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INFORMING THE SYSTEMS ENGINEERING APPROACH TO MAINTENANCE ACTIVITY DEVELOPMENT USING MAINTENANCE PERSONNEL RISK ATTITUDES

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THESIS

INFORMING THE SYSTEMS ENGINEERING APPROACH TO MAINTENANCE ACTIVITY DEVELOPMENT USING MAINTENANCE PERSONNEL RISK ATTITUDES

by

Benjamin W. Rathwell

December 2019

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13. ABSTRACT (maximum 200 words)

Systems engineering practices in the Navy consider operational availability as a system attribute determined by system components and a maintenance concept. A better understanding of the risk attitudes of system operators and maintainers may be useful in understanding potential impacts to operational availability that the system operators and maintainers have. The method presented in this thesis synthesizes the concepts of reliability, risk attitudes, and utility theory to quantify the effect that risk attitudes of systems operators and maintainers have on system operational availability. The method consists of four main steps providing the engineer with a risk-attitude-adjusted insight into the system's "utility" as determined by a system "value" parameter, which, in this case, is system reliability. This is accompanied by a final step that may be taken by systems engineers that uses the output of the previous four steps to inform any necessary iterations to the system design process. If it is deemed necessary to redesign the system (Step 5), the systems engineers will likely choose new system components and/or alter their configuration; however, redesign is not limited to physical alteration of the system. Several other options, which may be more practical depending the system's stage in the life cycle, address this issue from a maintainability or supportability perspective rather than a reliability perspective.

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INFORMING THE SYSTEMS ENGINEERING APPROACH TO MAINTENANCE ACTIVITY DEVELOPMENT USING MAINTENANCE PERSONNEL RISK ATTITUDES

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ABSTRACT

Systems engineering practices in the Navy consider operational availability as a system attribute determined by system components and a maintenance concept. A better understanding of the risk attitudes of system operators and maintainers may be useful in understanding potential impacts to operational availability that the system operators and maintainers have. The method presented in this thesis synthesizes the concepts of reliability, risk attitudes, and utility theory to quantify the effect that risk attitudes of systems operators and maintainers have on system operational availability. The method consists of four main steps providing the engineer with a risk-attitude-adjusted insight into the system's "utility" as determined by a system "value" parameter, which, in this case, is system reliability. This is accompanied by a final step that may be taken by systems engineers that uses the output of the previous four steps to inform any necessary iterations to the system design process. If it is deemed necessary to redesign the system (Step 5), the systems engineers will likely choose new system components and/or alter their configuration; however, redesign is not limited to physical alteration of the system. Several other options, which may be more practical depending the system's stage in the life cycle, address this issue from a maintainability or supportability perspective rather than a reliability perspective.

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LIST OF ACRONYMS AND ABBREVIATIONS

CNO	Chief of Naval Operations
DOSPERT	domain-specific risk-taking
HFE	human factors engineering
HSI	human systems integration
INCOSE	International Council on Systems Engineering
ILS	integrated logistics support
LOE	line of effort
MTBF	mean time between failure
MTBM	mean time between maintenance
ORM	occupational risk management
RBD	reliability block diagram
SE	systems engineering
SoS	system of systems

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EXECUTIVE SUMMARY

The Navy is a unique and complex organization with high tempo and extensive operational commitments. To perform well in such a dynamic environment and continue to meet the demand of prompt and sustained combat, operational availability is of paramount importance. Systems engineering practices within the Navy generally consider operational availability to be a system attribute determined by the quality and arrangement of the components within the system as well as the system's maintenance concept. One potential method of improving system engineering processes is by augmenting existing design considerations by measuring the risk attitudes of the individuals who will be interacting with the system and analyzing individuals’ risk attitudes to predict the impact on operational availability.

A better understanding of how risk attitudes of individuals specifically involved with operating and maintaining a system may be useful in modifying how a system is designed and/or operated to address potential impacts to operational availability from individuals’ risk attitudes that are not what systems engineers would otherwise have anticipated. The method developed in this thesis is intended to be implemented early in the systems engineering process during overall conceptual system design and architecture to aid in maintenance concept development. The method is targeted toward new systems; however, the method may be applicable to existing systems scheduled to go through periods of major overhaul or upgrade.

This author's methodology synthesizes the concepts of reliability, risk attitudes, and utility theory to quantify otherwise qualitative characteristics of system operators and maintainers (SOM) as they relate to operational availability. The process consists of four main steps providing the engineer with a risk-attitude-adjusted insight into the system’s “utility” as determined by a system “value” parameter, which in this case is system or component reliability. This is accompanied by a final step that may be taken by systems engineers that uses the output of the previous four steps to inform any necessary iterations to the system design process:

1. Identify key characteristics of the system.

2. Determine the risk attitudes of SOMs.

3. Develop the utility function.

4. Evaluate the utility of the system.

5. If necessary, implement adjustments to or redesign the system.

As systems engineering is an iterative and recursive process, should the engineer require execution of the fifth step, it may be necessary to perform steps four and five until reaching a satisfactory outcome.

The first step in determining how risk attitude impacts the operational availability of a system is to identify some of the key system attributes, including reliability. The reliability characteristics of each component are multiplied against each other pursuant to the overall reliability equations governed by component arrangements to determine the system's overall reliability level. This overall reliability level is then used as the “value” of the utility function in a utility theory approach. The next step of the method is to understand the aspirational risk attitudes of the personnel involved with the operation and maintenance of the system beginning with first selecting an appropriate risk attitude test. The (Domain-Specific Risk Taking) DOSPERT test covers five domains of risk-taking/aversion including ethics, finance, health/safety, recreation, and social (Blais and Weber 2006). While an individual’s risk attitude in each domain has an impact on the operational availability of the system, the impacts are not uniformly consistent across the set of domains for a given value. After determining both the SOM’s individual risk attitude in each of the domains, as well as determining the impact the domain itself has on operational availability, multiplying the two values together and summing each of the products provides a single value, R_{tot}, which is representative of the SOM’s overall risk attitude and expected impact on the reliability of the system with which he or she is interacting. Often times, ρ is even better defined by taking the average across a pool of SOMs’ R_{tot} results. The decision to analyze only one individual versus a group of SOMs should be based on whether many SOMs work on a specific system or if one dedicated SOM will work on that system. In the third step, utility theory is used to determine how this value impacts the "utility" of the system as it relates to reliability by generating the utility function in Equation 1 (Kirkwood 1997):

$$u(x) = \begin{cases} \dfrac{e^{-\frac{(x)}{\rho}} - 1}{e^{-\frac{100}{\rho}} - 1}, \rho \neq \infty \\ \dfrac{x}{100}, otherwise \end{cases}, \tag{1}$$

where ρ is the risk coefficient, which is inversely related to the risk tolerance of the SOM and given by Equation 2:

$$\rho = -\frac{1}{(R_{tot} - 1)(F_s)}, \tag{2}$$

where R_{tot} represents the overall risk attitude of the SOM and F_s represents a scaling factor indicating the impact of risk attitudes on system reliability. In the investigation of the impact of risk attitude on the reliability of the system (Equation 1), the *value, x*, is the reliability of the system and the *utility [u(x)]* is the risk-adjusted impact to the expected operational availability of the system. In the fourth step, the systems engineer relates the utility function to the system described in step one. Determining the revised system utility provides the systems engineer with several options. The system may still be of sufficient utility that despite the effects of the risk attitude of the SOM(s) and thus the engineering process may continue unhindered; however, there may be sufficient impact to require addressing the issue before proceeding further in the engineering process. If it is necessary to redesign the system (Step 5), systems engineers will likely choose new system components and/or alter their configuration; however, redesign is not limited to physical alteration of the system. Several other options which may be more practical depending the system's stage in the lifecycle address this issue from a maintainability or supportability perspective rather than reliability. For example, efforts could be made to utilize specialized training to reduce the system's mean time to repair. Additionally, efforts to reduce administrative or logistics delays may prove of use in boosting the system's operational availability levels; however, if any combination of these methods proves insufficient, it may be necessary to address the problem by addressing the risk attitudes of the SOM(s).

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I. INTRODUCTION

A. MOTIVATION

The Navy is a unique and complex organization with high tempo and extensive operational commitments. To perform well in such a dynamic environment, the Chief of Naval Operations (CNO), Admiral John Richardson, released a document titled *A Design for Maintaining Maritime Superiority* that states that "The United States Navy will be ready to conduct prompt and sustained combat incident to operations at sea" (Richardson 2018). This unified approach to naval strategy suggests that to meet the demand of prompt and sustained combat, operational availability is of paramount importance.

B. THE CURRENT OPERATIONAL AVAILABILITY APPROACH

Systems engineering practices within the Navy generally consider operational availability to be a system attribute determined by the quality and arrangement of the components within the system as well as the system's maintenance concept. In this approach to operational availability, no explicit consideration is given to the characteristics of the personnel interacting with the system as it assumes any individual responsible for operating or maintaining the system will follow all guidance set forth in the maintenance concept (Waeyenbergh and Pintelon 2002, 299). Continued reliable performance of the system is contingent on the system being properly operated and maintained in accordance with said guidance. In the Navy, this responsibility falls to the officers and enlisted personnel to promote and enforce procedural compliance as a means to ensure the system achieves designed availability levels. While this is a valid approach, it does not account for the potential of the system operator/maintainer (SOM) to be in non-compliance with the maintenance concept.

C. THE OBJECTIVE

In order to better predict the availability of a system, engineers must account for not only material considerations, but also the human element (Dhillon 2009, 2). One potential method of improving system engineering processes in this way is by augmenting existing design considerations by measuring the risk attitudes of the individuals who will be interacting with the system and analyzing individuals' risk attitudes to predict the impact on operational availability. A better understanding of how risk attitudes of individuals involved with operating and maintaining a system may be useful in modifying how a system is designed and/or operated to address potential impacts to operational availability from individuals' risk attitudes that are not what systems engineers would otherwise have anticipated.

D. RESEARCH QUESTIONS

How can risk attitude information collected from SOMs be linked to the reliability of the systems with which they interact to improve naval systems design for increased operational availability?

- How can risk attitudes be measured?
- How can risk attitudes be linked to operational availability?
- How can system operational availability be improved in light of this information?

E. SCOPE, LIMITATIONS, AND ASSUMPTIONS

This thesis is limited by the following scope, limitations, and assumptions, many of which provide the basis for future work.

1. Scope

Many psychological factors have the potential to impact operational availability, including changes in anthropometric, sensory, and physiological conditions (Wickens and Kramer 1985, 316). However, the scope of this investigation is limited to examination of risk attitudes as the factor under examination. Determining the interrelationships between the above mentioned psychological factors and the effects they have on risk attitude are beyond the scope of this thesis. As such, the investigation holds all other psychological factors aside from risk attitude as constant to demonstrate the impact of risk attitude itself on the operational availability of a system.

2. Limitations

This investigation is limited to publicly available research. No existing risk-attitude data for the population of interest (system operators and maintainers) is available, so representative but fictional risk attitude data is provided. The relationships, however, remain the same. Additionally, no empirical data is available to define the strength of risk attitude against other possible factors, such as physiological considerations, sufficient system training, or environmental conditions, on operational availability. Therefore, the coefficients used to represent the relationship of risk attitude to operational availability have been developed using engineering judgement but are not supported with either empirical data or from the literature. The engineering system data used to determine operational availability is representative of data found in naval systems but is intentionally fictional in nature to preserve confidentiality of data sources. Additionally, this investigation is limited to systems that are maintained by humans.

3. Assumptions

Several simplifying assumptions are made as part of this investigation. In the opinion of the author, the assumptions are reasonable and appropriate. This section presents and discusses the assumptions.

It is assumed that the risk attitude data of individuals involved with the operation and maintenance of naval systems has a measurable impact on system reliability and can be reasonably isolated from confounding factors. Furthermore, it is assumed that the risk domains covered in this investigation are dimensionally correct and applicable to the domain of engineering. Research on other distinct populations in several domains indicate that this is a reasonable assumption. For instance, risk attitude of patients to medical procedures has been isolated (Butler et al. 2012). In another instance, the risk attitudes of native German speakers have been investigated (Johnson, Wilke, and Weber 2004). Significant additional work within the domain of risk attitudes for specific situations and populations has been conducted and is available in the literature (Breuer et al. 2016;

Farnham et al. 2018; Mishra and Lalumière 2011; Van Bossuyt et al. 2013; Zhang, Foster, and McKenna 2018). Therefore, it is reasonable to make these assumptions.

In the context of this thesis, the assumption is made that the population of interest for risk attitude data is the operators and maintainers of naval systems, and more specifically the sailors who serve in those roles. Further, in alignment with research in the field of risk attitudes, it is assumed that sailors evaluate a decision where there is risk (e.g., option A carries a 20% chance of failure and a large reward while option B carries a 5% chance of failure and a small reward) in a favorable or unfavorable way and then act accordingly (Blais and Weber 2006; Van Bossuyt et al. 2013). Furthermore, this author stipulates that risk aversion has no effect on system performance, as it is indicative of the procedural compliance found in neutral risk attitudes.

In addition to assuming the risk attitudes of the population are representative of those of the SOMs, this author has assumed the risk attitudes of the SOMs will not change appreciably over the system lifecycle. Due to the structure of naval career progression, the average set of SOMs remains consistent as new personnel arrive and others progress to their next assignments. Given the lifespan of the system in comparison to the tour length, this ensures that any variations in risk attitude across a variety of factors would be mitigated across the life of the system (Bond et al. 2016; Doornbos 2018; Yardley et al. 2016, 10) making this a reasonable assumption.

While this author could have developed a unique psychometric risk assessment tool to aid in answering the research question, he chose to generate a generic data set utilizing the structures from existing psychometric risk surveys available in literature (Blais and Weber 2006; Johnson, Wilke, and Weber 2004; Van Bossuyt et al. 2013). The limitation of this approach is that the risk attitude information is from a generic population and not specific to maintenance and professional activity risk attitude information from sailors involved in maintenance activities. However, based on the literature, this approach can still produce some useful results (Farnham et al. 2018; Johnson, Wilke, and Weber 2004). Further, the purpose of this thesis is to develop a systems engineering analysis method rather than a new psychometric risk assessment tool. In future work, it may be valuable to develop a psychometric tool.

The method developed in this thesis is intended to be implemented early in the systems engineering process during overall conceptual system design and architecture to aid in maintenance concept development. The method is targeted toward new systems and the assumption is made throughout the thesis that only new systems are being analyzed. However, the method developed in this thesis may be applicable to existing systems scheduled to go through periods of major overhaul or upgrade.

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II. LITERATURE REVIEW AND THEORETICAL FRAMEWORK

This section presents background information necessary to understand the context of the research presented in this thesis, a review of existing literature that directly relates to the contribution of this thesis to the literature, and the framework in which this research exists.

A. OPERATIONAL AVAILABILITY

To understand the implications of the CNO's demand for an operationally ready force, one must understand the concept of availability. Engineering literature discusses availability in three main ways, with each of them increasing in complexity. The first of the three is inherent availability. Inherent availability is the simplest of the three forms and is determined by design; it takes into account only the hardware characteristics and assumes ideal support (Defense Acquisition University 2001, 2; Krueger, Walden, and Hamelin 2011, 313). Achieved availability is slightly more complex, and while continuing to assume an ideal support environment, it makes provision for scheduled, preventive maintenance (Blanchard and Fabrycky 2011, 493). The last, and most robust, form of availability is called operational availability and takes into consideration, in addition to all of the factors included in inherent and achieved availabilities, the logistics and administrative delays associated with the system (Defense Acquisition University 2001, 2; Krueger, Walden, and Hamelin 2011, 313). This research focused on operational availability as the central metric as it is the most representative of the environment the system will be operating in and factors in the impact of limited resources (Krueger, Walden, and Hamelin 2011, 313; Pryor 2008).

In the book, *Systems Engineering and Analysis*, Blanchard and Fabrycky (2011, 493) defines operational availability as the "probability that a system or equipment, when used under stated conditions in an actual operational environment, will operate satisfactorily when called upon." This is reiterated in the *Defense Acquisition University Operational Availability Handbook* as "the probability that a system will be ready to perform its mission or function under stated conditions when called upon to do so at a random time" (Defense Acquisition University 2001). Figure 1, taken from Pryor's "Methodology for Estimation of Operational Availability as Applied to Military Systems," illustrates operational availability in a temporal perspective (Pryor 2008, 422).

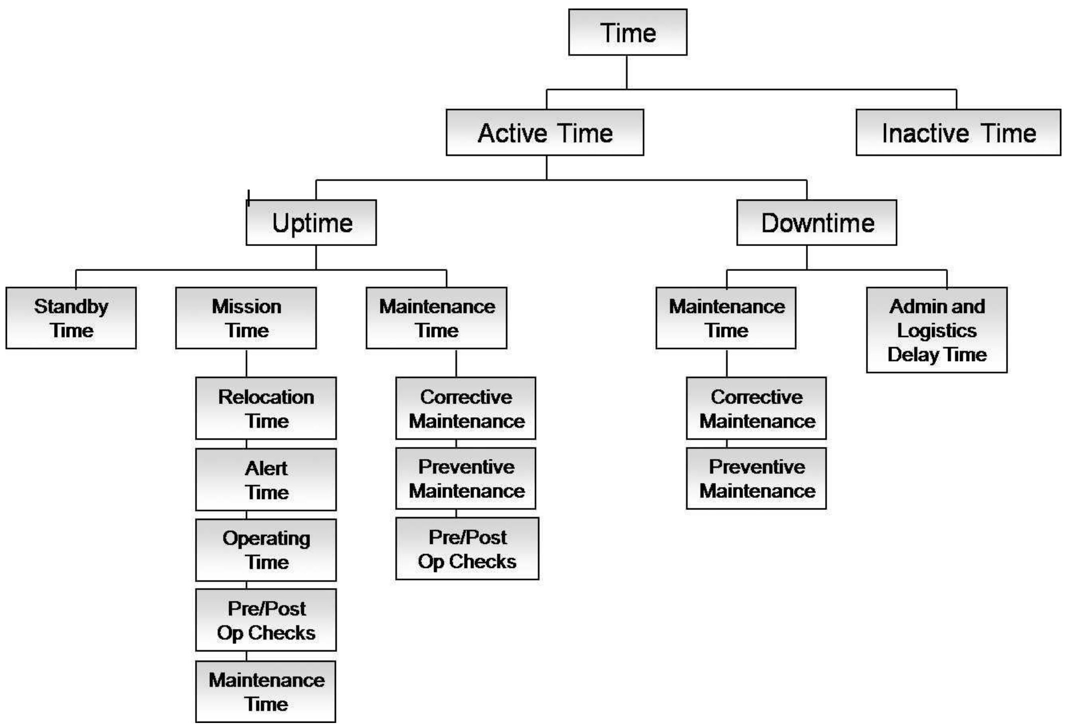

Figure 1. Operational Availability by Time. Source: Pryor (2008).

Pryor presents this illustration mathematically, defining operational availability as shown in Equation 1.

$$A_o = \frac{System\ Uptime}{System\ Uptime + System\ Downtime} \qquad (1)$$

System uptime and downtime can then be disaggregated further to reveal the three main factors contributing to a system's operational availability. According to the International Council on Systems Engineering (INCOSE), operational availability is a "function of operating time (reliability) and downtime (maintainability/supportability)," which are shown as system uptime and downtime respectively (Krueger, Walden, and

Hamelin 2011, 312). The first of these three factors, reflecting the expected system operating time, is reliability.

1. Reliability

According to INCOSE, reliability is the likelihood a system will work when expected (Krueger, Walden, and Hamelin 2011). This is similar to, but not the same as, availability. While availability is the ratio of system uptime to total time, reliability is simply the likelihood the system will be available when called upon. A system with low reliability has a low percentage chance of being in working condition when called upon (system downtime), which suggests over a given period of time, a system with lower reliability will have more downtime in that period compared to a system of higher reliability. Presented in terms of operational availability, this suggests that for a given set of conditions over a specified time, a system with lower reliability will also have lower operational availability.

According to Blanchard and Fabrycky (2011), reliability for an individual component is a function of the time period of interest and the mean time between failure (MTBF). The most commonly used reliability function that describes component reliability is the exponential reliability function. Blanchard and Fabrycky also disclose that not all types of equipment have the same failure characteristics; therefore, not all equipment will adhere to the formula presented in Equation 2. Exploration of non-exponential equipment failures is beyond the scope of this thesis; however, a more thorough discussion of reliability models can be found in the Handbook of Reliability Engineering (Pham 2003).

$$R(t) = e^{-\frac{t}{M}}, \qquad (2)$$

where *t* represents the time period of interest and *M* represents the MTBF of the component (Blanchard and Fabrycky 2011, 413). The inverse of MTBF is the failure rate, which is expressed as number of failures per given period. Under this model, increasing the period of interest for a given MTBF results in a lower reliability. Similarly, increasing the MTBF (lowering the failure rate) of a component for a given period raises the reliability of the component. Since reliability is a function of time and typically reliability calculations are given for a specified period of time, MTBF is often used as a stand-in (Defense Acquisition

University 2001). If no maintenance is performed on a system with a given MTBF, its availability can be defined by Equation 3:

$$A_i = \frac{MTBF}{MTBF + MTTR}\,, \qquad (3)$$

where *MTTR* is the mean time to repair the system and function of its design. This is the most rudimentary conceptualization of availability and referred to as inherent availability (A_i).

There are several schools of thought regarding methods to improve system availability. Some focus on system hardware attributes where changes to hardware can increase system availability while other approaches focus on component configuration or reformation of the maintenance concept (Fleischer, Weismann, and Niggeschmidt 2006; Waeyenbergh and Pintelon 2002). The most direct method is the hardware approach, which generally suggests replacing components with lower levels of reliability with components that have higher levels of reliability (Whitelock 1953). Replacing components that have lower reliability with components that have higher reliability is often very costly, especially as the expected reliability of the components reaches very high levels (Wang, Loman, and Vassiliou 2004).

In order to understand system reliability, the reliability of individual components must be gathered together, and a system-level reliability calculation must be developed. Reliability block diagrams (RBDs) are a very common method of analyzing system-level reliability from the component level (Guo and Yang 2007). Figure 2 shows an RBD for a generic system with three components placed in series configuration.

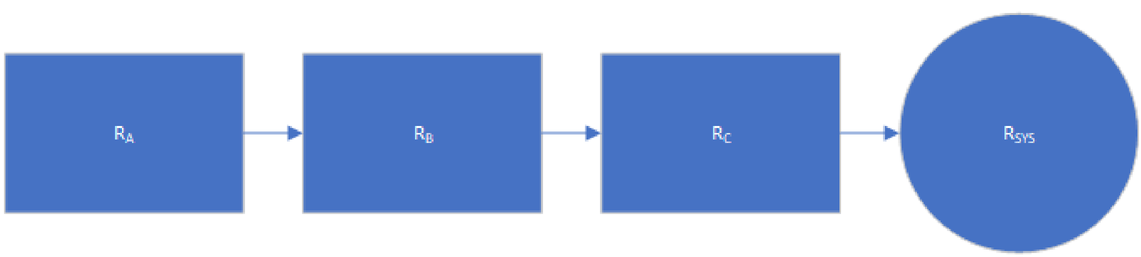

Figure 2. Series Reliability Diagram

This is the simplest form of a three-component system with a system reliability given by Equation 4:

$$R_{sys} = (R_A)(R_B)(R_C)\,, \tag{4}$$

where R_A, R_B, and R_C are the reliabilities of each of the components and the system reliability is their product (Blanchard and Fabrycky 2011, 419). Component configuration capitalizes on the use of series and parallel configurations to improve the reliability of a system (Coit and Smith 1996). There are two main methods of providing redundancy. The first is to place an energized, redundant component in parallel with the original. The second method differs only in that the component is de-energized until the failure of the original component (Coit 2001). This is the difference between active and standby redundancy (Amari and Dill 2010). The equivalent reliability for a number of identical components placed strictly in parallel is represented by Equation 5:

$$R_{eq} = \left(1 - \left(1 - R_{comp}\right)^n\right), \tag{5}$$

where n represents the number of components placed in parallel. Figure 3 shows a series-parallel system configuration with component B placed in parallel with a redundant part.

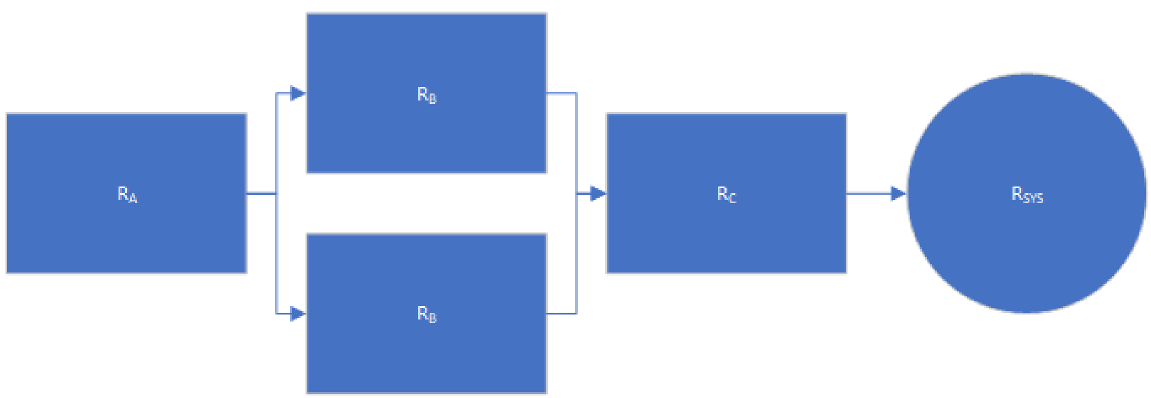

Figure 3. Series Parallel Diagram

The reliability for this series-parallel system is defined by Equation 6:

$$R_{sys} = (R_A)(1 - (1 - R_B)^2)(R_C)\,, \tag{6}$$

where the reliability of a component placed in parallel with a second identical component is represented by $(1-(1-R_{comp})^2)$ (Blanchard and Fabrycky 2011, 420–21).

Methods that focus on maintenance practices improve system reliability through the use of preventive maintenance to increase the effective MTBF of the system (Hong et al. 2014; Swanson 2001). When using preventive maintenance to increase system reliability, system downtime is determined not only by component failure, but also by scheduled preventive maintenance (Defense Acquisition University 2001). When used in reference to a maintenance concept, the MTBF of a system is re-designated $MTBM_u$ or the mean time between unscheduled maintenance. Its counterpart is $MTBM_s$, the mean time between scheduled maintenance. The terms are then combined and referred to as MTBM, or the mean time between maintenance. Mean time between maintenance, representing the mean time between maintenance activities, whether corrective ($MTBM_u$) or preventive ($MTBM_s$), is defined according to Equation 7 and is a measure of system uptime (Pryor 2008, 421–22).

$$MTBM = \frac{1}{\frac{1}{MTBM_u} + \frac{1}{MTBM_s}} \tag{7}$$

System downtime is then measured by the mean active maintenance time, $\bar{M}$, determined by both corrective and preventive maintenance times (Pryor 2008, 421). This form of availability is known as achieved availability and defined according to Equation 8:

$$A_a = \frac{MTBM}{MTBM + \bar{M}} \ , \tag{8}$$

where *MTBM* represents system uptime and $\bar{M}$ represents the mean active maintenance time. As MTBM is a characteristic of the maintenance concept of the system, it is considered part of the design for maintainability.

Once again, the purpose in discussing reliability is to understand its impact on a system's availability. While reliability is the dominant factor in determining a system's inherent availability, inherent availability fails to consider maintenance as a factor in determining the system's uptimes and downtimes (Krueger, Walden, and Hamelin 2011, 313). A more realistic understanding of the system's availability requires inclusion of factors related to system maintenance, necessitating a discussion of maintainability as a factor in determining system availability (Blanchard and Fabrycky 2011, 493).

2. Maintainability

Blanchard and Fabrycky (2011) describe maintainability as a "design characteristic (a design dependent parameter) pertaining to ease, accuracy, safety, and economy in the performance of maintenance functions." Systems designed to be maintainable capitalize on the system's maintainability characteristics to improve reliability, leading to better operational availability for the overall system; and while the reliability of a system is largely determined by the system's design, it can be positively or negatively impacted by the frequency and quality of maintenance performed on the components (Swanson 2001, 238). To ensure the system remains reliable throughout its operational life, one must ensure that the systems are properly maintained. In her article on linking maintenance strategies to performance, Swanson presents three strategies commonly used in the approach to maintenance (Swanson 2001). She names the first as reactive, in which maintenance is conducted in response to a failure in the equipment. In this method, MTBM is equivalent to $MTBM_u$. She describes the proactive strategy as one incorporating predictive and preventive maintenance practices to extend the MTBF of system components. In the event desired availability levels cannot be reached by improving system reliability through preventive maintenance, one may need to address the system design by providing redundancy in the form of additional components or functional paths in critical areas (Krueger, Walden, and Hamelin 2011). This is what Swanson refers to as the aggressive strategy, which is centered on the improvement system function and design. She also notes that as the strategies move from reactive to aggressive, the increased system performance comes at the cost of increased requirements for resources, training, and integration.

To this end, in their article on maintenance concept development, Waeyenbergh and Pintelon have expanded on maintenance strategies by suggesting maintenance strategies be introduced to the integrated business concept, and note that as maintenance strategies become more integrated, there has been "a shift from failure-based to use-based maintenance and increasingly towards condition-based maintenance" with increased emphasis on the production facilities in terms of reliability, availability, and safety (2002, 300).

Because the tradeoff between the frequency of preventive maintenance and system uptime can be complicated, many researchers have begun searching for solutions to optimize system availability. Monga, Zuo, and Toogood (1997), propose a genetic algorithm to optimize the balance between preventive and corrective maintenance actions. Coit and Smith (1996) take a similar approach. According to Coit and Smith, the procedure involves taking an initial population composed of solutions vectors (set of possible component configurations) and applying an objective function, which allows the component configurations to mutate over subsequent iterations until reaching a feasible solution.

While this method is useful for optimization of maintenance, it rests on the assumption of ideal logistics support, meaning that while the method is able to provide more resolution than inherent availability, it fails to include factors outside of the component characteristics and maintenance design. In an organization with limited resources, it is not often reasonable to assume system reliability and maintainability characteristics are the only significant factors in determining the system's availability (Defense Acquisition University 2001). For this reason, it is important to consider the supportability characteristics of the system.

3. Supportability

Supportability is a system aspect primarily concerned with the logistics and support mechanisms by which a system is acquired, installed, and subsequently maintained. Blanchard and Fabrycky define logistics as "that part of the supply chain process that plans, implements, and controls the efficient, effective forward and reverse flow and storage of goods, services, and related information between the point of origin and the point of consumption in order to meet customer requirements" (Blanchard and Fabrycky 2011, 568). However, with regard to operational availability, the most significant supportability aspects focus on system maintenance and support, and the integrated logistics support (ILS) system that provides the materiel. Taken from DoDI 5000.2, the *Integrated Logistics*

Support Guide from Defense Systems Management College defines ILS as “a disciplined, unified, and iterative approach to the management and technical activities” designed to accomplish four objectives (Defense Systems Management College 1994, 1–1). The first objective is to make considerations for system support integral to the design. The second objective is to develop coherent, design-focused support requirements to achieve readiness objectives. The third objective is to obtain adequate support. The fourth and final objective is to provide support at minimum cost throughout the system's operational phase. Integration of ILS characteristics in the calculation of availability leads to the most robust and relevant form of availability to operating forces; operational availability. In relation to system uptime and downtime, impacts from ILS consist of two parts which are then combined with the mean maintenance downtime to provide an overall system downtime. The two parts of ILS that have an impact on system downtime are administrative delay time (ADT) and logistics delay time (LDT) (Pryor 2008, 421). Administrative delay time is the amount of time that the system remains inoperable for administrative reasons including organizational constraints, administrative approval processes, or personnel assignment priories. Logistics delay time is the downtime incurred due to lack of parts availability arising from delays in obtaining facilities to perform maintenance, test equipment with which to diagnose issues, or lack of replacement part stock. System downtime is, thus, defined by Equation 9:

$$MDT = \bar{M} + ADT + LDT\ , \tag{9}$$

and operational availability by Equation 10:

$$A_o = \frac{MTBM}{MTBM + MDT}\ , \tag{10}$$

where *MTBM* is the mean time between maintenance and *MDT* is the mean maintenance down time, which includes active maintenance time, logistics delay, and administrative delay. Reducing administrative and logistics delay minimizes system downtime and improves operational availability. The emphasis on reduction in these two areas is embodied in the Lines of Effort (LOE) contained in the CNO's *Design for Maritime Superiority*. Logistics is addressed in the LOE Blue in the discussion of ashore logistics posture and in LOE Green in the discussion of the use of additive manufacturing. Similarly, administration is addressed in LOE Green which emphasizes the achievement of “high velocity outcomes” (Richardson 2018).

The operational demands of today's systems have driven research into quantifying the impact of supportability on the availability of a system such as that of Kumar and Knezevic (1998) in their article on analysis of supportability as a critical factor in system operational availability. In their paper, Kumar and Knezevic propose different ways in which supportability concepts can be developed and optimized to address different rates of system failure and repair time. The three cases addressed were constant failure rate with constant repair time, constant failure rate with arbitrary repair time, and arbitrary failure rate and repair time.

Having discussed reliability first as a means of understanding a system's inherent availability, expanding the discussion to include maintainability further refined system availability to an expression of achieved availability. This discussion of supportability has addressed the final factors for determining a system's availability, administrative and logistics delay, to provide the most robust form of availability: operational availability. While integrating the variables of reliability, maintainability, and supportability provides all of the factors necessary to understand operational availability, this discussion can be further refined by addressing the human element of the system and understanding how it impacts the reliability, and ultimately availability, of a system.

B. HUMAN SYSTEMS INTEGRATION

Naval vessels are comprised of systems and can be described as systems of systems (SoS) (Krueger, Walden, and Hamelin 2011, 11). Each system on a naval vessel is operated and maintained by personnel(Blanchard and Fabrycky 2011, 536–38) . With such a significant effort placed on reliability as a factor in maximizing operational availability (Krueger, Walden, and Hamelin 2011, 312–13), and with the understanding that a significant portion of the negative impacts on the reliability of the system are caused by human interaction with the system (Perrow 1983, 522), substantial effort must be made and great care taken to understand how to best design the systems to accommodate (and in some instances withstand) these interactions with SOMs. These considerations fall under a domain of engineering called human systems integration (HSI) (Army Research Laboratory 2017).

According to the *Handbook of Human Systems Integration*, HSI is a concept, both technical and managerial in nature, that leverages methods and technologies useful to the implementation of the concept during systems integration (Booher 2003). It defines the top-level objectives of HSI to be the management of the relationships between SOMs, government and industrial organization stakeholders, and system design, production, and operation methods and processes. Correspondingly, others like Blanchard and Fabrycky (2011, 536) convey HSI as a perspective that requires understanding of the physical system elements, to include humans, and their interfaces.

Two benefits of addressing the human element from an HSI perspective are significant reductions in waste and substantial system productivity and performance increases (Booher 2003, 2). According to Blanchard and Fabrycky, one of the goals of system design is to ensure effective and efficient operation and maintenance throughout the system life cycle according to the needs of the customer (2011, 549). They continue by stating that for the system to be effective it must be able to perform all operational and maintenance functions, in a specific manner, in a designated time frame, and without error. In addition, all of which, they note, must occur at minimum cost over the life cycle of the system. Finally, they conclude by stating the goal of the process as the maximization of all system-level goals to include availability, dependability, and performance (Blanchard and Fabrycky 2011, 549).

HSI, according to the Department of Defense (DoD), is comprised of seven domains: Manpower, Personnel, Training, Human Factors Engineering (HFE), System Safety, Soldier Survivability and Health Hazards (Army Research Laboratory 2017). While improvements in operational availability can be achieved for operational systems in many of these domains, improvements made during the design phase are reserved for the HSI domain of HFE, which attempts to account for these traits in the realms of human psychology, among others. This is relevant to this investigation as the model proposed by this author was designed to implement information gleaned from analysis of human factors to improve HSI during the design phase.

C. USABILITY AND HUMAN FACTORS ENGINEERING

To maintain high operational availability for a system, in addition to reliability, maintainability, and supportability; one must address the usability characteristics of the system. Hardware and software design alone does not guarantee good system usability (operability) no matter how well done (Blanchard and Fabrycky 2011); and to this end, the system must take into consideration a variety of human factors. Blanchard and Fabrycky insist that in addition to reliability and maintainability, consideration of human factors must be undertaken starting with conceptual design (2011, 550).

A variety of factors must be taken into consideration from a usability perspective when designing a system including the anthropometric characteristics, sensory factors, physiological factors, and psychological factors of the SOM as well as relationships between these factors and the larger system design (Blanchard and Fabrycky 2011, 536). Anthropometric characteristics involve human dimensions such as arm span, weight, and height (Perrow 1983, 523). Sensory factors include sight, sound, smell, and touch, while physiological factors relate to environment impacts such as temperature, humidity, or noise level (Booher 2003, 557). Finally, psychological factors relate to personal attitudes, risk tolerance, and motivation (Dhillon 2009, 36; Perrow 1983; Krueger, Walden, and Hamelin 2011, 330–31). The psychological factors are of special interest to this research as they relate to the likelihood that a SOM will perform his or her duties as expected.

Failure to take human factors into consideration during system design often results in poor usability which can lead to decreased reliability of the SOM as an effective part of the system. To counter this outcome, some engineers have proposed conducting human reliability analyses in an effort to mitigate the effects of the perceived "weak link in the chain" (Dhillon 2009; Dougherty and Fragola 1988). Dhillon expounds upon this point by giving examples of different types of maintenance errors. He notes six main categories of errors including "recognition failures, memory failures, skill-based slips, knowledge-based errors, rule-based slips, and violation errors." None of these errors is desirable and effectively constitutes abuse of the system. Blanchard and Fabrycky (2011, 562) note that most emphasis in HFE focuses on system abuse as a result of unintentional actions by the SOM; however, in addition to the abuse resulting from unintentional acts, systems also suffer from abuse arising from willful acts of negligence or malevolence. Willful acts of abuse are typically violation errors, which warrant investigation of the psychological component of HFE (Dhillon 2009, 66–67). This does not imply that a system cannot be designed without expressly addressing these factors, but rather available information on the psychological disposition of the SOMs should be incorporated to improve the system design process (Blanchard and Fabrycky 2011, 536).

D. PSYCHOLOGY

Many human factors engineers have backgrounds in engineering psychology, which often proves useful for basic human factors work; though, it has its limitations when trying to influence organizational desires (Perrow 1983, 523). Wickens and Kramer (1985) define engineering psychology as "the study of human behavior with the objective of improving human interaction with systems" (307). They expand by illustrating its connection to three related disciplines: HFE, ergonomics, and human skilled performance. HFE has already been discussed above and will not be expounded upon any further. Ergonomics, they assert, is similar to HFE, but it focuses more specifically on physiology and environmental factors. Lastly, they speak briefly on human skilled performance as it pertains to psychology, which addresses issues arising in the performance of complex tasks without the express objective of using the data to improve system design.

For purposes of this thesis, this author has explored engineering psychology as it pertains to psychological factors and their influences on maintenance. *System Engineering and Analysis* defines psychological factors as pertaining to the relationship between job performance and the human mind with its emotions, traits, and behavior patterns (Blanchard and Fabrycky 2011, 548). It continues by asserting that even if all other factors have been optimized, a poor psychological disposition in a SOM increases the probability of diminished performance. While Blanchard and Fabrycky (2011, 548) note physiological factors may greatly influence psychological factors, this author has chosen to hold the physiological factors constant to isolate the impact of the psychological factors on maintenance outcomes properly.

E. RISK

Existing research in risk attitudes with regard to risk tolerance and risk aversion across personal domains is available in the Domain-Specific Risk-Taking (DOSPERT) Scale (Blais and Weber 2006) and the Engineering-DOSPERT (E-DOSPERT) for engineers in their professional practice across several domains (Van Bossuyt et al. 2013). The DOSPERT recognizes five dimensions of risk: ethical, financial, health and safety, recreational, and social. Blais and Weber define risk attitude as the “willingness to trade off units of perceived risk for units of perceived return” (2006, 34).

While prior research on risk attitudes in engineering led to the ability to perform risk attitude-adjusted decision-making at the stakeholder level (Van Bossuyt et al. 2012), more recent research relating risk attitudes with ethical decision-making and associated behaviors has provided a foundation for the exploration of risk attitudes in engineering at the level of the technician (Blanchard and Fabrycky 2011; Booher 2003; Dhillon 2009, 68, 83). Using risk attitude data of SOMs is exemplary of aspirational, rather than predictive, risk-based system design. The aspirational versus predictive nature of different risk attitude survey techniques was noted by Pennings and Smidts (2000) when investigating lottery methods and psychometric methods of assessing risk attitude for Dutch hog farmers. Van Bossuyt et al. (2012) further investigated lottery methods and psychometric methods of risk attitude assessment from the perspective of engineers and found similar correlations to Pennings and Smidts. Out of this work, a method for understanding aspirational risk attitudes of engineers can be used to develop aspirational system designs was developed and implemented into trade-off studies to be used during space mission concept planning (Van Bossuyt 2012; Van Bossuyt, Tumer, and Wall 2013). Aspirational system designs use aspirational risk attitudes of stakeholders collected from psychometric risk surveys such as the DOSPERT or E-DOSPERT surveys to guide the design process toward designs that are more optimal from an aspirational risk attitude perspective and that likely would not have been designed had the stakeholders not investigated their aspirational risk attitudes. Conversely, predictive system designs use lottery method-derived risk attitude information which is predictive in nature to develop designs that the stakeholders would have likely designed themselves. Aspirational system design has generally been used to analyze the risk attitudes of the ultimate decision-maker in order to make design decisions in his or her absence (Van Bossuyt et al. 2012). While this research also adheres to the aspirational philosophy of risk attitudes in the context of system design, it differs from previous aspirational design research in that this research analyzes the risk attitudes of the SOMs, rather than the major stakeholders as in the case of Van Bossuyt et al (2012) to inform the system design process.

F. THE DESIGN PROCESS

In order to contextualize the research presented in this thesis, it is important to understand the systems engineering design process and how this research fits within the process. Figure 4 depicts the components of the systems engineering "Vee" model (one of several models used to describe the systems engineering process), beginning with the decomposition and definition sequence, proceeding to integration and verification as the design moves from concept to operation.

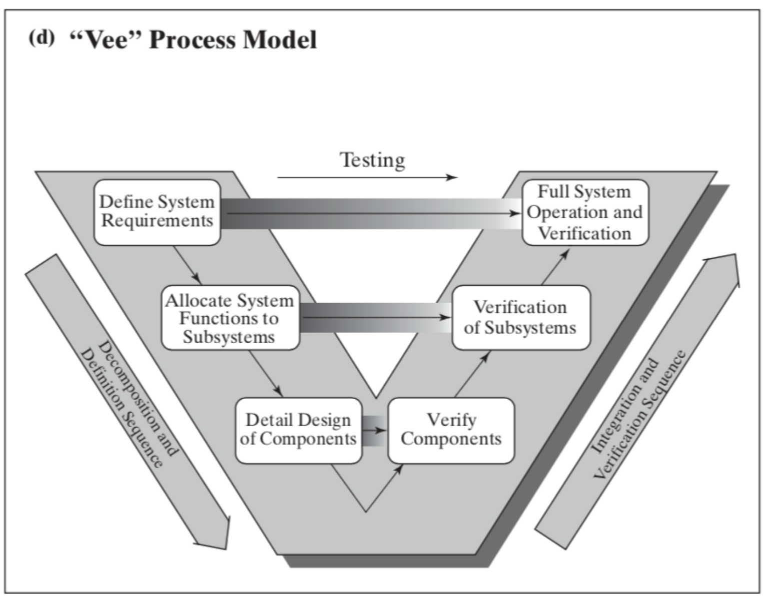

Figure 4. Vee Process Model. Source: Blanchard and Fabrycky (2011).

System effects related to risk attitudes manifest themselves during system operation, on the integration and verification side of the systems engineering “Vee” diagram (during the system operation phase), which can be factored into the decomposition and definition side of the diagram both iteratively and recursively during system design. The usefulness of employing a systems engineering approach to risk-based design is that it helps the Navy to better understand the relationship between risk attitudes in operators and maintainers of naval systems and their effects on system operational availability. In understanding how system operation and maintenance is likely to be conducted, engineers can apply lessons learned to both equipment overhauls and ground-up system development. Successful implementation of risk attitude-informed adjustments during the design phase through aspirational system designs as described above and as implemented in this research may provide improved system performance through matching system design to realistic operational and maintenance requirements, which may result in increased system operational availability. In order to implement risk attitude-informed adjustments, one method that has seen significant prior use is utility theory (Kirkwood 1997; Pennings and Smidts 2000; Van Bossuyt et al. 2012).

G. UTILITY THEORY

Utility theory is a method of decision making based on assigning a utility to a parameter based on its value (Fishburn 1970, 1). In his book, *Utility Theory for Decision Making*, Fishburn describes the fundamental theorem of utility as one that utilizes axiomatic preferences (values) to mathematically assign a number (utility) to each alternative in such a way that one is preferred over the other based on the utility each alternative provides (Fishburn 1970, 2). Often, the relationship between the value and its utility can be defined mathematically, resulting in a utility function with a shape determined by the decision maker's risk attitude (Kirkwood 1997, 3). The investigation undertaken by this author assumes an exponential utility function and, while no further discussion has been presented due to restrictions in scope, it is a common selection for risk attitude-based utility theory research (Blais and Weber 2006; Van Bossuyt et al. 2012).

The utility function compares the relationship between multiple sets of choice outcomes and, based on the nature of the relationships being investigated, the utility of the figure of merit (often assumed to be dollars in utility theory research although not exclusively) may increase or decrease depending on the utility value of the choice outcomes. For instance, with regard to operational availability, increased reliability (value) results in increased availability (utility). This kind of relationship is generally assumed to be monotonically increasing (Kirkwood 1997). However, some figures of merit, such as mean time to repair, are inversely related to operational availability. The increased time spent in the conduct of maintenance actions adversely impacts the overall availability of the system and the relationship is thus monotonically decreasing. These two relationships are defined mathematically as shown in Equation 11 for monotonically increasing relationships:

$$u(x) = \begin{cases} \dfrac{e^{-\frac{(x-Low)}{\rho}} - 1}{e^{-\frac{(High-Low)}{\rho}} - 1}, \rho \neq \infty \\ \dfrac{x - Low}{High - Low}, otherwise \end{cases}, \tag{11}$$

and Equation 12 for monotonically decreasing relationships:

$$u(x) = \begin{cases} \dfrac{e^{-\frac{(High-x)}{\rho}} - 1}{e^{-\frac{(High-Low)}{\rho}} - 1}, \rho \neq \infty \\ \dfrac{High - x}{High - Low}, otherwise \end{cases}, \tag{12}$$

where ρ represents risk tolerance (Kirkwood 1997, 6). The high and low values form the upper and lower bounds of the value in question. The depth of the function's curve when graphically plotted is dependent on the value of ρ. As shown in the equation, a larger value of ρ results in a less pronounced curve, while a smaller value results in a curve that is more pronounced, further exemplified in Figure 5.

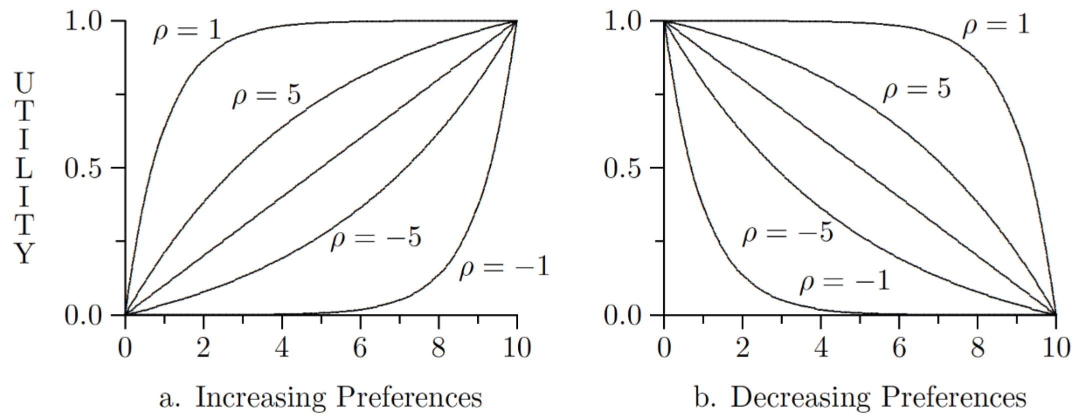

Figure 5. Monotonically Increasing and Decreasing Relationships.
Source: Kirkwood (1997).

The above chapter has provided the foundation and understanding necessary to introduce the main contribution of this thesis in the following chapter. It has provided discussion on reliability, risk attitudes, utility theory, all of which are essential for understanding how they relate to each other and ultimately to operational availability.

III. METHODOLOGY

This chapter presents a methodology synthesizing the concepts of reliability, risk attitudes, and utility theory to quantify otherwise qualitative characteristics of SOMs as they relate to operational availability. The ultimate goal of this process is to use the information to improve the operational availability characteristics of a system through design. The process consists of four main steps providing the engineer with a risk-attitude-adjusted insight into the system's "utility" accompanied by a final step which may be taken by systems engineers that uses the output of the previous four steps to inform any necessary iterations to the system design process:

1. Identify key characteristics of the system.
2. Determine the risk attitudes of SOMs.
3. Develop the utility function.
4. Evaluate the utility of the system.
5. If necessary, implement adjustments to, or redesign, the system.

As systems engineering is an iterative and recursive process, should the engineer require execution of the fifth step, it may be necessary to perform steps four and five until reaching a satisfactory outcome as shown in Figure 6.

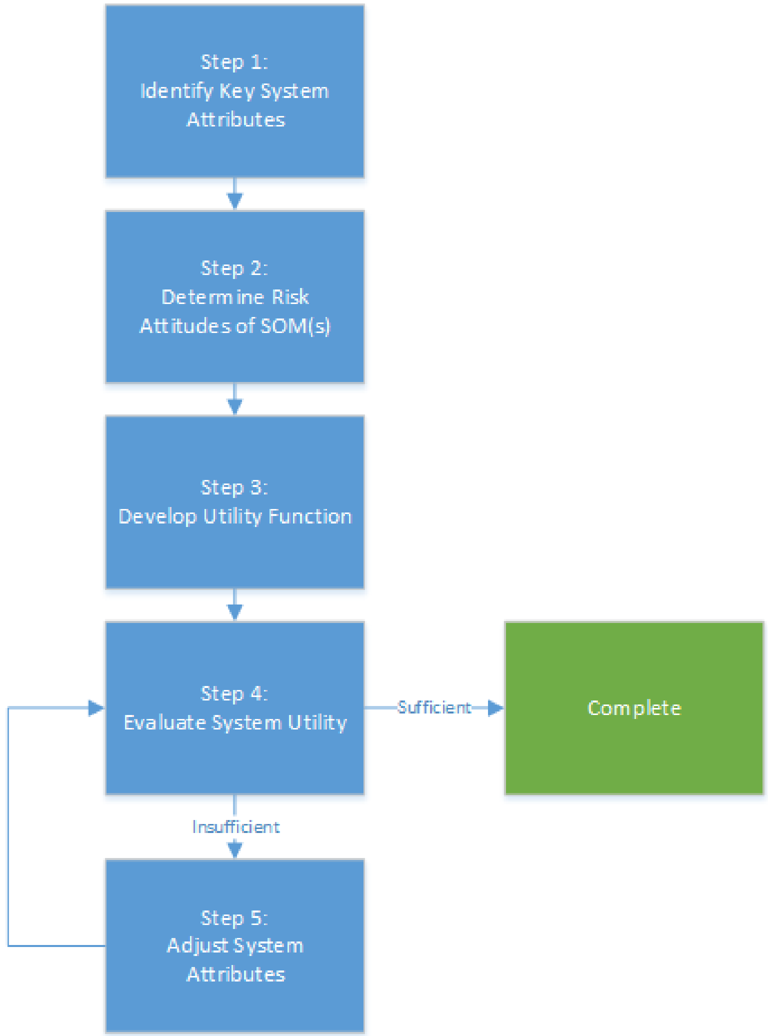

Figure 6. Methodology

A. STEP 1: IDENTIFY KEY SYSTEM ATTRIBUTES

The first step in determining how risk attitude impacts the operational availability of a system is to identify some of the key system attributes. Relevant attributes in determining the operational availability of a system include reliability, maintainability, and supportability characteristics. This method focuses on the reliability characteristics of the system as the mechanism by which risk attitudes affect operational availability.

The reliability of the system is determined by the characteristics and arrangement of the constituent components. As previously discussed, components can be arranged in series, parallel, or a combination thereof. Due to the nature of system reliability calculations, each successive component placed in series decreases the overall reliability of the system. For this reason, it is common to design systems in a series-parallel combination, placing multiple components in parallel at points in the system where individual components are more likely to fail.

The reliability characteristics of each component are multiplied against each other pursuant to the overall reliability equations government by component arrangements to determine the system's overall reliability level. This overall reliability level is the "value," x, of the utility function.

B. STEP 2: DETERMINE RISK ATTITUDES OF SOMS

The next step of the method is to understand the aspirational risk attitudes of the personnel involved with the operation and maintenance of the system beginning with first selecting an appropriate risk attitude test. Five sub-steps occur within Step 2 to determine the risk attitudes of the SOMs including 1) select risk assessment tool, 2) determine risk attitudes, 3) determine relative risk impact, 4) calculate risk coefficient, and 5) identify SOMs.

1. Select Risk Assessment Tool

In the case where aspirational system design is desirable, an aspirational risk attitude test is prescribed. Aspirational risk attitude tests are generally psychometric surveys such as the DOSPERT and E-DOSPERT while predictive risk attitude tests are often choice lottery-based (Blais and Weber 2006; Van Bossuyt et al. 2012; 2013). For the purposes of this research, the author takes the stance that aspirational system design is more appropriate than predictive system design, and thus warrants the use of a psychometric risk survey. This is because systems engineers and SOMs are aspiring to design and operate systems with higher operational availability by influencing system design through the analysis of risk attitudes. This is in line with what (Van Bossuyt et al. 2012) did for aspirational space mission designs.

While some evidence exists that custom tailored psychometric risk surveys are most appropriate to understand specific domains of risk attitudes, such as within a person's private life or professional life, developing a psychometric risk survey specifically tailored for SOMs within the context of naval vessels is beyond the scope of this thesis (Blais and Weber 2006; Van Bossuyt et al. 2013). Instead, the author advocates for practitioners to use either the DOSPERT or E-DOSPERT psychometric risk surveys to gain a high-level understanding of SOM risk attitudes. If further refinement of analysis conducted from the method presented in this chapter is desired, a tailored psychometric risk survey may be justified. Development of a psychometric risk survey is outside the scope of this thesis; information on developing psychometric risk surveys can be found elsewhere (Armstrong and Overton 1977; Fisher 1993; Fisher and Tellis 1998; Lusk and Norwood 2010; Moshagen et al. 2014).

For the purpose of this thesis, the DOSPERT test is used. The DOSPERT test covers five domains of risk-taking/aversion including ethics, finance, health/safety, recreation, and social. While the DOSPERT test and the five domains were developed from a personal, private life risk attitude perspective, these domains are generally well-aligned with potential broad domains of risk attitudes of SOMs at their jobs. This research is echoed in the investigations of decentralized decision-making in structural health monitoring systems as well as military operational risk taking (Valkonen and Glisic 2019; Momen et al. 2010).

2. Determine Risk Attitudes

To determine each SOM's individual risk attitudes in each of five domains of risk, the SOM is given a questionnaire asking for his or her perception of various scenarios involving risk-based decisions. The results of the questionnaire are then analyzed to identify his or her risk attitudes in relation to each domain. The risk attitude information is then translated into a set of coefficients indicating his or her risk tolerance or aversion in each domain.

For purposes of calculations performed in this method, the range of possible risk attitudes is set between -1 for completely risk averse to 1 for completely risk tolerant. Van Bossuyt et al. (Van Bossuyt et al. 2012), used a -3 to 3 scale in their work; however, the scales can be renormalized around any cardinal number set. A value of 0 indicates completely risk-neutral decision-making. Table 1 provides an example of a SOM's personal risk attitude composition across the five risk domains from the DOSPERT test. In this instance, the SOM is risk averse in two domains, risk seeking in two domains, and risk neutral in a single domain.

Table 1. Example Personal Risk Attitude Composition

Risk Domain	Value (nominal)	Risk Attitude
Ethics	-0.2	Risk Averse
Finance	0.2	Risk Seeking
Health/Safety	0.1	Risk Seeking
Recreation	0	Risk Neutral
Social	-0.3	Risk Averse

3. Determine Relative Risk Impact

While an individual’s risk attitude in each domain has an impact on the operational availability of the system, the impacts are not uniformly consistent across the set of domains for a given value. For instance, an individual’s desire for social acceptance may lead him or her to decision-making that has a significant impact on the system he or she maintains, whereas his or her risk attitude in the recreation domain would be inconsequential. While readily understandable using intuition and engineering judgement, there is limited research available to provide quantitative data for these relative impacts; however, the method presented in this thesis has the ability for systems engineers or other decision-makers to include such effects. It is beyond the scope of this thesis to quantify rigorously how a relative risk impact score is developed. This is an area that requires future work to be more rigorously developed. However, the method presented in this thesis is targeted for use during the system architecture phase of design as a tool for better understanding what impact risk attitudes of SOMs have on operational availability and, while quantitative in nature, is not intended to be used as a hard-and-fast decision-making tool. Instead, the method presented here is meant to be used to better inform decisions made about system design and maintenance concept. Table 2 provides a representative set of potential relative risk impact levels for a generic situation with reference to maintenance on board a naval vessel. A practitioner using this method is advised to develop relative impact scores appropriate to the system under analysis.

Table 2. Risk Domains with Relative Impact Levels

Risk Domain	Relative Impact
Ethics	1.2
Finance	1.1
Health/Safety	1.5
Recreation	0.2
Social	1.35

4. Calculate Risk Coefficient

After determining both the SOM's individual risk attitude in each of the domains, as well as noting the impact the domain itself has on operational availability, multiplying the two values together yields a domain-specific risk-decision impact. Upon determining the values for each domain, summing them together provides a single value which is representative of the SOM's overall risk attitude and expected impact on the reliability of the system with which he or she is interacting, R_{tot}, as shown in Equation 13:

$$R_{tot} = \sum_{n=1}^{5} T_n I_n \tag{13}$$

where n is the risk domain, T_n is the risk tolerance in domain n, and I_n is the risk impact of that domain on reliability. Reducing the set of domain values to a single number is useful for several reasons including its ability to be used as a scaling factor in a utility function. Van Bossuyt et al. (2012; 2012) advocated for a similar combination of multiple risk domains in situations where direct mapping from risk domains to a specific risk-informed design decision cannot be made. In the context of operational availability of naval vessels and when using DOSPERT or a similar psychometric risk survey that is not specifically tailored to answer naval vessel operational availability questions, this author suggests that it is appropriate to combine multiple risk domains together into one risk coefficient only after considering the relative risk impact levels of each risk domain.

5. Identify SOMs

Depending on the situation, ρ may be best defined by a single individual SOM's R_{tot} or by taking the average across a pool of SOMs' R_{tot} results. The decision only to analyze one individual versus a group of SOMs should be based on whether many SOMs work on a specific system or if one dedicated SOM will work on that system.

If many SOMs will work on the same system, analysis of risk attitudes across the domains of risk utilizing DOSPERT may reveal similar risk attitudes among the various factors within a group of SOMs. Alternatively, the analysis may reveal large standard deviations within the domains indicating disparate risk attitudes. Given a sufficiently low standard deviation, using the average risk attitude of the SOMs may be desirable for encapsulating SOM risk aversion or risk seeking at a high level.

While this approach works with any group of SOMs, analysis of certain subsets of personnel prove more useful than others. For instance, an engineer may survey all personnel who do a specific kind of maintenance on a specific class of ship, or a representative subset of them. Depending on the magnitude of deviation from an average score, the population can be said to have a relatively homogeneous risk attitude connoting confidence in any subsequent risk impact determination. Conversely, large deviations suggest the average risk attitude to be of low utility as an input to the risk utility function.

In the case of naval vessels for which this method is specifically tailored, this author suggests averaging R_{tot} across a representative respondent pool of SOMs that may serve aboard a vessel of interest. This is in line with how current naval personnel and staffing actions are taken where the vast majority of systems are operated and maintained by many different individual SOMs and no one system is the sole purview of one individual SOM. Equation 14 demonstrates how to combine the R_{tot} of several SOMs to be used in utility theory calculations:

$$R_{tot_{avg}} = \sum_{x=1}^{n} R_{tot\_x} \tag{14}$$

where n is the number of SOMs being analyzed and R_{tot_x} is the R_{tot} value for SOM x.

Due to the nature of engineered systems, the risk tolerance coefficient does not remain constant over the entire spectrum. Systems with very high or very low nominal availability remain relatively unaffected by risk tolerance. Systems with extremely low reliability levels are relatively unaffected by the SOM as inherent availability, and therefore operational availability, is already poor. Similarly, systems with extremely high reliability levels are relatively unaffected by SOM risk attitudes due to the decreased need for maintenance corresponding to decreased human-system interaction. Conversely, systems with moderate reliability levels are more susceptible to negative impacts from risk-seeking decisions due to the interaction between the higher inherent availability over low reliability systems from the presence of better components and the increased human-system interaction incurred by the maintenance requirements of systems with moderate reliability levels. These two factors combine in such a way that risk decisions have a more significant impact on system reliability (Blanchard and Fabrycky 2011, 485–90). This author suggests quantification using Equations 11 or 12, depending on the “value” by which the investigator wants to estimate the system’s “utility.” Using utility theory to determine the impact on system operational availability avoids the complexities of multi-objective optimization in determining the impact of risk decisions on the system (i.e., reliability, maintainability, suitability, supportability, economic viability) (Hazelrigg 1996). Since this research has been undertaken to understand how risk attitudes affect the operational availability of a system, this author has chosen to focus on reliability as a parameter of measure as risk attitudes as many of the other factors contributing to the system's operational availability are, at least indirectly, related to the system's reliability. In nominally holding each of the other parameters constant, this author utilized reliability as the single parameter of value to revise the system's utility (operational availability).

C. STEP 3: DEVELOP THE UTILITY FUNCTION

Since reliability is the parameter (value) by which the utility function provides insight into the expected operational availability (utility) of the system, the relationship is monotonically increasing and defined by Equation 11 (Kirkwood 1997, 6). Adaptation of Equation 11 to represent the impact of risk attitudes on operational availability yields Equation 15:

$$u(x) = \begin{cases} \dfrac{e^{-\frac{(x)}{\rho}} - 1}{e^{-\frac{100}{\rho}} - 1}, \rho \neq \infty \\ \dfrac{x}{100}, otherwise \end{cases} \tag{15}$$

where ρ is the risk coefficient, which is inversely related to the risk tolerance of the SOM; the *value, x,* is the reliability of the system; and the *utility [u(x)]* is the risk-adjusted impact to the expected operational availability of the system. Two further sub-steps must occur to fully develop the utility function and are detailed below.

1. Inversion and Application of a Scaling Factor

Evident in Equation 15, increasing the value of ρ produces a less pronounced curve, which incorrectly associates increased risk-attitude with decreased impact on the system. Equation 16 corrects the relationship of ρ with risk attitudes:

$$\rho = -\frac{1}{(R_{tot} - 1)(F_s)}\ , \tag{16}$$

where ρ indicates the depth of the utility function, R_{tot} represents the overall risk attitude of the SOM, and F_s represents a scaling factor indicating the impact of risk attitudes on system reliability. While the scaling factor can be empirically derived given the right information, in the absence of quantitative historical data, exact determination of the scaling factor has been reserved for future work. This is similar to how Van Bossuyt et al. (2012) and others have treated scaling factors in previous utility theory-based risk attitude work. Having now obtained both x and ρ, Equation 15 solves for the risk adjusted “utility” of the system.

2. Graphical Representation (The Utility Curve)

The relationship between the reliability of a system and its utility is shown in Figure 7, with more risk seeking attitudes deviating further from risk neutral and producing more pronounced curves. Recall from the previous step that the value of ρ is inversely related risk attitude; therefore, increased risk attitude diminishes the value of ρ, thereby producing a more pronounced curve. This author has given a notional 1:1 relationship between reliability and system utility, the positive correlation characteristic of a monotonically increasing system. Exemplified, this indicates that for a system with a nominal reliability of 90%, the utility of the system, given a risk-neutral SOM, is also 90%. However, for a risk-seeking SOM, the utility would be diminished according to the magnitude of the SOM's risk attitude, as defined in Equation 14. Note that the curves depicted in Figure 7 are likely more extreme than what would be typically observed based on the literature (Van Bossuyt 2012); however, this author has chosen to display them in this manner to demonstrate how the magnitude of ρ can significantly change the utility of a specific decision set for a given value. Risk seeking attitudes that are shown in red, while risk-averse attitudes are shown in brown. Although the various levels of risk aversion are depicted in the figure for completeness, as previously discussed, this author has stipulated that risk aversion as it pertains to reliability is equivalent to risk neutrality. This is based on the understanding SOMs exhibiting either risk neutral or risk averse attitudes will all exhibit the same levels of procedural compliance, namely, full compliance. Low levels of risk aversion or risk seeking are represented by dotted lines, moving to dashed lines and then to solid lines as the aversion or seeking increases in magnitude.

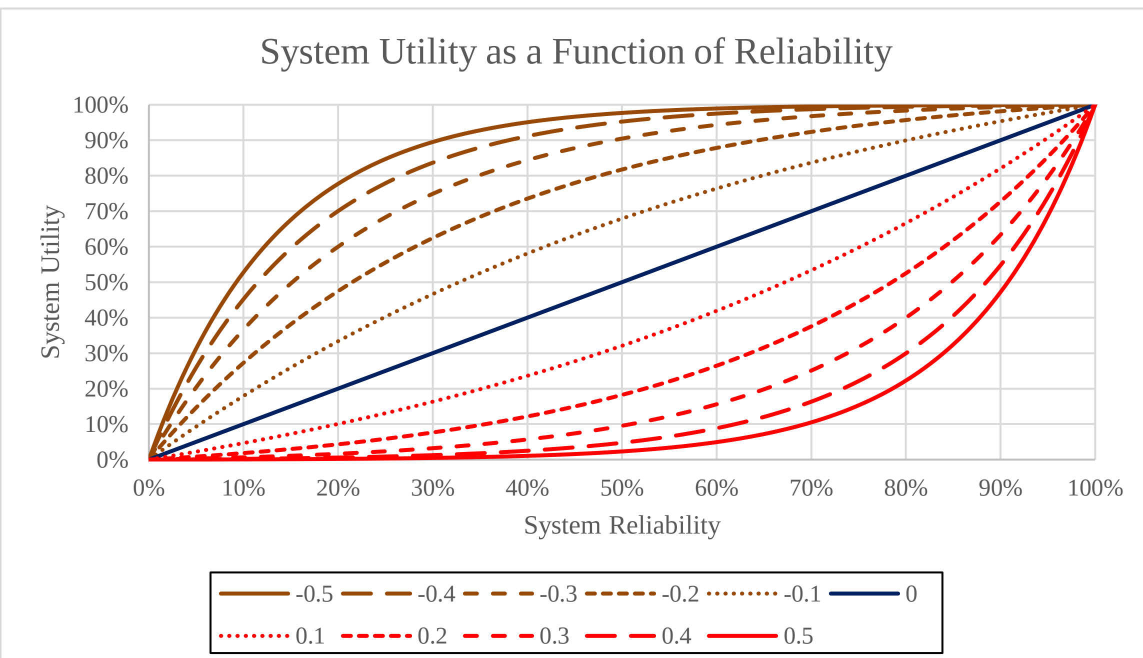

Figure 7. Risk Attitude Utility Curve

D. STEP 4: EVALUATE THE SYSTEM

Possessing the information from the utility function, the engineer is able to determine the effect of a SOM or group of SOMs' risk attitude on system utility. For instance, a system designed with an objective reliability of 95% has a risk neutral utility of 95%, but if the outcome is adjusted to account for a risk-seeking SOM, it may be that the risk-attitude adjusted utility is 92%. While the objective utility of the system is defined as 95%, if the threshold utility for that system is 90%, a risk-attitude adjusted utility of 92% may be sufficient and fail to trigger iteration of the design process. However, if the objective and threshold values are equal or the stakeholder has sufficient motivation to achieve the objective design requirements rather than threshold requirements, system redesign may be the desired course of action.

The information obtained from the risk-adjusted profile is used as an informative tool during the iteration and recursion of system design to ensure these stakeholder requirements are met based on the outcome of the utility function; however, this author notes that redesign need not only include physical alteration of the system. Several other options, which may be more practical depending the system's location in the SE process, do not address the issues from a reliability perspective, but from a maintainability, or supportability perspective. For example, efforts could be made to utilize specialized training to reduce the system's mean time to repair. Additionally, efforts to reduce administrative or logistics delays may prove of use in boosting the system's operational availability levels; however, if any combination of these methods proves insufficient, it may be necessary to address the problem by addressing the risk attitudes of the SOM. A more thorough discussion of options is reserved for Chapter V.

E. STEP 5: ADJUST SYSTEM ATTRIBUTES

If the engineer decides to redesign the system, he or she will choose new system components and/or alter their configuration. As discussed in the previous section, design may be an iterative process. Notionally, based on the utility function, it is possible to determine the necessary system reliability for a given utility and SOM risk attitude; but this author must reemphasize that although this process attempts to quantify otherwise qualitative data, the complex and interdependent nature of the many factors contributing to a system's operational availability limit implementation of this model in an exclusively quantitative manner. Rather, this model is designed to be used as a reference tool to aid in the process of system design. After the new system has been designed, the engineer will determine the revised system reliability and obtain a new system utility from the utility curve. If the outcome is still unsatisfactory, the process with continue to iterate. This iteration process is essentially a repetition of steps 4 and 5 until attainment of a satisfactory outcome.

F. SUMMARY

This author has presented a methodology for the development of the model as well as provided a short discussion of how the outputs of the model can be used by systems engineers to inform design decisions. Given reasonable estimates of the impact of risk decisions on system reliability, the only necessary data to utilize this method are risk attitude information of expected SOMs, which can be obtained by questionnaire, and the reliability data of the system in question, which is already used to determine system reliability. The following chapter provides an example of this methodology applied to a simple series-parallel system.

IV. IMPLEMENTATION OF THE METHOD

This chapter provides an example scenario demonstrating how a risk-attitude-based approach to human systems integration is applied by systems engineers concerned with improving the operational availability of their systems. The example is applied to a generic system broadly representative of a system which may be found aboard naval vessels and shows the implementation of the model discussed in the previous chapter.

A systems engineer has been assigned to a project team developing a system to support various maritime operations with operating periods of 500 hours. Over these time periods, the system must maintain high levels of operational availability. To support these requirements, the systems engineer has determined the system requires a threshold reliability level of at least 90%.

A. STEP 1: IDENTIFY KEY SYSTEM ATTRIBUTES

The system used for this analysis is a notional four-component system with a series-parallel configuration. The component reliability data for the system are representative of a system with reasonable reliability levels.

1. Component Data

Table 3 shows notional parameters for the system components. The MTBF value accounts for the inclusion of a preventive maintenance plan. The reliability data are based on the operating period of 500 hours.

Table 3. Component Reliability Data

Time (Hours)	500		
Component	**MTBF (Hours)**	**Failure Rate**	**Reliability**
1	14000	0.000071	0.964916
2	16500	0.000061	0.970152
3	8000	0.000125	0.939413
4	15000	0.000067	0.967216

Component three has the highest failure rate, mitigated only by the component configuration.

2. Component Configuration

The system has four components, the third of which has a parallel redundancy as shown in Figure 8.

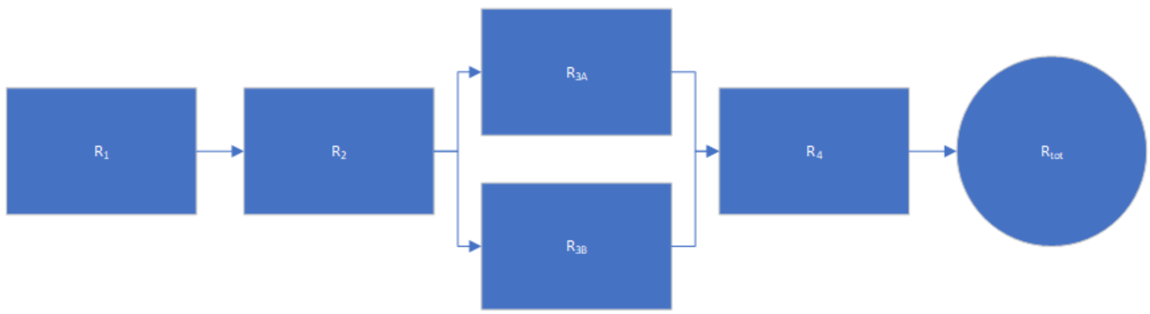

Figure 8. Example Component Configuration RBD

3. System Reliability

To find the overall reliability, the below equation can be used to match the reliabilities of the components to their layout.

$$R_{tot} = R_1(R_2)\big(R_{3A} + R_{3B} - (R_{3A})(R_{3B})\big)(R_4)$$
$$= 0.965(0.970)(0.939 + 0.939 - 0.939^2)(0.967)$$
$$= 0.902$$

Given this reliability, one could expect that given a risk neutral system operator/maintainer in full compliance with the maintenance plan, the system would achieve roughly 90% reliability, meeting the threshold requirement for reliability.

B. STEP 2: DETERMINE RISK ATTITUDES OF SOMS

This example uses the DOSPERT test to analyze the risk attitudes of the SOMs. Determination of risk attitude using DOSPERT contains four to five sub-steps depending on whether the system has a single or multiple SOMs; however, the number of sub-steps may differ depending on the risk assessment tool the engineer chooses to utilize. For this example, the outputs for sub-steps 2.1 through 2.5 have been summarized in Table 4, but a discussion of the explicit execution of the sub-steps is given in the previous chapter. While DOSPERT is capable of measuring the risk attitude of a single person, greater utility is found in analyzing the risk attitudes of a pool of SOMs. This is especially true in the case of naval systems, where the individuals responsible for operating and maintaining the systems are distributed among the divisions, departments, or even the entire crew.

Table 4 shows a notional average risk attitude composition summary for the group of personnel responsible for operating and maintaining the system shown in Figure 8. As shown in Table 4, negative risk attitude values have been reassigned a value of zero to represent the equivalence of risk averse attitudes with risk neutral risk attitudes. This author used a scaling factor of one and solved for the ρ value according to Equation 16 with R_{tot} representative of the average total risk attitude of the group.

Table 4. Risk Attitude Summary

Risk Domain	Raw Risk Attitude	Adj Risk Attitude	Risk Impact
Ethics	0.8021	0.8021	1.2
Finance	-0.7397	0.0000	1.1
Health/Safety	0.8750	0.8750	1.5
Recreation	-0.3131	0.0000	0.5
Social	0.5581	0.5581	1.35

R_raw	R_tot_avg	Rho	F_s
0.447	0.606	-1.651	1

C. STEP 3: DEVELOP THE UTILITY FUNCTION

After defining the system characteristics to obtain the "value," x, and determining the raw risk attitudes, impact-adjusted risk attitudes, population average risk attitude, and scaling factor to find the value of ρ, the systems engineer has all of the necessary components to generate the utility function. Although the SOMs are risk averse in finance and recreation, their moderate social risk seeking coupled with significant risk seeking in ethics and health/safety result in a significant effect on system reliability. For a system with a nominal 85% reliability, with a reasonable scaling factor of one, the risk-attitude adjusted system utility would be approximately 81%. The example system has a reliability of 90.2% which has a risk-attitude-adjusted utility of just over 87% as shown in Equation 17 and depicted by Figure 9.

$$u(x) = u(0.902) = \frac{e^{-\frac{(0.902)}{-1.651}} - 1}{e^{-\frac{100}{-1.651}} - 1} = 87.31\%. \qquad (17)$$

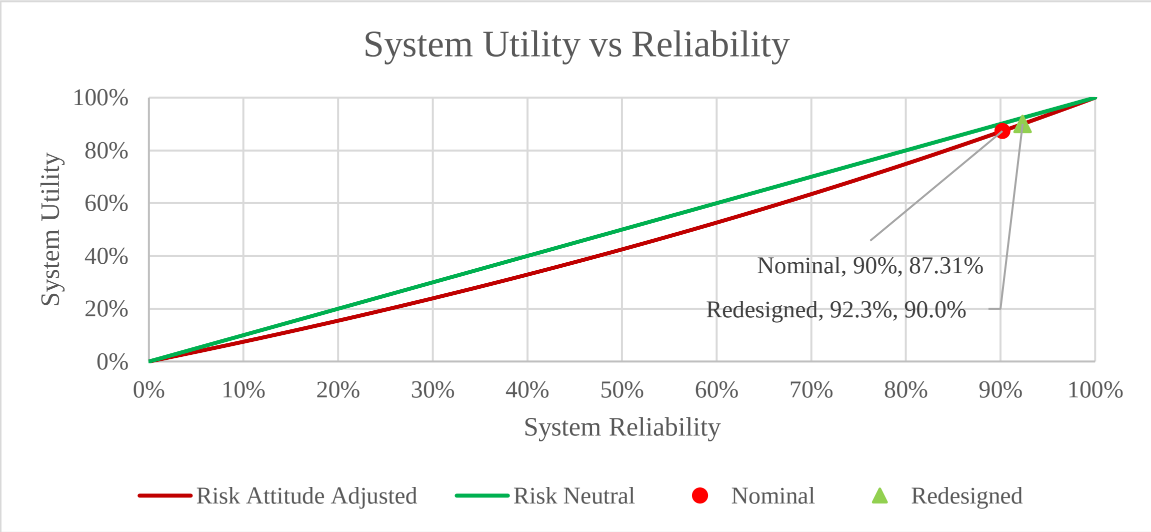

Figure 9. Risk-Adjusted Reliability as a Function of Nominal Reliability

D. STEP 4: EVALUATE THE SYSTEM

Given the threshold reliability of 90%, this means the system and associated processes, as designed, are insufficient to achieve threshold reliability levels. For a system utility of 90%, assuming the risk data remains constant, solving for "value" indicates the redesigned system must have a reliability of at least 92.33%. To ensure the system achieves the desired utility, the engineer must find a method to improve the reliability of the system by over two percent.

E. STEP 5: ADJUST SYSTEM ATTRIBUTES

Having already determined the required reliability value for the adjusted system, the engineer is presented with several options to improve the system. Improvement of system reliability will require modification of either the system or the maintenance concept. Depending on the nature of the components, component design is an effective method of influencing the reliability characteristics of the system. For a system with a configuration that is malleable, adding components in parallel to boost reliability levels in that subsystem is often a cost-effective way to improve reliability. If the design is less flexible, replacing the components with others of higher reliability levels may be suitable. However, it should be noted that components with abnormally high reliability levels is often prohibitively expensive and is typically used for systems where no other alternative is available. Finally, modifying the maintenance concept to include more preventive maintenance may be able to improve reliability through extension of the components' MTBFs. For improvements in operational availability other than reliability improvement, the systems engineer may consider changing how SOMs are interacting with the system (i.e., training, changing the SOM). A further discussion of these recommendations is provided in the following chapter.

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V. CONCLUSION AND RECOMMENDATIONS

Given a system with insufficient utility when accounting for SOM risk attitude, the engineer must provide a path to achieve the necessary utility or the system should not be produced. Fortunately, there are several ways to compensate for the unsatisfactory utility, though not all of the methods require altering the system components. This is especially important for systems, which have already been fielded and are in the operational phase of the system lifecycle. However, for engineers designing new systems to be fielded, early analysis provides information to the engineer in adequate time to incorporate material changes.

A. RECOMMENDATIONS

Below is a brief discussion of these changes followed by a few other considerations should material changes be prohibitive.

1. Modify the System

Among the several ways of improving performance through system modification, there are two main methods. The first of which, although costly, would be to get better components. Better components with higher MTBFs yield better inherent reliability, even if that reliability requires a larger capital investment. A second method of redesign, which may be less expensive depending on the stage of the system life cycle, would be to change the component configuration. Adding redundancies and spares as appropriate has the potential to significantly increase the overall reliability of the system. Furthermore, these two approaches are not mutually exclusive. It may be beneficial to spend more money for certain parts which are already expensive, but then redesign the configuration to place some of the less expensive parts in a parallel configuration.

2. Redesign the Maintenance Concept

Another method to addressing the issue of decreased reliability would be to make modifications to, or completely redesign, the maintenance concept. Since preventive maintenance has the potential to effectively increase the MTBF of system components, a more robust, if more manpower-intensive, method would be to adjust the frequency or type of preventive maintenance. Depending on the system and the original maintenance concept, there may be potential for a substantial increase in reliability. A maintenance plan resulting in a 50% greater MTBF yields the following shown in Table 5.

Table 5. MTBF Extension by Maintenance

Standard Configuration			
Time (Hours)	500		
Component	MTBF (Hours)	Lambda	Reliability
1	14000	0.000071	0.964916
2	16500	0.000061	0.970152
3	8000	0.000125	0.939413
4	15000	0.000067	0.967216
		System Reliability	0.90210155

Improved Maintenance Concept			
Time (Hours)	500	MTBF Extension	50%
Component	MTBF (Hours)	Lambda	Reliability
1	21000	0.000048	0.976472
2	24750	0.000040	0.980001
3	12000	0.000083	0.959189
4	22500	0.000044	0.978023
		System Reliability	0.93435329

As evidenced by the table and using the same equation for reliability using the new effective values for MTBF, the system reliability improves by just over 3%.

3. Other Considerations

Training is an effective way to reduce a system's mean time to repair, which would provide more system "uptime." Additionally, efforts may be undertaken to make improvements to administrative and logistics requirements. This could include reducing administrative overhead, streamlining the paperwork routing processes, and/or using administrative methods utilizing more automation. Logistically, keeping replacement parts on hand reduces any logistics delay and ready spares may be able to reduce system diagnostics prior to corrective maintenance.

4. Replace the SOM

If no combination of these methods allows the system to reach the desired operational availability, perhaps it is unattainable without a less risk-seeking SOM. This author is aware of two options, though information surrounding the desirability and/or efficacy of either is beyond the scope of this investigation. The first method is to attempt to influence the psychology of the SOMs in such a way that their risk attitudes become acceptable. If changing the risk attitudes of the SOMs proves infeasible, the situation may warrant replacing the SOM with one who is less risk seeking. This is often difficult for many reasons to include the appearance of targeting specific groups whether intentional or unintentional, constraints on time to obtain replacements, or expenses associated with replacement. Finally, it simply may be that the position requires a great deal of specialized training which is difficult to acquire.

B. FUTURE WORK

This author's investigation into the effects of risk attitude on system operational availability has revealed some potential areas for future research. The first area of research this author proposes is an investigation into the applicability of the dimensions of DOSPERT as applied to the military. While DOSPERT is meant to be field independent, no exhaustive study has been done demonstrating universality. Given sufficient time and resources, it may be worthwhile to conduct research into the applicability of DOSPERT in specific fields across DOD. One such outcome of the research would be the relative risk impacts of each of the risk domains as applied to various functions within DOD, such as maintenance, ORM, or development of local standard operating procedures.

Another possible avenue of investigation is into the consistency of risk attitudes within DOD. An analysis of sufficient sample size should reveal the presence, or absence, of common factors across a variety of metrics to include age, type of duty (sea or shore), duty location, gender, age, and point in the ship's lifecycle among others. Furthermore, the investigation should include an analysis of risk attitude consistency over time. If the risk attitude of a population shifts appreciably over the life of the system, and if it changes in a consistent and predictable manner, such information should be taken into consideration during system design. Finally, as verification of this method was demonstrated using notional data, future work should focus on data collection for full validation of the method.

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