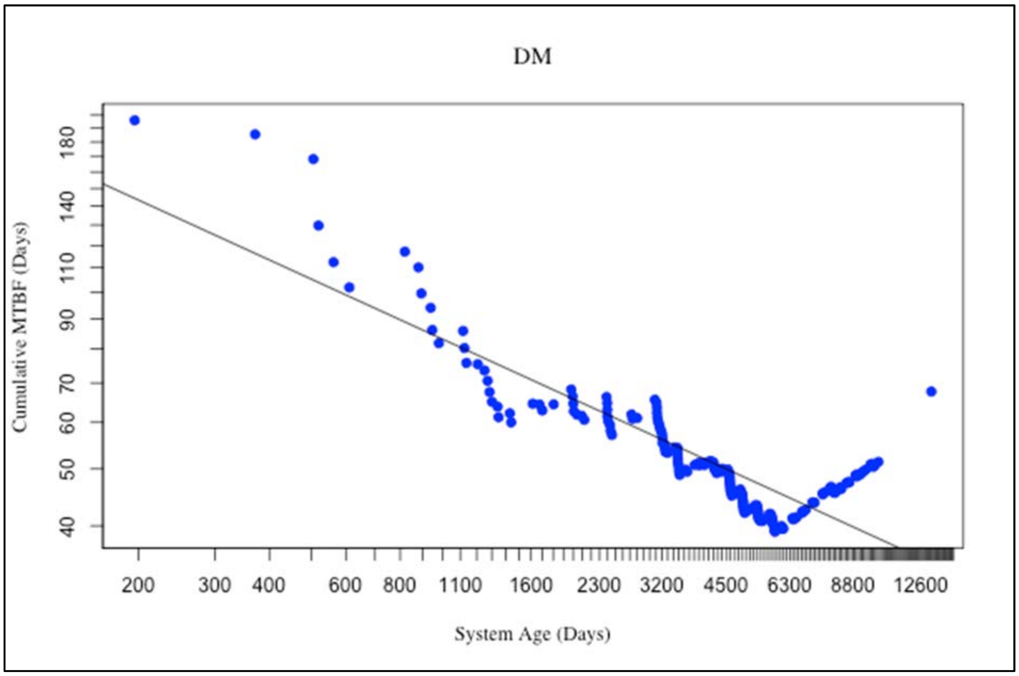


Figure E-3: Davis Monthan AFB HVAC Duane Plot

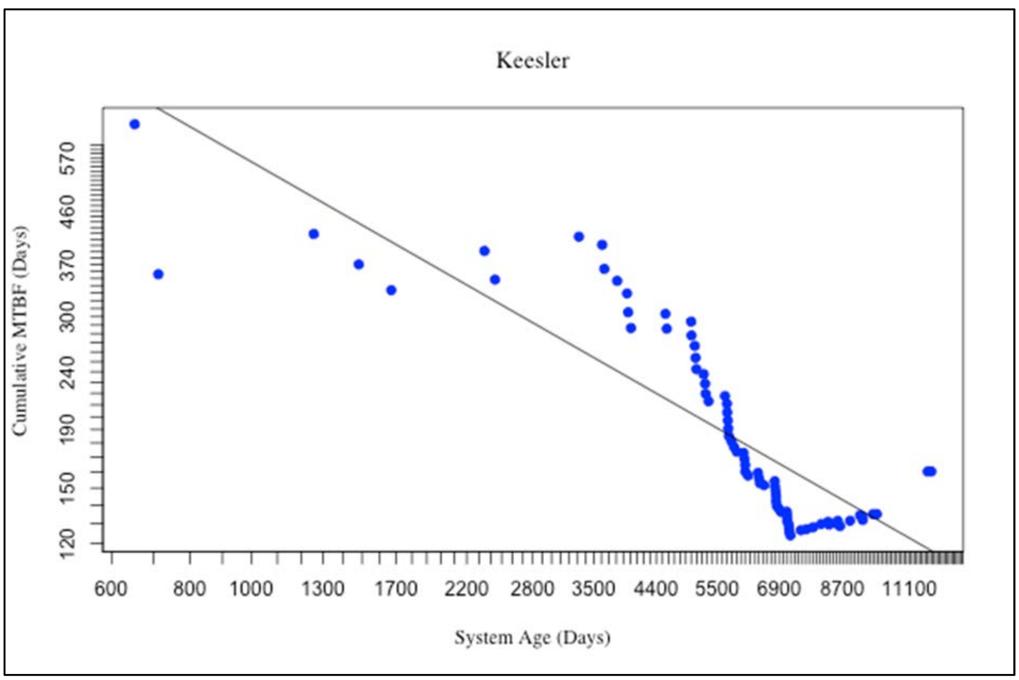


Figure E-4: Keesler AFB HVAC Duane Plot

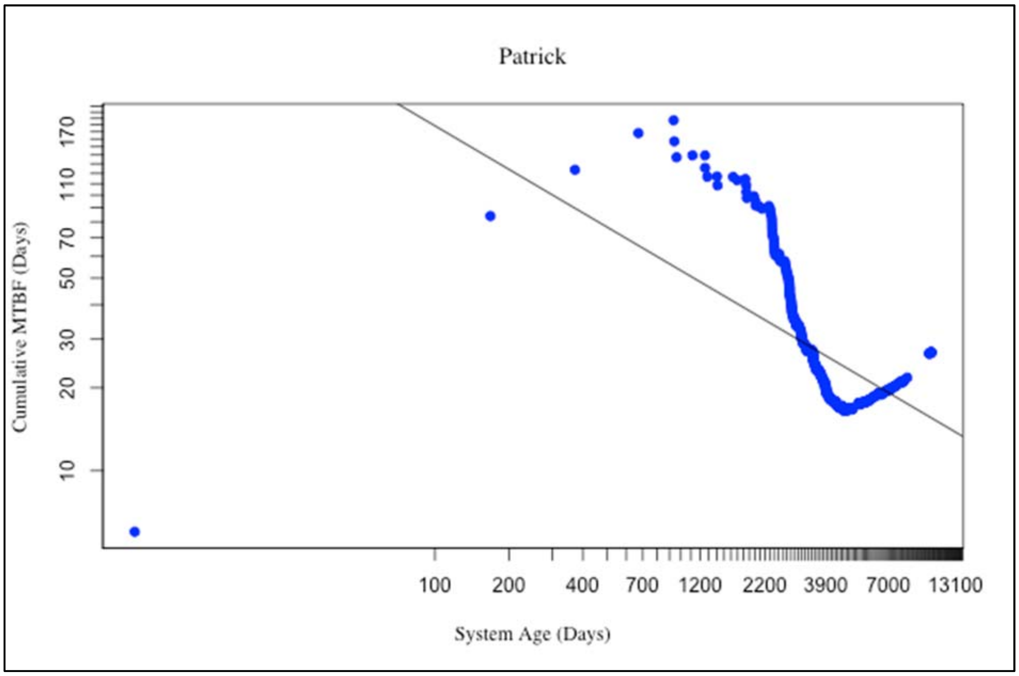


Figure E-5: Patrick AFB HVAC Duane Plot

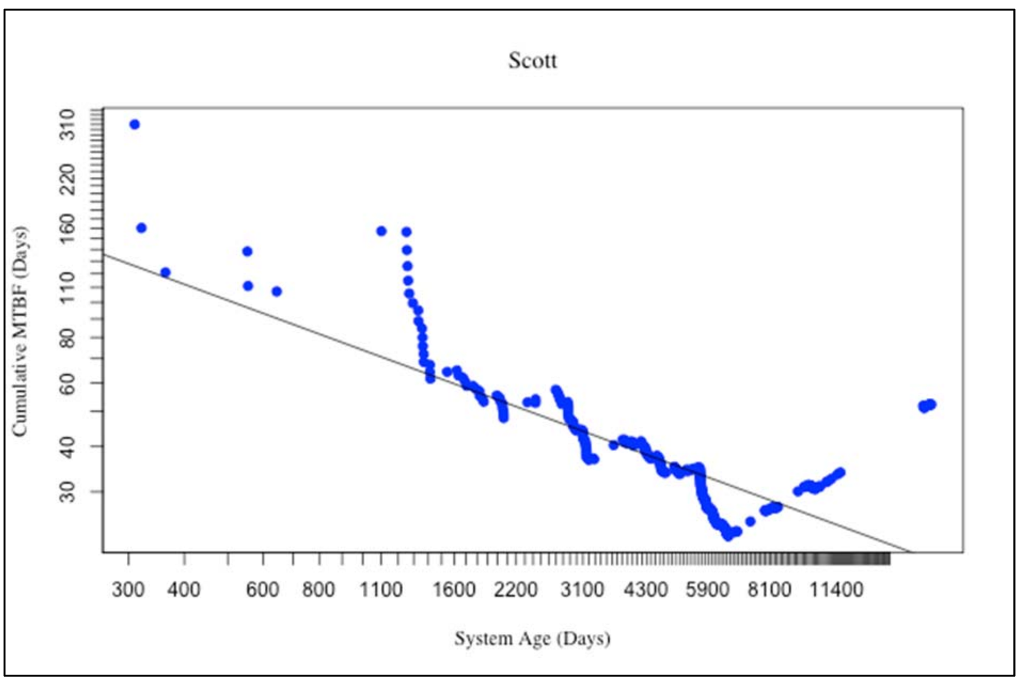


Figure E-6: Scott AFB HVAC Duane Plot

Appendix F. Cannon AFB HVAC System Duane Plots

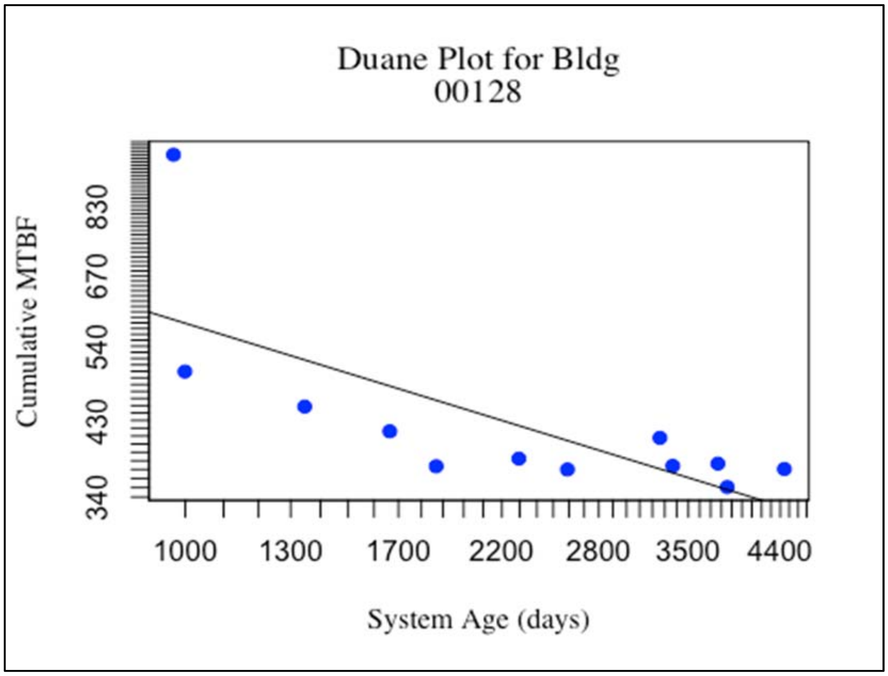
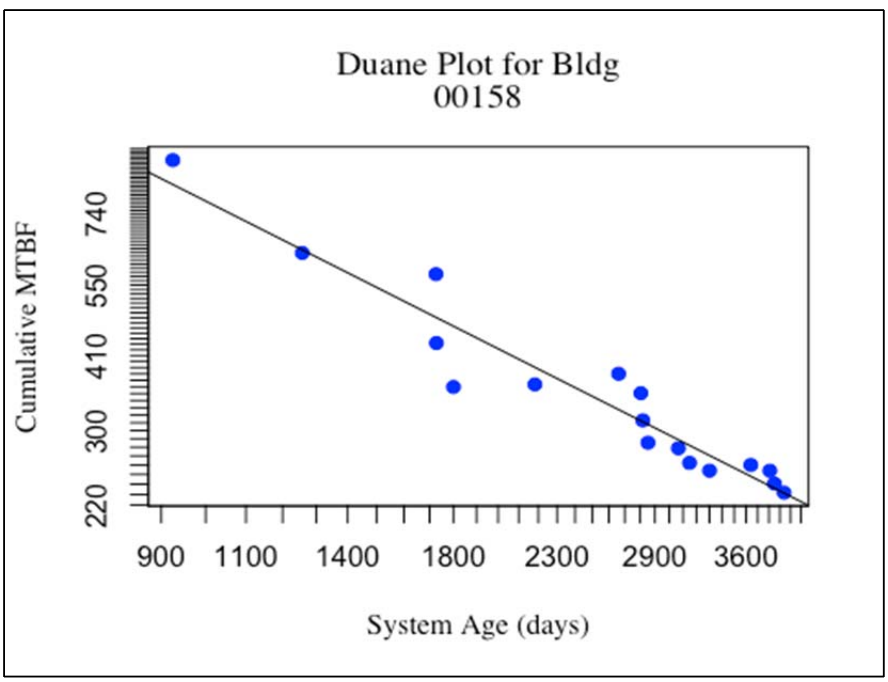


Figure F-1: Building 128 HVAC Duane Plot



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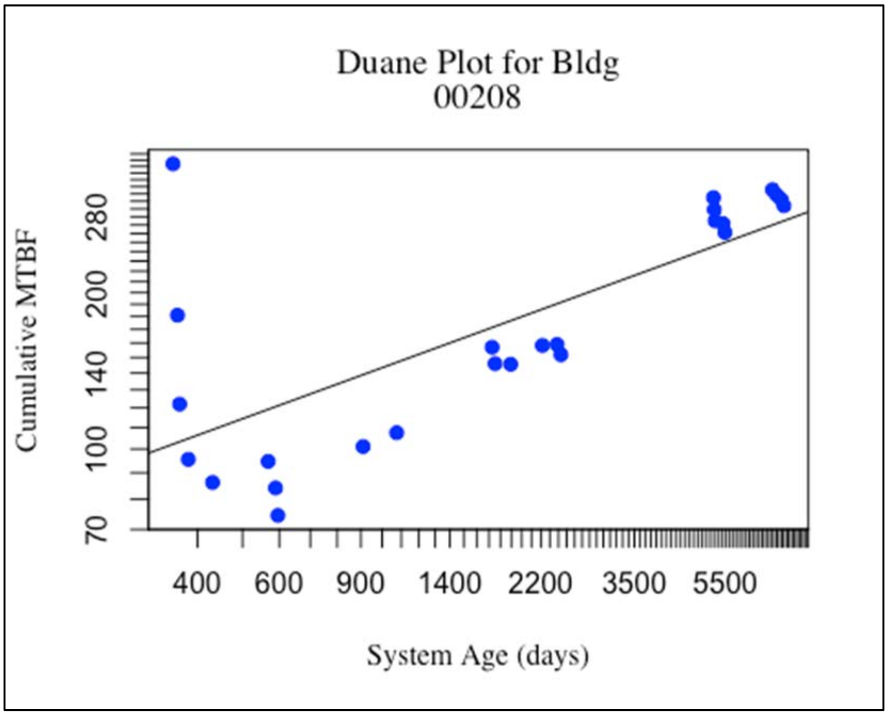

Figure F-3: Building 208 HVAC Duane Plot

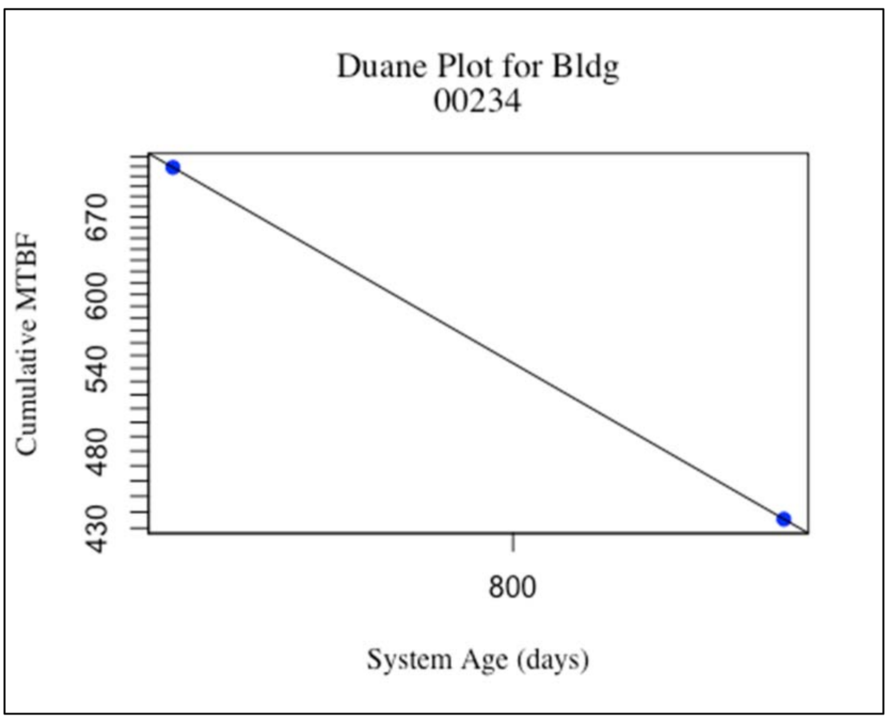

Figure F-4: Building 234 HVAC Duane Plot

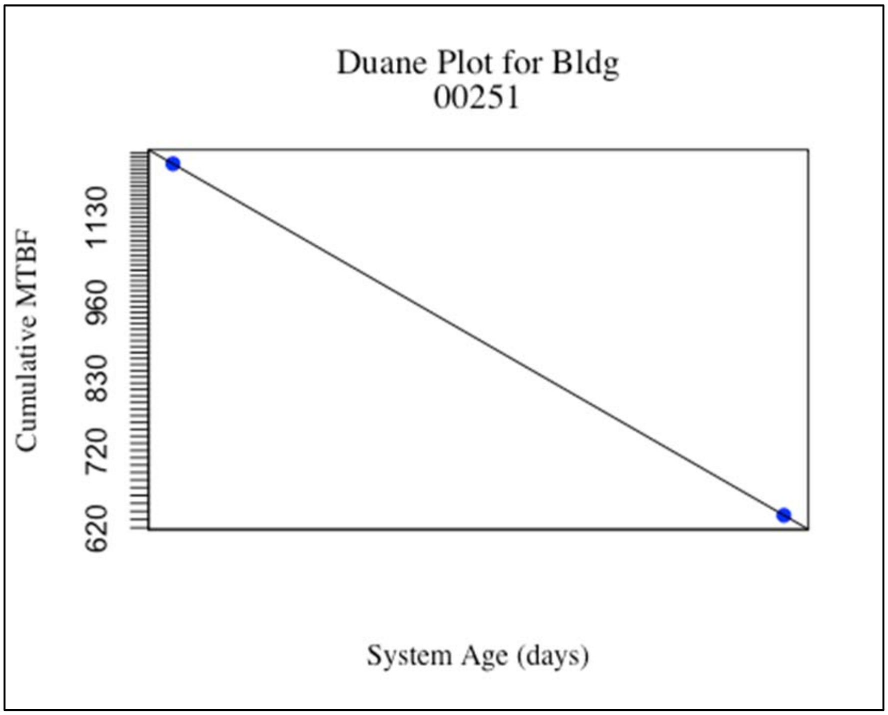

Figure F-5: Building 251 HVAC Duane Plot

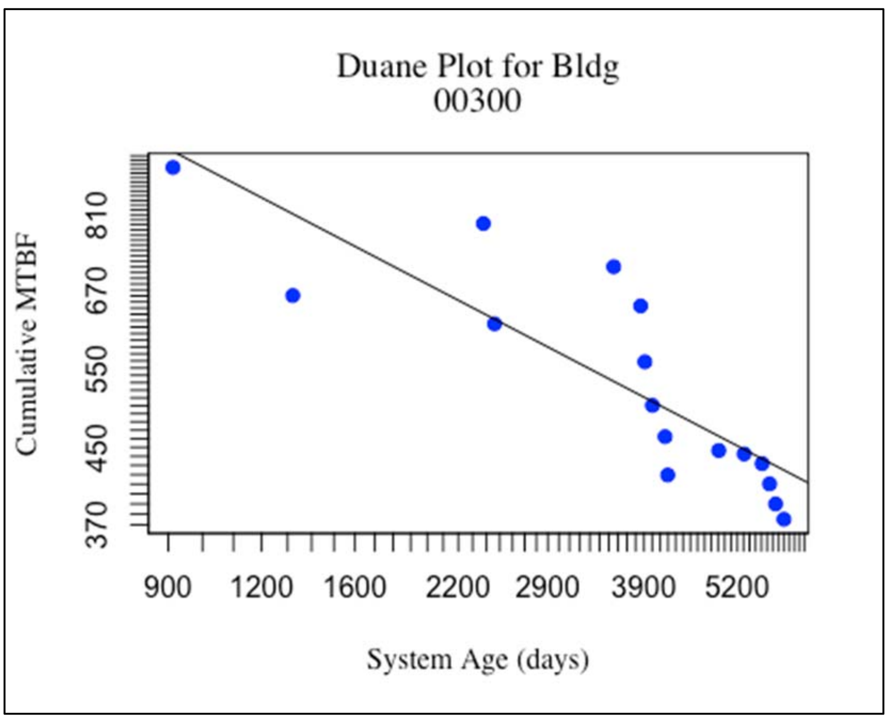

Figure F-6: Building 300 HVAC Duane Plot

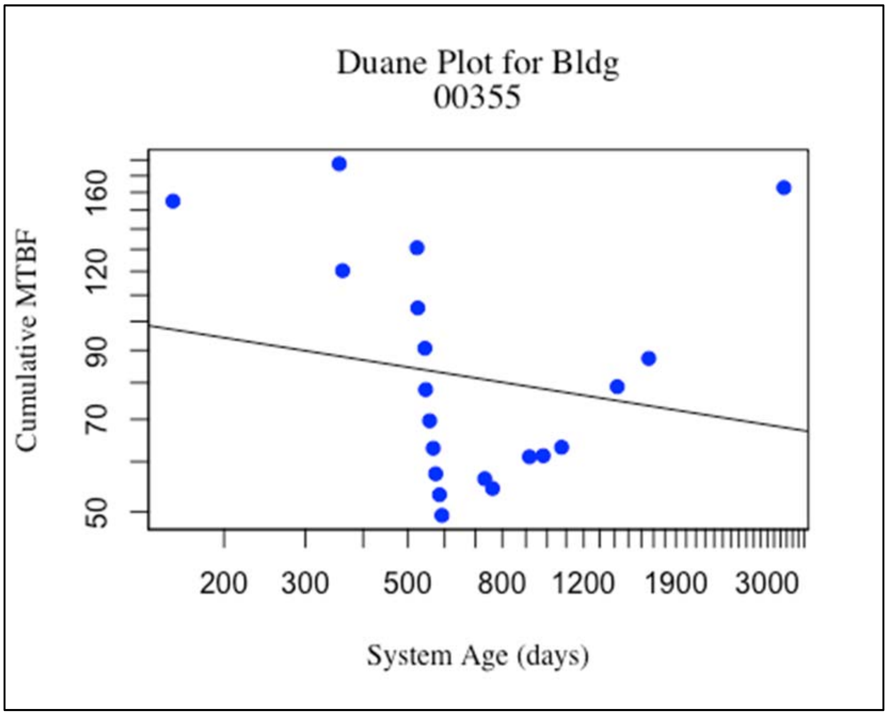

Figure F-7: Building 355 HVAC Duane Plot

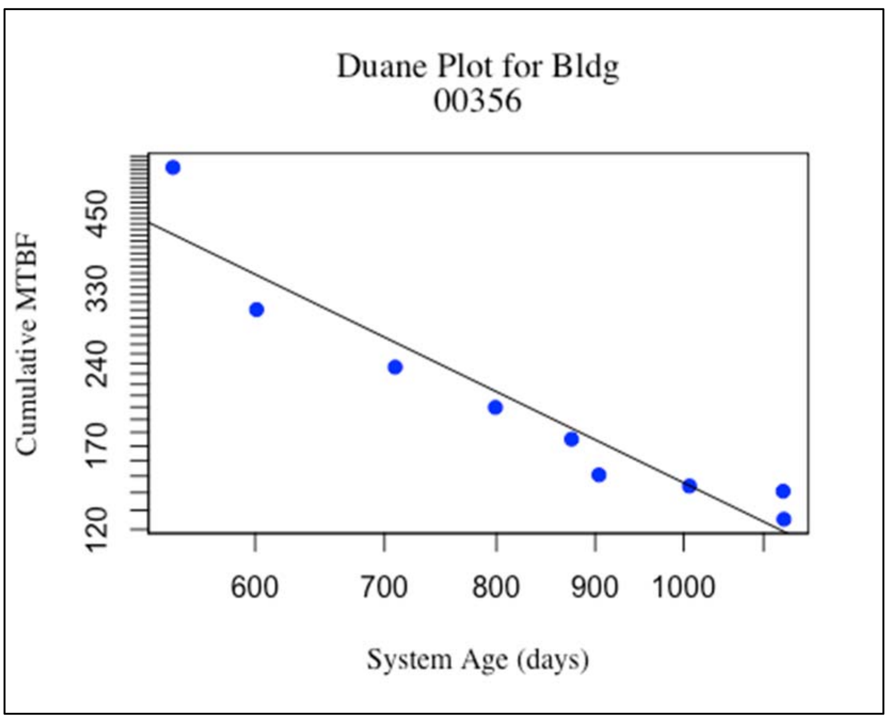

Figure F-8: Building 356 HVAC Duane Plot

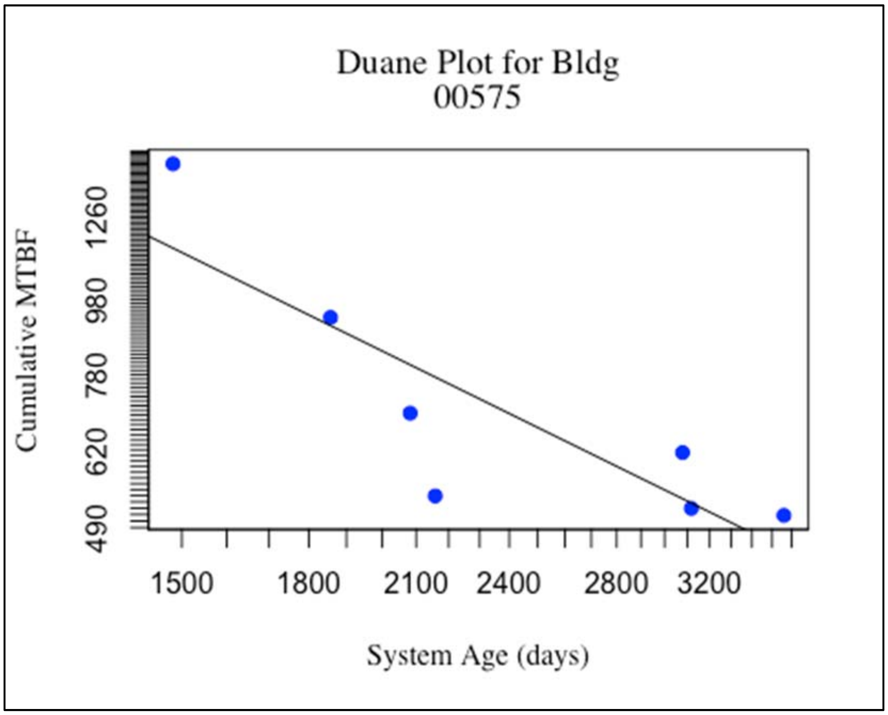

Figure F-9: Building 575 HVAC Duane Plot

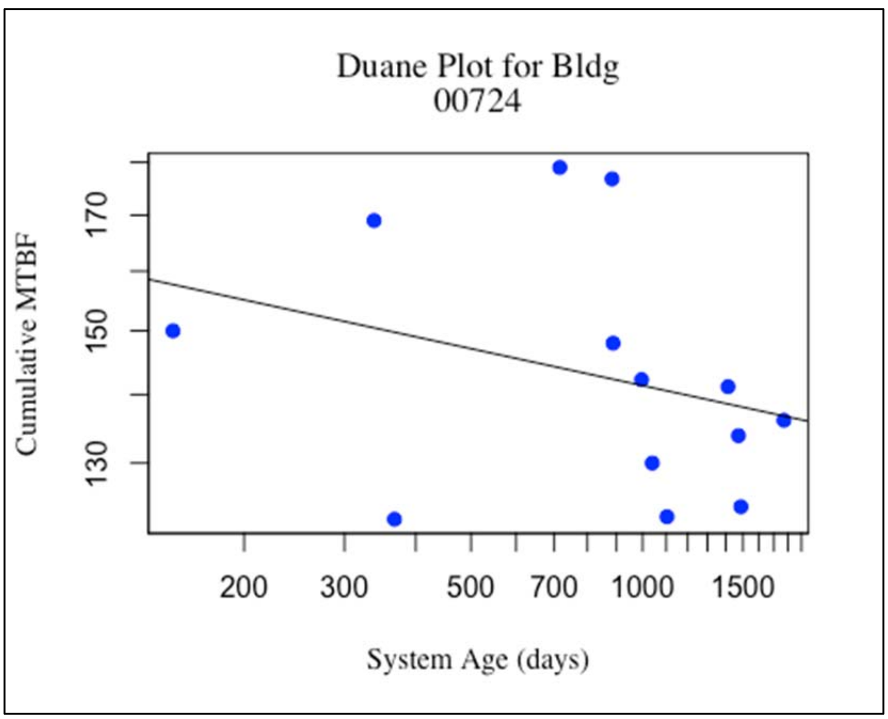

Figure F-10: Building 724 HVAC Duane Plot

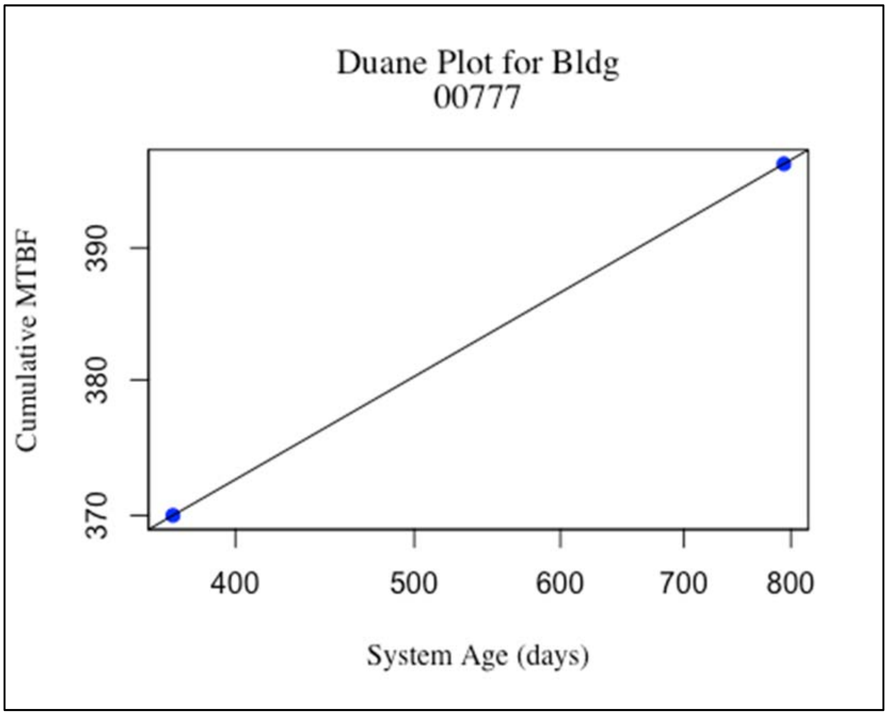

Figure F-11: Building 777 HVAC Duane Plot

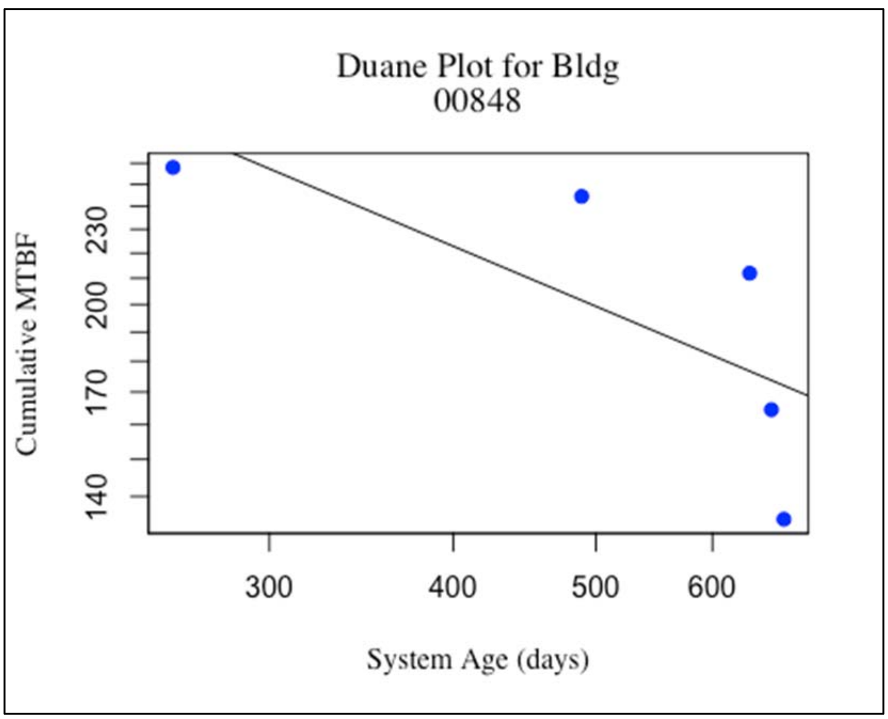

Figure F-12: Building 848 HVAC Duane Plot

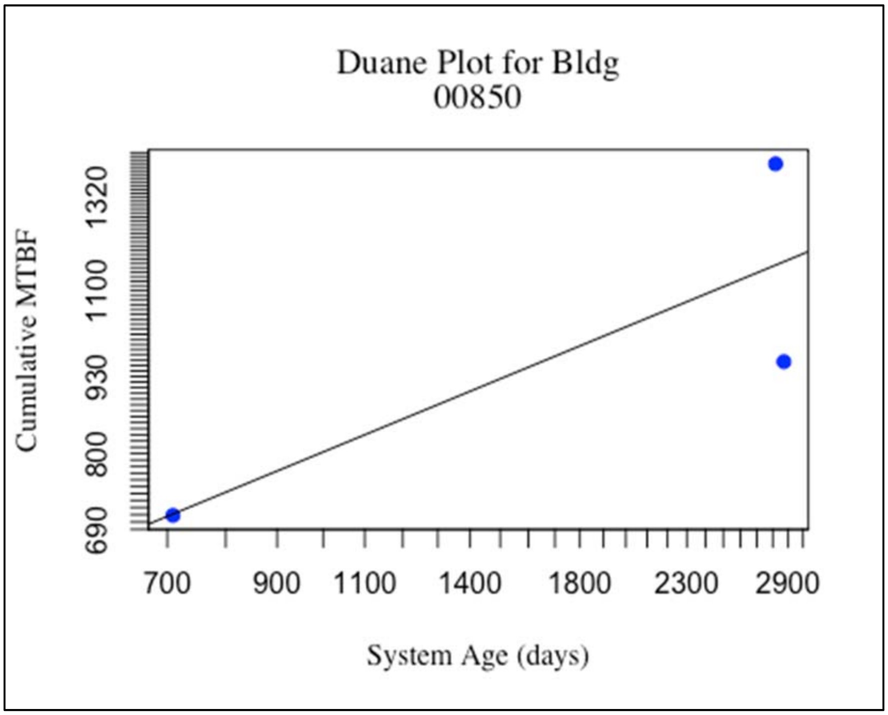

Figure F-13: Building 850 HVAC Duane Plot

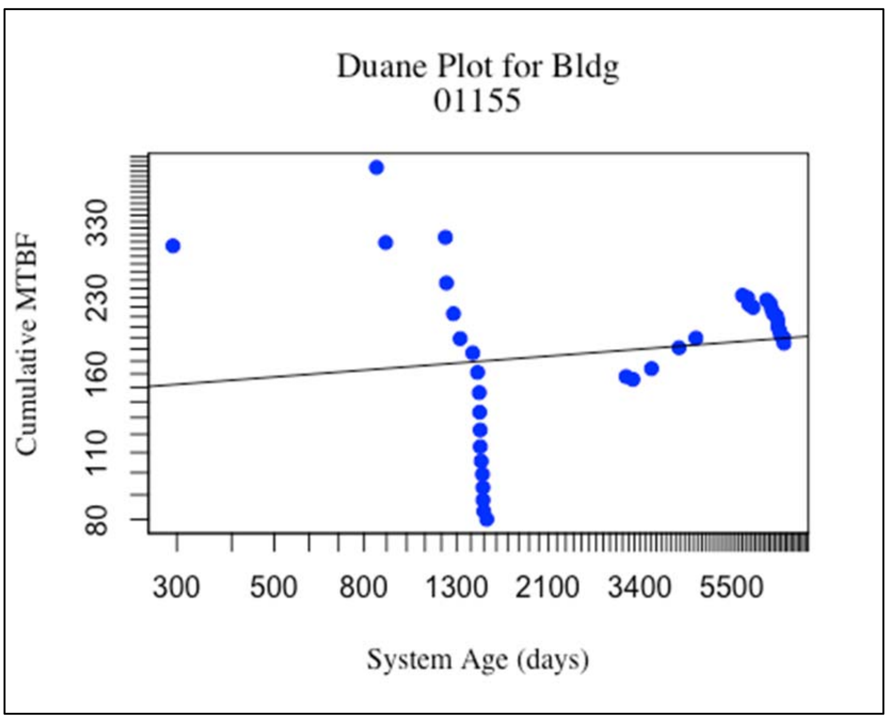

Figure F-14: Building 1155 HVAC Duane Plot

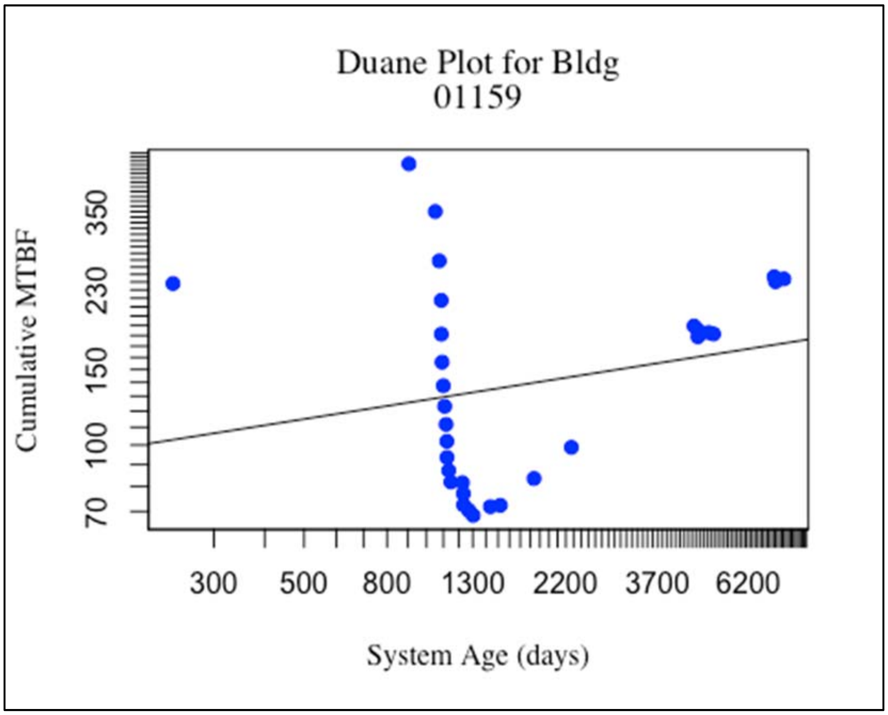

Figure F-15: Building 1159 HVAC Duane Plot

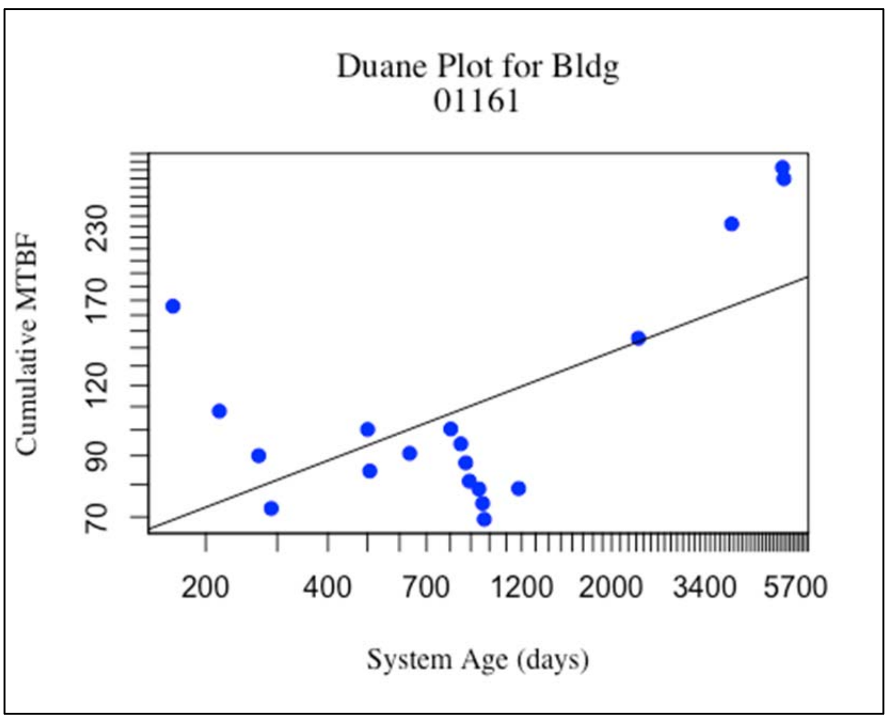

Figure F-16: Building 1161 HVAC Duane Plot

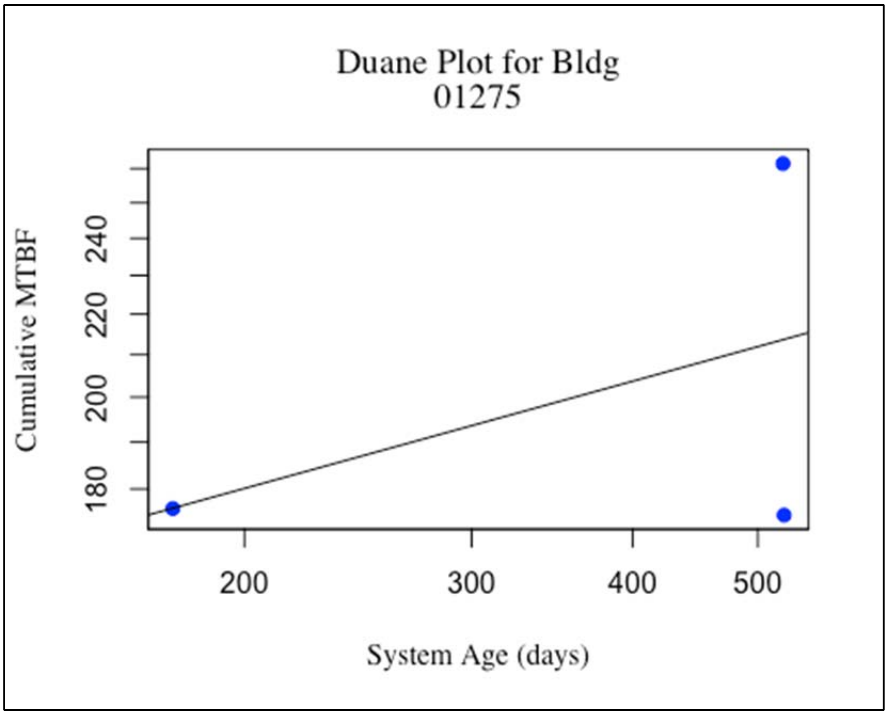

Figure F-17: Building 1275 HVAC Duane Plot

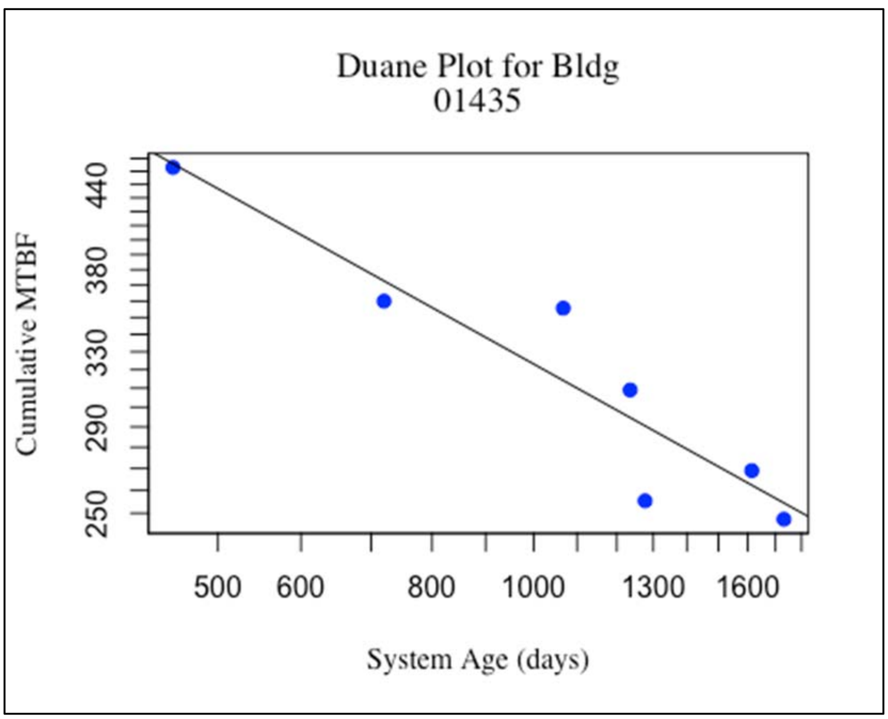

Figure F-18: Building 1435 HVAC Duane Plot

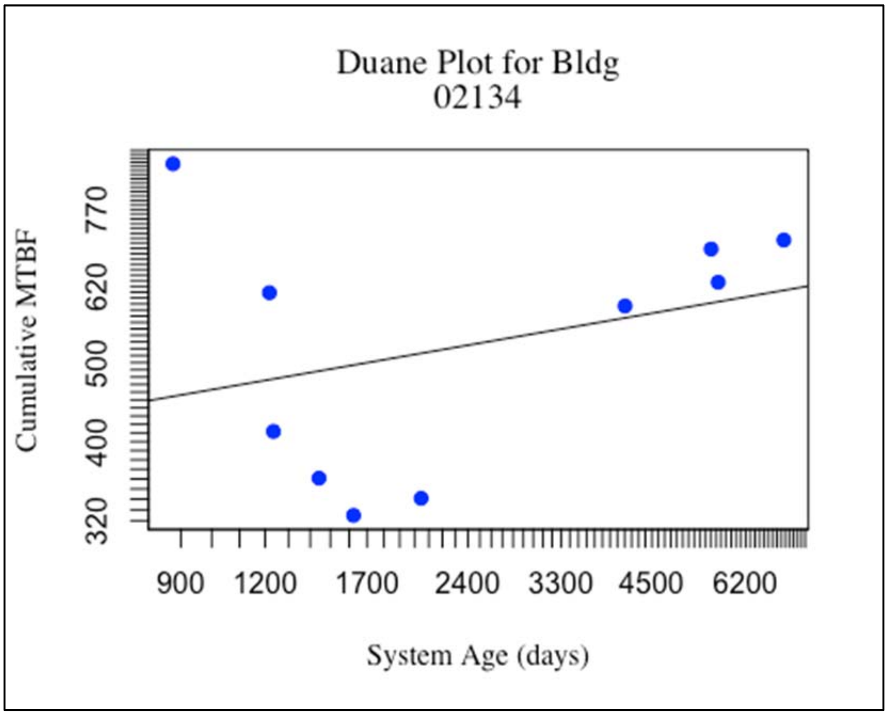

Figure F-19: Building 2134 HVAC Duane Plot

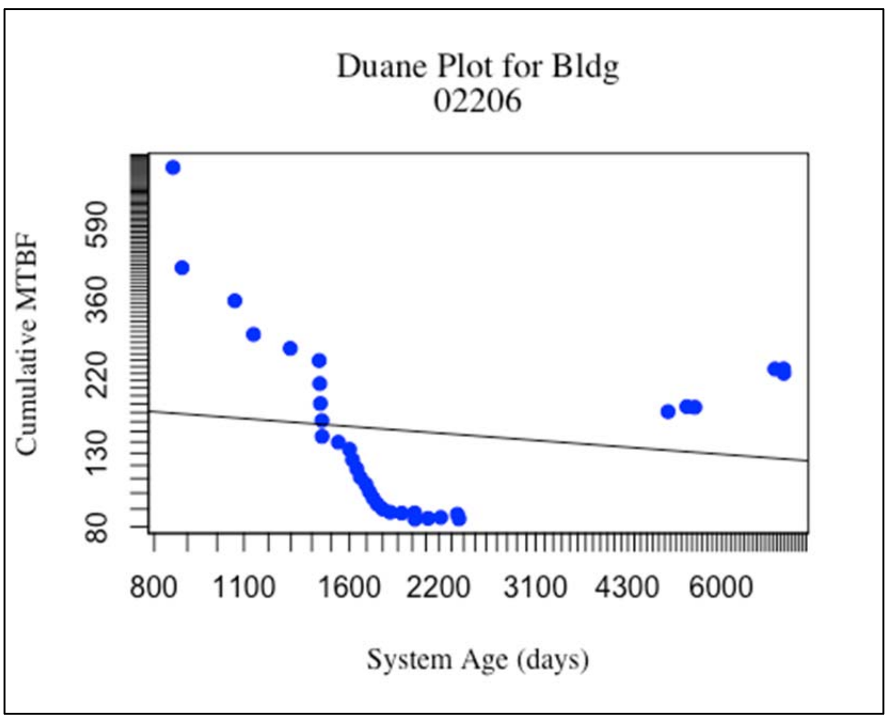

Figure F-20: Building 2206 HVAC Duane Plot

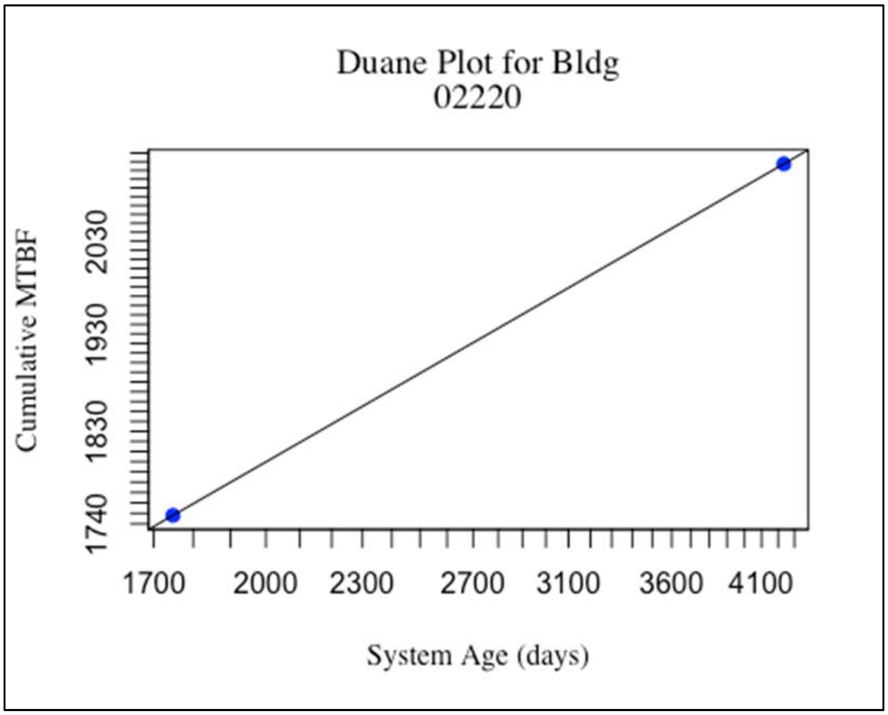

Figure F-21: Building 2220 HVAC Duane Plot

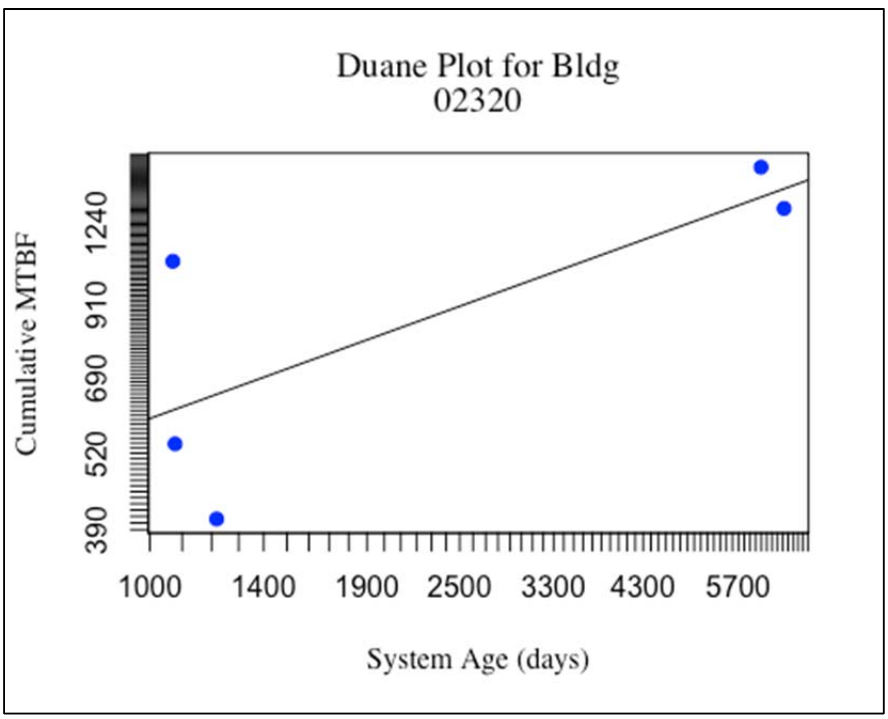

Figure F-22: Building 2320 HVAC Duane Plot

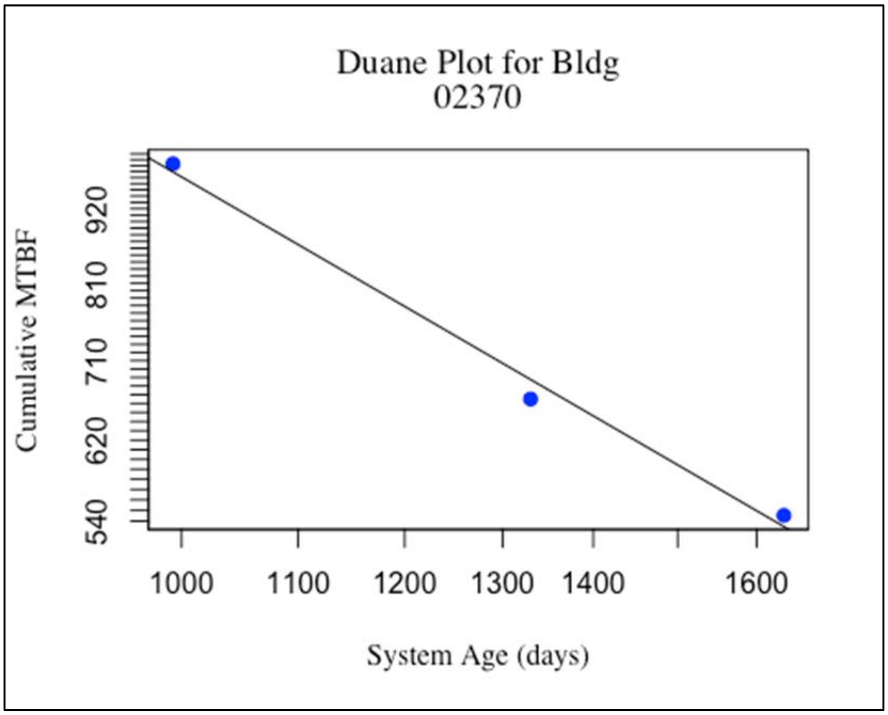

Figure F-23: Building 2370 HVAC Duane Plot

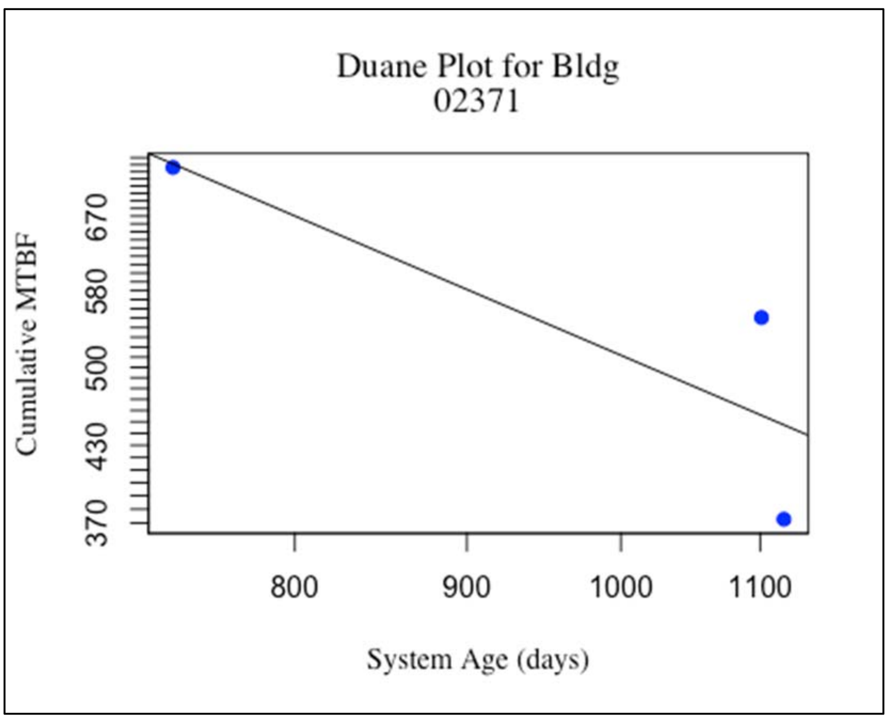

Figure F-24: Building 2371 HVAC Duane Plot

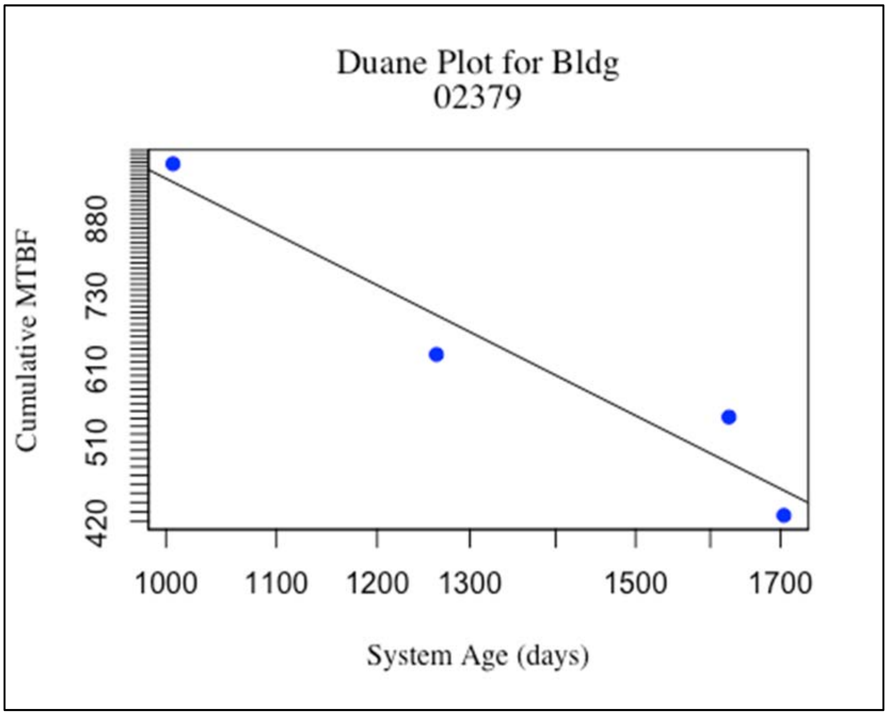

Figure F-25: Building 2379 HVAC Duane Plot

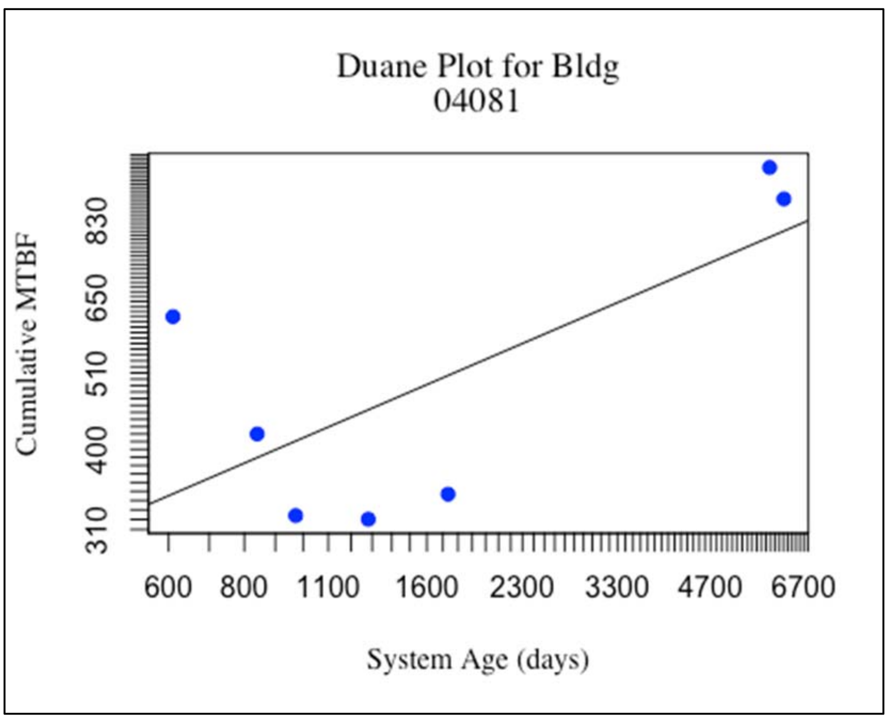

Figure F-26: Building 4081 HVAC Duane Plot

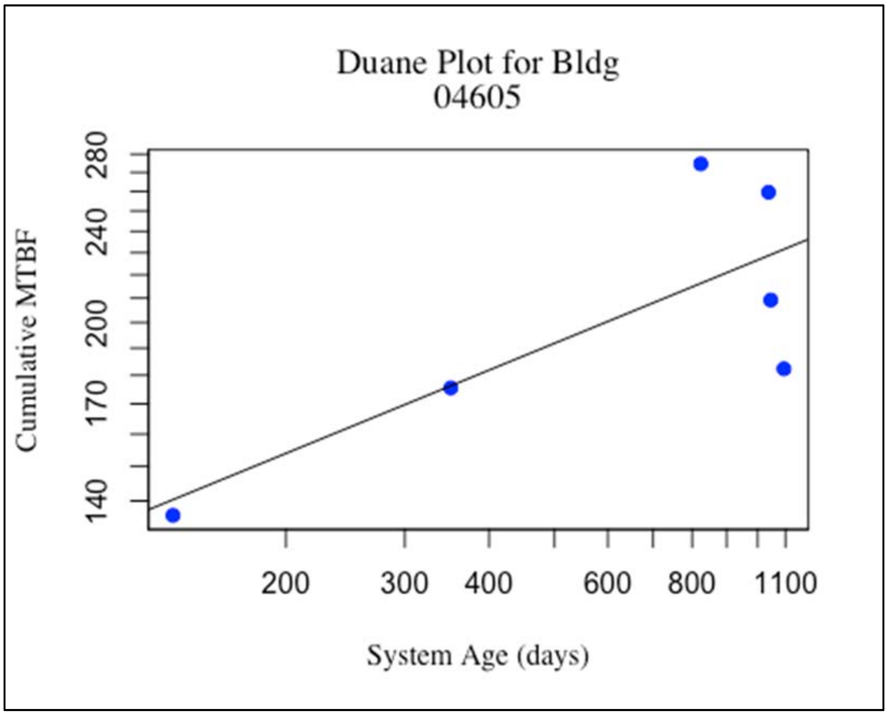

Figure F-27: Building 4605 HVAC Duane Plot

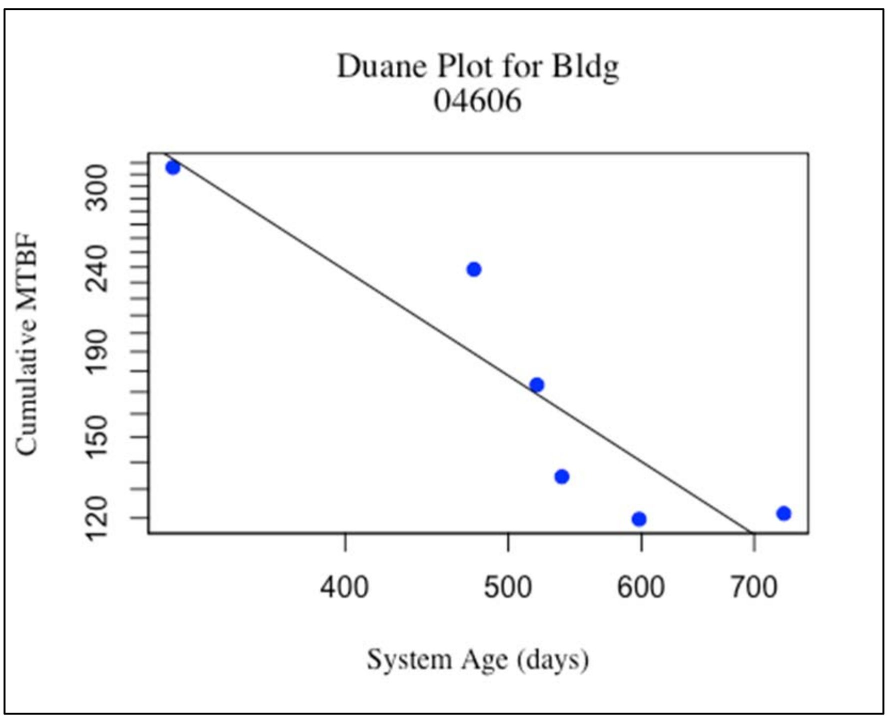

Figure F-28: Building 4606 HVAC Duane Plot

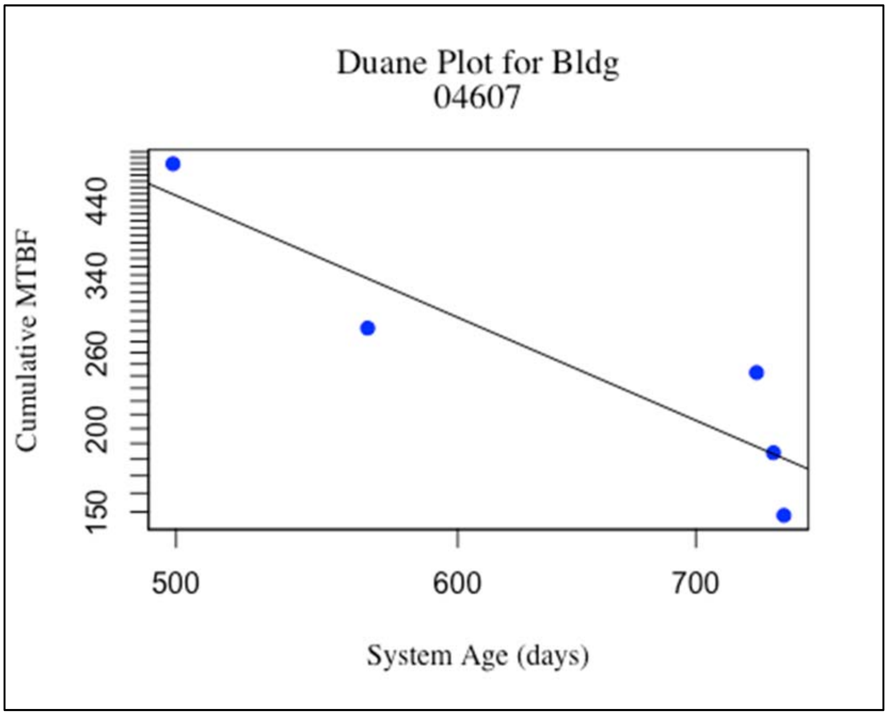

Figure F-29: Building 4607 HVAC Duane Plot

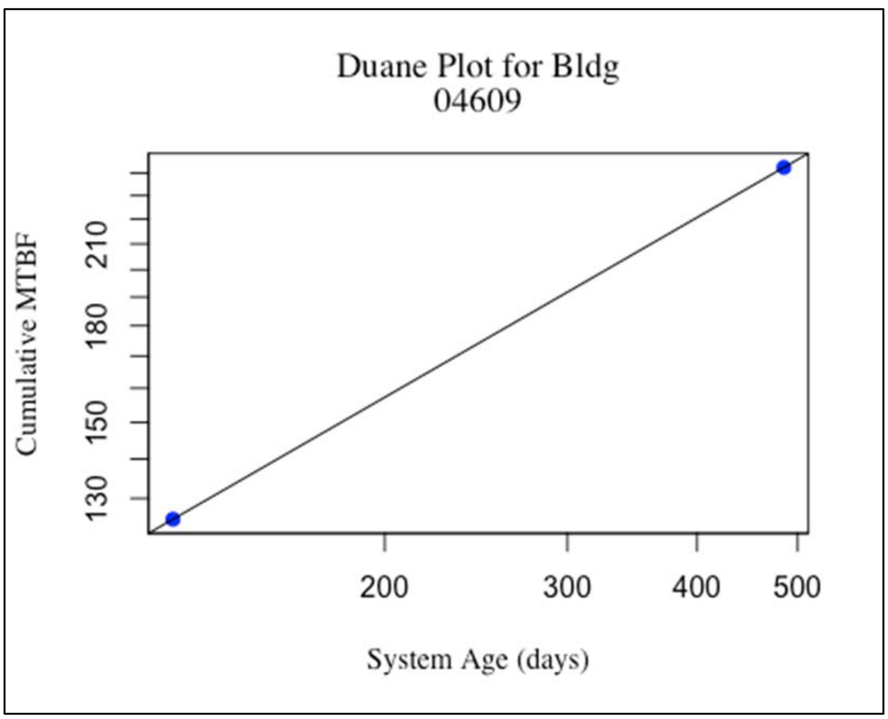

Figure F-30: Building 4609 HVAC Duane Plot

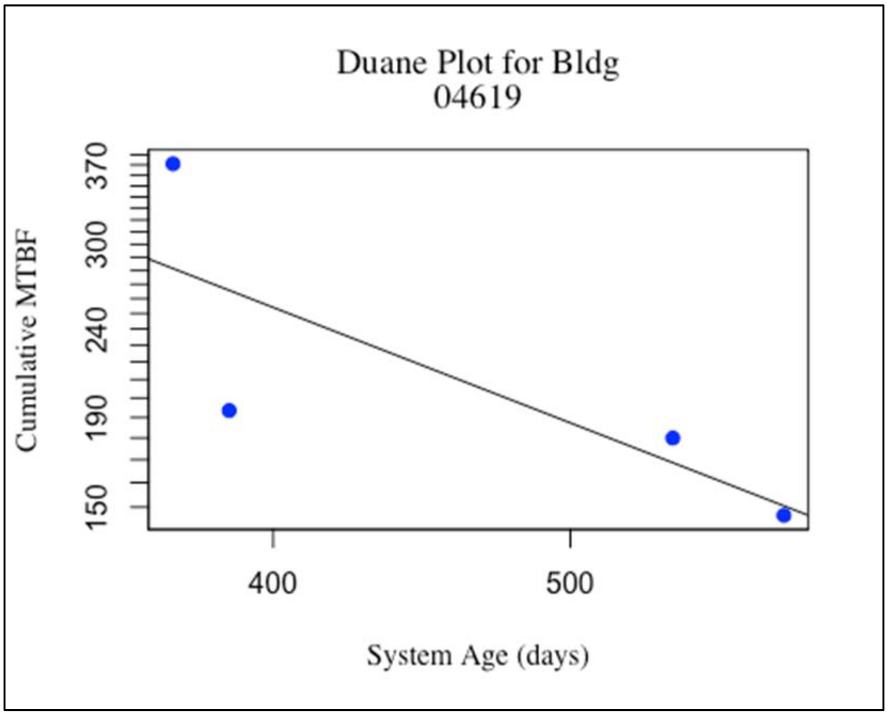

Figure F-31: Building 4619 HVAC Duane Plot

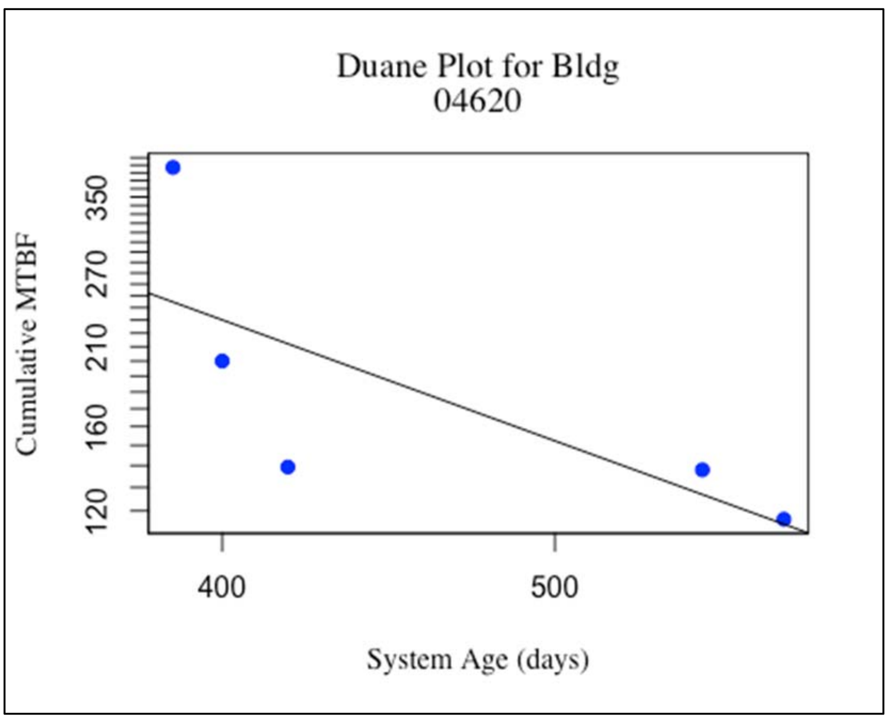

Figure F-32: Building 4620 HVAC Duane Plot

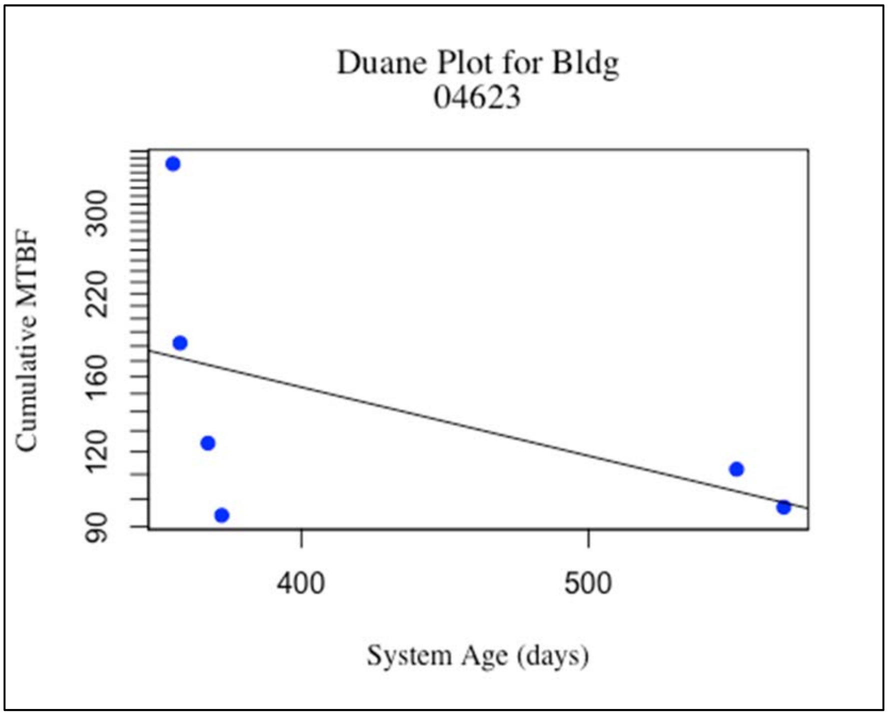

Figure F-33: Building 4623 HVAC Duane Plot

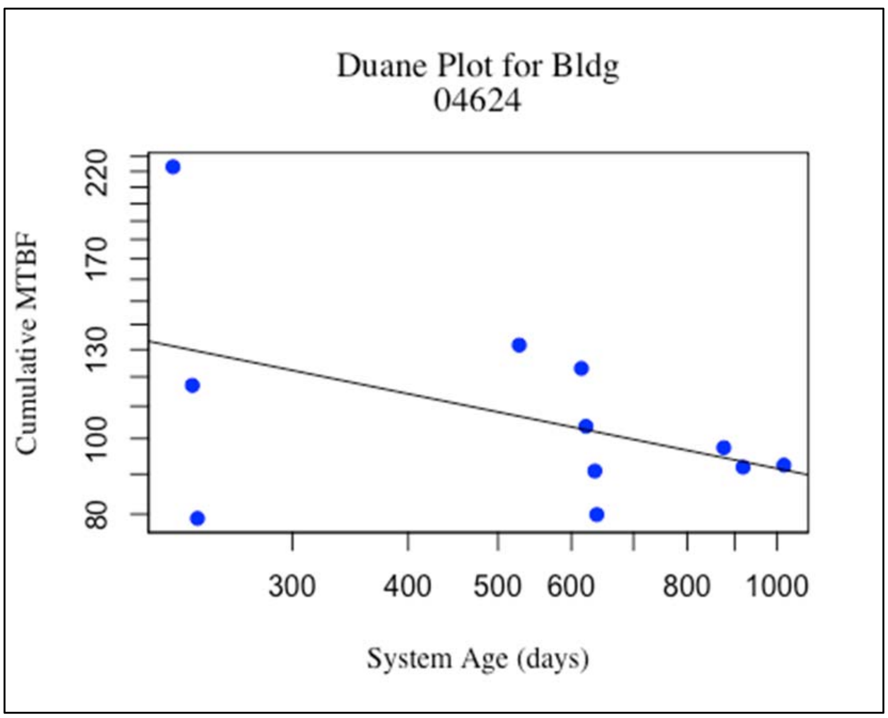

Figure F-34: Building 4624 HVAC Duane Plot

Appendix G: Method and preliminary results for Semi-Markov Process

To serve as stimuli for follow on research, this appendix demonstrates and alternative method for evaluating civil system reliability via a finite state Semi-Markov Process. The below method is adapted from Warr (n.d.) in which the author simplifies the Semi-Markov process. The reliability results calculated use the data collected from Cannon AFB HVAC systems as presented in Appendix D. The calculated results are the output of the R statistical software code developed by Freels and Warr (2015). Due to the time constraints of this thesis effort, this research was unable to holistically evaluate the proposed method. However, based on preliminary results, this research deems the below method worthy of further analysis to determine its effectiveness in providing accurate reliability calculations for repairable civil systems.

Finite State Semi-Markov Process (SMP)

Semi-Markov Processes (SMP) is a stochastic process used to understand statistical properties in survival analysis, reliability analysis, DNA analysis, and other transition or "state" type processes. Despite their general applicability, Warr (n.d.) discusses that practitioners don't widely use SMPs. Moreover, Warr (n.d) also summarizes the straightforward nature of solving SMPs. Using the data from Appendix D, this research employed Warr's method to calculate a measure of reliability for Heating, Ventilation, and Cooling (HVAC) systems given a systems age in order assess the accuracy of the PoF model and SCI model for HVAC systems.

This research will model the reliability of a systems using SMP with a finite number of failure states. A section discussing these states and their properties will be offered later in this appendix. The below sections introduces statistical quantities that can be obtained when employing SMPs. Subsequent sections will explain how to solve these quantities and how they relate to a measurement of reliability.

Figure G-1 displays a simple example of a finite state SMP. State 1 represents a "working" state, state 2 an "under repair" state, and state 3 an "unrepairable" state. $F_{ij}(x)$ and p_{ij} are notations for cumulative distribution function (CDF) of transition time and probability of transitioning from state i to state j, respectively. Ultimately, Figure G-1 highlights the three necessary pieces of information to define an SMP: 1) the number of states, n; 2) the CDF of the waiting time distribution from state i to state j, $F_{ij}(x)$; and 3) the probability that the next state in the process is j, given the process entered state i (Warr, n.d.). These three pieces of information will enable the use of the SMP to calculate statistical quantities of interest. Table G-1 displays the statistical quantities available via a SMP. This research will utilize $P_{ij}(t)$ to calculate a measure of system reliability (Warr, n.d.).

Table G-1: Statistical Quantities available through SMP

Notation	**Description**
$P_{ij}(t)$	The probability the process is in state j (as a function of time).
$G_{ij}(t)$	The first passage distribution of the time to reach state j.
$v_{ij}(k;t)$	The probability of reaching a state j, k number of times (as a function of time).
$V_{ij}(k;t)$	The probability of reaching a state j, k or fewer times (as a function of time).
$M_{ij}(t)$	The expected number of times the process has been in state j at time t

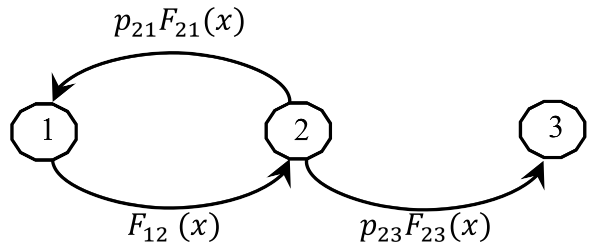

Figure G-1: semi-Markov Process Example (adapted from Warr, n.d.)

Notation Convention

This section will explain some of the basic notations associated with SMPs. This method will utilize cumulative probability distributions (CDFs) of the waiting time with basic form $F_{ij}(x)$ and basic transition probabilities p_{ij}. From these values and statistical quantities identified in Table G-1, the following notations are presented:

$$f_{ij}(x) = F_{ij}(x)\frac{d}{dx} \tag{28}$$

$$g_{ij}(x) = G_{ij}(x)\frac{d}{dx} \tag{29}$$

$$q_{ij}(x) = p_{ij}f_{ij}(x) \tag{30}$$

$$\delta_{ij}(x) = \begin{cases} 0 & if\ i \neq j \\ 1 & if\ i = j \end{cases} \tag{31}$$

$$h_{ij}(x) = \delta_{ij}\sum_{j=1}^{n} q_{ij}(x) \tag{32}$$

Additionally, SMPs involve some basic matrix algebra. Many of the values listed in equations 28-32 will populate a matrix with similar notation. Therefore, this research will represent matrices in boldfaced print. For example, matrix ***F****(x)* represents the matrix containing $F_{ij}(x)$ for all i and j. Lastly, SMPs utilize Laplace transforms to simplify calculations. This research will represent the Laplace transform of a generic function *F(x)* with a tilde as such, $\tilde{F}$*(s)*. Similarly, a matrix containing transformed functions is represented with boldfaced text and a tilde, i.e. $\tilde{\boldsymbol{F}}$*(s)* (Warr, n.d.).

Laplace Transforms

Matrix operations combined with statistical distributions can result in very complicated calculations. For simplicity SMPS use Laplace transformations to make calculations similar to solving a system of linear equations (Warr, n.d.). Given a generic function *F(t)*, its Laplace transform $\tilde{F}$*(s)* is:

$$\tilde{F}(s) = \int_0^{\infty} e^{-st} F(t) dt \tag{33}$$

Once a function is transformed, matrix operations are completed in the transform domain to compute functions of the statistical quantity of interest. After functions are computed in the transform domain, they must be inversed back to the time domain. For a function *F(t)* and its Laplace transform $\tilde{F}$*(s),* the inversion is:

$$F(t) \approx \sum_{j=0}^{N} (-1)^j \, \omega_j Re\left[\tilde{F}\left(\frac{A}{2t} + \frac{j\pi}{it}\right)\right] \tag{34}$$

where *Re[.]* is the real portion of the function and ω_j is a weight associated with each term. *N*, *A*, and ω_j control the accuracy of the approximation (Warr, n.d.). Due to the complex nature of Laplace transforms and their inversions, this research will employ the R statistical software in conjunction with the code developed by Freels and Warr (2015) to compute the Laplace transforms and inversions for all statistical distributions.

Time-Dependent State Probabilities

Table G-1 presented statistical quantities this research can compute using a SMP. The primary statistical quantity of interest to this research is the time-dependent state probability. This quantity provides the probability that a SMP is in a particular state at time, *t*. Equation 35 shows the formula necessary to find these probabilities,

$$\widetilde{\boldsymbol{P}}(s) = \frac{1}{s}\left(\boldsymbol{I} - \widetilde{\boldsymbol{q}}(s)\right)^{-1}\left(\boldsymbol{I} - \widetilde{\boldsymbol{h}}(s)\right) \tag{35}$$

where **I** is the identity matrix (Warr, n.d.). Given the matrix $\widetilde{\boldsymbol{P}}(s)$ in the transform domain, equation 34 inverses the functions in this matrix back into the time domain. Once in the time domain, this research will input a given systems age to determine the individual state probabilities for each state.

Future researchers must define the state space, *E*, in a manner that lends itself to the desired reliability calculations. During this preliminary analysis, this research focused on calculating the state probability for a given system. *E* consisted of multiple sequential states with individual transition CDFs. If *E* is the number of failures a system has encountered, this preliminary analysis calculated the probability that a system has seen 0, 1, 2, 3, 4, …etc. failures in a given time, *t*.

In contrast to strict failure state probabilities, future research may focus on availability as introduced by Høland and Rausand (1994) as a more appropriate measure for assessing the probability that a repairable system will be in a operational state at time *t*. Limnious (2011) employs a method for calculating availability from general state SMPs. In this method, Limnious (2011) classifies states into two general categories: failed, *D*, or operational, *U*. Given failed and operational states, availability at time *t*, *A(t)*, is calculated as:

$$A(t) := \boldsymbol{P}(Z_t \in U) \tag{36}$$

Defining the transition probabilities

Transition probabilities p_{ij} define the probability that the next state in the SMP is j, given that the process is currently in state i (Warr, n.d.). The transition probabilities for this preliminary analysis was simple and required no data collection. Because E was defined as sequential failure states, the transitional probability for the next state was always $p_{ij} = 1.0$.

Defining the transition CDFs

This analysis used the HVAC failure data from Cannon Air Force Base in Appendix D to determine the failure time distributions for each state. The goodness of fit tests displayed that the failure time distributions fit both the Weibull and Lognormal distributions. Table G-2 displays the goodness of fit results for both distributions. In addition to the goodness of fit results, this table displays a decreasing trend in the meant time between failures, an intuitive assumption for repairable systems. Future research should focus on data collection to improve the fit of failure time distributions for higher-count system failures.

Table G-2: State transition time CDF parameters and goodness of fit

State	n	Weibull scale	Weibull shape	A.D. test	A.D. result	Log-normal mean	Log-normal std dev	A.D. test	A.D. result
1	33	774.086	1.421	0.392	not rejected	6.265	0.789	0.403	not rejected
2	29	287.268	0.709	0.784	rejected	4.865	1.695	1.152	rejected
3	24	164.942	0.742	0.295	not rejected	4.298	1.768	0.686	rejected
4	21	133.967	0.964	0.452	not rejected	4.258	1.422	0.704	rejected
5	19	173.316	0.755	0.362	not rejected	4.442	1.445	0.330	not rejected
6	17	176.528	0.516	0.361	not rejected	4.158	2.057	0.293	not rejected
7	15	192.991	0.638	0.225	not rejected	4.415	1.751	0.271	not rejected
8	12	137.891	0.571	0.370	not rejected	3.972	1.935	0.432	not rejected
9	12	84.030	0.803	0.216	not rejected	3.680	1.634	0.362	not rejected
10	11	128.280	0.561	0.317	not rejected	3.900	1.934	0.231	not rejected
11	10	148.836	0.678	0.311	not rejected	4.165	1.747	0.350	not rejected
12	9	90.137	0.599	0.227	not rejected	3.570	1.923	0.203	not rejected
13	8	96.023	0.708	0.443	not rejected	3.703	1.861	0.450	not rejected

State Probability Results

Given the transition CDFs displayed in Table G-2, this analysis determined both the Weibull and Lognormal distributions effectively represent the transition distributions for successive failures. With these distributions and the R statistical software code developed by Freels and Warr (2015), this analysis calculated reliability measures for the HVAC systems at Cannon AFB. The state space defined is a simple 3 state system, depicted in Figure G-2.

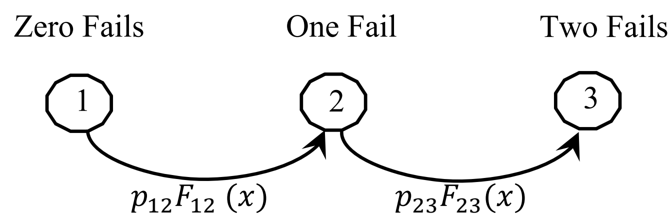

Figure G-2: HVAC System Failure State Space

The states defined represent a HVAC system having zero, one, and two failures as its current state. The specific state probabilities displayed in Table G-3 provide a probability for a system in a specific state, what is the probability that the system will remain in that state over the next 365 days. Additionally, Table G-3 displays the probability, give a system is currently in State 1, what is the probability it will stay in state 1 or transition to States 2 and 3 in 365 days.

Table G-3: Cannon AFB HVAC Reliability Calculations, t = 365 days

Specific State Probabilities		
	Lognormal	Weibull
State 1	0.6753	0.7092
State 2	0.2793	0.3057
State 3	0.1848	0.1648
Probability of Reaching a state: Given current state = State 1		
State 1	0.6753	0.7092
State 2	0.1804	0.1620
State 3	0.0702	0.0637

The results of this analysis show realistic reliability calculations and are representative of what should be expected for a repairable system. The results show that as systems begin to accumulate failures, the probability of seeing a successive failure increases. Additionally, based on the nature of the failure documented (Emergency and Urgent), the method displays realistic calculations for seeing an event of that magnitude multiple times in a single year. These preliminary results display that SMPs are a viable tool for reliability analysis of repairable systems. The results and methods above provide a general framework for reliability analysis using SMPs. However, further research is required to determine the legitimacy of this method for use with repairable civil systems and its application to Air Force civil systems.

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Vita

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14. ABSTRACT
The United States Air Force manages its civil infrastructure resource allocation via a two-dimensional risk model consisting of the consequence of failure and reliability. Air Force civil engineers currently use the BUILDER® Sustainment Management System to estimate and predict reliability at multiple levels within its civil infrastructure systems. Alley (2015) developed and validated a probabilistic model to calculate reliability at the system level. The probabilistic model was found to be a significant improvement over the currently employed BUILDER® model for four major building systems (electrical, HVAC, fire protection, and electrical). This research assessed the performance and accuracy of both the probabilistic and BUILDER® model, focusing primarily on HVAC systems.This research used contingency analysis to assess the performance of each model for HVAC systems at six Air Force installations. Evaluating the contingency analysis results over the range of possible reliability thresholds, it was found that both the BUILDER® and probabilistic model produced inflated reliability calculations for HVAC systems. In light of these findings, this research employed a stochastic method, a Nonhomogenious Poisson Process (NHPP), in an attempt to produce accurate HVAC system reliability calculations. This effort ultimately concluded that the data did not fit a NHPP for the systems considered but posits that other stochastic process can provide more accurate reliability calculations when compared to the two models analyzed.

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