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A gap exists in the methods used in industry and available in academia that prevents customers and engineers from having a voice when considering engineering risk appetite in the dynamic shaping of early-phase conceptual design trade study outcomes. Current methods used in Collaborative Design Centers either collect risk information after a conceptual design has been created, treat risk as an afterthought during the trade study process, or do not consider risk at all during the creation of conceptual designs. This dissertation proposes a risk-informed decision making framework that offers a new way to account for risk and make decisions based upon risk information within conceptual complex system design trade studies. A meaningful integration of the consideration of risk in trade studies is achieved in this framework thus elevating risk to the same level as other important system-level design parameters. Trade-offs based upon risk appetites of individuals are explicitly allowed under the framework, enabled by an engineering-specific psychometric risk survey that provides aspirational information to use in utility functions. This dissertation provides a novel framework and supporting methodologies for risk-informed design decisions and trades to be made that are based upon engineering risk appetites in conceptual design trade studies.

A Risk-Informed Decision Making Framework Accounting for Early-Phase Conceptual Design of Complex Systems

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I understand that my dissertation will become part of the permanent collection of Oregon State University libraries. My signature below authorizes release of my dissertation to any reader upon request.

Douglas Lee Van Bossuyt, Author

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DEDICATION

To all the friends I made along the way.

Chapter 1 –Introduction

A gap exists in industry and academia in giving customers and engineers a voice when considering risk appetite in the dynamic shaping of the outcome of early-phase conceptual design trade studies. Current methods of capturing risk data during conceptual design trade studies either consider risk only after a conceptual design has been created, treat risk as a secondary concern to developing conceptual designs, or do not consider risk at all during the creation of conceptual designs via trade studies. This dissertation proposes a framework to fill the gap in existing academic and industry methods to allow customer and engineering risk preference to dynamically shape the outcome of early-phase conceptual design trade studies. A framework is developed that allows individual participants in a collaborative trade study to trade risk as a system-level parameter and further takes into account risk appetite of both individual engineers and customers. In this dissertation, risk appetites are determined by developing and using a psychometric risk appetite test and scale. This scale is used to generate risk utility functions that are broadly applicable to a wide variety of engineering risk-informed decision making cases and without the need for time-consuming lottery methods. The framework and methods developed in this dissertation are verified in a simulated Collaborative Design Center (CDC) using undergraduate and graduate student participants and in a computer simulated CDC environment.

1.1 Intellectual Merit

This dissertation offers a new framework to account for and make decisions based upon risk information within conceptual complex system design trade studies. This framework meaningfully integrates the consideration of risk into trade studies, thus elevating the consideration of risk in conceptual design trade studies to the same level of consideration as other system-level metrics, parameters, and design choices. The approach specifically allows design decisions and design trade-offs to be made based upon the risk preferences of individual engineers, and the risk preferences of customers. The research in this dissertation has the potential to change the outcome of, and bolster trade studies with additional validity via a more rigorous consideration of risk and risk appetite during the trade study process. This dissertation provides a framework for risk-based design decisions to be made based upon risk appetites which will inspire more confidence in the resulting conceptual designs.

1.2 Broader Impacts

The success of the research effort chronicled in this dissertation will yield benefits for education, for industrial and government customers of CDCs, and for CDCs themselves. Using the framework developed in this dissertation, CDCs will benefit by creating conceptual designs that quantitatively take into account risk appetite when making risk-based design decisions. Those decisions will be made during the trade study process rather than before or after a conceptual design has been created as a result of risk being elevated to a tradeable system-level variable. Government and industrial customers of CDCs will be the beneficiaries of conceptual designs that match their risk appetites.

These designs will be quantitatively generated, and the risk-based decisions made as part of the trade study process will be made based upon the risk appetites of the customers. In academia, undergraduate education will benefit from the risk appetite component of this research being integrated into design curricula as has been done with the Meyers Briggs Personality Type test. At the graduate level, courses on complex system design will benefit from the framework developed in this research. The framework can be taught as a component of trade study methods, thus expanding students' ability to make risk-based decisions and account for risk appetite in trade studies.

1.3 Organization of this Dissertation

This dissertation is organized into a number of chapters; several of which contain a total of three journal articles that are either accepted for publication, awaiting acceptance after revision, submitted, or will be submitted shortly. Chapter 2 provides background information on several relevant areas of the literature including design trade study fundamentals, conceptual design centers, the psychology of risk attitude, an engineering definition of risk attitude, risk analysis tools, decision-based design, and risk-based utility theory. Chapter 3 introduces a risk-informed decision making framework for early-phase conceptual design of complex systems. Chapter 4 presents a journal manuscript submitted to Research in Engineering Design (RIED) that presents a case for trading risk in complex conceptual design trade studies. Chapter 5 presents a journal manuscript submitted to Journal of Mechanical Design (JMD) on measuring engineering risk attitudes using a psychometric risk scale. Chapter 6 presents a method of considering risk attitude using utility theory in risk-based design that is accepted for publication in Artificial Intelligence for Engineering Design, Analysis, and Manufacturing (AIEDAM). Chapter 7 presents development; implementation in MATLAB, Excel, and ModelCenter; and simulations of the risk-informed decision making framework for early-phase conceptual design of complex systems. Future work is outlined in Chapter 8. The dissertation concludes in Chapter 9 with a review and discussion of the dissertation's contributions.

Chapter 2 –Background

The Risk-Informed Decision Making Framework developed in this dissertation draws from several disparate bodies of research and knowledge. This chapter reviews the most pertinent information that is necessary for the framework and objectives.

2.1 Design Trade Studies Fundamentals

Design trade studies are used in conceptual complex system design to generate different design alternatives and compare amongst them. Trade studies can be performed either automatically using software packages or by teams of people. Whereas automated, computer generated trade studies can create many thousands of design points quickly, manually-conducted human generated trade studies are often seen as having higher fidelity and are more likely to be accepted [1].

Metrics such as cost, mass, power, volume, and other parameters are often traded in such trade studies. Each subsystem within a complex system is initially allocated specific amounts of the constraining parameters. During the course of the design process, several subsystems are often found to be lacking in one or multiple constraint parameters but have additional quantities of other parameters available. These parameters can be traded between different subsystems and contain intrinsic value of varying degrees for different subsystem designers [2, 3, 4]. The resulting conceptual designs can then be ranked according to appropriate selection rules [5, 6].

Where there is a defined "measure of goodness," the basic mathematical concept behind trade studies is simple and straight-forward. Trade-offs are made between design variables to achieve maximum design utility [7]. This generally takes the form of $max\ f(U)$ where U represents relevant system utility metrics.

This simple equation provides the foundation for a wide range of analytic methods that all aim to find the optimal design given system constraints. Many different methods have been developed to computationally find the optimal solution. The difficulties, however, are in developing a series of equations that adequately model the system to then efficiently find the optimum solutions to those equations [7].

2.2 Conceptual Design Centers

Many companies and institutions have teams who perform trade studies as part of the early complex system design process. The first and most cited example is the National Aeronautics and Space Administration (NASA) Jet Propulsion Laboratory (JPL)'s Project Design Center (PDC) and the associated design team, commonly referred to as Team X. The group, formed in June 1994 [8], functions as a conceptual spacecraft mission design team and includes engineers and scientists from all major spacecraft mission subsystems co-located in the PDC which gives Team X the ability to complete spacecraft architecture, mission, and instrument design trade studies very rapidly [9]. The design iteration portion of most Team X trade studies are completed in two to three days, compared to three to nine months to complete a comparable trade study and reduced costs by a factor of five [10]. The success of Team-X spurred other NASA research centers to adopt the methods used by Team-X [11, 12, 13, 14, 8]. Similarly, the European Space Agency (ESA) has replicated the methods used by Team-X [15]. A collection of academic institutions have also created Collaborative Design Centers (CDCs) to perform trade studies for simulated complex system design [8, 1, 16, 17]. Finally, several private companies have adopted the Team-X approach to Trade Studies [18, 8].

Within Team X and other CDC groups, there are often desired ranges of system level risk. While it might appear that a design minimizing risk is always desired this is often not the case. Sometimes designs with a specific level of risk above the absolute potential minimum are desired. In the case of Team X, this is due to the desire to launch missions that are both cost-effective and challenging. Missions at NASA are selected for further development based on several factors including the mission risk profile. A risk target range has been defined that balances pushing the boundaries of engineering and science with a desired cost and level of mission success [19].

Some CDCs currently employ tools and methods to capture risk in the conceptual design process. However, establishment of mission risk posture usually happens before conceptual designs have been generated, and risk evaluation happens afterward; or risk evaluation is part of a process that happens in lieu of trade studies; or worse yet, risk does not play any role in early conceptual design development. But there is generally no accepted method to measure risk within each subsystem model as a parameter to be controlled and developed by individual subsystem chairs during conceptual design trade studies.

The Risk and Rationale Assessment Program (RAP) tool is a Probabilistic Risk Assessment (PRA)-based assessment software package that is employed during a trade study session [20]. Each subsystem chair has the ability to enter information into the tool as he/she sees fit. Observations indicate that during Team-X sessions RAP is either used as an afterthought once most of the conceptual design work had finished or not used at all. Further, risk cannot be traded within RAP nor does it find its way into the trade studies. Instead risk assessment is conducted as an afterthought to the conceptual designs being created. Other groups outside of NASA have also used tools similar to RAP and with similar implementations yielding similar results and problems [21, 22, 23].

In addition to RAP, JPL has also developed Defect Detection and Prevention (DDP), a tool that helps engineers determine what mitigation steps will provide the largest reduction in system-level risk [24]. Literature on DDP does state that risk should be traded and provides a framework for trading but trade studies are not suggested to be performed in CDCs. The literature does suggest that risk can be compared against performance metrics to find the optimum level of risk versus performance; but to examine risk, conceptual designs must be developed and solidified before the DDP method can be used to analyze risk [25].

While RAP and similar tools have been adopted in many CDCs and DDP has found some use outside of the CDC environment, several other methods have remained purely academic. For instance, a risk management method developed by Dezfuli et al. embeds the NASA Continuous Risk Management (CRM) process into a broader decision framework [26]. The method presents a risk management approach intended to be used throughout the product life-cycle. Performance measures and NASA's CRM process are relied on to assess risk. While the method does state that risk must be accounted for in the conceptual design phase and further briefly mentions the trade study process, the actual analysis of risk still happens after conceptual designs have been created [27]. Thus the method does not place risk directly in the trade study process.

2.3 The Psychology of Risk Attitude

The 'classic' definition of risk is the parameter that differentiates between the utility functions of different individuals [28, 29]. The Expected Utility (EU) hypothesis theorizes that the preference of an individual choosing between risky options can be determined by a function of the return of each option, the probability of that option coming to fruition, and the individual's risk aversion [30]. The EU framework and related methods including prospect theory [31] traditionally view the curves of an individual's utility function as denoting either risk aversion or risk seeking. The definition of risk aversion in the context of risk attitudes is framed in the context of someone who prefers to take the expected value of a gamble over playing the gamble as being a person who does not like to take risks [32]. As a result, risk attitude can be defined as a person's position on the risk aversion-risk seeking axis and is thought of as a personality trait.

However, two issues have arisen that challenge the idea of risk attitudes in the context of EU being a personality trait: cross-method utility instability and inconsistent risk profiles across risk domains. When different methods are employed to measure people's utility, different classifications of risk-taking or risk aversion often result [33]. Further, individual respondents are not consistently risk averse or risk seeking across different risk domains [34].

The validity of EU-based risk attitude assessment is limited due to these issues. There has been little success in predicting individuals' choices and behaviors in domains not assessed by EU-based instruments [35]. Even with the limitations of EU-based survey instruments, many are still in use [36].

A more recent method of determining risk attitude takes inspiration from the world of finance [37]. The risk-return framework of risky choice assumes people's preferences for risky options reflects a trade-off between riskiness of a choice and the Expected Value (EV). The financial world equates riskiness of an option with its variance. In psychology risk-return models, perceived riskiness is treated as a variable that can be different between individuals due to differences in individuals' content and context interpretations [38, 39]. The risk-return framework allows for people to have similar perceptions of risk and return between different domains but in one domain prefer risk while in another prefer caution [40]. Having such preferences and perceptions would result in different outcomes, as the risk-return framework predicts.

The term *perceived risk attitude*, previously conceptualized as risk-repugnance [41], was coined to reflect the assumption that risk in its pure form is negative and undesirable but that perceived risk might be attractive to some individuals in certain domains and circumstances [42]. Variances in perceived risk attitude are thus a result of discrepancies between the perception of the risks and benefits as determined by a decision-maker and an outside observer. This is exemplified in research conducted in the management field where what differentiates between entrepreneurs and managers is a highly optimistic perception of risk on the part of the entrepreneurs rather than a greater preference for risk, as one might expect [43].

Many studies have highlighted differences in the perception of the riskiness of decisions in individuals, between groups, and between cultures [44, 45]. Differences in risk perception have also been found due to outcome framing [46]. In the context of risk-return based models, perceived risk attitude has been found to have cross-situation and cross-group consistency when differences in the perception of riskiness are factored out [39, 40]. Rather than differences in risk attitude, risk-return models suggest that the way people perceive risk affects the choice outcomes.

In summary, risk attitudes vary by domain, so that the attitude to taking risks at work may differ from the attitude to taking risks at home. One may enjoy taking risks in leisure activities, but be risk averse handling of financial affairs. To assess risk perceptions and attitude toward perceived risk in different domains of risk, Weber et al. developed the *Do*main-*Spe*cific *R*isk-*T*aking (DOSPERT) test and related scale [40, 47]. Six independent domains were identified including ethical, investment, gambling, health/safety, recreational, and social domains [40, 48, 49, 50]. Risk-taking was found to be highly domain-specific between the identified domains where individual respondents were risk averse in some domains and risk-neutral or risk seeking in others. Respondents were found to not be consistently risk averse or risk seeking across the six domains.

It was also found that preference for risk seeking or risk aversion was influenced by the perceived benefits and risks of the activity in question. This resulted in identifying two psychological variables including risk perception and attitude toward perceived risk, as had been found in previous risk-return based models [43]. Previous risk attitude indexes have been confounded by not distinguishing between the two psychological variables of risk perception and attitude toward perceived risk [51]. Distinguishing between the risk perception and risk attitude variables is largely irrelevant if only prediction of future actions is desired. However, the distinction between these variables becomes important when risk-taking is assessed with the goal of changing risk-taking behavior [40].

Since the DOSPERT scale was developed and validated, many other studies have replicated the results. Strong correlation was found with the various subscales of Bunder's scale for intolerance [52] and with Zuckerman's sensation-seeking scale [53]. Paulhus' social desirability scale [54] was found to have significant correlation between the impression management subscale and the ethics and health/safety subscales of DOSPERT. Thus, the DOSPERT scale was found to have favorable correlations with established scales. The DOSPERT scale has also been translated into several different languages and contexts including the DOSPERT-G scale, a German-language version [55], a French-language DOSPERT scale [56], and others [47]. The DOSPERT scale is quickly becoming the most preferred risk attitude scale in psychology for its predictive abilities and its ability to show whether observed risk behavior is based upon the person's perception of risk or the person's attitude toward the perceived risk, which allows for intervention and behavior modification.

2.4 An Engineering Definition of Risk Attitude

The definition and application of risk in engineering is more straight-forward than in psychology. The ISO 31000:2009 document [57] defines risk as the effect of uncertainty on objectives. An effect is a positive or negative deviation from the expected. Objectives are defined as having different aspects such as environmental, health and safety, and financial goals, and can be applied at different levels of a project or organization. The ISO 31000:2009 definition of risk is further defined as the probability of occurrence of an event multiplied by the severity of the consequences. It should be noted that uncertainty is often defined as a lack of knowledge about system specifications and errors resulting from imperfect models [58]. Some researchers further break down uncertainty into multiple subcategories that often contain elements of risk, reliability, and robustness [59]. For the purposes of this research, the ISO 31000:2009 definition of risk shall be used in the context of engineering.

If this is used as the operating definition of risk, then risk attitude in engineering is the 'state of mind' of the engineer in response to the perception of uncertainty on objectives [60]. The engineer's attitude will influence actions, or inactions, taken. The behavior an engineer takes toward risk can be to retain, pursue, take, or turn away from that risk. In other words, when presented with a situation, it is important to determine how the engineer's risk attitude will influence behavior.

2.5 Risk Analysis Tools

Risk is generally defined in engineering as the probability of occurrence multiplied by the severity of impact [57]. Often engineers group other related concepts such as reliability [61], robustness [62], and uncertainty [58] with the strict definition of risk into a meta-risk category that is also referred to as "risk."

Many methods exist to analyze and account for risk in the design process. Examples include: Reliability Block Diagram (RBD) [63], PRA [64], Failure Modes and Effects Analysis (FMEA) [65], Fault Tree Analysis (FTA) [66], and other methods are commonly found in industry. Other methods such as Functional Failure Identification Propagation (FFIP) [67], Function Failure Design Method (FFDM) [68], and Risk in Early Design (RED) [69] are being actively developed in academia and will see industrial deployment in the future.

Several tools have been developed to support risk analysis in trade studies for CDCs. Team-X uses RAP, a PRA-based assessment software package [20]. The RAP tool is used to capture unusual risks that are identified during trade study sessions. One engineer is tasked with cataloging these risks and with the assistance of stakeholder subsystems engineers develops likelihood and impact assessments, and mitigation methods with associated costing information. Other risk analysis programs and methods are under development and in use by other CDCs.

The methods, such as FTA and FMEA, and tools, such as trade studies, commonly deployed in industrial settings, view risk as an expected value choice. For example, if an engineer must make a decision between one risk that has a 1% chance of occurrence and has a consequential cost of $10,000 and another risk that has a chance of 0.1% of occurrence and a consequential cost of $100,000, engineering risk methods would indicate that both risks are equal with regards to expected value. Therefore, either can be chosen with the same expected value outcome. However, this ignores individual and company risk preferences.

2.6 Decision-Based Design

To address the growing recognition within industry and the engineering research community [70, 71, 72, 73] that decision-making is a fundamental part of the design process, the Decision-Based Design (DBD) framework was developed. A decision-theoretic methodology is utilized to select preferred product design alternatives and set target product performance levels. A single selection criterion, V, in the DBD implementation represents economic benefit to the enterprise [73]. This approach avoids the difficulties of weighting factors and multi-objective optimization which can violate Arrow's Impossibility Theorem [74]. A utility function, U, which expresses the value of a designed artifact to the enterprise when considering the decision-maker's risk attitude, is created as a function of the selection criterion, V. A preferred concept and attribute targets are selected through the maximization of enterprise utility.

In order to effectively use the single criterion approach to DBD, the selected criterion must be able to capture all of the issues involved in the engineering design such as system features, costs, risks, physical restrictions, and regulatory requirements. The single criterion should allow both the interests of the users and producers of the system to be considered. In most industrial cases, the most universal unit of exchange is money. Material, energy, information, faults and time can all be assigned a monetary value. This can be seen in many design decision-making processes and is practiced widely in industry.

One use of single criterion DBD developed by Hoyle et al. [75] employs profit as the criterion in a method to determine optimum system configuration for Integrated Systems Health Management (ISHM). The determination of system profit is made from the product of system availability and revenue, minus the summation of cost of system risks and the cost of fault detection. This method can determine optimal ISHM while also determining the optimum detection/false alarm threshold and inspection interval. Using the method has been found to increase profit by 11%, decrease cost by a factor of 2.4, and increase inspection intervals by a factor of 1.5 [75].

2.7 Risk-Based Utility Theory

One approach to analyzing choice outcomes from a non-neutral expected value perspective is to use risk-based utility theory [31]. The utility of a range of probabilistic outcomes can be determined in order to aid decision-makers. This is done by translating monetary outcomes to utilities. A risk-tolerant decision-maker's higher intrinsic value for riskier decisions skews the utility of those decisions higher than a risk-neutral or risk-averse decision maker's utility of the same decisions. For a normal distribution of outcomes, a risk-tolerant person's utility distribution will shift to be more heavily skewed toward higher value outcomes. Utility distributions for risk-averse individuals will skew more heavily toward lower value outcomes. The risk neutral state does not weight outcomes in either direction along the utility axis. In other words, different utilities are found based upon a decision-maker's risk appetite.

Currently accepted methods of developing utility risk curves require a series of lotteries to be conducted [31]. Several sets of paired choices are presented sequentially to an individual. These are often presented as lotteries where a participant selects amongst paired probabilistic alternatives. A utility risk curve is then fitted to the lottery results. Common functions include quadratic, logarithmic, and exponential functions [76]. In currently accepted methods of risk utility curve generation, the choice of which form a risk utility curve should take is at the discretion of the decision-maker and based upon results of lotteries. The scale of the value axis of the utility curve is set to the minimum and maximum limits of the values used to conduct the lotteries.

Developing and conducting lotteries is time-consuming and not intuitive to end-users [77]. Also, the utility curves derived from lotteries are only valid for the range of values used in the lottery. Therefore, while useful to experts in many areas, lottery-based methods of utility risk curve generation are not always useful to practitioners or lay users.

Chapter 3 –A Risk-Informed Decision Making Framework for Early-Phase Conceptual Design of Complex Systems

In this chapter a risk-informed decision making framework for risk and risk appetite during the early phase conceptual complex system design process is proposed and specific objectives are laid out which must be completed in order to achieve the goals of the framework. Subsequent chapters meet these objectives.

3.1 Opportunity for a Risk-Informed Decision Making Framework

Early phase conceptual complex system design trade studies conducted in collaborative design centers do not currently allow individual subsystem engineers to control risk models associated with their subsystems. Risk is often an afterthought in the creation of conceptual designs. Sometimes it is not considered at all. Ignoring or marginalizing risk information and potential risk-based decisions hurts the utility of the final conceptual complex system design. Further, risk appetite is not formally taken into account during conceptual design trade studies. Several methods have attempted to address these issues but none has fully addressed the problem. A higher utility design that inspires more confidence in the engineers responsible for creating the design and the customers who have ordered the design can be realized by the successful development of the framework and supporting objectives.

The Risk-Informed Decision Making Framework is completed by integrating the methods developed in working towards three objectives described next. This is done by linking traditional engineering risk methods traded in Objective #1 with the risk appetite curves generated as a result of Objective #3 with the help of the psychometric risk survey data produced as a result of Objective #2. Decisions between several different options, with varying risk profiles, taking into account risk appetites, will thus be able to be made during trade studies. The framework is implemented and demonstrated in software in Chapter 7. The framework allows risk to be traded in trade studies as a system-level parameter. When trade-off decisions involving risk must be made, the framework provides a method of quantitatively taking into account risk appetites of engineers, stakeholders, and customers. This empowers subsystem design engineers to make explicit risk-based decisions that take into account risk appetite during trade studies.

The following sections discuss how each of the three objectives necessary to realize the goals of the Risk-Informed Decision Making Framework are met by the development of the new methodologies detailed in Chapters 4, 5, and 6. This chapter concludes with discussion of how the objectives will be integrated into the framework and how the framework will deployed into CDCs.

3.2 Objective #1: Trade Risk as a System-Level Parameter

The first objective is to develop a method of trading risk as a system-level parameter in trade studies. This objective allows for new design selection preferences to be created that otherwise would not be available to design engineers. Thus, risk can be brought on par with other important system-level variables and further can be analyzed during the creation of conceptual designs in trade study sessions rather than being considered after designs have been developed.

3.2.1 Background

Several methods have been developed that relate to Objective #1. A normative method that attempts to balance cost, risk, and performance for decision makers in preliminary spacecraft mission design is presented by Thunnissen [78]. The method focuses on uncertainty and classifies it into four different categories (ambiguity, epistemic, aleatory, and interaction), three subcategories of epistemic uncertainty (model, phenomenological, and behavioral), three sub-sub categories of model uncertainty (approximation errors, numerical errors, and programming errors), and four sub-sub categories of behavioral uncertainty (design, requirement, volitional, and human errors). To deal with the uncertainties, probabilistic methods and Bayesian techniques [79] are employed. However, risk in the form of Thunnissen's uncertainty definitions is not considered during trade studies. Instead, it is analyzed for a specific subset of the overall mission conceptual design during the very early stages of conceptual design prior or in lieu of trade studies.

Another method developed by Thunnissen formalizes design margins in trade studies and also attempts to trade risk in trade studies [80]. However trading risk is presented as an afterthought to the primary concern of design margins in the method. The risk model presented simply replaces an expected design constraint. Rather than setting a fixed minimum value for a design constraint, a 100% risk of failure is produced when the minimum value is crossed. The primary contribution of the work is the formalization of margins in trade studies – not implementing risk in trade studies.

Finally, Charania et al. present a collaborative design method that utilizes Probabilistic Data Assessment to trade risk in trade studies conducted using Phoenix Integration Inc.'s ModelCenter software package [81]. However risk is treated as a separate "subsystem" in the trade studies. Risk is not explicitly incorporated into each subsystem model. Rather, like the RAP methods used by Team X and others, one person or one "subsystem" model is in charge of risk.

In summary, some methods such as RAP and DDP have found use in CDCs and elsewhere while other methods such as those developed by Thunnissen, Charianian et. al., and others remain academic. Some of the methods analyze risk after conceptual designs have been created using trade studies. Others analyze risk prior to trade studies or bypass trade studies all together. One even analyzes risk within trade studies during the creation of conceptual designs as a separate subsystem. However, to the authors' knowledge no method currently places risk within each subsystem model to be controlled and developed by individual subsystem chairs during the creation of conceptual designs in trade studies. Research presented in this dissertation fills the gap in existing methods.

3.2.2 Method

Risk has traditionally been an afterthought in the conceptual complex system design process. Risk is typically only formally assessed after a conceptual design has been created and does not explicitly play a role in the creation and selection of conceptual designs. Instead, implicit assumptions are often made about the "riskiness" of conceptual design models. This research's hypothesis is that by moving risk into trade studies and giving it a place among more traditional system-level variables such as power, mass, etc., conceptual designs will be explicitly created and selected based on risk, reliability, robustness, and uncertainty metrics. Specifically, this research will develop a method of explicitly trading and evaluating designs based upon risk in design trade studies among subsystems with the end goal of maximizing system utility and system integrity.

The method develops a risk vector, $\overrightarrow{Risk}$, that is traded as a system-level parameter. Common risk methods such as Risk Priority Number (RPN), Failure Modes and Effects Criticality Analysis (FMECA), FTA, and others can be used to populate $\overrightarrow{Risk}$. These risk methods can contain either static models where the models do not change irrespective of any change in subsystem input variables or they can be dynamic where, for example, an FTA top level probability of failure would change based on the probabilities attached to the sub-elements of the fault tree. The sub-element probabilities are no longer static quantities as they would be in a stand-alone FTA. Instead, the sub-element probabilities are directly fed from input variables that can vary between each iteration of a trade study model based upon other subsystem models and system-level parameters. This makes trading risk between subsystems easy as any change in input variables as a result of system-level parameter trading creates an immediate response in the risk vector. Thus, rather than having a static FTA or FMECA, a dynamic version is available.

The risk trading method allows for new design selection preferences to be created that otherwise would not be available to design engineers. Adding new design variables in the form of $\overrightarrow{Risk}$ enables engineers to find designs with higher utility as partially defined by risk metrics than if risk was ignored in design trade studies. This allows risk to be brought on par with other important system-level variables rather than being considered only after conceptual designs have been developed.

Chapter 4 presents a journal paper that as of the time of this writing is under a second round of reviews to be published in the journal of Research in Engineering Design.

The paper in Chapter 4 details the method that was developed in order to satisfy Objective #1. A conference version of this paper (paper number DETC2010-29016) was presented at the American Society of Mechanical Engineers (ASME) 2010 International Design Engineering Technical Conferences and Computers and Information in Engineering Conference (IDETC and CIE) in the Systems Engineering, Information and Knowledge Management track of the Computers and Information in Engineering (CIE) conference [82]. It is omitted from this dissertation but is available from ASME.

3.3 Objective #2: Determine Engineering Risk Appetites

The second objective of this research develops a psychometric risk survey designed to assess engineering risk attitude. Understanding the risk attitudes of engineers is useful for several reasons. For instance, the need for training to bring an engineer's risk attitude in line with the attitude expected by a company can be assessed. Many other opportunities are available to make use of an engineering-specific psychometric risk survey.

3.3.1 Background

Risk is an integral part of engineering design. Risk propensity is often considered an essential ingredient for innovative design, perhaps best exemplified in the IDEO motto "Fail often to succeed sooner," implying a willingness to take the risk to allow a product concept to fail to enable learning. On the other hand, risk aversion pervades certain industries, such as power generation and aerospace. There is no one correct level of attitude to risk across all engineering sectors; rather, risk is a factor that must be managed in order for an organization to reach its objectives. Research by Van Bossuyt et al. in risk trading in engineering design has shown that what one engineer thinks is 'risky', another engineer may not [83].

Within engineering design, there is no shortage of methods to identify the risk of failure of components [84]. At the organizational level, standards such as ISO 31000:2009 [57] prescribe a framework for organizations to manage risk. The standard usefully identifies four aspects to risk management: risk identification (I), risk analysis (A), risk evaluation (E), and risk treatment (T). While the standard prescribes effective principles and guidelines for organizations to establish risk management policies and procedures, it, like formal engineering risk analysis methods, falls short in the assessment of organizational and personal *attitudes* to engineering risk.

3.3.2 Method

In order to achieve Objective #2, a psychometric engineering risk test is developed which is designed to assess engineering risk attitude, an engineer's mental response to the perception of uncertainty of objectives that matter [60]. The psychometric engineering risk test is modeled after the DOSPERT test [40, 47] and is based in part upon principles and guidelines in the ISO 31000:2009 standard on risk management [57] while also being partially based upon findings from initial research [85]. The DOSPERT test is quickly becoming the most preferred risk attitude scale in psychology for its predictive abilities and ability to show whether observed risk behavior is based upon the person's perception of risk or the person's attitude toward the perceived risk. ISO 31000:2009 is the International Organization for Standards risk management principles and guidelines standard. The DOSPERT test has demonstrated both a high level of reliability and construct validity. The standard systematically lays out the principles behind risk management and outlines guidelines for risk management practitioners to follow.

Survey questions are initially developed by following the ISO 31000:2009 definitions of the four aspects of risk management (risk identification, risk analysis, risk evaluation, risk treatment) and associated recommended activities. The items present respondents with typical scenarios or tasks they would encounter in dealing with each of these aspects. Each aspect and associated questions are briefly described in Appendix 5.10. Following an initial round of data collection and analysis, survey questions were revised. They are presented in Appendix 5.11.

Understanding the risk attitudes of engineers is useful for several reasons. By understanding the risk attitudes of engineers, training can be conducted to bring an engineer's professional perception of risk – subjective judgment of the severity and characteristics of a risk – and risk appetite – the amount of risk that is willingly taken on in order to realize a gain – in line with the company's risk perception and risk appetite. In systems engineering, understanding individual engineers' risk perception and appetite holds the promise of helping engineers to collaborate more effectively and deliver a higher utility product with a lower development cost and shorter development time [86]. Risk and reliability engineering stand to benefit from knowing their risk attitude. Expert judgment is directly affected by how engineers perceive risk and their risk appetites. By understanding individual risk perceptions and appetites, risk experts can explicitly normalize their expert opinions with peers [83]. In terms of theory of decision-based design, it is already known that decision makers are subject to a set of psychological biases, one of which is a framing effect. If outcomes are framed in terms of gains, people tend to be risk averse; conversely, when outcomes are framed in terms of losses, people tend to be risk seeking. Thus, how engineering data is merely presented can bias decision makers, irrespective of the data presented. For these reasons, an instrument to assess engineering risk attitude with the aim that such an instrument can become a standard for the assessment of engineering risk attitudes is needed.

Many methods exist in engineering design to account for risk such as FFIP [67], RED [69], FFDM [68], FMEA [87], and others. However these methods do not account for risk appetites of enterprises or individual decision-makers. Research in psychology has produced the well-respected DOSPERT test which enables risk appetite determination in several different domains of daily life [40]. The proposed research will create a psychometric test similar to the DOSPERT test with the goal of categorizing and determining engineering-specific risk domains [85]. Objective #2 seeks to find a link between the engineering risk appetite information that engineering-specific psychometric test will provide with traditional and widely used engineering risk methods.

Chapter 5 presents a journal paper that as of the time of this writing has been submitted to the Journal of Mechanical Design. The paper in Chapter 5 details the creation, testing, analysis, and validation of an engineering risk appetite survey. A conference paper version (paper number DETC2011-47106) was presented on the subject at the ASME 2011 IDETC and CIE in the Design Theory and Methodology Conference, Uncertainty and Risk in Design track [85]. It is omitted from this dissertation but is available from ASME.

3.4 Objective #3: Account for Risk Appetite in Decision Making

The third objective of this research develops a risk-informed decision support method that helps decision-makers choose between risk mitigation choices and make decisions between multiple design alternatives. The method is differentiated from traditional lottery-based utility functions in that the method is aspirational in nature while lottery-based methods are predictive. The decision support method makes use of the engineering psychometric risk survey as outlined in the description of Objective # 2.

Using this approach, risk-based design decisions can thus be made under risk tolerant or risk averse risk attitudes rather than the expected value approach. For example, the risks in Equations 3.1 and 3.2 are equal in the context of risk-based design. In Equation 3.1, a 1% chance exists that a risk costing \$10,000 to return the system to a nominal operating state will occur while in Equation 3.2, there is a 0.1% chance of realizing a risk that costs \$100,000 in order to return the system to a nominal state. Equation 3.2 represents a case in which additional system complexity has been added to the base design of Equation 3.1, which has lowered the probability of losing system functionality but has increased the repair cost in the event of a fault. Both risks have an expected value of -\$100. Therefore, a decision-maker using risk-based design would have no guidance if choosing between the two designs. The designs are of equal value using the expected value approach.

$$R_1 = 0.99(0) + 0.01(-\$10,000) = -\$100 \tag{3.1}$$

$$R_2 = 0.999(0) + 0.001(-\$100,000) = -\$100 \tag{3.2}$$

3.4.1 Background

Two methods exist in the literature to account for risk appetite in decision making including a discarded method using psychometric risk attitude test results and the traditional and widely used lottery methods. Pennings and Smidts [77] investigated using psychometric risk attitude test results to create risk curves for Dutch hog farmers to predict individual farmer behavior in hog futures markets. The results of the research found lotteries to be the most accurate method of predicting behavior in the context of the hog futures market. However, the hog farmers' self-reported behavior predictions were most closely correlated with the psychometric risk attitude test results. The farmers also indicated that the psychometric risk attitude test was more understandable than the lottery method.

In this dissertation, the author[1] postulates that, while lottery methods of utility risk curve generation are satisfactory for many DBD situations, they are not as useful for early-phase conceptual design. In early phase conceptual design of new products it is important to aspire to create new and innovative designs. While lottery methods are useful for cases where following past performance and predicted performance is desirable, in the case of conceptual design it is desirable to create the designs which the psychometric risk survey test taker aspires to create. Chapter 8.1 details a survey that at the time of writing this dissertation is under review by the Institutional Review Board and will be administered following the completion of this dissertation. The survey will either confirm or deny the postulation that lottery methods are less appropriate than psychometric risk surveys for early-phase conceptual design.

Lottery-based risk curves are only valid over the range of values used in the initial lotteries. In case of early-phase conceptual design, the range of values might not be fully known or could change during the design process. Re-running lotteries to create

[1]The postulation that lottery methods of utility risk curve generation are satisfactory for many DBD situations but not as useful for early-phase conceptual design was developed as part of the journal paper presented in Chapter 6 which is authored by Douglas Lee Van Bossuyt, Chris Hoyle, Irem Y. Tumer, and Andy Dong.

expanded risk curves thus would quickly become burdensome to the practitioner. Further, in cases where utility risk curves are developed based upon client or customer risk appetites, conducting multiple lottery sessions is impractical. Finally, as hinted at in Pennings and Smidts' research [77], lotteries do not closely match what individuals believe they will do. However, actions of individuals more closely align to the predictions of lottery methods than to self-reported methods. This can be interpreted as a disconnect between what individuals aspire to do and what they actually do. Utility risk curves generated by alternative methods could potentially provide new insights for practitioners that will allow decisions to be made based upon aspirations rather than upon past performance, as is the case with lotteries.

In summary, several methods exist and are used in the risk-based design approach to determine engineering risk, manage identified risks, and make decisions based upon that risk. However, these methods approach risk from an expected value choice perspective where the decision-makers and stakeholders are expected to be risk neutral. Utility functions which account for risk attitude have been used in the DBD framework; however, these functions have generally been developed for consumer products, where there is a trade-off between product features, price and demand, and not risk-based design applications. While utility risk curves can be useful for risk-based design applications, they are not satisfactory for early-phase conceptual design problems. As has been shown with the DOSPERT test and has been developed to meet Objective #2, people can be risk-averse, neutral, or tolerant. Therefore, a method is needed that can support decision-making for different risk appetites within the risk-based design paradigm. Psychometric risk attitude test-generated utility risk curves hold promise for use in early-phase conceptual system design. Objective #3 develops such a method.

3.4.2 Method

One result from meeting Objective #2 is the creation of a psychometric risk survey similar to the DOSPERT that has the goal of categorizing and determining engineering-specific risk domains [85]. Objective #3 develops a link between the engineering risk appetite information that Objective #2 will provide and traditional and widely used engineering risk methods. This allows practitioners to make risk-informed decisions in an aspirational context rather than a predictive context as traditional lotter-based utility methods do and in a manner that allows deviation from the expected value theorem found in standard engineering risk methods.

Traditional engineering risk methods view a risk that has an occurrence likelihood of 1% and a consequential cost of -$10,000 as equal to a risk with an occurrence likelihood of 0.1% and consequential cost of -$100,000. The outcome is valued at -$100. Therefore, a decision-maker using risk-based design methods would have no guidance if choosing between the two risk alternatives. The designs are of equal value and merit in an expected value framework and to someone with a risk neutral risk appetite. However, a risk-averse decision-maker will choose the second risk in order to have more certainty about the likelihood of occurrence of the risk. A risk-tolerant decision-maker will choose the first risk as she is less concerned with certainty and due to the lower financial cost.

It becomes less clear in instances where risks are not of equivalent value for in an expected value framework what risk a risk-tolerant or risk-averse decision-maker prefers. A risk-tolerant decision-maker can prefer a risk that a risk-neutral decision maker would find unpalatable. Rationalizing the choice of a risk that has a larger negative expected value because the risk-tolerant decision-maker is more concerned with the lower financial consequences than the certainty of the outcome is impossible in an expected value framework, as found in engineering risk methods in risk-based design.

In order to provide decision support assistance for decision-makers that do not hold a risk-neutral risk appetite, an exponential utility function is proposed as appropriate for use in conjunction with engineering psychometric risk scale test results. The results of the survey proposed in Section 8.1 are expected to confirm this suggestion. The utility function may be either of the monotonically increasing or decreasing exponential type [88]. An exponential function was chosen over other potential utility functions because it is believed that practitioners will be either constantly risk averse or constantly risk tolerant during the early phases of conceptual system design. The choice of an exponential curve also allows the direct use of psychometric risk survey test results in the creation of a risk curve [76].

This objective develops a novel way to account for risk appetite in risk-based design. A single criterion decision based design approach is adapted by way of engineering risk appetite utility functions to bring risk data from the expected value domain into a risk appetite domain appropriate to individual stakeholder or an enterprise's general risk appetite. The risk appetite utility function is developed via psychometric risk survey test results, derived from the results of Objective #2, rather than traditional lottery methods. By viewing risk data through a risk appetite lens, stakeholders and decision-makers can make risk decisions with analytic backing that would traditionally be justified with "gut feeling." An important distinction is drawn between appropriate uses of lottery-derived risk utility functions and psychometric test-derived risk utility functions. Lottery methods of risk utility curve generation are suitable for later stage conceptual system design and beyond where the predictive benefits of lottery methods are desired while the authors advocate for using psychometric risk test-derived utility functions for early phase conceptual system design where the aspirational benefits of a psychometric risk survey are desired.

Chapter 6 presents a journal paper that at the time of this writing is scheduled to be published in the AIEDAM Fall 2012 special issue on intelligent decision support and modeling (Volume 26, Number 4) [89]. The paper in Chapter 6 details the development of a decision support and decision automation method that allows the psychometric risk survey developed to meet Objective #3 to be used to create utility risk curves. The utility risk curves are then used to make risk-informed decisions in the conceptual complex system design process. A forthcoming conference paper (paper number DTM-70399) on the topic will appear in the ASME 2012 IDETC and CIE in the Design Theory and Methodology Conference in the Uncertainty and Risk in Design track. It is omitted from this dissertation but will be available from ASME.

3.5 Validation and Application

Objective #1 was initially validated by testing the risk trading methodology in a computer simulated CDC environment. A simplified spacecraft model developed from Wertz and Larson [90] was used as the basis for a test of the methodology. Chapter 4 includes a journal article that demonstrates the methodology using a computer simulation. The method was further tested using undergraduate and graduate student research participants who were formed into collaborative design teams. These teams then conducted trade studies using standard trade study methodologies. Following that, the methodology developed to meet Objective #1 was introduced to the research participants. Observations were made on the utility of the resulting spacecraft designs and on the desirability and ease-of-use of the method. Chapter 4 details the testing of the methodology on a limited population of research study participants.

Following the tests in a simulated CDC environment, an attempt has been made to introduce the method developed to meet Objective #1 to an industrial, production-level CDC such as JPL's, Team-X. Ideally, the methodology will be tested on a small real-world design trade study. To date the method has been introduced to key personnel at JPL but the methodology has yet to be tested or adopted. When the method is tested, feedback will be collected from the participants to further refine the method and prepare it for full deployment in a CDC environment.

Objective #2 was validated by administering the psychometric engineering risk survey to a population of graduate and undergraduate engineering students at Oregon State University (OSU) and University of Sydney (USyd). Initial administration was to a small group of participants to receive feedback on the survey instrument. Further administration of the survey instrument was conducted on a group of roughly 100 participants to check for statistical validity of the proposed engineering risk domains. It was found that refinement and redevelopment of the scale questions was necessary.

A second round of surveying on a larger population in the range of 200 student participants occurred to further verify the survey instrument. A final list of questions was selected that properly loads onto five engineering risk domains that were uncovered as part of the research connected to Objective #2. After this dissertation has been completed, an attempt will be made to administer the survey to a large population of professional engineers at a corporate engineering firm such the Boeing Company or JPL. The resulting data will be used to do a final statistical validation of the survey instrument developed for meeting Objective #2.

Objective #3 was initially validated through proof-of-concept demonstrations using a simplified spacecraft or aircraft model similar to that used to validate Objective #1 [89]. Further validation and a sensitivity analysis of the method is presented in Section 7.6. User tests will be performed on a population of students and a group of professional engineers at a firm such as the Boeing Company or JPL following the completion of this dissertation.

Initial verification and demonstration of the integrated Risk-Informed Decision Making Framework has occurred in a computer simulated CDC environment. The implementation of the framework into software is presented in Chapter 7 and will be part of a forthcoming journal article. In the future, following the completion of this dissertation, the framework will be tested in a simulated CDC environment staffed by engineering student research participants. Following successful completion of simulated CDC tests and further refinement of the framework and underlying methods, an attempt at testing the framework will occur at either the Boeing Company or the Jet Propulsion Laboratory. Both organizations host production-level collaborative design centers where the methods developed as part of this research are most applicable.

3.6 Impact of the Risk-Informed Decision Making Framework

By developing a framework to account for risk at the system level using risk models from the subsystems and risk appetite information from the customer, the voice of the customer will be more accurately reflected in conceptual designs. Risk tolerant customers will be given conceptual designs with high utility and high risk where innovation can occur to realize high profits. Risk averse customers will receive conceptual designs with high utility and low risk where the risks that are present have more certainty. Government and industrial customers will benefit from this framework by having conceptual designs created that more accurately reflect their risk appetites.

3.6.1 Objective #1 Impacts

The successful development of methods to meet this objective gives power to individual subsystems chairs to analyze individual subsystem risks and control subsystem risk models. This objective provides a new means for stakeholders to account for risk in conceptual designs and a new way for engineers to choose subsystem designs or components based upon risk information will become available. Managers will be able to base decisions during a trade study upon risk levels present in subsystems and the overall system. Further, customers will have a different, more nuanced feel for the risk profile of the design at the end of the conceptual design trade study process. Finally, conceptual design trade study results will have more accurate and trustworthy risk information.

3.6.2 Objective #2 Impacts

A better understanding of engineers' mental response to the perception of uncertain objectives has resulted from the successful completion of this objective. Targeted training will be able to be conducted to harmonize an engineer's professional perception of risk (subjective judgment of the severity and characteristics of a risk) and risk appetite (amount of risk that is willing to be taken in order to realize a gain) with that of the engineer's company or specific position. Being able to understand an individual engineer's risk perception and appetite will help engineers to collaborate more effectively and deliver higher utility products with lower development costs and shorter development times. Understanding individual risk perceptions and appetites can also be used to develop a method of normalizing expert opinions with peer groups enabling direct comparison and trading of expert risk judgments.

3.6.3 Objective #3 Impacts

The satisfactory completion of this objective produced a link between engineering risk appetite information and traditionally widely used engineering risk methods. The ability to account for risk appetite in risk-based design will be further advanced. Viewing risk data through a risk appetite lens will allow stakeholders and decision makers to make risk-based decisions with analytic backing that traditionally would be justified by "gut feeling." Risk-averse decision makers will have decisions with higher certainty highlighted. People with this risk appetite prefer risks that are more certain over uncertain risks. Risk tolerant organizations will find that identifying large risks will drive potential innovation and profit.

3.7 Contributions

This dissertation makes several significant contributions to the literature. Objective #1 develops a novel method to trade risk as a system-level variable in trade studies where individual subsystem chairs analyze subsystem risks and control subsystem risk models. Objective #2 introduces a novel method of assessing engineering risk appetite using a purpose-built psychometric risk appetite survey. Objective #3 produces a novel method of making risk-informed decisions through the lens of risk appetite from an aspirational perspective. The framework contributes a novel method of accounting for risk and risk appetite during the conceptual design trade study process where risk is traded between subsystems as a system-level parameter and risk-based design decisions are made by quantitatively taking risk appetite into account. Thus four important, novel contributions are made to the literature from this dissertation.

Chapter 4 –A Case for Trading Risk in Complex Conceptual Design Trade Studies

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[2]A conference version of this article appeared in the ASME 2010 IDETC and CIE in the Systems Engineering, Information and Knowledge Management track of the CIE conference as paper number DETC2010-29016 [82].

4.1 Abstract

Complex conceptual system design trade studies traditionally consider risk after a conceptual design has been created. Further, one person is often tasked with collecting risk information and managing it from each subsystem. This paper proposes a method to explicitly consider and trade risk on the same level as other important system-level variables during the creation of conceptual designs in trade studies. The proposed risk trading method advocates putting each subsystem engineer in control of risk for each subsystem. A risk vector is proposed that organizes many different risk metrics for communication between subsystems. A method of coupling risk models to dynamic subsystem models is presented. Several risk visualization techniques are discussed. A trade study example is presented based upon a simplified spacecraft model. Results from introducing the risk trading methodology into a simulated CDC are presented. The risk trading method offers an approach to more thoroughly consider risk during the creation of conceptual designs in trade studies.

Keywords: Trade Study, Complex System Design, Risk, Collaborative Design Center, Risk Trading

4.2 Introduction

Risk has traditionally been an afterthought in the conceptual complex system design process. Risk is typically only formally assessed after a conceptual design has been created and does not explicitly play a role in the creation and selection of conceptual designs. Instead, implicit assumptions are often made about the “riskiness" of conceptual design models. Our hypothesis is that by moving risk into trade studies and giving it a place among more traditional system-level variables such as power, mass, etc., conceptual designs will be explicitly created and selected based on risk, reliability, robustness, and uncertainty metrics. Specifically, this research presents a method of explicitly trading and evaluating designs based upon risk in design trade studies among subsystems with the end goal of maximizing system utility and system integrity.

In this paper, various risk metrics are placed in a vector denoted as $\overrightarrow{Risk}$. Risk in the engineering context is defined as the severity of a risk outcome multiplied by the probability that the event will occur [57]. The risk vector is traded in design trade studies. Based upon the desired level of $\overrightarrow{Risk}$ for a system, specific point designs or portions of the design space can be identified for further study and development. The risk trading methodology presented in this paper is implemented in Phoenix Integration Inc.'s ModelCenter [91] and demonstrated in a simulated CDC environment using undergraduate and graduate participants as subsystem engineers with direct control over subsystem decisions. In a previous conference paper [83], the authors tested an earlier version of the method using an automated trade study.

The idea for this paper started after observing several Team X trade study sessions at the JPL. Through conversations with personnel currently and previously involved in Team X and similar groups, it became evident that the issue of accounting for risk in a meaningful way in trade studies needed to be addressed beyond what can be found in literature and practice. Development of the method presented in this paper followed. After positive feedback from a conference paper on the method [83], the method was then tested on a simulated CDC environment using college students as subsystem engineers. In the future, the authors plan to test the method in an industrial CDC environment.

The following sections include background on trade studies; CDCs; trade study software; risk, reliability, robustness, and uncertainty methods; related work; and other necessary background information. The methodology to trade risk is developed and demonstrated in a trade study using a simplified spacecraft model adopted from Wertz and Larson [90]. Future work to expand the methodology is outlined.

The risk trading method presented in this paper allows for new design selection preferences to be created that otherwise would not be available to design engineers. Adding new design variables in the form of $\overrightarrow{Risk}$ enables engineers to find designs with higher utility as partially defined by risk metrics than if risk was ignored in design trade studies. This allows risk to be brought on par with other important system-level variables rather than being considered only after conceptual designs have been developed.

4.2.1 Design Trade Studies Fundamentals

Design trade studies are used in conceptual complex system design to generate different design alternatives and compare amongst them. Trade studies can be performed either automatically using software packages or by teams of people. Whereas automated, computer generated trade studies can create many thousands of design points quickly, manually-conducted human generated trade studies are often seen as having higher fidelity and are more likely to be accepted [1]. The demonstrative trade studies in this paper are all manual trade studies conducted with the assistance of computers.

Metrics such as cost, mass, power, volume, and other parameters are often traded in such trade studies. Each subsystem within a complex system is initially allocated specific amounts of the constraining parameters. During the course of the design process, several subsystems are often found to be lacking in one or multiple constraint parameters but have additional quantities of other parameters available. These parameters can be traded between different subsystems and contain intrinsic value of varying degrees for different subsystem designers [2, 3, 4]. The resulting conceptual designs can then be ranked according to appropriate selection rules [5, 6].

When there is a defined "measure of goodness," the basic mathematical concept behind trade studies is simple and straight-forward. Trade-offs are made between design variables to achieve maximum design utility [7]. This generally takes the form of $max\ f(\overrightarrow{U})$ where $\overrightarrow{U}$ represents relevant system utility metrics.

This simple equation provides the foundation for a wide range of analytic methods that all aim to find the optimal design given system constraints. Many different methods have been developed to computationally find the optimal solution. The difficulties, however, are in developing a series of equations that adequately model the system to then efficiently find the optimum solutions to those equations [7].

4.2.2 Conceptual Design Centers

Many companies and institutions have teams who perform trade studies as part of the early complex system design process. The first and most cited example is the NASA JPL's PDC and the associated design team, commonly referred to as Team X. The group, formed in June 1994 [8], functions as a conceptual spacecraft mission design team.

The Team X design team includes engineers and scientists from all major spacecraft mission subsystems co-located in the PDC, which is outfitted with the latest technology to aid in spacecraft mission development and concurrent design. This gives Team X the ability to complete spacecraft architecture, mission, and instrument design trade studies very rapidly [9]. The design iteration portion of most Team X trade studies are completed in two to three days, compared to three to nine months to complete a comparable trade study [10]. Team X has also reduced the cost of concept-level spacecraft mission design by a factor of five compared to conventional design processes [10].

Within Team X and other CDC groups, there are often desired ranges of system level risk. While it might appear that a design minimizing risk is always desired this is often not the case. Sometimes designs with a specific level of risk above the absolute potential minimum are desired. In the case of Team X, this is due to the desire to launch missions that are both cost-effective and challenging. Missions at NASA are selected for further development based on several factors including the mission risk profile. A risk target range has been defined that balances pushing the boundaries of engineering and science with a desired cost and level of mission success [19].

4.2.3 Trade Study Software

Many formal trade studies are conducted using software packages. Several different commercial and academic packages are available. Commercially available and academic software packages exist that support both manual and automated trade studies. They include ICEMaker [92], Advanced Trade Space Visualization (ATSV) [93], and ModelCenter [91] among others [94].

This paper uses ModelCenter in the development of a risk trading methodology. Details of ModelCenter's use in CDC environments can be found in [82]. However, the methods developed here are applicable in any other trade study software tool, whether for manual or automated trade studies.

4.2.4 Risk, Reliability, Robustness, and Uncertainty

Trading any variable in a trade study requires agreed-upon definitions and values of the variables. While it is easy to define a cost variable as the dollars it will take to build something or a mass variable as the mass of an object, defining the value of "risk" is difficult and more abstract. This paper uses the strict engineering definition of risk where risk is defined as the probability of an event occurring multiplied by the impact of that event.

Risk is often defined in engineering as the probability of occurrence multiplied by the severity of impact [57]. However many people including engineers think of risk more by its dictionary definition: the possibility of suffering harm or loss, or a danger. Other concepts such as reliability, robustness, and uncertainty are also often lumped in the same category as the engineering definition of risk. Reliability can be defined in engineering as "the ability of a system or component to perform its required functions under stated conditions for a specified period of time [61]." Robustness in the systems engineering context refers to a system that is resistant to failure due to inputs that are beyond the expected and designed for input range [62]. Uncertainty is a result of a lack of knowledge about system specifications, and errors resulting from imperfect models [58]. Some researchers further break down uncertainty into multiple subcategories that often contain elements of risk, reliability, and robustness [59]. This research uses the engineering definition of risk: probability of occurrence multiplied by severity of impact.

4.2.5 Risk Analysis Techniques

It is necessary for the methodology presented in this paper to be able to quantify risk, as defined by the probability of occurrence of a risk multiplied by the severity of the realization of the risk [57], in a repeatable and robust manner. Many risk evaluation tools exist that are commonly used in industry. For instance, FMEA and its extension, FMECA, adding criticality analysis, find use across many industrial sectors [65, 87]. FMEA provides probability and severity information for each identified and analyzed risk.

In early conceptual design or when more rigorous risk analysis cannot be performed, expert judgment is often used. One or a group of experts is asked to rate the level of risk present in a component or subsystem. The resulting rating can take the form of “low, medium, high,” a numeric scale, or many other options [95]. This is the case for both the severity and occurrence portions of risk. Expert judgment has found widespread use in various settings such as the aerospace industry, nuclear engineering, and other areas for many decades [96, 97]. Several methods exist to elicit expert judgment and are covered in detail in the literature [98, 99, 100, 95, 101, 102, 103]. Another commonly used fault analysis tool is FTA. FTA is employed when a top-down graphical approach to failure analysis is desired [66].

The risk methods presented in this section are only a small selection of the wide array of robust quantified methods available including Qualitative Risk Assessment (QRA) [104], Event Tree Analysis (ETA) [105], RBD [63], PRA [64], FFIP [67], FFDM [68], RED [69, 106], and Risk and Uncertainty Based Integrated and Concurrent design methodology (RUBIC) [86] among others [107, 84, 108]. This paper specifically uses

FMEA, expert judgment, and FTA for illustration purposes; however, any risk method can be used.

4.3 Related Work

Some CDCs such as Team X currently employ tools and methods to capture risk in the conceptual design process. However, establishment of mission risk posture usually happens before conceptual designs have been generated, and risk evaluation happens afterward; or risk evaluation is part of a process that happens in lieu of trade studies; or worse yet, risk does not play any role in early conceptual design development. But there is generally no accepted method to measure risk within each subsystem model as a parameter to be controlled and developed by individual subsystem chairs during conceptual design trade studies. This section will review several relevant tools and methods that are currently used in CDCs, have been proposed for such use, or could be adapted to the CDC environment.

4.3.1 Risk and Defect Detection Based Methods

The RAP tool is a PRA-based assessment software package that is employed during a trade study session [20]. Each subsystem chair has the ability to enter information into the tool as he/she sees fit. This data contains a RPN comprised of the likelihood of a specific risk occurring multiplied by the effects if the risk is realized. Mitigation information can also be entered in a free-form text box. In Team X, one person, the "risk chair," is dedicated to monitoring the RAP tool and compiling the data entered by the subsystem chairs to create an overall system-level risk assessment. Other groups outside of NASA have also used tools similar to RAP and with similar implementations yielding similar results and problems [21, 22, 23].

In addition to RAP, JPL has also developed DDP, a tool that helps engineers determine what mitigation steps will provide the largest reduction in system-level risk [24]. Literature on DDP does state that risk should be traded and provides a framework for trading but trade studies are not suggested to be performed in CDCs. The literature does suggest that risk can be compared against performance metrics to find the optimum level of risk versus performance; but to examine risk, conceptual designs must be developed and solidified before the DDP method can be used to analyze risk [25]. In the authors' opinion, the DDP method suffers from the perception that it is an overly complicated tool and methodology.

While RAP and similar tools have been adopted in many CDCs and DDP has found some use outside of the CDC environment, several other methods have remained purely academic. For instance, a risk management method developed by Dezfuli et al. embeds the NASA CRM process that is used in practice in many NASA groups into a broader decision framework that has not found use outside of academia [26]. The method presents a risk management approach intended to be used throughout the product lifecycle. Performance measures and NASA's CRM process are relied on to assess risk. While the method does state that risk must be accounted for in the conceptual design phase and further briefly mentions the trade study process, the actual analysis of risk still happens after conceptual designs have been created [27]. Thus the method does not place risk directly in the trade study process.

4.3.2 Uncertainty and Design Margin Based Methods

A normative method that attempts to balance cost, risk, and performance for decision makers in preliminary spacecraft mission design is presented by Thunnissen [78]. The method focuses on uncertainty and classifies it into four different categories (ambiguity, epistemic, aleatory, and interaction), three subcategories of epistemic uncertainty (model, phenomenological, and behavioral), three sub-sub categories of model uncertainty (approximation errors, numerical errors, and programming errors), and four sub-sub categories of behavioral uncertainty (design, requirement, volitional, and human errors). To deal with the uncertainties, probabilistic methods and Bayesian techniques [79] are employed. However, risk in the form of Thunnissen's uncertainty definitions is not considered during trade studies. Instead, it is analyzed for a specific subset of overall mission design during the very early stages of conceptual design prior or in lieu of trade studies.

Another method developed by Thunnissen formalizes design margins in trade studies and also attempts to trade risk in trade studies [80]. However trading risk is presented as an afterthought to the primary concern of design margins in the method. The risk model presented simply replaces an expected design constraint. Rather than setting a fixed minimum value for a design constraint, a 100% risk of failure is produced when the minimum value is crossed. The primary contribution of the work is the formalization of margins in trade studies – not implementing risk in trade studies.

Browning presents a method of modeling impacts of process architecture on cost and schedule risk in product development [109, 110, 111]. The method examines how rework cascades throughout a process, and the resulting cost and schedule trade-offs. Risk, as partially defined by uncertainty of outcome, can be examined through a utility function in order to incorporate characteristics such as risk aversion into the method. The primary focus of Browning's method is the general process of product development rather than the creation of conceptual designs in trade studies.

Finally, Charania et al. present a collaborative design method that utilizes Probabilistic Data Assessment to trade risk in trade studies conducted using Phoenix Integration Inc.'s ModelCenter software package [81]. However risk is treated as a separate "subsystem" in the trade studies. Risk is not explicitly incorporated into each subsystem model. Rather, like the RAP methods used by Team X and others, one person or one "subsystem" model is in charge of risk.

4.3.3 Robustness Methods

Robust design methods have been used for more than 20 years in western engineering practices. Taguchi popularized the use of such robustness methods as factorial experiments and other statistical methods that are now widely used to improve the quality of industrial products [112, 113]. While Taguchi originally advocated for his methods to be used during parameter design, the portion of the design process following conceptual design, others have since expanded his work into the conceptual portion of the design process [114]. In order to improve the product, the methods that comprise robust design strive to make the product insensitive to environmental inputs. Several of the methods developed for the conceptual design process have the potential to be used in trade studies but to the authors' knowledge, none have been implemented.

The Robust Concept Design Methodology (RCDM) proposed by Ford and Barkan loosely mirrors the trade study process [115]. Stages 3 and 4 of the method develop a conceptual design, evaluate the design, and iterate as necessary. The main difference of this method as compared to trade studies is that robustness is treated as the only system-level parameter of merit. In trade studies, many different system-level variables can be considered at once.

Andersson presents a semi-analytic method based upon the error transmission formula with the goal of achieving conceptual robustness [116]. The method aids engineers in making preliminary assessments of the levels of design variables to prepare for subsequent phases of design. A means of analyzing predetermined dependency relationships is also provided. In order to make these assessments, well-defined design functions are required which can be a hindrance during early-phase conceptual design where strong analytic functions are not always available.

Ziv Av and Reich develop the Subjective Objective System (SOS) method which generates optimized conceptual designs for diverse disciplines [117] and a complementary procedure to develop robust conceptual designs [118]. SOS has the ability to model design information at several different levels of resolution which resemble the House of Quality [119]. The SOS method integrates market, technology, and organization information in order to produce design concepts matched to the market. The robust product concept generation method, an expansion of SOS, allows robustness to be traded with other aspects of a conceptual design as it is being generated. The method further allows a local sensitivity analysis of the resulting conceptual designs to determine how stable the concept is when customer parameters vary. While the methods developed by ziv Av and Reich can model risk as a system goal, the methods are not explicitly developed for trade studies and do not place control subsystem risk models with subsystem engineers.

The robust decision-making concept developed in [120] presents a 12 step method put forward as necessary to make robust decisions. Steps 5 through 7 extend Quality Function Deployment (QFD) to accept robustness product information. Step 8 develops multiple design alternatives with an allusion to performing trade studies while Step 9 evaluates the design alternatives. The concept could conceivably be further extended to include risk, reliability, and uncertainty metrics as important system parameters and does advocate for appropriate decision-makers to be selected and queried. However, the concept does not produce a methodology focused on trading risk as a system-level parameter where all subsystem risk models are controlled by individual subsystem engineers as the method presented in this paper does.

4.3.4 Summary and Contributions

In summary, some methods such as RAP and DDP have found use in some CDCs and elsewhere while other methods such as those developed by Thunnissen, Charianian et. al., others remain academic, and some such as SOS and RCDM have not been developed for CDC trade studies. Some of the methods analyze risk after conceptual designs have been created using trade studies. Others analyze risk prior to trade studies or bypass trade studies all together. One even analyzes risk within trade studies during the creation of conceptual designs as a separate subsystem. However, to the authors' knowledge no method currently places risk within each subsystem model to be controlled and developed by individual subsystem chairs during the creation of conceptual designs in trade studies. This research fills the gap in existing methods.

This paper contributes a method that gives the power to analyze subsystem risk and trade system-level risk to subsystems chairs during the creation of conceptual designs in trade studies. The method provides a new means for stakeholders to account for risk in conceptual designs, and for engineers to choose subsystem designs or components based upon risk. Managers selecting specific risk profiles can use this method to identify the most interesting designs. Customers of Team X sessions can use this method to get a different feel for the risk profile of the end design than has been previously available. This will produce results that are more accurate and more trustworthy than currently available methods, resulting in a method that can be adopted in practice.

4.4 Methods

In this section a methodology is presented to trade risk as a system level parameter in trade studies during the creation of conceptual designs. Risk trading will happen between separate subsystems and be overseen by each subsystem. Risk will be tradeable as a system-level parameter. To facilitate risk trading, a risk vector ($\overrightarrow{Risk}$) is developed that can be used to contain risk, reliability, robustness, and uncertainty metrics. In this paper, only risk as defined by the probability of an event multiplied by the consequences of its occurrence is used. However, other related concepts such as reliability, robustness, and uncertainty can be similarly traded. Methods are presented to create a system-level risk vector from the constituent subsystem risk vectors. Ways of using the system-level vector in trade studies are then presented to demonstrate how to use the risk trading methodology. The four steps involved are summarized in the following list and mathematically demonstrated in Equation 4.1. Note that to maximize system utility, $\overrightarrow{Risk}$ does not necessarily need to be minimized.

1. Create risk vector schema and choose appropriate risk metrics
2. Implement risk vector into subsystems and populate subsystems models with risk methods
3. Combine subsystem vectors into system-level risk vector

4. Perform trade study using risk vector as a tradeable system-level parameter

$$\text{Max(Utility)} = [\text{Sys Metric 1, Sys Metric 2, ...}, \overrightarrow{Risk}] \tag{4.1}$$

4.4.1 A Risk Trading Methodology: Main Steps

The following sections detail the four steps outlined earlier in Section 4.4 that are required to implement and make use of the risk trading methodology. Subsequent sections make use of the risk trading methodology implementation using an illustrative case study to show the utility of the risk trading methodology to practitioners.

4.4.1.1 Creating a Risk Vector Schema

The first step in the risk trading methodology is to create a risk vector schema. It is often the case in industry and academia that the definitions of risk, reliability, robustness, and uncertainty become blurred and mixed together [59]. While it is important to tightly define these terms for the project at hand, one can think about this family of concepts under the meta-category of risk [59]. Especially when talking with non-subject experts, grouping all of the related ideas into a risk meta-category can be very useful.

The concept of grouping risk, robustness, reliability, and uncertainty into one meta-category can be extended to create risk vectors. A risk vector, $\overrightarrow{Risk}$, is defined to include all components of risk, reliability, robustness, and uncertainty in a design. As an example, Equation 4.2 shows one potential generic $\overrightarrow{Risk}$ configuration.

$$\overrightarrow{Risk} = \begin{Bmatrix} \textit{Engineering risk metric \#1} \\ \textit{Engineering risk metric \#2} \\ \textit{Robustness metric \#1} \\ \textit{Robustness metric \#2} \\ \textit{Reliability metric \#1} \\ \textit{Reliability metric \#2} \\ \textit{Uncertainty metric \#1} \\ \textit{Uncertainty metric \#2} \end{Bmatrix} \tag{4.2}$$

4.4.1.2 Implementing and Populating the Risk Vector

The second step in the risk trading methodology is to implement and populate the risk vector, $\overrightarrow{Risk}$. The trade study facilitator and subsystems chairs must agree upon the risk metrics to be included and the construction of the vector. Depending upon the risk methods employed, the resulting risk metrics can either be directly placed into the risk vector or will need to be transformed into a metric or suite of metrics that have meaning and value in a trade study setting. For instance, FTA data should be aggregated into several risk metrics, as discussed in Section 4.4.1.3. On the other hand, subsystem FTA data can be directly reported to the system-level risk vector. As long as the specific types of risks being analyzed are properly defined so that there is agreement between subsystems and between subsystem chairs, $\overrightarrow{Risk}$ can be compared between different components, subsystems, and functions. This opens the door to trading $\overrightarrow{Risk}$ in trade studies. A robust method for properly defining risk in this context will be developed in future work.

Expert judgment, when conducted in a repeatable and quantifiable way, can be directly placed into risk vectors. FTA produces a top-level probability of failure that can be directly used in risk vectors [66]. Other methods that produce a top-level quantifiable metric can be directly integrated into risk vectors.

FMECA and other risk methods that have multiple metrics must be dealt with differently. The Risk Priority Numbers (RPNs) resulting from a FMECA are often prioritized from highest to lowest RPN in order to address the highest risks first.

While using the highest RPN score from a FMECA can be effective in flagging a risky component or function, it does not tell the whole story. One informative way of using FMECA is by summing the RPNs and dividing by the total number of risk elements, producing an averaged RPN number. By looking at both the maximum RPN and the averaged RPN of a function or subsystem, a more complete picture of the FMECA can be obtained without having to review the entire FMECA.

A risk vector containing engineering risk metrics including FMECA and FTA data can take the form of Equation 4.3.

$$\overrightarrow{Risk} = \left\{ \begin{array}{l} Max\ FMECA\ RPN \\ Average\ FMECA\ RPN \\ FTA\ \%\ Chance\ of\ Loss \end{array} \right\} \tag{4.3}$$

Risk models found in the literature and in practice are typically static, and do not automatically change based upon new inputs. In fact, standard risk methods do not normally take new inputs. For effective risk trading, a dynamic approach to risk methods must be taken.

Three options have been identified by the authors to implement risk methods to derive the risk vector for trade studies. The first option is to use risk methods without any modification. Only one static risk model represents a subsystem, irrespective of any change in input variables. This option is only valid if the risks being accounted for in the risk vector do not change as the rest of the subsystem design changes. Except in rare cases, this option will not accurately capture risk and further voids any ability to trade risk between subsystems.

The second option is to make the inputs to risk methods dynamic. This means that an FTA top level probability of failure, for instance, would change based on the probabilities attached to the sub-elements of the fault tree. The sub-element probabilities are no longer fixed static quantities as they would be in a stand-alone FTA. Instead, the sub-element probabilities are directly fed from input variables that can vary between each iteration of a trade study model based upon other subsystem models and system-level parameters. This makes trading risk between subsystems easy as any change in input variables as a result of system-level parameter trading creates an immediate response in the risk vector. Thus, rather than having a static FTA or FMECA, a dynamic version is available.

The third option requires the creation of several static risk models to represent a subsystem. The correct static risk model is then chosen either automatically or manually based upon subsystem input variables. This can be especially useful if the subsystem model involves choosing between components or discrete functions.

For any of the risk model trade study options, the risk models must be integrated into the existing subsystem models. Further, the risk models must be created, managed, and be accessible by the individual subsystem chairs.

To create a practically useful risk trading method, each subsystem chair must be in control not only of their normal subsystem models but also of the risk models for their subsystems. The full set of subsystem risk models cannot be managed by one person. The implicit risk knowledge present in each subsystem chair would no longer be captured in the subsystem risk models.

At the end of this step, the appropriate risk models have been created and integrated into the subsystem models. The risk vectors are populated with the risk metrics produced by the individual subsystem risk models. Next the subsystems are unified into trade studies where risk can be traded like any other system-level parameter.

4.4.1.3 Creating a System-Level Risk Vector

The third step in the risk trading methodology creates the system-level risk vector. Bringing subsystem risk vectors together to create an overall system-level risk vector is necessary to be able to conduct trade studies. The system-level risk vector is analogous to any other system-level parameter such as cost or mass. However, unlike other system-level parameters, the subsystem risk vectors cannot always be directly summed together. Each constituent risk metric and the risk method behind it must be examined and a determination must be made about how to best represent that metric's system-level risk. Figure 4.1 graphically demonstrates how subsystem risk metrics are combined into subsystem risk vectors which are then developed into a system-level risk vector, and finally are used in a trade study with other system-level variables.

In the case of FTA, a system-level fault tree can be created that is inclusive of the subsystem fault trees. A dynamic FTA risk model is then easy to create. The top level probability of failure is then reported to the system-level risk vector.

Expert judgment must be handled on a case-by-case basis. The type of judgment being made will affect how the expert judgment metrics from each subsystem will be combined to create a meta expert judgment for the entire system. For instance, if

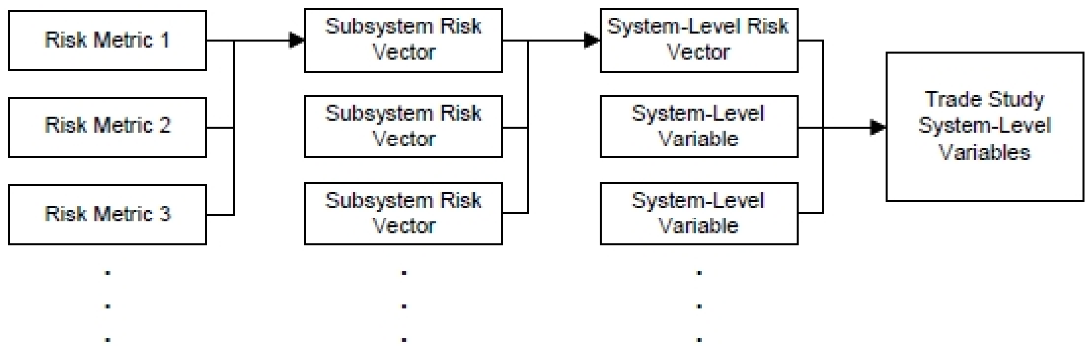

Figure 4.1: Formation of Risk Vectors and Their Use in Trade Studies.

experts are asked to estimate the probability of failure of their individual subsystems, it is appropriate to create a system-level FTA using the expert judgments as the subsystem probabilities. If subsystems experts are asked to rate individual subsystem risk either high or low it is useful to display the total number of high-rated subsystems versus low-rated subsystems. In the example, the expert judgment of system-level schedule uncertainty is simply the sum of each subsystem schedule uncertainty metric. Similarly, the system-level expert judgment of cost uncertainty is a summation of the individual subsystem cost uncertainty metrics.

Each risk method requires careful analysis to determine the best method to combine subsystem-level risk metrics into system-level risk metrics. FTA, expert opinion, and FMECA all have their own ways of combining subsystem-level risk metrics to the system-level. Other risk methods must be adapted in a similar fashion to report useful and meaningful information to the system-level risk vector. With the system-level risk vector prepared, the next step is to perform the trade study.

4.4.1.4 Trading Risk

Trading risk follows exactly the same procedures as trading any other system-level variable. The risk vector can be treated as either a set of design variables or as response variables. As a design variable the risk vector is able to be manipulated with the full gamut of design of experiments methods. The authors assert that as a response variable the risk vector acts as a bounding constraint. Further, the risk vector is able to be used in objective functions to drive the population of the trade space. In other words, it works exactly the same as any other system-level design variable.

In order for engineers to easily understand the risk vector, there are several ways to visualize the data that the vector contains. These methods allow for the risk vector to play an integral role in developing conceptual designs during manually conducted trade studies. Risk vector visualization information can be found in [83].

The system-level risk vector and its constituent parts are traded back and forth between subsystems for other system-level parameters. Risk can now be traded for mass, power, cost, or any number of important system-level variables.

4.5 Implementation in a CDC Environment

To demonstrate and test the risk trading methodology described in this paper, simplified spacecraft models and risk models detailed in the following section were implemented in a simulated CDC environment at the Complex Engineering Systems Design Laboratory at Oregon State University. Study participants traded risk both without and with the risk trading methodology. The results of the manually conducted trade studies demonstrate the usefulness of the risk trading to a CDC in creating and choosing conceptual designs.

4.5.1 An Illustrative Example of Trading Risk

In order to illustrate the risk trading methodology, a simplified spacecraft model based upon [90] and a manually conducted trade study are introduced in this section. The model was initially created without any risk methods or data. Four representative subsystems were chosen to represent the spacecraft including Communication, Data Handling, Attitude Control, and Power. Each subsystem model was programmed to have two user inputs and three function or component-driven outputs. The inputs were specific to each subsystem. They consisted of either a drop-down menu where several component options could be chosen or an input box where bounded numeric values could be input to drive function-based models.

Three outputs were chosen to represent spacecraft output data from the subsystems to replicate real-world CDC trade studies: Subsystem Power Requirements, Subsystem Mass, and Subsystem Cost. All values and variables including user-selectable inputs, internal variables, and outputs had their units intentionally removed. Additionally, all formulas and other numeric information were altered to only generally correspond to real-world spacecraft systems. This is exemplified by the subsystem cost parameter that generally ranged between a unitless value of 1 and 30. The models and results presented in this section are for demonstrative purposes only and should not be misconstrued as viable spacecraft models or conceptual designs.

4.5.2 Subsystem Development

To represent the spacecraft, four representative subsystems including Communication, Data Handling, Attitude Control, and Power were chosen. The *Communication Subsystem* is a function-based model that accepts user input for the Antenna Size and Frequency Downlink variables. Function-based subsystem models are function-driven over a range of numeric inputs while component-based subsystems have a predefined, limited selection of potential subsystem components. Antenna size can range from 1 to 4 and Frequency Downlink can range from 1 to 18, including decimal values. Both of the user input fields have corresponding instructions for the user to maintain input values between the allowable ranges. The Communication Subsystem *Power* requirements, *Mass*, and *Cost* output variables were computed using the formulas shown in Equations 4.4, 4.5, and 4.6, respectively.

$$\text{Power} = -\text{Antenna Size} + 0.6 \times \text{Frequency Downlink} + 3 \tag{4.4}$$

$$\text{Mass} = \text{Antenna Size} \times 2.5 + 2 \tag{4.5}$$

$$\text{Cost} = \text{Antenna Size} \times 0.75 + \text{Frequency Downlink} \times 0.1 \tag{4.6}$$

The *Data Handling Subsystem* is a component-based model that contains two user inputs in the form of drop-down selection boxes. The first user input, System Complexity, has the options of “simple,” “typical,” and “complex.” The other user input is Spacecraft Bus Configuration which allows the user to select either “one unit,” “two unit,” or “integrated” which refer to the spacecraft having one or two primary com-

Table 4.1: Data Handling Subsystem Input and Output Variables

Input Variables		Output Variables		
System Complex.	Bus Config.	Power	Mass	Cost
Simple	One Unit	7.5	4.8	0.9
Typical	One Unit	11.25	6.6	1.35
Complex	One Unit	15	12	1.8
Simple	Two Unit	11.25	3.6	1.575
Typical	Two Unit	16.875	4.95	2.3625
Complex	Two Unit	22.5	9	3.15
Simple	Integrated	6	2.8	1.35
Typical	Integrated	9	3.85	2.025
Complex	Integrated	12	7	2.7

Table 4.2: Attitude Control Subsystem Input and Output Variables

Input Variables		Output Variables		
Spin method	Pointing Method	Power	Mass	Cost
Gravity Grad.	Nadir Pointing	4.5	1.05	0.99
Gravity Grad.	Scanning	6	2.55	1.485
Gravity Grad.	Off-Nadir Point.	3	1.05	1.188
Spin	Nadir Pointing	9	4.2	3.3
Spin	Scanning	12	10.2	4.95
Spin	Off-Nadir Point.	6	4.2	3.96
3-Axis	Nadir Pointing	13.5	2.8	2.53
3-Axis	Scanning	18	6.8	3.795
3-Axis	Off-Nadir Point.	9	2.8	3.036

puting units and distributed subsystem computers, or an integrated unit that handles all command and data handling functionality. The resulting Data Handling subsystem outputs are shown in Table 4.1.

The *Attitude Control Subsystem* is a component-based model that gives the user control over two inputs via drop-down selection boxes. The inputs are "Stability Method" and "Pointing Method." Table 4.2 displays the full range of user-selectable components and the corresponding output variable values.

Table 4.3: Power Subsystem Input and Output Variables

Input Variables		Output Variables		
Power Source	Battery	Power	Mass	Cost
Photovoltaic	Primary Only	41.25	3.8	1.9
Photovoltaic	Prim. and Second.	70.125	7.6	3.8
Static	Prim. Only	27.5	6.65	20
Static	Prim. and Second.	46.75	13.3	40
Dynamic	Prim. Only	82.5	13.3	1.4
Dynamic	Prim. and Second.	140.25	26.6	2.8

Table 4.4: Payload Subsystem Input and Output Variables

	Navigation	Weather
Power	50	30
Mass	2	3
Cost	6	7

The *Power Subsystem* is driven by a component-based model that has two inputs, namely, "Power Source" and "Energy Source," which are controllable via drop-down selection boxes. Table 4.3 presents the range of possible user-selectable input variable combinations and their corresponding output variables. Unlike the other three subsystems, the Power output variable for the Power Subsystem indicates how much power is available to the entire spacecraft system from the power produced within the Power Subsystem.

In addition to the four participant-controlled subsystems, a *Payload Subsystem* was also developed from Wertz and Larson [90]. It is used only to set the mission objectives and requirements. The two possible payloads consist of a weather and navigation package. Only one payload package is selectable at any given time. The Payload Subsystem outputs power, mass, and cost variables. It also produces data on system constraints due to the payload. Table 4.4 presents the two payload choices and corresponding output data.

4.5.3 Subsystem Risk Models

For the illustrative example used in this paper, a dynamic FMEA was developed for each of the four user-operable subsystems. Each subsystem FMEA contained ten identified failure modes. The three component-based subsystem FMEAs were stepwise risk models. Individual failure modes were activated or deactivated based on what inputs had been selected. The function-based subsystem FMEA was a dynamic risk model. Failure mode RPN values dynamically varied based upon the user inputs. The subsystem FMEA Maximum RPN and Average RPN values changed as a result of changing the user input variables. The Power Subsystem FMEA, shown in Figure 4.2, is representative of the four user-operable subsystems.

A dynamic FTA was created at the system level that represents the four user-operable subsystems and representative sub-subsystems or components, as shown in Figure 4.3. The FTA uses OR gates at all levels of the tree. Sub-subsystem percentages are derived from subsystem input parameters. The percentages represent the chance of total system failure during the course of the system life.

4.5.4 Study Population

Two distinct populations participated in the research study: one group of graduate mechanical engineering students, and two groups of undergraduate junior and senior level mechanical engineering students at Oregon State University participated. Each graduate and undergraduate group consisting of four people. The graduate mechanical engineering student group consisted of four people specializing in areas related to complex design, conceptual design, and collaborative design including trade studies. All

Function	Failure Mode	Effects	S	Cause(s)	O	Current Controls	D	RPN	Power Source	Energy Storage
power provided	Power surge	end of mission	10	EMI	1	shielding	3	30	all	all
power provided	Failure of primary battery	end of mission	10	Radiation	2	shielding	5	0	all	primary battery only
power provided	Failure of secondary battery	degraded performance	10	Radiation	1	shielding	8	0	photovoltaic	primary and secondary
power provided	Failure of power cable	degraded performance	7	Micro meteor	3	redundant cable	5	0	simple	all
power provided	Loss of solar panel	degraded performance	10	Meteor	1		5	0	photovoltaic	all
power provided	Short circuit	degraded performance	4	Johnny 5	2	Nova Laboratories	4	32	all	all
power provided	Failed-open breaker	degraded performance	10	EMI	3		10	300	static, dynamic	all
power provided	Faded out solar array	degraded performance	3	Space dust on panels	3		6	0	photovoltaic	all
power provided	Premature fuel exhaustion	end of mission	10	Micro meteor	1	shielding	4	40	dynamic	all
power provided	Cooling loop failure	end of mission	10	Micro meteor	1	shielding	5	0	static	all

Total RPNS	MAX RPN	Average RPN
4	300	100.5

Figure 4.2: Power Subsystem FMEA

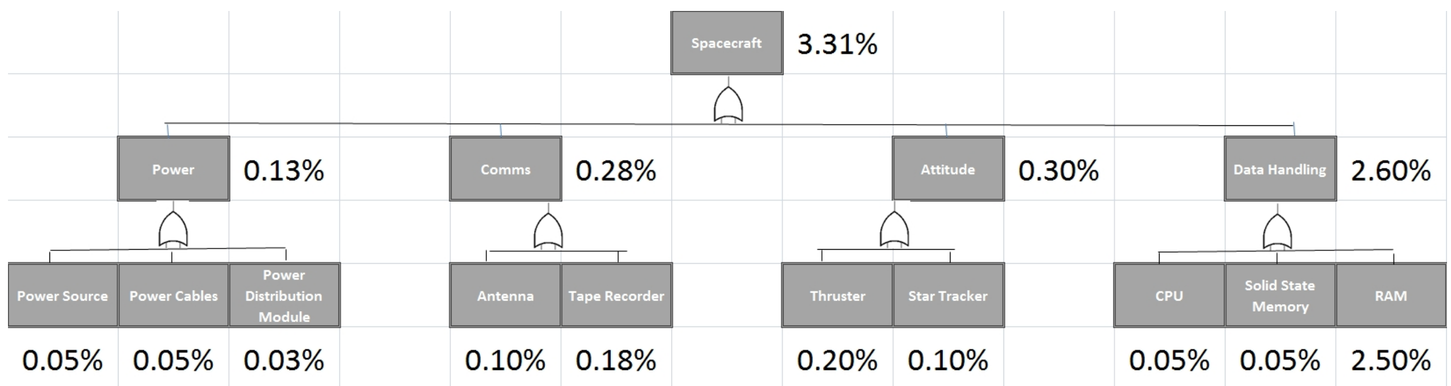

Figure 4.3: System-Level FTA

had experience with CDC environments, and were familiar with the general concepts of trade studies. All four participants have taken graduate level coursework at Oregon State University in state-of-the-art risk and model-based design methods. Two of the participants had previously interned with NASA, and hence also possessed general knowledge of conceptual satellite design. This group of participants can be viewed as an experienced user group. A analogous group of people in an established CDC would be people with some experience within the CDC.

Two groups of undergraduate mechanical engineering students participated in the experiment. Each group of four was a mix of junior-level and senior-level students who had satisfactorily completed junior level design courses that contained material on the mechanical design process, and had a collaborative design project. The undergraduate mechanical engineers did not have prior knowledge of trade studies. This group of participants can be considered a general user group. A similar group in a CDC might be engineers and scientists who are just being introduced to the CDC.

All study participants were recruited through classroom and professional society email lists. Students were compensated $40 for their participation. Informed consent was obtained from all participants. Each experimental run lasted approximately three hours including pre-participation screening, obtaining informed consent, acquainting participants with the software and hardware configuration, and performing the experiments.

4.5.5 Mission Scenarios

Two mission scenarios were used for the three phases of the experiment including a weather satellite and a navigation satellite. The missions were both earth-orbiting

Table 4.5: Mission Constraints

	Weather	Navigation
Energy Storage:	Primary and Secondary Battery	N/A
Power Source:	N/A	Photovoltaic
Spacecraft Bus:	2 Unit	N/A
Stability Method:	N/A	N/A
Required Processing:	105	140
Maximum Mass:	27	45
Maximum Cost:	15	15

satellites that consisted of a series of design constraints and requirements. All constraints, requirements, and mission data were based upon information from [90] but were intentionally modified so that information used in this experiment did not closely resemble real-world or proposed conceptual satellite design information.

Both missions contained payload power, mass, and cost output variable data. Constraints placed upon subsystem design decisions were also provided. Table 4.5 details the payload requirements and design constraints of each mission.

In addition to payload output variables and subsystem design constraints, each mission also demanded that cost and mass be minimized while also assuring that a positive power balance was achieved. Additional general information about the function of a particular payload was provided to several groups who requested more details on the purpose of the mission and its scientific goals. The problem statements given to the participants can be seen in Appendix A.

4.5.6 Questionnaires, Work Products, Discussions

To gather information on participants' opinions of and interactions with the risk trading method, four methods of data collection were used during the experiments. One method which was invisible to the participants was subsystem and system-level passively collected data from ModelCenter. The other three methods including work products, questionnaires, and group discussions required user input and interaction. At the end of each trade study session, the participants were asked to fill out a "System Design Report" document. The document asked the participants to write down all design decisions they made, the rationale behind those design decisions, and any comments that they had about the session. Participants were instructed to concentrate on their own individual subsystems but also record pertinent information on decisions and rationale of other subsystems with which they interacted. Following the completion of the System Design Report, a questionnaire was administered to the participants and a group discussion was held. Questionnaire questions are available in Appendix B. Group discussion questions are available in Appendix C. The work product template is available in Appendix D.

4.6 CDC Implementation Results

While the number of participants does not lend itself to statistically significant results, several anecdotal insights can be drawn from the experiments. Both the graduate and undergraduate research populations generally preferred conducting trade studies using the risk trading methodology. For instance, one participant stated "I liked the risk trading method" while another stated "the resulting design is more complete when using the risk trading method." In addition, many participants found the results of trade studies that included risk as a system-level parameter made them more confident that the end result of the trade study being of the highest possible utility. For instance, one participant stated "I am more confident in conceptual designs created using the risk trading method." Rather than implicit assumptions and no real conversation taking place about the risk of various subsystem choices, both participant populations openly discussed the risks in the design and negotiated to determine the optimum trade-off point between mass, power, cost, and risk. Appendixes E and F provide additional relevant participant questionnaire and group discussion responses respectively.

Many of the participants indicated that they would be more comfortable showing the result of a trade study with risk as a system-level variable to their boss or a client than showing a trade study result that had not considered risk. For instance, three participants stated "I would be more comfortable to show my boss the conceptual design created using the risk trading method." One participant reported that including the risk models gave him more confidence that the subsystem models were more complete and that the resulting designs would be more in line with the desired risk propensity of the organization or individual that had commissioned the study.

The results were presented in various forms. Numeric and dynamic FTA displays of system-level risk information were found to be the most preferred representations of risk for both groups of participants. Glyph plots and parallel axis plots were identified as less useful. The participants believed that with more training, glyph plots and parallel axis plots could be an interesting addition to help understand risk and other multi-dimensional data. However, especially amongst the undergraduate participants, glyph and parallel axis plots were found to be difficult to understand. Further information about the various display techniques can be found in [83].

As compared to the risk-less portion of the study, the participants took 10 minutes or about 30% longer to complete the trade study with risk trading. The graduate student participants identified trading risk variables as a factor in the extra time required to finish the study. However, the graduate students also pointed toward risk trading as the motivator and inspiration for their creative solution to the over-constrained problem. The undergraduates felt the need to understand how each piece of risk data was derived and how it affected the overall risk profile of the system and subsystems. There was much questioning of how risk model numbers were derived and if they were realistic or not. In an effort to understand the risk models more fully, the undergraduate participants left their individual stations, a rare occurrence in previous sessions, and investigated how all of the subsystem models worked to gain a better overall understanding of the way the models interacted with one another. Had the undergraduates not required such a detailed understanding of the models, the trade study would have concluded more quickly. However, the undergraduate participants felt that the time spent understanding the risk models was well-spent and helped them to produce a result that was more confidence-inspiring. Likewise, in spite of the extra time required to complete the trade study and extra mental effort needed to understand the methodology, the graduate student participants had a strong preference for conducting trade studies using risk as a tradeable system-level parameter.

While the risk trading method presented in this paper was tested on teams of undergraduate and graduate students in a simulated CDC environment, it has not yet been tested in a production-level CDC. In order to test new trade study methods in well-respected CDCs that are open to being used as test cases, the time of the CDC must be purchased. In the case of Team X, this amounts to many tens of thousands of dollars for a single trade study. This is an ongoing challenge for researchers developing new methods for CDCs.

One of the goals of this method was to create conceptual designs that are of higher utility as partially defined by risk metrics than when not using the risk trading methodology. This goal was met when the final spacecraft models selected by the experiment participants using the risk trading method as having the highest utility were different and of higher utility than the highest utility models generated without using the risk trading method. This mirrors the results found in [83]. When the risk trading methodology is used, designs with higher utility as partially defined by risk metrics can be found. The other central goal of the method is to explicitly trade risk at the subsystem level and give the power to analyze subsystem risk to the subsystem chairs during the creation of conceptual designs in trade studies. The trade study experiments clearly demonstrated that subsystem chairs do explicitly trade based upon risk metrics in order to maximize system utility. From anecdotally observing the trade study sessions, the authors additionally feel that in this limited test case, a balance was struck between the risk metrics and other important system-level parameters such as cost, mass, and power.

4.7 Discussion and Specific Contributions

This paper presents a risk trading method that allows for new design selection preferences to be created that otherwise would not be available to design engineers. Using $\overrightarrow{Risk}$ as a tradeable design variable enables engineers to find designs with higher utility as partially defined by risk metrics than if risk was ignored. This elevates risk to the same level as other important system-level variables rather than having risk considered as an afterthought to creating conceptual designs. It is therefore desirable to include $\overrightarrow{Risk}$ in trade studies.

Risk methods such as FMECA, FTA, and expert judgment can be used with the risk trading method. When developing FMECA, FTA, or similar numeric models for use with the risk trading method, one can base risk calculations on variables. This is used on most of the risk models embedded in the simplified spacecraft example used in this research. When accurate, dynamic risk models can be very beneficial to help shape conversations in CDC environments during trade study sessions.

Participants in trade studies generally indicated their preference of using the risk trading methodology over not considering risk during the trade study process. They found that the risk trading methodology inspired greater confidence in the end product of the trade study. Additionally several stated that they would be more comfortable with showing superiors results produced using the risk trading methodology. Several participants went so far as to state that the extra time and extra mental effort imposed by the learning curve in implementing the risk trading methodology was outweighed by the benefits of the methodology.

One major drawback to this method is the level of training and coordination required for subsystems engineers to generate useful risk data. All of the people involved in generating risk data to be used in a trade study must speak the same risk language. If one person produces data under a different set of assumptions, different definitions, or using different methods, $\overrightarrow{Risk}$ becomes an invalid parameter for multi-attribute decision making when setting design preferences and for trading parameters during the design process. However, bringing an entire CDC team up to speed and teaching everyone how to speak the same risk language can add great value.

One potential solution to address differences in the understanding of risk between different people is to introduce a normalized risk vector. This could take several forms including but not limited to the following. Normalization of the risk vector can occur by normalizing the risk metrics that comprise the risk vector to present all components of the risk vector on the same scale. Risk data being produced and consumed by individual subsystems engineers can be normalized to each person's individual risk profile. Doing this will allow people to produce and consume risk information naturally and without having to conform to risk concepts that might not hold significant meaning to some individuals.

Another potential drawback of this method is the lack of subsystems interaction effects in risk models. No way of effectively capturing risks of emergent behaviors is provided. This is an area that must be developed further in the future for this method to more comprehensively capture risk in the early stages of conceptual design. One potential method of addressing subsystem interaction effects is to use geometric proximity models to model spurious energy, mass, and signal propagation between disconnected subsystems [67].

4.8 Conclusion and Future Work

In typical complex system design trade studies, risk does not explicitly play a role in the creation and selection of conceptual designs. It is only assessed after a conceptual design has been created. This research presents a method of explicitly trading, and evaluating designs based upon risk in design trade studies among subsystems with the goal of maximizing system utility and system integrity.

The method presented in this paper details a novel way to assess risk and make decisions based on risk in the complex conceptual design process. Risk is treated as a vector with multiple components defined by the requirements of the system. The risk vector is traded in design trade studies. Based upon the desired level of risk for a system, specific point designs or portions of the design space can be identified for further study and development. Risk has traditionally been treated as an afterthought or completely ignored in the conceptual complex system design process. By moving risk into trade studies and giving it a place among other important more traditional system-level variables such as power, mass, etc., conceptual designs will be explicitly created and selected based on risk metrics.

Future work includes developing methods to efficiently and effectively generate subsystem risk models. The models must be matched between subsystems in order to ensure a fair comparison of risk vectors across subsystems. An effective method of normalizing and harmonizing individual subsystem chair interpretations of risk is also needed.

Trading risk in early conceptual complex system design holds great promise. This paper aims to start a larger effort to set risk in line with system-level design parameters. Specifically, a method to include risk in trade studies was developed and implemented in a mock CDC using a simple example to show the utility of the method in practice.

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4.9 Appendix A: Problem Statements

The riskless trade study session used a simple navigation satellite problem. The problem statement is as follows:

This satellite is designed as a navigation satellite to add to the GPS network allowing GPS units to acquire more accurate data on Earth. It carries equipment on board to support its mission. Because of this, the following constraints are given for the mission:

POWER SUBSYSTEM Power Source: photovoltaic

COMMUNICATIONS SUBSYSTEM: Frequency downlink: 18

DATA HANDLING SUBSYSTEM: Required processing: 110

TOTAL SPACECRAFT: Maximum mass: 30 Maximum cost: 18

The trade study session conducted using the risk trading methodology used a simple weather satellite problem. The problem statement is as follows:

This satellite is designed as a weather satellite to monitor the climate on Earth and carries equipment on board to support its mission. Because of this the following constraints are given for this mission:

POWER SUBSYSTEM Energy Storage: primary and secondary battery

DATA HANDLING SUBSYSTEM: Spacecraft bus: 2 units Required processing: 105

TOTAL SPACECRAFT: Maximum mass: 27 Maximum cost: 17

4.10 Appendix B: Questionnaire Questions

Following each trade study session, participants were asked to fill out a questionnaire individually. The following questions were common to both trade studies.

- Rank the ease of use of each subsystem model on an Easy (1) to Hard (5) scale:
  - Attitude control
  - Data handling

  - Power
  - Communications
- Indicate the ease of use of the two types of subsystem models on an Easy (1) to Hard (5) scale:
  - Component-based
  - Function-based

Additional questionnaire questions were tailored to the risk-trading session including:

- Describe any difficulties you encountered while understanding and using the subsystem risk models
- How did you find the transition from conducting trade studies without risk models to trade studies with risk models on an Easy (1) to Hard (5) scale?
- Indicate which set of models produced results in which you feel more confident on a Confident in no-risk model results (1) to confident in models with risk results (5) scale
- Indicate the ease of understanding risk data for each risk visualization technique on an Easy (1) to Hard (5) scale:
  - Fever charts
  - Glyph plots
  - Parallel axis
  - Numeric data

  - Dynamic fault tree

- Is there anything that should have been done differently when transitioning from trade study models not containing risk information to trade study models with components?

- Do you have any additional comments about the study or anything else you wish to convey to the researchers?

4.11 Appendix C: Group Discussion Questions

Group discussion followed completion of the System Design Report and the questionnaire in both trade study sessions. The following questions were repeated at the end of both sessions:

- Were any of the subsystem models hard to understand and use? Were any particularly easy?

- Did you prefer component-based or function-based subsystem models?

The following questions were used in the group discussion only for the second trade study:

- Did you encounter any difficulties using subsystem models with risk data?

- Were you able to understand the graphical representations of risk? Which did you prefer? (Glyph plot, fever chart, parallel axis plot, dynamic fault tree)

- Is there anything that should have been done differently when transitioning from trade study models not containing risk information to trade study models with risk components?
- Do you have any additional comments about the study or anything else you wish to convey to the researchers?

4.12 Appendix D: Work Product Template

At the end of both trade study sessions, participants completed brief reports about the work that they had just completed. The following free entry form was provided to the participants:

- Subsystem:
- Design Decisions:
- Rationale:
- Comments:

Most participants wrote a paragraph or more for each of the last three questions.

4.13 Appendix E: Questionnaire Results

Relevant questionnaire responses are aggregated in this appendix. Identifying information has been removed and data has been anonymized.

Describe any difficulties you encountered while understanding and using subsystem risk models

- The risk models were extremely helpful and intuitive.
- The risk models were easy to understand but mitigating design problems was difficult.
- The only challenge was to observe how design changes propagated through the subsystem and system models.

How did you find the transition from conducting trade studies without risk models to trade studies with risk models

- Risk is just one more thing to analyze. Engineers should already be doing this.
- Trading risk was straight forward.
- The risk trading method provided more perspective and helps me to feel confident in the final design.
- Risk adds another variable for consideration that can make it more difficult to find a satisfactory solution.
- The risk method is more all-encompassing.
- Risk adds another parameter and is not hard to deal with.

Indicate which set of models produced results in which you feel more confident

- Knowing that design decisions are backed by the science of risk methods such as FMEA makes me very confident in our design choices.

Is there anything that should have been done differently when transitioning from trade study models not containing risk information to trade study models with risk components?

- No.
- The brief training was straight-forward.
- The transition was straight-forward.
- A better understanding of the trade-offs between risk metrics and other system variables would be useful.

Do you have any additional comments about the study or anything else you wish to convey to the researchers?

- The risk trading method and dynamic FMEA model are big improvements over existing methods. The method provides for another layer of reliability in the design.

4.14 Appendix F: Group Discussion Results

Relevant group discussion responses are aggregated in this appendix. Identifying information has been removed and data has been anonymized.

- Using the risk trading method was not harder than not using the method.
- I liked the risk trading method. It validates that there is more to the model.
- The resulting design is more complete when using the risk trading method. The resulting design is safer.
- The risk trading method was as easy to use as standard trade study methods. It was more complex but not more difficult.

- I would be more comfortable to show my boss the conceptual design created using the risk trading method. (three participants stated this)
- Using the risk trading method helped me to make design decisions more comfortably.
- It makes sense from an engineering perspective that there is a trade-off between traditional variables such as power, mass, and cost, and engineering risk metrics.
- I am more confident in conceptual designs created using the risk trading method.
- I prefer using the risk trading method over not using the method.

Chapter 5 –On Measuring Engineering Risk Attitudes

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5.1 Abstract

Theories of rational decision making hold that decision makers should select the best alternative from the available choices, but it is now well known that decision makers employ heuristics and are subject to a set of psychological biases. Risk aversion or risk seeking attitude has a framing effect and can bias the decision maker towards inaction or action. Understanding decision-makers' attitudes to risk is thus integral to understanding how they make decisions and psychological biases that might be at play. This paper presents the development of the *E*ngineering-*Do*main-*Sp*ecific *R*isk-*T*aking (E-DOSPERT) test to measure the risk aversion and risk seeking attitude that engineers have in five domains of engineering risk appetite identified during the course of this research including: Processes, Procedures, and Practices; Engineering Ethics; Training; Product Functionality and Design; and Legal Issues. The iterative creation of the instrument, an analysis of its reliability based on surveying engineering students in Australia and the United States, and the validity of the five identified domains are discussed. The instrument is found to be statistically reliable to measure engineering risk aversion and risk seeking in the Processes, Procedures, and Practices; and Engineering Ethics domains. Factor analysis strongly points toward the other four sub-domains being present. This paper closes with discussion of potential applications and uses for the E-DOSPERT scale.

5.2 Introduction

Risk is an integral part of engineering design. Risk propensity is often considered an essential ingredient for innovative design, perhaps best exemplified in the IDEO motto

"Fail often to succeed sooner," implying a willingness to take the risk to allow a product concept to fail to enable learning. On the other hand, risk aversion pervades certain industries, such as power generation and aerospace. There is no one correct level of attitude to risk across all engineering sectors; rather, risk is a factor that must be managed in order for an organization to reach its objectives. Research by Van Bossuyt et al. in risk trading in engineering design has shown that what one engineer thinks is 'risky', another engineer may not [83].

Within engineering design, there is no shortage of methods to identify the risk of failure of components [84]. At the organizational level, standards such as ISO 31000:2009 [57] prescribe a framework for organizations to manage risk. The standard usefully identifies four aspects to risk management: risk identification, risk analysis, risk evaluation, and risk treatment. While the standard prescribes effective principles and guidelines for organizations to establish risk management policies and procedures, it, like formal engineering risk analysis methods, falls short in the assessment of organizational and personal *attitudes* to engineering risk.

This paper presents the E-DOSPERT test, which is designed to assess engineering risk attitude, an engineer's mental response to the perception of uncertainty of objectives that matter [60]. The E-DOSPERT test is modeled after the DOSPERT test [40, 47] and was originally based upon principles and guidelines in the ISO 31000:2009 standard on risk management [57, 85]. The DOSPERT test is quickly becoming the most preferred risk attitude scale in psychology for its predictive abilities and ability to show whether observed risk behavior is based upon the person's perception of risk or the person's attitude toward the perceived risk. The DOSPERT test has demonstrated both a high level of reliability and construct validity. ISO 31000:2009 is the International Organization for Standards risk management principles and guidelines standard. The standard systematically lays out the principles behind risk management and outlines guidelines for risk management practitioners to follow.

Understanding the risk attitudes of engineers is useful for several reasons. By understanding the risk attitudes of engineers, training can be conducted to harmonize an engineer's professional perception of risk – subjective judgment of the severity and characteristics of a risk – and risk appetite – the amount of risk that is willingly taken on in order to realize a gain – with the company's risk perception and risk appetite. In systems engineering, understanding individual engineers' risk perception and appetite holds the promise of helping engineers to collaborate more effectively and deliver a higher utility product with a lower development cost and shorter development time [86]. Risk and reliability engineers stand to benefit from knowing their risk attitude. Expert judgment is directly affected by how engineers perceive risk and their risk appetites. By understanding individual risk perceptions and appetites, risk experts can explicitly normalize their expert opinions with peers [83]. The theory of decision-based design has already shown that decision makers are subject to a set of psychological biases, one of which is a framing effect [75]. If outcomes are framed in terms of gains, people tend to be risk averse; conversely, when outcomes are framed in terms of losses, people tend to be risk seeking. Thus, how engineering data is merely presented can bias decision makers, irrespective of the data presented. Work has already been done in the field of decision support using utility theory risk curves to augment engineering decision-making based upon risk information [89], and a preliminary version of the E-DOSPERT test was published in the proceedings of the IDETC/CIE211 [85].

For these reasons, the authors developed an instrument to assess engineering risk attitude with the aim that such an instrument can become a standard for the assessment of engineering risk attitudes. The following sections present necessary background material on the DOSPERT test and related psychology of risk research, and on risk in engineering. A methodology for the creation of the E-DOSPERT scale is presented. Testing and validation results are then discussed. This paper concludes with discussion of future work and implications of the E-DOSPERT scale.

5.3 Background

Risk can be defined in a variety of ways. Alternative definitions of risk and how those definitions relate to methods for assessing risk attitudes are briefly examined in the following section.

5.3.1 The Psychology of Risk Attitude

The 'classic' definition of risk is the parameter that differentiates between the utility functions of different individuals [28]. The utility function of individuals is often expressed as an exponential, quadratic, or logaritmic curve [29, 28, 76]. The EU hypothesis theorizes that the preference of an individual choosing between risky options can be determined by a function of the return of each option, the probability of that option coming to fruition, and the individual's risk aversion [30]. The EU framework and related methods including prospect theory [31] traditionally view the curves of an individual's utility function as denoting either risk aversion or risk seeking. The definition of risk aversion in the context of risk attitudes is framed in the context of someone who prefers to take the expected value of a gamble over playing the gamble as being a person who does not like to take risks [32]. As a result, risk attitude can be defined as a person's position on the risk aversion-risk seeking axis and is thought of as a personality trait. Hillson and Murray-Webster [60] further refine this risk aversion-risk seeking scale by inserting a mid-point "risk tolerant" as being comfortable with uncertainty and able to handle the uncertainty if necessary and by including "risk neutral" as taking necessary short-term actions to deliver certain long-term outcomes.

However, two issues have arisen that challenge the idea of risk attitudes in the context of EU being a personality trait: cross-method utility instability and inconsistent risk profiles across risk domains. When different methods are employed to measure people's utility, different classifications of risk-taking or risk aversion often result [33]. Further, individual respondents are not consistently risk averse or risk seeking across different risk domains [34]. For example, managers have been found to have different risk attitudes when evaluating financial and recreational risks, and when using company money versus personal money [49].

The concept of relative risk attitude was introduced in an attempt to identify the component of risk-taking that has cross-situational stability for individuals [121]. The hypothesis was that the domain differences in apparent risk attitudes might be as a result of domain-specific outcome marginal values. With the marginal values factored out, stability across domains was expected. However, this was not the case under further review. No evidence was found of cross-situational relative risk attitude stability in empirical studies [38].

The validity of EU-based risk attitude assessment is limited due to these issues. There has been little success in predicting individuals' choices and behaviors in domains not assessed by EU-based instruments [35]. Even with the limitations of EU-based survey instruments, many are still in use. For instance, the Choice Dilemma scale combines four different domains into one risk attitude score [36]. In spite of its flaws, the scale is widely used.

A more recent method of determining risk attitude takes inspiration from the world of finance [37]. The risk-return framework of risky choice assumes people's preferences for risky options reflects a trade-off between riskiness of a choice and the EV. The financial world equates riskiness of an option with its variance. In psychology risk-return models, perceived riskiness is treated as a variable that can be different between individuals due to differences in individuals' content and context interpretations [38, 39].

The risk-return framework allows for people to have similar perceptions of risk and return between different domains but in one domain prefer risk while in another prefer caution [40]. Having such preferences and perceptions would result in different outcomes, as the risk-return framework predicts. The term *perceived risk attitude*, previously conceptualized as risk-repugnance [41], was coined to reflect the assumption that risk in its pure form is negative and undesirable but that perceived risk might be attractive to some individuals in certain domains and circumstances [42]. Variances in perceived risk attitude are thus a result of discrepancies between the perception of the risks and benefits as determined by a decision-maker and an outside observer. This is exemplified in research conducted in the management field where what differentiates between entrepreneurs and managers is a highly optimistic perception of risk on the part of the entrepreneurs rather than a greater preference for risk, as one might expect [43].

Many studies have highlighted differences in the perception of the riskiness of decisions in individuals, between groups, and between cultures [44, 45]. Differences in risk perception have also been found due to outcome framing [46]. In the context of risk-return based models, perceived risk attitude has been found to have cross-situation and cross-group consistency when differences in the perception of riskiness are factored out [39, 40]. Rather than differences in risk attitude, risk-return models suggest that the way people perceive risk affects the choice outcomes.

In summary, risk attitudes vary by domain, so the attitude to taking risks at work may differ from the attitude to taking risks at home. One may enjoy taking risks in leisure activities, but be risk averse in handling of financial affairs. To assess risk perceptions and attitude toward perceived risk in different domains of risk, Weber et al. developed the DOSPERT test and related scale [40, 47]. Six independent domains were identified including ethical, investment, gambling, health/safety, recreational, and social domains. Four of the domains were originally identified based upon the risk-taking behavior literature [48] while the fifth and sixth domains were found through analysis of survey results where the financial meta-domain was split into investment and gambling domains [40], which were suggested in previous research [49, 50]. Risk-taking was found to be highly domain-specific between the identified domains where individual respondents were risk averse in some domains and risk-neutral or risk seeking in others. Respondents were found to not be consistently risk averse or risk seeking across the six domains.

It was also found that preference for risk seeking or risk aversion was influenced by the perceived benefits and risks of the activity in question. This resulted in identifying two psychological variables including risk perception and attitude toward perceived risk, as had been found in previous risk-return based models [43]. Previous risk attitude indexes have been confounded by not distinguishing between the two psychological variables of risk perception and attitude toward perceived risk [51]. Distinguishing between the risk perception and risk attitude variables is largely irrelevant if only prediction of future actions is desired. However, the distinction between these variables becomes important when risk-taking is assessed with the goal of changing risk-taking behavior [40].

Since the DOSPERT scale was developed and validated, many other studies have replicated the results. Strong correlation was found with the various subscales of Bunder's scale for intolerance [52] and with Zuckerman's sensation-seeking scale [53]. Paulhus' social desirability scale [54] was found to have significant correlation between the impression management subscale and the ethics and health/safety subscales of DOSPERT. Thus, the DOSPERT scale was found to have favorable correlations with established scales. The DOSPERT scale has also been translated into several different languages and contexts including the DOSPERT-G scale, a German-language version [55], a French-language DOSPERT scale [56], and others [47]. Other scales developed since DOSPERT was introduced have not found widespread adoption. The DOSPERT scale is quickly becoming the most preferred risk attitude scale in psychology for its predictive abilities and its ability to show whether observed risk behavior is based upon the person's perception of risk or the person's attitude toward the perceived risk, which allows for intervention and behavior modification.

5.3.2 An Engineering Definition of Risk Attitude

The definition and application of risk in engineering is more straight-forward than in psychology. The ISO 31000:2009 document [57] defines risk as the effect of uncertainty on objectives. An effect is a positive or negative deviation from the expected. Objectives are defined as having different aspects such as environmental, health and safety, and financial goals, and can be applied at different levels of a project or organization. The ISO 31000:2009 definition of risk is further defined as the probability of occurrence of an event multiplied by the severity of the consequences. It should be noted that uncertainty is often defined as a lack of knowledge about system specifications, and errors resulting from imperfect models [58]. Some researchers further break down uncertainty into multiple subcategories that often contain elements of risk, reliability, and robustness [59]. For the purposes of this research, the ISO 31000:2009 definition of risk shall be used in the context of engineering.

If this is used as the operating definition of risk, then risk attitude in engineering is the 'state of mind' of the engineer in response to the perception of uncertainty on objectives [60]. The engineer's attitude will influence actions, or inactions, taken. The behavior an engineer takes toward risk can be to retain, pursue, take, or turn away from that risk. In other words, when presented with a situation, it is important to determine how the engineer's risk attitude will influence behavior.

To assess this behavior, the ISO 31000:2009 document for the standard of risk management was applied as the initial basis for assessing behavior toward risk management, that is, the engineer's attitude to perceived risk and, simply, 'what they would do'. The ISO 31000:2009 document [57] prescribes four key factors in risk management: risk identification, risk analysis, risk evaluation, and risk treatment. Risk Identification is defined as the process of finding, recognizing, and describing risks. Risk Analysis is the process of comprehending the nature of a risk and determining the associated level of risk. Risk Evaluation is the process of comparing the results of risk analysis with the significance of the risk as compared to a reference risk scale. Risk Treatment is the process of dealing with a risk [57]. Each of these aspects of risk management may also be considered theoretical risk domains because they cover the range of conditions associated with increased probability of outcomes that compromise the certainty of objectives. Each domain has a direct effect on risk behavior and is a separate source for risk.

5.4 Hypotheses and Scale Development

Five objectives of the research are presented in this section. Six supporting hypotheses are developed from the five objectives and methods of testing the hypotheses are outlined. Confirmation of the hypotheses using E-DOSPERT test results is briefly discussed.

5.4.1 Objective 1

The first objective of this research was to determine if engineering risk appetite can be assessed on a risk tolerant/risk averse scale. Research in the psychology domain shows that the general public holds six risk sub-domains that can be placed on risk tolerant/risk averse scales [48, 40, 47]. While the standard practice of reliability engineering is to use the expected value theorem which dictates a risk-neutral approach, based upon utility theory and lottery method research [31, 76, 75, 73, 88, 89] it was hypothesized that engineers will have risk appetites specific to the engineering risk domain that are not risk neutral.

Hypothesis 1 *Engineers have risk appetites specific to the engineering risk domain and do not follow the expected value theorem.*

In order to test this hypothesis and others detailed below, the E-DOSPERT, a psychological survey, was developed, as outlined in Section 5.5, based upon the ISO

31000:2009 document's four key factors in risk management. The result of the analysis, presented in Section 5.5.3, demonstrate that engineers do have engineering-specific risk appetites that do not follow the expected value theorem.

5.4.2 Objective 2

The second objective of this research was to determine if the four key factors in risk management described by ISO 31000:2009 are the four sub-domains of engineering risk appetite. It was hypothesized that engineering risk appetite will have four sub-domains of risk including risk identification, risk analysis, risk evaluation, and risk treatment as defined in ISO 31000:2009 and further that engineers will have a different attitude toward risk depending upon the particular aspect of the engineering risk sub-domain. That is, each of these aspects is a separate content domain in the language of the psychology of risk.

Hypothesis 2 *Engineering risk appetite contains four sub-domains of risk including risk identification, risk analysis, risk evaluation, and risk treatment as defined by ISO 31000:2009.*

Hypothesis 3 *Engineers have different attitudes toward different risk sub-domains.*

The initial version of the E-DOSPERT used to test Hypothesis 1 was designed to also provide data to test Hypotheses 2 and 3. The result of the analysis, presented in Section 5.5.4 and in a prior conference paper [85], show that risk identification and risk treatment are present as sub-domains. However, further factor analysis presented a different interpretation of the data which shows the potential for a related four factor scale including engineering practice and processes, product functionality, legal matters, and engineering ethics. These potential sub-domains and two others were then explored in a second survey that is detailed in Section 5.6.

5.4.3 Objective 3

The third objective of this research was to determine if there are any major differences in engineering risk appetites between engineering students in Australia and the United States of America. It was hypothesized that there would be no major difference in engineering risk appetite between Australian and American engineering students.

Hypothesis 4 *There are no major differences in engineering risk appetite between Australian and American engineering students.*

Hypothesis 4 was tested by analyzing the results of the E-DOSPERT survey developed for the first two hypotheses. The survey data was collected from mechanical, industrial, and manufacturing engineering students at Oregon State University and students enrolled in a mechatronics program at the University of Sydney. The analysis shows that there are no significant differences between American and Australian engineering students.

5.4.4 Objective 4

The fourth objective of this research was to determine if engineering risk appetite can be measured on a unidimensional scale. The scale was expected to run from risk averse to risk seeking as is the case in the DOSPERT scale [40, 47]. It was hypothesized that respondents would answer inversely worded paired questions consistently.

Hypothesis 5 *Engineering risk appetite can be measured on a unidimensional scale (risk averse to risk seeking).*

In order to test Hypothesis 5, the initial version of the E-DOSPERT was designed to contain paired inversely worded questions. A total of 25 questions were intentionally inversely phrased. Based upon sufficiently high Cronbach's Alpha scores, the authors found that engineering risk appetite sub-domains are unidimensional. This mirrored the findings of the DOSPERT test [40, 47].

5.4.5 Objective 5

The fifth objective of this research was to determine if the potential engineering risk appetite sub-domains identified as part of the analysis of the second objective results are the true sub-domains present. It was hypothesized that the four potential domains identified as part of the second objective including practice and processes, product functionality; legal matters; and engineering ethics as well as two additional potential sub-domains including product testing, and training are present.

Hypothesis 6 *Six engineering risk appetite sub-domains exist including: practice and processes, product functionality; legal matters; engineering ethics; product testing; and training.*

Questions from the initial version of the E-DOSPERT that loaded heavily onto the four predicted domains were used in the second iteration of the test while additional questions were generated to test all six predicted sub-domains. The survey data analysis indicates that there are only five sub-domains present including the majority that were predicted. However, other domains appear to be present that were not initially anticipated. The five sub-domains identified through analysis include: Processes, Procedures, and Practices; Engineering Ethics; Training; Product Functionality and Design; and Legal Issues.

In the remainder of the paper, the iterative development of the E-DOSPERT test, statistical analysis of initial and revised survey data to test the reliability of the instrument and the validity of above hypotheses will be presented. The paper closes with a discussion of the significance of the research findings, implications for practitioners, and current and future research on this topic.

5.5 Initial E-DOSPERT Scale Development

In order to predict the behavior of engineers in their professional capacity and in order to change the risk-taking behavior of engineers within the field of engineering, a purpose-built scale must be constructed. This section documents the construction of a new risk scale specific to professional engineering, the E-DOSPERT scale, including respondent consistency tests using replicated and paired questions and reliability based on values of Cronbach's alpha. Cronbach's alpha is a measure of internal consistency of a set of related questions [122]. The authors conducted an exploratory factor analysis to determine whether the four domains identified from the ISO31000:2009 document underlie the risk behavior judgments (Hypothesis 2), to determine if engineers have engineering-specific risk appetites that vary from the expected value theorem (Hypothesis 1) and between sub-domains (Hypothesis 3), and to determine if engineering students in Australia and America have similar engineering risk appetites (Hypothesis 4). Further analysis was conducted to determine if engineering risk appetite sub-scales are unidimensional (Hypothesis 5).

5.5.1 Initial Scale Development Method

Risk judgment questions were developed for each of the domains including risk identification, risk analysis, risk evaluation, and risk treatment, based upon common professional mechanical and manufacturing engineering-related situations involving risk. Usefully, the ISO 31000:2009 document provides descriptions of the types of activities that should be undertaken in an effective framework for risk management. Recommended activities associated with risk management become the basis for creating scenarios (items) in the E-DOSPERT test to assess how engineers would respond to them. Their risk judgments toward risk management activities are influenced by their risk attitude. For example, the engineer may have a process to identify risks by having a process in place to record all failure data for a component in a system. In order to estimate the likelihood of occurrence of an event, an engineer might trust informed estimation. In evaluating the risk based on this estimation, the engineer might place more weight on a regularly occurring fault than one that may never occur. To treat the risk, the engineer may operate the associated machinery far below the limits of safety.

The authors developed survey questions (items) by following the ISO 31000:2009 definitions of the four aspects of risk management and associated recommended activities. The items present respondents with typical scenarios or tasks they would encounter in dealing with each of these aspects. Each aspect and associated questions are briefly described.

The risk identification portion of the standard recommends comprehensive identification of risks. The identification of risks entails generating the set of events that may detract from the achievement of desired objectives. The authors considered ways in which risk events could be generated and how new risks may be introduced but not identified. Sample questions for risk identification include:

- *"not having complete data on the probability of failure for each component in a system"*
- *"introducing a design change (i.e., a new type of screw) without full documentation because you think it's a minor change"*

Risk analysis comprises the set of activities associated with understanding the risk factors, the magnitude of consequences, and the likelihood of consequences. The authors considered different ways in which this information could be generated, how divergent stakeholder opinions should be canvassed, and the types of instruments and technologies associated with engineering analysis and how they can introduce risk into risk analysis. Sample questions include:

- *"not trusting informed estimations of probabilities in a structured decision making process"*
- *"accepting the results of computational simulation and analysis without experimental corroboration of results"*

Risk evaluation examines the data from risk analysis by comparing the level of risk found during risk analysis to the acceptable level of risk. Acceptable levels of risk may come from company policy or industry standards. The authors generated sociotechnical methods for risk evaluation, considered ways in which evaluations can be biased, and simple, hypothetical situations of risk evaluation. Sample questions include:

- *"placing more weight on a major fault that occurs on a regular basis than one that may never occur"*

- *"using a technology with a lower failure rate than another one but at the expense of functionality"*

Finally, risk treatment deals with actions taken to mitigate, eliminate or modify the source of risk or its consequences. Sample questions include:

- *"staying quiet about your company's cover up of a significant design flaw"*
- *"operating machinery well below capacity and far within the limits of safety"*

In the initial E-DOSPERT test, the original Likert scale [123] used in the original DOSPERT test [40] was employed to measure the likelihood of engaging in a risky (or non-risky) behavior. The scale ranges from 1 to 5 with 1 corresponding to "very unlikely", 2 corresponding to "unlikely", 3 corresponding to "not sure", 4 corresponding to "likely", and 5 corresponding to "very likely" to engage in an activity related to risk identification, analysis, evaluation and treatment. The questions were not grouped by domain. The authors kept the mid-point as "not sure" to maintain consistency with the original DOSPERT test. Some have argued that the middle-point should be "neutral" and an "undecided" or "not sure" option should also be available to respondents [124]. Offering both mid-point and not sure response options, termed Non-Substantive Responses (NSRs) [125], has been found to change the results of opinion surveys [126, 127]. In spite of the evidence that NSRs should be used in surveys, the middle point on the E-DOSPERT scale was chosen to be "not sure". This avoided confusion between the DOSPERT test and E-DOSPERT test in the event that both tests are administered in succession to respondents. Not using both NSRs allows for direct comparison between DOSPERT and E-DOSPERT results. Finally, the concept of "neutral" as in a risk neutral risk attitude is about taking short-term action to secure a certain long-term outcome [60], and this is not the same as being risk neutral in the EU framework. Thus, using the term "neutral" would not be appropriate. The term "not sure" more closely matches the situation of risk tolerant, which is considered the mid-point between risk seeking and risk averse in the Hillson and Murry-Webster framework [60].

The initial E-DOSPERT questions were phrased to measure risk averse and risk seeking attitudes along the Likert scale described above. 25 questions were intentionally phrased inversely. For example, the authors asked respondents' attitudes towards technology use. The risk averse version asked respondents to rate their likelihood of *"using a technology with a lower failure rate than another one but at the expense of functionality."* The risk seeking version asked respondents about their likelihood of *"using a technology that has a higher failure rate than a current one but that has a better functionality."* Thus, the sub-set of inversely worded questions provides a consistency check. If the respondents are consistent and the scales are unidimensional (risk averse or risk seeking), then the coefficient alpha will be sufficiently high. Further, if the scales are unidimensional, Hypothesis 5 will be validated. A complete list of questions is presented in Appendix A.

The questions in the E-DOSPERT survey were developed with the aim of being applicable to engineers regardless of national origin - that is, the questions relate to matters of engineering which would occur anywhere. Like the DOSPERT scale, the authors aimed to create an instrument with eight-item sub-scales. However, for this initial study, the authors constructed a larger set of sub-items (test questions), 25 risk averse, 29 risk seeking, and 54 questions in all. The number of items can be reduced in later versions, using questions with high inter-item correlations within a domain, once there is a better understanding of engineering risk attitude, the domains of engineering risk, and how to measure engineering risk attitude. This larger set also allows the authors to perform an exploratory factor analysis to determine if factors other than the four from the ISO 31000:2009 standard underlie risk behavior judgments.

5.5.2 Initial Scale Implementation and Testing

The initial E-DOSPERT scale was administered to undergraduate and graduate students at the USyd and OSU. The survey contained two parts consisting of the DOSPERT test and the initial E-DOSPERT test. The survey was administered using SurveyMonkey. Prior to full testing, the survey was administered to several small groups of graduate students, undergraduate students, and researchers in order to validate the questions.

At USyd, the participant population was comprised of undergraduate and graduate students in the mechatronics program. A total of 23 students participated in the survey. They ranged in age from 18 to 34, averaging 20 years of age. Three women and 20 men responded to the survey. The participant population at OSU consisted of both graduate and undergraduate students in the school of Mechanical, Industrial, and Manufacturing Engineering. A total of 87 students responded. They ranged in age from 20 to 35 with an average of 23. Eight women and 79 men responded. The total sample population was comprised of 110 respondents completing the survey. The administration of the survey and its content was approved by the relevant review boards at USyd and OSU.

5.5.3 Descriptive Statistics

Table 5.1 shows the sub-scale means (M) and standard deviations (SD) for the 110 respondents for the risk averse and risk seeking dimensions. For risk averse, the mean level of risk is $M = 3.16$ $(SD = 0.48)$ and for risk seeking, the mean level of risk is $M =$

2.84 (SD = 0.52). Based on a one-tailed ANOVA, the means are significantly different *(p<0.001)*, meaning that the risk attitudes are domain-specific. The sub-scale means and standard deviations, and one-tailed ANOVA tests clearly indicate that engineering risk appetite does exist and further that engineering risk appetites do not follow the expected value theorem. This data strongly supports Hypothesis 1.

Table 5.1: Risk Averse and Seeking Means and Standard Deviations

Subscale	Risk Averse Mean (SD)	Risk Seeking Mean (SD)
Identification	3.42 (0.32)	2.61 (0.12)
Analysis	2.96 (0.39)	2.78 (0.63)
Evaluation	2.25 (0.38)	3.30 (0.51)
Treatment	3.47 (0.31)	2.80 (0.49)

Since the scale ranges from "very unlikely" to "very likely", the higher the mean for risk averse, the more risk averse the respondents are, and, conversely, the lower the mean for risk seeking, the less risk seeking the respondents are. The data shows that the population of respondents are quite unsure about their risk attitude, that is, they are in the category of "risk tolerant" according to Hillson and Murray-Webster's scale [60]. They either believe that they can handle uncertainty when they encounter it, or, given the undergraduate student status of respondents, may not have yet developed the capacity to assess their engineering risk attitude. The authors postulate that this is an indication that more attention should be paid to educating engineering students on appropriate risk methods and practices.

Risk attitudes were compared between the OSU and USyd students. In general, no statistically significant difference was found (two-tailed, independent samples t-test). Table 5.2 summarizes the mean and standard deviation of the OSU and USyd response groups for the E-DOSPERT scale under risk seeking and risk aversion for all domains and sub-scales. The results show that risk attitudes are largely the same across the USyd and OSU respondents, except for on the risk averse-risk treatment subscale, which in turn affected the statistical difference between the USyd and OSU on the risk averse scale because of the higher proportion of items on the risk treatment subscale. This imbalance in items is a flaw in the scale, which was addressed in the next iteration of the E-DOSPERT test. The data supports Hypothesis 4.

Table 5.2: Comparison of the USyd and OSU respondent populations

Subscale	Uni	Mean (SD)
Risk Seeking Identification Domain	OSU	2.62 (0.984)
	USyd	2.58 (0.930)
Risk Seeking Evaluation Domain	OSU	3.30 (1.056)
	USyd	3.29 (0.977)
Risk Seeking Analysis Domain	OSU	2.77 (1.054)
	USyd	2.85 (1.096)
Risk Seeking Treatment Domain	OSU	2.81 (1.075)
	USyd	2.79 (1.042)
Risk Seeking All Domains	OSU	2.84 (1.069)
	USyd	2.85 (1.048)
Risk Averse Identification Domain	OSU	3.40 (1.043)
	USyd	3.50 (0.925)
Risk Averse Analysis Domain	OSU	3.12 (0.999)
	USyd	3.25 (0.958)
Risk Averse Evaluation Domain	OSU	3.40 (1.043)
	USyd	3.50 (0.925)
Risk Averse Treatment Domain	OSU	3.39** (1.036)
	USyd	3.59** (0.848)
Risk Averse All Domains	OSU	3.21** (1.051)
	USyd	3.34** (0.962)
** p-value is <0.05		

5.5.4 Initial Scale Results

Factor analysis is a statistical technique used to identify clusters of variables [128, 129, 130]. In this research, it was important to investigate whether the variables in the E-DOSPERT scale were measuring the underlying variables proposed in the engineering risk domains identified. Several steps were taken in the exploratory factor analysis of the data collected from the initial E-DOSPERT scale. First an exploratory factor analysis with oblique target rotation (oblimin) on the correlation matrix of the initial E-DOSPERT scale items was performed. Items on both the risk averse and risk seeking scales were removed where the anti-image correlations were <0.50. The KMO measure of sampling adequacy was sufficiently high (>0.70) and Bartlett's test of sphericity was significant, so that a factor analysis could proceed. Based on the number of hypothesized sub-scales, a four-factor model was specified. A four-factor model explained 49.683% of the variance in the Risk Seeking Category and 48.536% of the variance in the Risk Averse Category. Due to space limitations, and to make interpretation of the model simpler, only those items that load onto only one factor in the models' factor structure are shown in Table 5.3 for the Risk Averse dimension and Table 5.4 for the Risk Seeking dimension [131].

Values in Table 5.3 and 5.4 show that four factors were identified in the data. The loadings are arranged from higher to lower values in each factor. Substantive loadings are considered to be those that are >0.40 when ignoring the minus sign. Although the analysis of these tables suggest that questions in the proposed scale would be composed by four sub-scales, the identified factors in the tables do not mirror the engineering risk domains initially proposed.

Table 5.3: Factor model structure for risk averse dimension. Cutoff value of 0.400 used to eliminate items.

	Component			
	1	2	3	4
Following standard operating procedures (replicated question)	0.902			
Following standard operating procedures	0.880			
Following maintenance strategies according to manufacturer's	0.752			
Having complete data on probability of failure	0.625			
Documenting all maintenance procedures	0.540			
Referring to authoritative source to check technical matter		0.586		
Miss deadline to complete experimental testing		0.565		
"Whistle-blowing" company's cover up of significant flaw		0.549		
Operating machinery below limits		0.464		
Not Upgrading Software		0.416		
Investigating unlikely to occur design flaw			-0.735	
No need for corroboration of experimental results			0.643	
Using new equipment after voluntary formal training				0.808
Regular training on risk management				0.764

Table 5.4: Factor model structure for risk seeking dimension

	Component			
	1	2	3	4
No formal review process	0.774			
Ensuring staff awareness of only of major risks	0.716			
Conducting root cause analysis only for major failures	0.639			
Cut experimental testing to meet deadline	0.523			
Not calculating loss at the minimum probability of failure	0.488			
Emphasis on legal, regulatory, and other requirements		0.332		
Not recording the repairing of a fault			0.750	
Never conducting root cause analysis for failures			0.736	
Not updating training on risk management			0.646	
Quiet about company's cover up of significant flaw			0.513	
Not Documenting all maintenance procedures			0.441	
Technology with higher failure but better functionality				-0.632
No full documentation				-0.580
Not having complete data on probability of failure				-0.579
Allowing minor flaws				-0.561
Accepting colleague's opinion on a technical matter				-0.520

Each separate factor contains items from all four of the hypothesized content domains, suggesting that these four content domains as proposed by ISO 31000:2009 are not underlying factors in risk behavior judgment. Despite this discrepancy, there is some uniformity in the interpretation of the factor model structure. In the Risk Averse dimension, Factor 1 includes items about following established processes and procedures including maintenance and standard operating procedures, Factor 2 relates to professional ethics and conduct such as 'whistle-blowing' and relying on professional bodies to set standards for technical standards, Factor 3 relates to product testing and Factor 4 relates to training. In the Risk Seeking dimension, Factor 1 includes items on processes and procedures such as having a formal review process and following best practice in root cause analysis, Factor 2 contains one item related to legal matters, Factor 3 relates to professional ethics and conduct such as covering up a significant flaw and not documenting repairs due to faults and Factor 4 includes items relating to product functionality and design. Thus the data supports Hypothesis 2 in that four factors are present but rejects Hypothesis 2 in that the four factors present are not the factors predicted.

Table 5.5 summarizes the values of Cronbach's Alpha for the initially proposed E-DOSPERT scales. The reliability values are shown for the Risk Averse and Risk Seeking Categories and are sufficiently high (>0.70) given the test length [132]. Based upon the high Cronbach's Alpha statistics in Table 5.5, there is strong evidence in support of the hypothesis that risk tolerant and risk averse behavior is present in engineering risk appetite in a unidimensional scale (Hypothesis 5), and further support for the hypothesis that engineering risk appetite does not follow the expected value theorem (Hypothesis 5).

Table 5.5: Reliability Statistics

E-DOSPERT	Cronbach's Alpha	N of Items
Risk Averse	0.758	25
Risk Seeking	0.813	29

Table 5.6 summarizes the values of coefficient alpha and number of items for the initial E-DOSPERT scale under each of the originally proposed content domains. The values are shown for the Risk Averse and Risk Seeking dimensions on the initial E-DOSPERT scale. Only the risk treatment and risk identification sub-scales have a sufficiently high reliability, although the reliability for assessing risk treatment along the risk seeking scale is below the generally accepted threshold (> 0.70). This presents further evidence that Hypothesis 2 should be rejected. Respondents were consistent in answering replicated questions with nearly 100 % answering the questions in the same way.

Table 5.6: Reliability Statistics

	Risk Averse		Risk Seeking	
E-DOSPERT	Cronbach's Alpha	N of Items	Cronbach's Alpha	N of Items
Identification	0.731	4	0.796	6
Analysis	0.289	8	0.469	9
Evaluation	-0.384	3	0.257	5
Treatment	0.726	10	0.614	9

Thus it can be concluded that the four factors originally proposed by the ISO 31000:2009 document including risk identification, risk analysis, risk evaluation, and risk treatment, are not the underlying factors in engineering risk behavior. However, there is some uniformity in the interpretation of the underlying model structure. Four factors appear to be present and can be interpreted.

5.5.5 Discussion

The results support the hypothesis that engineering risk attitude is domain-specific (Hypotheses 1, 2, and 3). The authors were able to obtain suitable reliability for at least two of the sub-scales, risk identification and risk treatment, but not for risk analysis and evaluation. In the factor analysis, items had moderate to high loadings on their specified factors, and these factors were not highly correlated, which supports the idea that risk attitudes are multi-faceted and cannot be captured by a single index. This is evidence against Hypothesis 2 although analysis did show that four factors exist.

The reliability values for the risk analysis and risk evaluation sub-scales were particularly low. This means that the respondents were not able to discriminate between situations that dealt with the analysis of a risk, which concerns understanding the nature and the degree of the risk through actions such as gathering empirical data, identifying sources of risk, running numerical simulations, and estimating likelihoods of occurrence, and questions dealing with the evaluation of risk, which entails reviewing data from the risk analysis. Given that the means and standard deviations for overall risk aversion and risk seeking were very close to 3, meaning "not sure", and that the population of respondents were undergraduate students who were unfamiliar with risk management, the authors speculate that the reliability values may improve if a population of engineering professionals familiar with engineering risk management was surveyed. That the students were "not sure" of their risk attitude suggests that this is an engineering attribute that should be developed.

Nonetheless, the reliability analysis allows the following conclusion about the initial E-DOSPERT scale:

1. The scale is suitable to measure engineering risk aversion and risk seeking.

2. The scale is suitable to measure engineering risk aversion and risk seeking along the subscales of risk identification and risk treatment.

3. The scale is not suitable to measure engineering risk aversion and risk seeking along the subscales of risk analysis and risk evaluation.

The premise of the initial E-DOSPERT scale was that the four aspects of risk management could provide commonly encountered content domains by engineers (Hypothesis 2). The authors used these domains to draw out risk behavior judgments from respondents. While most of the items in the four factor model loaded onto one of the four factors, they did not load onto them in the predicted way, that is, onto the associated content domain. Generalizing from the interpretation of the factor models from the data, the authors proposed a different set of factors (Hypothesis 6), which were theorized to provide better coverage of risk-taking situations encountered by engineers [107, 133].

1. Engineering practice and processes: Situations associated with project processes and the work of engineering

2. Product functionality: Situations associated with the objectives, requirements, performance, or failure of the engineered product [107]

3. Legal: Situations associated with legal and regulatory requirements in engineering and of engineers

4. Engineering ethics: Situations associated with professional and ethical conduct

These factors correspond to domains of engineering risk identified by other researchers [107, 133]. The factors associated with engineering processes and product functionality have been identified by Eckert [133] as generic risk factors based on their study of design processes across disciplines. The engineering ethics factor has a correlation to the general risk domain of social risk [40] and are suggestive of the generic engineering risk to the engineer's reputation [133].

5.6 Retooling of the E-DOSPERT Scale

Based upon the results of the initial E-DOSPERT scale, the authors revised, refined, and expanded the E-DOSPERT to examine the four factors isolated within the initial E-DOSPERT data and two additional potential factors the authors identified from other sources [107]. The six predicted domains include: engineering practice and processes, product functionality, legal, engineering ethics, product testing, and training (Hypothesis 6). This section outlines the revision of the initial E-DOSPERT scale, its administration, analysis, and a discussion of the results.

5.6.1 Revised E-DOSPERT Scale Development

Questions were developed for each of the six domains based upon professional engineering-related situations involving risk that practicing engineers commonly encounter. The engineering practices and processes portion of the scale is comprised of questions related to situations associated with project processes and the work of engineering. The authors consulted project management texts and professional engineering references when generating the questions. Sample questions include:

- *"not fully complying with company procedures in order to meet a project deadline"*

- *"having incomplete historical data on the performance of a component"*

The engineering ethics portion of the scale focuses on situations associated with professional and ethical engineering conduct. Classical engineering ethics case studies were reviewed for inspiration in developing the questions. Sample questions include:

- *"taking credit for work done by a colleague"*
- *"copying design work done for one client for another client"*

The testing portion of the scale focuses on product testing. The authors drew upon their backgrounds in product testing and upon relevant texts to develop questions that examine the thoroughness and completeness of testing plans. Specific attention was paid to several areas including verifying calculated data with testing. Sample questions include:

- *"not corroborating computational simulations with experimental results"*
- *"take reported product malfunctions at face value"*

The training portion of the scale was developed to examine how engineers are trained and how engineers train others. Attention was paid to new equipment, and upgraded equipment, and the need for additional training or in-depth training. Sample questions include:

- *"not providing training for upgraded machines"*
- *"not attending continuing education courses to learn new skills"*

The legal portion of the scale focused on situations associated with regulatory and legal requirements in the engineering profession and of professional engineers. Sample questions include:

- *"you are flexible about complying with engineering regulations"*
- *"not maintaining full written records of all product testing for compliance with relevant product regulations"*

The product functionality and design portion of the scale was based upon situations associated with the objectives, requirements, performance, or failure of engineered products [107]. Sample questions include:

- *"sub-contracting critical design work to a third party"*
- *"using an unknown component to perform a critical function because it less expensive than a known suitable component"*

In the revised E-DOSPERT test, a seven point Likert scale was used, as was used in the revised version of the DOSPERT test [47]. The scale ranged from 1 corresponding to "very unlikely" to 4 corresponding to "not sure" to 7 corresponding to "extremely likely." The full Likert scale can be seen in Appendix B. The questions were ordered randomly.

The revised E-DOSPERT questions were all phrased to measure risk seeking attitudes along the above described Likert scale. The authors intentionally did not include the consistency check of inversely worded questions that was present in the initial E-DOSPERT questions based upon the data found in the analysis of the initial E-DOSPERT scale that supports Hypothesis 5. Based upon the results of the initial

E-DOSPERT scale analysis and similar research [47], inversely worded questions are not needed to show that the factors are bi-dimensional (risk tolerant to risk averse). A complete list of questions is presented in Appendix B. The questions were developed with the goal of being national origin independent. In other words, the questions relate to engineering matters which are expected to occur anywhere. A total of 65 questions were tested. The number of items can be reduced in future versions of the E-DOSPERT survey. The survey in its current form takes approximately 20 minutes to complete. This large set of questions and resulting data allows exploratory factor analysis to be performed to determine if the six proposed factors are present or if other factors underlie risk behavior judgments thus either validating or rejecting Hypothesis 6.

5.6.2 Revised Scale Implementation and Testing

The revised E-DOSPERT scale was administered to undergraduates and graduate students at OSU. The survey was administered using SurveyMonkey. Prior to full testing, the survey was administered to several small groups of students and researchers in order to validate and refine the questions.

The participant population was comprised of graduate and undergraduate students enrolled in courses or associated with in the School of Mechanical, Industrial, and Manufacturing Engineering. In total, 206 students responded. The age range was from 19 to 43, averaging 22 years old. A total of 22 women and 184 men responded to the survey. The administration of the survey and its contents were approved by the OSU Institutional Review Board. In future revisions of the E-DOSPERT, larger participant pools will be sought. Larger data sets allows for higher statistical reliability and a more thorough vetting of the survey instrument.

5.6.3 Revised Scale Results

Factor analysis was performed on the resulting data in a manner similar to Section 5.5.4. An exploratory factor analysis with oblique target rotation (oblimin) and using Maximum Likelihood Extraction (MLE) [130] was performed. The Kaiser-Meyer-Olkin (KMO) was sufficiently high (0.795) and Bartlett's test of sphericity was significant (< 0.05) allowing factor analysis to proceed. Based upon the number of hypothesized sub-scales, a six factor model was specified. A six factor model explained 43.696% of the variance in the scale. Several iterations of purging items that loaded poorly or onto multiple factors and verifying item communalities were performed. However, the analysis ran into ultra-Heywood cases, an impossible outcome where factor loadings are greater than 1.0 [130]. This led the authors to reexamine the supposition of a six factor model. The scree plot indicated that a five factor model might also be present. A five factor model explained 40.617% of the variance in the scale. Several iterations of removing poorly loaded items and verifying communalities were performed. The resulting scale has a KMO of 0.806 and Bartlett's test of sphericity was significant. The goodness-of-fit test was not significant indicating that the model is a good match to the data. Table 5.8 provides additional statistics for the full scale. Table 5.7 presents the five factors that were identified and the associated values. Table 5.9 shows the reliability of each factor that was identified.

Table 5.7: Factor model structure for revised E-DOSPERT

	Component				
	1	2	3	4	5
Not documenting every single step that was taken to design a new component (PnP)	.740				
Not fully complying with company procedures in order to meet a project deadline (PnP)	.667				
Having incomplete historical data on the performance of a component (PnP)	.626				
Not having complete data on the probability of failure for each component in a system (PFnD)	.560				
Copying design work done for one client for another client (E)	.445				
Exaggerating your company's competencies in order to win a contract (E)		.813			
Accepting a weekend holiday(vacation) from potential contractors (E)		.612			
Use consumable work resources for home projects (E)		.543			

Table 5.7 – Factor model structure for revised E-DOSPERT (Continued)

	Component				
	1	2	3	4	5
Reverse engineer a competitor's technology with the intent to bring to market a nearly identical copy (E)		.470			
Protect your client's confidentiality by not reporting to a regulatory agency a negligent behavior by the client (E)		.433			
Not giving much consideration about whether the product can be recycled or disposed of in a safe, secure and environmentally sound manner (E)		.428			
Not attending compulsory formal training for new machines (T)			-.778		
Not providing training for upgraded machines (T)			-.691		
Not following standard operating procedures systematically (PnP)			-.497		
Not investigating a suspected design flaw because you don't think it is likely to happen (PT)				.620	

Table 5.7 – Factor model structure for revised E-DOSPERT (Continued)

	Component				
	1	2	3	4	5
Using an unknown component to perform a critical function because it less expensive than a known suitable component (PFnD)				.520	
Relying upon the risk management practices you learned at university rather than regular continuing education on new risk management techniques (T)				.513	
Going into detailed design with the first design concept you came up with (PFnD)				.441	
Verifying that your product is in compliance with all applicable environmental, health, and safety laws and regulations (L)					.590
Glance at the operating procedures for a new product prior to use (T)					.566
Placing higher emphasis on legal, regulatory, and other requirements over operating profitability (L)					.436

Note: (E) = Ethics, (PT) = Product Testing, (PFnD) = Product Functionality and Design, (L) = Legal, (PnP) = Processes and Procedures, (T) = Training. This represents the proposed six factors of engineering risk appetite.

Table 5.8: Scale Statistics

Mean	Variance	Std. Dev.	N	Cronbach's Alpha
73.02	188.074	13.714	21	0.800

Table 5.9: Factor Reliability

Factor	Cronbach's Alpha	N of Items
Factor 1	0.759	4
Factor 2	0.750	6
Factor 3	0.699	3
Factor 4	0.638	4
Factor 5	0.521	3

5.6.4 Discussion

The results of the revised E-DOSPERT analysis show strong evidence of a five factor scale. The authors were able to obtain suitable reliability for Factors 1 and 2 where Cronbach's Alpha was significant (> 0.70) [134] and marginal reliability for Factors 3 and 4 (> 0.60) [128]. The reliability of Factor 5 is low but there is evidence that a fifth factor exists.

The premise of the revised E-DOSPERT scale is that six factors of engineering risk appetite are present. The six proposed domains were identified in the analysis of the initial E-DOSPERT test data. While many of the items in the six factor model loaded onto one of the six factors, an ultra-Heywood case was encountered that indicated a six factor model was incorrect. Based upon indications from the scree plot, a five factor model was then adopted and explored. Based upon an interpretation of the factor models from the data, the authors propose the following set of factors:

1. Processes, Procedures, and Practices: all five of the questions relate to the best processes, procedures, and practices that an engineer should follow in their professional lives.

2. Engineering Ethics: All six questions are based upon ethical dilemmas encountered by practicing engineers.

3. Training: The three questions that loaded onto Factor 3 relate to conducting training and following guidance given by training.

4. Product Functionality and Design: The four questions that loaded onto Factor 4 relate to the functionality and design of products.

5. Legal Issues: Two of the three questions that load onto Factor 5 relate to legal issues.

Of the six factors anticipated by the authors, five factors are present and interpretable in the revised E-DOSPERT survey data. Additional analysis was conducted to verify that higher numbers of factors were not present. Based upon the authors' analysis, no additional interpretable factors appear in the data. While the pool of participants was lower than desired (n=206) and the reliability of several factors was lower than ideal, the evidence points toward a five factor model that contains factors predicted by the authors. Further replication of the test should be performed with other sample populations to confirm and further strengthen these findings.

5.7 E-DOSPERT Applications

The E-DOSPERT survey in its current form and in future revisions is useful to the practitioner and researcher for several reasons. For instance, administering an E-DOSPERT test to an engineer can provide valuable insight into how that engineer will behave in engineering risk situations. This allows for targeted training to be given to the engineer in order to correct for any differences in engineering risk appetite from what the position requires that the engineer fills.

The E-DOSPERT test could be used as part of a hiring process. Already many companies administer personality type tests such as the Meyers-Briggs Type Indicator (MBTI) [135] and others. With a proper understanding of the results of an E-DOSPERT test, hiring managers can be expected to make more informed choices on hiring engineers.

Stakeholder risk preference can be collected using the E-DOSPERT. Rather than requiring stakeholders to be present to provide input on their engineering risk appetite, design engineers can refer to the stakeholders' E-DOSPERT scores. This can be expected to save time and produce results more in line with what the stakeholders intrinsically desire.

A method can feasibly be developed based upon the E-DOSPERT survey that translates expert opinions from individual scales to a normative scale. In other words, judging the risk of a product failure on a scale of 1 to 10 might elicit a response of 7 from one expert and a response of 5 from another. Those two different numbers might simply be the result of different internal scales. Normalizing those expert opinions using the E-DOSPERT might result in the discovery that both experts mean the same thing.

Another area that is already being actively developed is using E-DOSPERT test results to generate utility risk curves. These utility risk curves can then be used to analyze early conceptual system design trade studies that contain risk as a tradeable parameter. Decision aids and decision automation can also take place using utility risk curves generated from E-DOSPERT results [89].

5.8 Conclusion

This paper presented the incremental development of an instrument, the E-DOSPERT scale, to measure the risk aversion and risk seeking attitude of engineers. The initial version of the E-DOSPERT scale tested the validity of the ISO 31000:2009 standard and its recommended four content domains for risk management as the basis for risk behavior judgment. Two of the domains, analysis and evaluation, were found to be not easily discriminated, at least in a population of engineering undergraduates. Based on an exploratory factor analysis with oblique target rotation, the authors suggested four other factors that may underlie the risk behavior judgments. Based upon further insight into the data, two potential domains were added. A revised version of the E-DOSPERT scale was then produced and tested.

Items in the revised E-DOSPERT scale are based on commonly encountered engineering risk scenarios and scenarios based in risk management. The results show that the scale is suitably reliable to measure engineering risk appetite in two domains including processes, procedures, and practices; and engineering ethics. The scale is marginally suitable to measure engineering risk appetite in two additional domains including training, and product functionality and design. A fifth domain, legal issues, appears to be present but is not statistically reliable.

Thus, in its current form, the E-DOSPERT scale can be used to assess processes, procedures, and practices; and engineering ethics domains, and at the option of the practitioner, two additional domains including training, and product functionality and design may be assessed. The authors suggest that users of the scale remove items on legal issues domain. In future work, the authors will revise items on the three factors that do not have as significant of statistical backing as the other two factors. Additional testing of the survey will be performed over larger sample populations to gain further statistical validity. Tests at multiple universities and in multiple countries will be performed. An examination of the role that educational level and tenure length in career play will be examined in forthcoming research. A survey of engineers different industries shall be conducted in order to understand variation between industries and sub-disciplines. After careful vetting, the E-DOSPERT will be made available in multiple languages. Once these further steps are taken, such an instrument can then be used as a standard to assess risk attitude across industries, within organizations, by gender and national origin, and as pre and post tests on the development of risk-assessment as an engineering attribute in engineering education. The authors believe that such information is crucial in interpreting how individual engineers approach design and design decision-making.

5.9 Acknowledgments

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5.10 Appendix A: The Initial E-DOSPERT Scale

The initial E-DOSPERT test presented in this appendix was administered online using Survey Monkey. The questions were automatically randomized when presented to the respondents. Below the questions are presented in alphabetical order.

For each of the following statements please indicate the likelihood of engaging in each activity. Please provide a rating using the following scale:

Very Unlikely	Unlikely	Not Sure	Likely	Very Likely
1	2	3	4	5

1. "Whistle-blowing" your company's cover up of a significant design flaw. (T)

2. Accepting the results of computational simulation and analysis without experimental corroboration of results. (A)

3. Accepting your colleagues' opinion about a technical matter without checking the originating source. (A)

4. Adjusting standard operating procedures to handle a design flaw to better fix the flaw. (T)

5. Allowing minor flaws through on a production line to keep the line moving. (T)

6. Applying a new process recommended in a prestigious journal even if it is not an industry-wide standard. (A)

7. Calculating potential loss from a design fault at the minimum probability of failure. (A)

8. Conducting a root cause analysis every time that a failure occurs. (A)
9. Conducting a root cause analysis of major failures but not of minor failures. (A)
10. Conducting maintenance according to what you think is best rather than following manufacturer recommended maintenance strategies. (T)
11. Continuing to use an outdated but robust piece of software even if others in your group choose to upgrade to a new version. (A)
12. Cut back on experimental testing to meet a project deadline. (A)
13. Ensuring that all staff know about potential risks no matter how minor. (I)
14. Following maintenance strategies exactly according to manufacturer specifications. (T)
15. Following standard operating procedures word-for-word for the handling of any design flaw. (T)
16. Formally documenting all maintenance procedures. (T)
17. Fully documenting every design change, no matter how minor. (I)
18. Further investigating a design you suspect has a flaw that you estimate is not likely to occur. (I)
19. Halting a production line immediately if any flaw, no matter how minor, is identified. (T)
20. Having complete data on the probability of failure for each component in a system. (I)

21. Having formal review processes to review and analyse the history of design faults. (A)

22. Having no formal review process to analyse and review the history of design faults. (A)

23. Ignoring a colleague's suggestion to investigate a major but unlikely design flaw. (A)

24. Informing staff only about potential major risks but not about minor risks. (I)

25. Introducing a design change (i.e., a new type of screw) without full documentation because you think it's a minor change. (I)

26. Making a design change if a component's failure rate is close to but below the industry standard for component failure. (T)

27. Miss a project deadline to conduct complete experimental testing. (A)

28. Never conducting root cause analysis for failures. (A)

29. Not bothering to calculate potential loss from a design fault at the minimum probability of failure. (A)

30. Not documenting all maintenance procedures. (T)

31. Not having complete data on the probability of failure for each component in a system. (I)

32. Not making a design change if its failure rate is close to but below the industry standard for component failure. (T)

33. Not trusting informed estimations of probabilities in a structured decision making process. (A)
34. Operating machinery at the limits of safety and availability. (T)
35. Operating machinery well below capacity and far within the limits of safety. (T)
36. Placing more emphasis on legal, regulatory, and other requirements over operating profitability. (E)
37. Placing more weight on a major fault that may never occur than a major fault that occurs often. (E)
38. Placing more weight on a major fault that occurs on a regular basis than one that may never occur. (E)
39. Recording a major fault but not a minor fault. (I)
40. Referring to an authoritative source to check your colleagues' opinion about a technical matter. (A)
41. Relying on experience over formal processes when vetting decisions. (E)
42. Repairing a fault but not recording the number times you have needed to fix the fault. (I)
43. Staying quiet about your company's cover up of a significant design flaw. (T)
44. Trusting experimental results even when they do not align with analytical calculations. (E)
45. Trusting informed estimation of probabilities in a structured decision making process. (A)

46. Upgrading your design analysis software as soon as a new version is available even if it is not used by others in your group. (A)

47. Using a new piece of equipment without optional formal training. (T)

48. Using a technology that has a higher failure rate than a current one but that has better functionality. (E)

49. Using a technology with a lower failure rate than another one but at the expense of functionality. (E)

50. Using an industry-wide standard rather than a new process recommended in a prestigious journal. (A)

51. Using risk management practices that were industry best practices when you learned them but not keeping up-to-date with current practices. (A, E, T, I)

52. Voluntarily attending formal training before using a new piece of equipment. (T)

53. Voluntarily taking formal training on a regular basis on industry best practices in risk management. (I)

54. Using risk management practices that were industry best practices when you learned them but not keeping up-to-date with current practices. (I)

Note: (A) = Risk Analysis, (T) = Risk Treatment, (E) = Risk Evaluation, (I) = Risk Identification

5.11 Appendix B: The Revised E-DOSPERT Scale

The revised E-DOSPERT test presented in this appendix was administered online using Survey Monkey. The questions were automatically randomized when presented to the respondents. Below the questions are presented in alphabetical order.

For each of the following statements please indicate the likelihood of engaging in each activity. Please provide a rating using the following scale:

Very Unlikely	Moderately Unlikely	Somewhat Unlikely	Not Sure	Somewhat Likely	Moderately Likely	Very Likely
1	2	3	4	5	6	7

1. Accepting a weekend holiday(vacation) from potential contractors (E)
2. Adding many extra features to a product beyond original specifications (PFnD)
3. Assuming unfavorable test results from an early production prototype will improve after the next prototype is constructed (PT)
4. Certify a document as a qualified, professional engineer that is outside of your area of expertise (E)
5. Competent professional engineers need not be registered with a professional body that regulates appropriate professional practice (L)
6. Comply with your supervisor's instruction to withhold information from a client (E)
7. Consult the professional engineering code of conduct regularly (L)

8. Contracting product testing to a specialist outside firm (PT)

9. Copying design work done for one client for another client (E)

10. Designing a product in a manner that emphasizes profitability over protecting the environment, and the health, safety and security of end-users (E)

11. Developing only general but not detailed operation guidelines for a piece of equipment (PnP)

12. Disregarding the company Standard Operating Procedures on design processes when starting a new design (PnP)

13. Exaggerating your company's competencies in order to win a contract (E)

14. Glance at the operating procedures for a new product prior to use (T)

15. Going into detailed design with the first design concept you came up with (PFnD)

16. Having incomplete historical data on the performance of a component (PnP)

17. Including a component in a product for which there is only one supplier (PFnD)

18. Investigating product failures only when you think it is important (PT)

19. Leave it up to your customers to decide if they want to receive training on the safe operation of your product (T)

20. Let your workgroup discover new industry standards on their own (T)

21. Making decisions based on personal experience and intuition rather than evidence (PnP)

22. Not actively seeking information about the patent law in countries where you are operating (L)
23. Not assessing failure risk for incremental changes to a product (PFnD)
24. Not attend continuing education courses to learn new skills (T)
25. Not attending compulsory formal training for new machines (T)
26. Not consult legal counsel on how to proceed if accused of improper conduct related to an engineering matter (L)
27. Not corroborating computational simulations with experimental results (PT)
28. Not documenting every single step that was taken to design a new component (PnP)
29. Not following standard operating procedures systematically (PnP)
30. Not following the exact manufacturer-recommended maintenance strategies (PnP)
31. Not formally benchmarking your product against competing products (PFnD)
32. Not fully complying with company procedures in order to meet a project deadline (PnP)
33. Not fully understanding the limitations of "canned" calculations prior to using them (PT)
34. Not giving much consideration about whether the product can be recycled or disposed of in a safe, secure and environmentally sound manner (E)

35. Not having an independent person or department audit quality assurance programs (PnP)

36. Not having complete data on the probability of failure for each component in a system (PFnD)

37. Not investigating a suspected design flaw because you don't think it is likely to happen (PT)

38. Not maintaining full written records of all product testing for compliance with relevant product regulations (L)

39. Not providing training for upgraded machines (T)

40. Not testing a product for functionality beyond its intended purposes (eg: using a hammer handle as a lever) (PT)

41. Offer no follow-up, refresher training on how to operate equipment (T)

42. Placing higher emphasis on legal, regulatory, and other requirements over operating profitability (L)

43. Protect your client's confidentiality by not reporting to a regulatory agency a negligent behavior by the client (E)

44. Rely only upon the manual of a new product that your company is deploying to learn safe operating procedures (T)

45. Relying on unwritten knowledge rather than documenting minor changes to procedures (PnP)

46. Relying upon computer simulation models to predict product failure modes without confirming by empirical testing (PT)

47. Relying upon the risk management practices you learned at university rather than regular continuing education on new risk management techniques (T)

48. Reverse engineer a competitor's technology with the intent to bring to market a nearly identical copy (E)

49. Seeking legal counsel about tort(liability) laws that might have an impact on your product (L)

50. Selling a product claiming high reliability based upon calculations but without extended field testing to back up the computational models (PT)

51. Staying quiet about your company's cover up of a significant design flaw (E)

52. Sub-contracting critical design work to a third-party (PFnD)

53. Take reported product malfunctions at face value (PT)

54. Taking credit for the work done by a colleague (E)

55. Use consumable work resources for home projects (E)

56. Using a new technology with better functionality but that has a higher failure rate than a current technology (PFnD)

57. Using an unknown component to perform a critical function because it less expensive than a known suitable component (PFnD)

58. Verifying that your product is in compliance with all applicable environmental, health, and safety laws and regulations (L)

59. When serving as an expert witness, letting your previous experience with one of the litigating companies influence your testimony on the resolution of a dispute of a technical matter (E)

60. Withhold information from the general public about risks associated with a specific technology that is relevant to the public's health and welfare (E)

61. You are flexible about complying with engineering regulations (L)

Note: (E) = Ethics, (PT) = Product Testing, (PFnD) = Product Functionality and Design, (L) = Legal, (PnP) = Processes and Procedures, (T) = Training.

Chapter 6 –Considering Risk Attitude Using Utility Theory in Risk-Based Design

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[2]A conference version of this article will appear in the ASME 2012 IDETC and CIE in the Uncertainty and Risk in Design track of the Design Theory and Methodology conference as paper number DTM-70399 [85].

6.1 Abstract

Engineering risk methods and tools account for and make decisions about risk using an expected value approach. Psychological research has shown that stakeholders and decision-makers hold domain-specific risk attitudes that often vary between individuals and between enterprises. Further, certain companies and industries such as the nuclear power industry and aerospace corporations are very risk-averse while other organizations and industrial sectors such as IDEO, located in the innovation and design sector, are risk-tolerant and in fact thrive by making risky decisions. Engineering risk methods such as FMEA, FTA, and others are not well-equipped to help stakeholders make decisions under risk-tolerant or risk-averse decision-making conditions. This paper presents a novel method to translate engineering risk data from the expected value domain into a risk appetite corrected domain using utility functions derived from E-DOSPERT psychometric test results under a single criterion decision based design approach. The method is aspirational rather than predictive in nature on the basis of using a psychometric test rather than lottery methods to generate utility functions. Using the method, decisions can be made based upon risk appetite corrected risk data. We discuss development and application of the method based upon a simplified space mission design in a collaborative design center environment. The method is shown to change risk-based decisions in certain situations where a risk-averse or risk-tolerant decision-maker would likely choose differently than the expected value approach dictates.

Keywords: Risk-Based Design, Utility Theory, Risk Appetite, E-DOSPERT, Decision Support.

6.2 Introduction

Risk is found throughout engineering design. Engineering risk methods such as FMEA, FTA, and others are used across the spectrum of complex system design to identify these risks. Specifically, such methods are designed to guide decision-makers to choose the least risky options, mitigate the largest risks, and create risk-averse or fault-tolerant designs. Such an approach works well for traditionally risk-averse sectors such as the aerospace and nuclear power industries. However, not all industries and enterprises thrive on risk aversion. Many of the most successful Web 2.0 companies such as Google and Facebook and product design companies such as IDEO have become wildly successful because they take risks that traditional, risk-averse companies are not willing to take. There is no one correct level of risk attitude across all industries.

Many methods exist in engineering design to account for risk such as FFIP [67], RED [69], FFDM [68], FMEA [87], and others. However these methods do not account for risk appetites of enterprises or individual decision-makers. Research in psychology has produced the well-respected DOSPERT test which enables risk appetite determination in several different domains of daily life [40]. Recent advancements have created the E-DOSPERT test that has the goal of categorizing and determining engineering-specific risk domains [85]. This research seeks to find a link between the engineering risk appetite information that the E-DOSPERT test provides with traditional and widely used engineering risk methods.

Specifically, this paper presents a novel way to account for risk appetite in risk-based design. A single criterion decision based design approach is adapted by way of engineering risk appetite utility functions to bring risk data from the expected value domain into a risk appetite domain appropriate to the enterprise or individual stakeholder. The risk appetite utility functions are developed via E-DOSPERT test results rather than traditional lottery methods. By viewing risk data through a risk appetite lens, stakeholders and decision-makers can make risk decisions with analytic backing that would traditionally be justified with "gut feeling." An important distinction is drawn between appropriate uses of lottery-derived risk utility functions and E-DOSPERT-derived risk utility functions. Lottery methods of risk utility functions generation are suitable for later stage conceptual system design and beyond while the authors advocate for using E-DOSPERT-derived risk utility appetite functions for early phase conceptual system design. Psychometric tests such as E-DOSPERT are aspirational in nature while lottery methods are predictive of future decisions [77]. The method presented in this paper specifically provides a means of aspiring to the intrinsic risk appetite of the E-DOSPERT test-taker rather than using past performance as gaged by lottery methods to predict future performance. In the early phases of conceptual design it is more useful to aspire to create something new than to use the same decision patterns as have been done in the past.

The method presented in this paper can be used upon any type of risk to which a dollar figure can be attached. This paper uses product-related risk examples. However, other risks such as those found in project management or elsewhere may also be used with this method.

It is important to note that this method does not claim to produce a "right" or "wrong" decision. The suitability of the decisions that can be supported with the method presented in this paper are based in the attitude of the decision-maker as defined by the decision-maker's decision criteria. There are no "right" or "wrong" decision criteria but instead criteria that are more or less important to the decision-maker [136]. The method developed in this paper provides a different, novel criteria that decision-makers may use when making risk-based decisions. As the case study demonstrates, decisions can have different results when made based upon the information produced by this method.

Risk-averse decision-makers and enterprises will find this method useful in highlighting risks with higher certainty. A risk-averse stakeholder tends to favor high certainty over low certainty options. Similarly, risk-tolerant decision-makers and enterprises will find that identifying large risks will drive potential innovation and profit [137]. For these reasons, this paper develops a novel way to account for risk appetite in risk-based design.

The method presented in this paper holds significance for intelligent decision support systems based upon the method's ability to inform the user of the preferred design choice, based upon risk information, of the stakeholder for whom the user is designing. In this way, partial automation of the engineering risk decision-making process can be realized. Additionally, the method can be used by an engineer to support their own decision-making process by providing quantitative backing to "gut feeling" decisions. Further, the method is intended to be used as a real-time decision support system rather than a post-design confirmatory tool. The method presented in this paper can be automated if decision-maker risk attitudes are known. This would be useful in automated design trade studies and other design automation applications where decision-maker input is desired but where each design iteration does not need fresh decision-maker input.

In the following sections, background is provided in several highly relevant fields for the proposed method. Coverage includes design trade studies, risk analysis in collaborative design centers, the psychology of assessing and judging risk, decision-based design, and risk-based utility theory. The novel method of accounting for risk appetites in risk-based design is then developed and demonstrated using an illustrative example. A case study based upon a simplified satellite conceptual design development and selection process is presented next to emphasize the benefits of this new method in a realistic complex design setting. The paper concludes with a discussion of the benefits and drawbacks of the proposed method, and presents future work to expand the method.

6.3 Background

The method presented in this paper makes use of several domains of engineering and psychology. This section reviews the topics of engineering risk, trade studies, the psychology of assessing and judging risk, and decision-based design, each of which is used in developing the risk appetite utility function method.

It is important early on in this paper to define the terms risk, utility, riskiness, value, and uncertainty. Risk can hold many different meanings but, unless otherwise noted, for the purposes of the method developed in this paper, risk is defined as the probability of uncertain events [138] and the values of potential outcomes. A certainty equivalent value ($CE(V)$), based upon utility theory, is developed and found in conjunction with the probability of an outcome in order to find the equivalent value of a specific risk. This is analogous to the classical engineering context where risk can be defined as the probability of occurrence multiplied by the severity of the outcome of the event but is more closely aligned with the ISO 31000:2009 definition of risk which defines risk as the effect of uncertainty on objectives [57]. In this paper, utility is defined as a measure of satisfaction of a choice or result [76]. In the context of finance, riskiness refers to the riskiness of an option which is equated to its variance. However, in psychological risk-return models, perceived riskiness is treated as a variable that can differ between individuals as a function of the context and content of the decision choice [40]. Value is defined as the worth of a decision, outcome, good, or service. Often this is given a monetary designation. This paper uses the Dollar ($) as a monetary value designator. Finally, uncertainty is defined as the potential of more than one outcome, state, or result where the probabilities are ill-defined [139]. It should be noted that engineers often group together related concepts such as reliability [61], robustness [62], and uncertainty [58] with the strict definition of risk into a meta-risk category that is also referred to as "risk."

6.3.1 Trade Studies and Different Priorities

Design trade studies are found throughout the design process. They are often employed in creating conceptual complex system designs. Trade studies can be used to create many potential designs quickly through automated software packages such as ModelCenter (http://www.phoenix-int.com) or ATSV [93] as part of ModelCenter. Trade studies are also used by teams of people to conduct manual trade study sessions [10]. Automated trade studies can also be performed by computers using conditions and bounds set by users. Many thousands of conceptual designs can be quickly created with an automated trade study. Manual trade studies are conducted by groups of system experts where only one or a handful of conceptual designs will result.

Trade studies are based upon the search for maximum system utility. Trade-offs are made between system design variables in order to achieve maximum utility [7]. This is represented as $max\ f(\overrightarrow{U})$ where $\overrightarrow{U}$ represents relevant system utility metrics. System utility metrics are to be chosen by design stakeholders. In the case of automated trade studies, different stakeholders will have different design preferences. The most preferred design of one engineer will most likely not be the most preferred design of another engineer. In practice, little guidance exists in the literature on how to create utility functions with appropriate selection criteria for different design situations, such as design of high risk space exploration.

CDCs often will perform manual trade studies as part of the design process. The most cited example of a CDC is Team-X which is housed in the PDC at JPL and develops conceptual spacecraft mission designs [10]. In such manually conducted trade studies, subsystem experts often disagree over which tradeable parameters are the most important [2, 3, 4]. A variety of methods are available to resolve design decision conflicts in both automated and manual trade studies [5, 6]. However, these methods do not take into account individual or enterprise-level risk appetites.

6.3.2 Risk Analysis Tools

Many methods exist to analyze and account for engineering risk in the design process. Examples are: RBD [63], PRA [64], FMEA [65], FTA [66], and other methods are commonly found in industry. Other methods such as FFIP [67], FFDM [68], and RED [69] are being actively developed in academia and will see industrial deployment in the future.

Several tools have been developed to support risk analysis in trade studies for CDCs. Team-X uses RAP, a PRA-based assessment software package [20]. The RAP tool is used to capture unusual risks that are identified during trade study sessions. One engineer is tasked with cataloging these risks, and, with the assistance of stakeholder subsystems engineers, develops likelihood and impact assessments, and mitigation methods with associated costing information. Other risk analysis programs and methods are under development and in use by other CDCs.

The methods such as FTA and FMEA, and tools such as trade studies commonly deployed in industrial settings, and reviewed in the previous section, view risk as an expected value choice. For example, if an engineer must make a decision between one risk that has a 1% chance of occurrence and has a consequential cost of $10,000 and another risk that has a chance of 0.1% of occurrence and a consequential cost of $100,000, engineering risk methods would indicate that both risks are equal with regards to expected value. Therefore, either can be chosen with the same expected value outcome. However, this ignores individual and company risk attitude. The method presented in this paper allows for individual and enterprise risk appetites to be expressed during the risk decision-making process.

6.3.3 The Psychology of Assessing and Judging Risk

Risk plays an integral role in engineering design. Highly innovative design firms embrace risk as an essential ingredient in their success. On the other hand, some entire industries such as aerospace and nuclear power, are very risk-averse. Research in risk trading in engineering design shows that different engineers have different opinions of what makes an acceptable risk [83]. Clearly there is no single correct level of acceptable risk for all situations or all people.

In psychology, risk is classically defined as the parameter that differentiates between different individuals' utility functions [28]. The utility function of individuals is generally expressed as a quadratic, logarithmic, or exponential function [76]. This classic EU approach to risk theorizes that an individual can be modeled choosing between risky

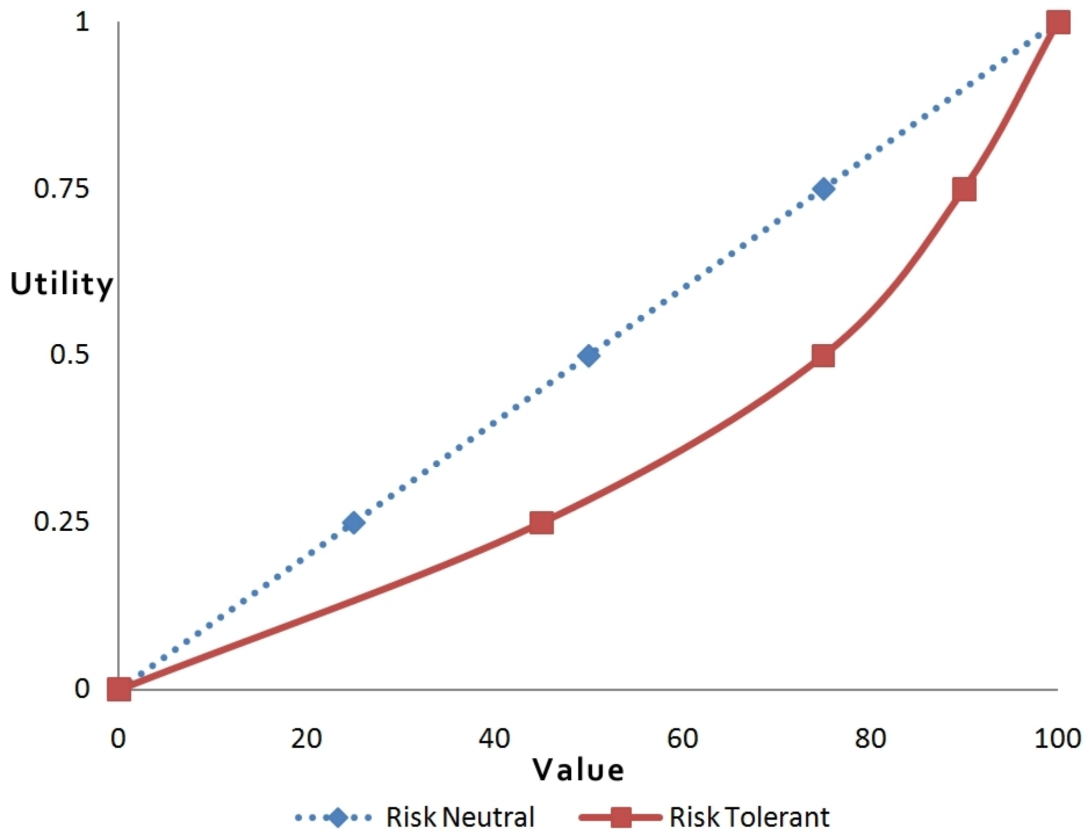

Figure 6.1: Risk-Tolerant Utility Function for Money.

options as the function of the return of the options, the probability of the options occurring, and the risk aversion of the individual [30]. Figure 6.1 shows a risk-tolerant utility function for money. Within the EU framework and other related methods [31], the function of an individual's utility function denotes the individual's risk attitude as either risk-averse (i.e., someone who does not like to take risks), risk neutral (i.e., someone who takes necessary short-term risks to deliver long-term outcomes), or risk-tolerant (i.e., someone who is comfortable with handling larger risks if necessary) behavior [60, 32].

The theory of risk attitudes in the context of EU has been challenged by the twin issues of inconsistent risk profiles across risk domains and cross-method utility instability [33, 140, 49, 34]. Different risk-averse or risk-tolerant classifications often result when different methods are used to measure people's utility [33]. Further, individuals are not consistent across different risk domains. While a person might be risk-averse making financial decisions, they could be risk-seeking in social situations [34].

Other methods have been developed within psychology to make up for the shortcomings of the EU framework. For instance, the risk-return framework of risky choice models people's preference for risky options based upon a trade-off between the EV and the riskiness of the choice. This is analogous to the way most engineering risk methods differentiate between risk choices. Psychology extends this to treat perceived risk as a variable that differentiates individuals based upon content and context interpretations. The framework allows people to have different risk preferences in different domains [40] and accounts for desiring risk in some areas while preferring caution in others by the concept of perceived risk attitude. Variances in perceived risk attitude are viewed to be the result of differences in perception of risks and benefits between a decision-maker and an outside observer. For instance, in the management field, managers have less optimistic perceptions of risk than entrepreneurs [43]. The risk-return framework shows that a person's perception of risk affects the choices that person will make.

In order to assess risk perceptions and attitudes within different domains, the DOSPERT test and related scale were created [40]. Six independent domains were identified including the ethical, investment, gambling, health/safety, recreational, and social domains within which the majority of day-to-day activities can be categorized. The DOSPERT test is seeing widespread adoption in psychology. Recently, the E-DOSPERT test [85] was proposed as a method to determine engineering-specific risk attitudes as defined by four engineering risk domains including risk identification, analysis, evaluation, and treatment [57]. The E-DOSPERT scale has been shown to reliably measure general engineering risk aversion and risk seeking attitudes. It can also measure risk seeking and risk aversion attitudes in the risk identification and risk treatment domains. Additional research is underway in order to fully measure the four engineering risk domains. The DOSPERT and E-DOSPERT tests provide evidence of the need for a method to make risk decisions based on tolerant or averse risk appetites.

6.3.4 Decision-Based Design

To address the growing recognition within industry and the engineering research community [70, 71, 72, 73] that decision-making is a fundamental part of the design process, the DBD framework was developed. A decision-theoretic methodology is utilized to select preferred product design alternatives and set target product performance levels. A single selection criterion, V, in the DBD implementation represents economic benefit to the enterprise [73]. This approach avoids the difficulties of weighting factors and multi-objective optimization which can violate Arrow's Impossibility Theorem [74]. A utility function, U, which expresses the value of a designed artifact to the enterprise when considering the decision-maker's risk attitude, is created as a function of the selection criterion, V. A preferred concept and attribute targets are selected through the maximization of enterprise utility.

In order to effectively use the single criterion approach to DBD, the selected criterion must be able to capture all of the issues involved in the engineering design such as system features, costs, risks, physical restrictions, and regulatory requirements. The single criterion should allow both the interests of the users and producers of the system to be considered. In most industrial cases, the most universal unit of exchange is money. Material, energy, information, faults and time can all be assigned a monetary value. This can be seen in many design decision-making processes and is practiced widely in industry.

One use of single criterion DBD developed by Hoyle et al. [75] employs profit as the criterion in a method to determine optimum system configuration for ISHM. The determination of system profit is made from the product of system availability and revenue, minus the summation of cost of system risks, and the cost of fault detection. This method can determine optimal ISHM while also determining the optimum detection/false alarm threshold and inspection interval. Using the method has been found to increase profit by 11%, decrease cost by a factor of 2.4, and increase inspection intervals by a factor of 1.5 [75].

6.3.5 Risk-Based Utility Theory

One approach to analyzing choice outcomes from a non-neutral expected value perspective is to use risk-based utility theory [31]. The utility of a range of probabilistic outcomes can be determined in order to aid decision-makers. This is done by translating monetary outcomes to utilities. A risk-tolerant decision-maker's higher intrinsic value for riskier decisions skews the utility of those decisions higher than a risk-neutral or risk-averse decision maker's utility of the same decisions. Figure 6.2 shows that for a Normal distribution of outcomes, a risk-tolerant person's utility distribution will shift to be more heavily skewed toward higher value outcomes. Utility distributions for risk-averse individuals will skew more heavily toward lower value outcomes, as can be seen in Figure 6.3. The risk neutral state, shown in Figure 6.4, does not weight outcomes in either direction along the utility axis. As can be seen in Figures 6.2 through 6.4, different utilities are found based upon a decision-maker's risk appetite.

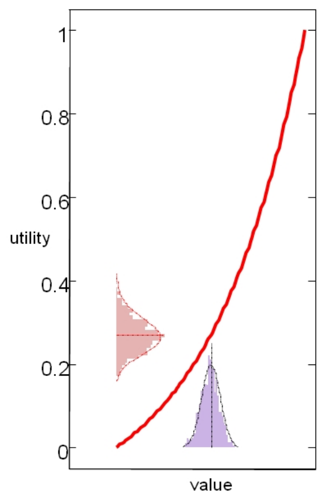

Figure 6.2: Risk-Tolerant Utility Function.

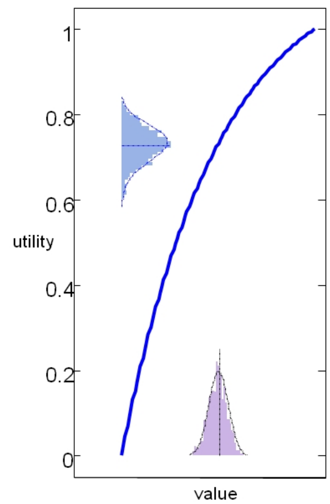

Figure 6.3: Risk-Averse Utility Function.

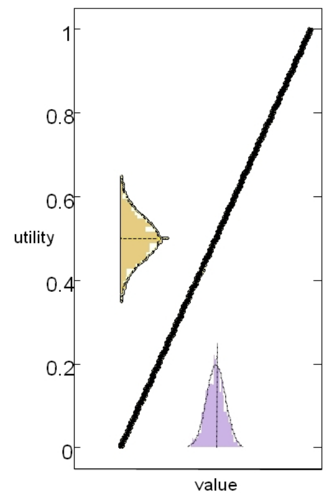

Figure 6.4: Risk Neutral Utility Function.

Currently accepted methods of developing utility risk functions, such as those in Figures 6.2 through 6.4, require a series of lotteries to be conducted [31]. Several sets of paired choices are presented sequentially to an individual. These are often presented as lotteries where a participant selects amongst paired probabilistic alternatives. A utility risk function is then fitted to the lottery results. Common functions include quadratic, logarithmic, and exponential functions [76]. In currently accepted methods of risk utility function generation, the choice of which form a risk utility function should take is at the discretion of the decision-maker and based upon results of lotteries. The scale of the value axis of the utility function is set to the minimum and maximum limits of the values used to conduct the lotteries.

Developing and conducting lotteries is time-consuming and not intuitive to end-users [77]. Also, the utility functions derived from lotteries are only valid for the range of values used in the lottery. Therefore, while useful in many areas, lottery-based methods of utility risk function generation are not always useful. Pennings and Smidts [77] investigated using psychometric risk attitude test results to create risk functions for Dutch hog farmers to predict individual farmer behavior in hog futures markets. The results of the research found lotteries to be the most accurate method of predicting behavior in the context of the hog futures market. However, the hog farmers' self-reported behavior predictions were most closely correlated with the psychometric risk attitude test results. The farmers also indicated that the psychometric risk attitude test was more understandable than the lottery method.

In this paper, the authors postulate that, while lottery methods of utility risk function generation are satisfactory for many DBD situations, they are not as useful for early-phase conceptual design. Lottery-based risk functions are only valid over the range of values used in the initial lotteries. In the case of early-phase conceptual design, the range of values might not be fully known or could change during the design process. Re-running lotteries to create expanded risk functions thus would quickly become burdensome to the practitioner. Further, in cases where utility risk functions are developed based upon client or customer risk appetites, conducting multiple lottery sessions is impractical. Finally, as hinted at in Pennings and Smidts' research [77], lotteries do not closely match what individuals believe they will do. However, actions of individuals more closely align to the predictions of lottery methods than to self-reported methods. This can be interpreted as a disconnect between what individuals aspire to do and what they actually do. Utility risk functions generated by alternative methods could potentially provide new insights for practitioners that will allow decisions to be made based upon aspirations rather than upon past performance, as is the case with lotteries.

In summary, several methods exist and are in use in the risk-based design approach to determine engineering risk, manage identified risks, and make decisions based upon that risk. However, these methods approach risk from an expected value choice perspective where the decision-makers and stakeholders are expected to be risk neutral. Utility functions which account for risk attitude have been used in the DBD framework; however, these functions have generally been developed for consumer products, where there is a trade-off between product features, price and demand, and not risk-based design applications. While utility risk functions can be useful for risk-based design applications, they are not satisfactory for early-phase conceptual design problems. As has been shown with the DOSPERT and E-DOSPERT tests, people can be risk-averse, neutral, or tolerant. Therefore, a method is needed that can support decision-making for different risk appetites within the risk-based design paradigm. Psychometric risk attitude test-generated utility risk functions hold promise for use in early-phase conceptual system design.

6.4 Methodology

Risk-based design methods are used to make decisions about risk in system design. Risk analysis tools such as FMEA and FTA are commonly used to evaluate system safety and reduce the likelihood of failure. The risk-based design methods take an expected value approach toward all engineering risk domains. However, design stakeholders often have domain-specific risk attitudes that are not risk neutral. The authors propose a novel method to determine the true value of risk decisions using utility theory and the

E-DOSPERT risk appetite research. This method translates engineering risk method data into utility functions, the line along which a value can be translated into a utility on a two-dimensional plot, using the single criterion DBD approach.

To show how risk appetite can be ignored in standard utility calculations, the risks in Equations 6.1 and 6.2 are equal in the context of risk-based design. In Equation 6.1, a 1% chance exists that a risk costing \$10,000 to return the system to a nominal operating state will occur while in Equation 6.2, there is a 0.1% chance of realizing a risk that costs \$100,000 in order to return the system to a nominal state. Equation 6.2 represents a case in which additional system complexity has been added to the base design of Equation 6.1, which has lowered the probability of losing system functionality but has increased the repair cost in the event of a fault. Both risks have an expected value of -\$100. Therefore, a decision-maker using risk-based design would have no guidance in choosing between the two designs. The designs are of equal value using the expected value approach.

$$R_1 = 0.99(0) + 0.01(-\$10,000) = -\$100 \tag{6.1}$$

$$R_2 = 0.999(0) + 0.001(-\$100,000) = -\$100 \tag{6.2}$$

In contrast, taking into account a risk appetite can change the resulting valuation. Risk-based design instructs decision-makers that the choice between the risk in Equation 6.1 and the risk in Equation 6.2 does not matter because both outcomes have the same expected value. However, a risk-averse decision-maker will choose the design in Equation 6.2 in order to have more certainty about the likelihood of occurrence of the risk. A risk-tolerant decision-maker is not as concerned with certainty and will choose the design in Equation 6.1 due to the lower financial consequence. The example in Equations 6.1 and 6.2 has a clear choice outcome for risk-averse and risk-tolerant decision-makers.

Equations 6.1 and 6.2 are of the form $R_n = B + A_m + A_{m+1} + \ldots + A_{m+x}$ where B = *probability of benefit* × *outcome of benefit* and A_{m+x} = *probability of risk*$_{m+x}$× *outcome of risk*$_{m+x}$. The benefit and risk probabilities all sum to 100%. This research is only interested in risks and their costs. Therefore all benefits are considered to be identical between risk choices, i.e., the full system benefit is realized when the system is not in a fault state and is equal among all design variants. For the purposes of this paper, the outcome of the benefit is taken to always be zero.

While the example in Equations 6.1 and 6.2 has a clear choice outcome for risk-averse and risk-tolerant decision-makers, the design choice presented in Equations 6.3 and 6.4 is less clear for decision-makers that are not risk neutral. Rationalizing choosing the design characterized by Equation 6.3 is impossible under risk-based design. However, the risk-tolerant decision-maker might still choose the design with a larger negative expected value because she is more concerned with the lower financial consequence than the certainty of the outcome.

$$R_1 = 0.99(0) + 0.01(-\$15,000) = -\$150 \tag{6.3}$$

$$R_2 = 0.999(0) + 0.001(-\$100,000) = -\$100 \tag{6.4}$$

The risk-tolerant decision-maker's higher intrinsic value for the riskier decision in this example can be examined through the lens of utility theory. Figures 6.2, 6.3, and 6.4 demonstrate how risk attitude can affect the utility of a value distribution.

Figure 6.2 shows that for a Normal distribution of outcomes, a risk-tolerant person's utility distribution will shift to be more heavily skewed toward higher value outcomes. Utility distributions for risk-averse individuals will skew more heavily toward lower value outcomes, as can be seen in Figure 6.3. The risk neutral state, shown in Figure 6.4, does not weight outcomes in either direction along the utility axis.

Utility functions derived from discrete outcome distributions can also be affected by risk attitudes. The utility for a system feature with two potential discrete outcomes takes the form of Equation 6.5 where $u(s)$ represents the system utility, p_0 is the probability of the first outcome, $u(x_H)$ is the utility of the first outcome, $(1-p_0)$ is the probability of the second outcome, and $u(x_L)$ is the utility of the second outcome.

$$u(s) = p_0 \times u(x_H) + (1 - p_0) \times u(x_L) \tag{6.5}$$

To explicitly show how taking risk appetite into account can change resulting valuation, a generic utility problem where risk is represented as a dollar figure is shown in Equation 6.6. Figure 6.5, developed via a series of lotteries, where the minimum value is \$250 and maximum is \$1,050, provides a risk-averse quadratic utility function. As was discussed previously in Section 6.3.5, while lottery-generated risk functions are appropriate for many situations, the authors postulate that they are not appropriate for early-phase conceptual complex system design.

$$u(s) = 0.4 \times u(\$900) + 0.6 \times u(\$400) \tag{6.6}$$

Determining the utility of each potential outcome is demonstrated in Equation 6.7 where the utility of \$900 is found to be 0.91 via inspection of the utility function, as shown in Figure 6.5, and the utility of \$400 is found to be 0.35 from the risk utility

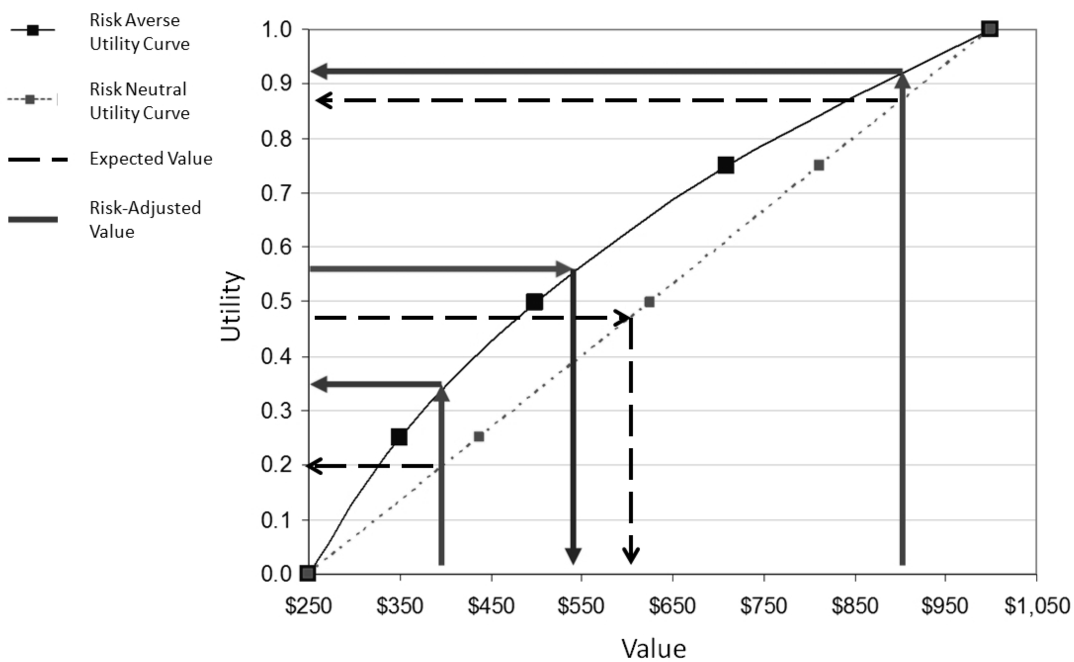

Figure 6.5: Risk-Averse Quadratic Utility Function Developed Using the Lottery Method. The value of the potential outcomes is translated via the risk averse risk function to the utility domain. The two utilities are then combined using the generic Equation 6.5, as applied in Equation 6.7, and translated back through the risk averse utility function to find the risk-adjusted value of \$540. Using the risk neutral utility function, a value of \$600 is found.

function as demonstrated in Figure 6.5. These utilities are then multiplied by their respective probabilities and summed together to find the overall system utility, $u(s) = 0.57$, for a risk-averse decision-maker. Reversing the procedure, a utility of 0.57 produces a risk-adjusted value of u^{-1} = \$540 while a neutral utility function results in a risk-adjusted value of u^{-1} = \$600. This clearly shows that using a risk appetite function in a utility function results in a different valuation of the system than would be found without using a risk appetite function.

$$u(s) = 0.4 \times (0.91) + 0.6 \times (0.35) = 0.57 \tag{6.7}$$

As previously discussed, while risk functions generated using lottery methods are useful in many situations, early-phase conceptual design can benefit from an alternative method. The authors propose using risk functions generated from E-DOSPERT test results. Based upon the findings of Van Bossuyt et. al. [85], the 25 question E-DOSPERT test provides sufficient statistical reliability to determine general engineering risk tolerance or risk aversion. The mean of the 25 question instrument is proposed by the authors to be the most appropriate metric for use with risk function development. The E-DOSPERT makes use of a 1-5 Likert Scale with 1 corresponding to “Very Unlikely” and 5 corresponding to “Very Likely.” A score of 3 corresponds to the neutral answer of “Not Sure.” Using the 25 risk tolerant questions in the E-DOSPERT test, a mean score of 3 indicates a neutral risk appetite, a mean score of 5 indicates extreme risk tolerance, and a mean score of 1 indicates an extremely averse risk appetite. An individual engineer, customer, or stakeholder’s E-DOSPERT test result is used to generate utility functions. Note that multiple E-DOSPERT test results cannot be combined due to Arrow’s Impossibility Theorem [141].

In this research, the authors suggest that an exponential function is an appropriate utility risk function to use with psychometric risk scale test results. The function may be either of the monotonically increasing or decreasing exponential type [88]. An exponential function was chosen over other potential functions because it is believed that practitioners will be either constantly risk averse or constantly risk tolerant during the early phases of conceptual system design. In one study where a risk survey was compared to the lottery method, it was found that risk functions generated by the lottery method were exponential in nature. Further, there was reasonable correlation between the risk survey results and lottery method results [77]. Research is ongoing in this area to verify that this holds true for the E-DOSPERT.

The choice of an exponential function also allows the direct use of E-DOSPERT test results in the creation of a risk function [76]. The monotonically decreasing exponential utility function developed by Kirkwood [88] shown in Equation 6.8 is used throughout the rest of this paper. $U(V)$ represents utility of the potential value(s). $CE(V)$ represents the risk-adjusted value of the potential values of interest, otherwise known as the certainty equivalent. V_{Max} is the maximum possible value. It should be noted that V_{Max} need not be the maximum value of the range of potential values of interest but can be a larger number than the maximum potential value of interest. This property is useful in situations where a larger maximum value is possible than the set of potential values currently being investigated or when multiple sets of potential values, representing multiple sets of outcomes of a decision choice, span different numerical ranges. Similarly, V_{Min} is the minimum possible value which need only be smaller than or equal to the smallest potential value of interest. Note that V_{Min} can either be a positive or negative number. $R_{T/A}$ is the risk tolerance/aversion coefficient of the utility function. In order to convert an E-DOSPERT mean score (EDS_{Mean})

to an $R_{T/A}$ value, Equation 6.9 was developed by the authors based upon the work of Kirkwood [88], Howard [142], and McNamee and Celona [143]. In Equation 6.9, R_{SF} is a scaling factor. Several different rules of thumb based upon financial measures are available to determine R_{SF} such as finding a sufficient R_{SF} that $R_{T/A}$ will be roughly %6 of net sales, a 100-150% of net income, and about $\frac{1}{6}$ of equity [142]. These rules of thumb have been found useful in the oil and chemical industries [142]. Additional suggestions are given by Kirkwood [88] and McNamee and Celona [143]. It is important that the practitioner select an R_{SF} that is appropriate to their industry, company, and the specific analysis being performed. It is beyond the scope of this paper to provide strict guidance on domain and situation-appropriate R_{SF} values. It is also beyond the scope of this paper to judge if practitioner level of expertise can influence the selection of appropriate rules of thumb. For the examples and illustrations presented in this paper, R_{SF} = 60 will be used to clearly demonstrate the novel method to determine true value of risk decisions using utility theory and the E-DOSPERT test.

$$U(V) = \frac{e^{-\frac{V_{Max}-V}{R}} - 1}{e^{-\frac{V_{Max}-V_{Min}}{R}} - 1} \tag{6.8}$$

$$R_{T/A} = \frac{V_{Max} - V_{Min}}{1000} * \frac{R_{SF}}{EDS_{Mean} - 3} \tag{6.9}$$

The inverse of Equation 6.8, shown in Equation 6.10, is used to calculate the certainty equivalent. In the special case of an E-DOSPERT test result where the test-taker is found to have a perfectly risk neutral risk appetite, Equations 6.11 and 6.12 are used to generate the risk function and find the risk-adjusted value of the potential values. Examples of monotonically increasing exponential utility functions can be found in Kirkwood [88]. Other risk utility functions of potential interest to the practitioner are

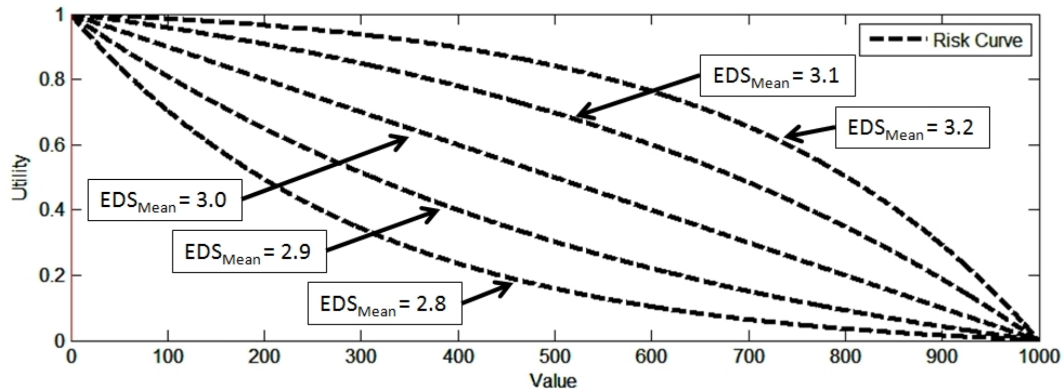

Figure 6.6: Monotonically Decreasing Exponential Risk Utility Functions Developed Using Equation 6.8 where $EDS_{Mean} = 2.8, 2.9, 3.0, 3.1, 3.2$, $R_{SF} = 60$, $V_{Max} = 1000$, and $V_{Min} = 0$.

available in Keeney and Rafta [76]. A series of risk functions generated in MATLAB using Equation 6.8 from E-DOSPERT mean scores of $EDS_{Mean} = 2.8, 2.9, 3.0, 3.1, 3.2$, $V_{Max} = 1000$, $V_{Min} = 0$, and $R_{SF} = 60$ is shown in Figure 6.6.

$$CE(V) = R_{T/A} * log(-U(V) * (e^{\frac{V_{Max}}{R_{T/A}}} - e^{\frac{V_{Min}}{R_{T/A}}} - e^{\frac{V_{Max}}{R_{T/A}}}) \tag{6.10}$$

$$U(V) = \frac{V_{Max} - V}{V_{Max} - V_{Min}} \tag{6.11}$$

$$CE(V) = U(V) * (V_{Min} - V_{Max}) + V_{Max} \tag{6.12}$$

In order for engineering risk methods to make use of risk appetite functions in utility theory, risk metrics generated by the various engineering risk methods must be translated into an easily comparable unit of measure. The authors advocate using consequential cost as it is a convenient and easily understood unit of measure. Therefore, in order to use this risk appetite utility method, both consequential cost and probability must be determinable for the risks identified by engineering risk methods. Standard engineering tools used in the design process often contain the necessary risk information, but require translation into the appropriate probability and cost metrics. For example, translating risk information from an FMEA into probability and consequential cost is relatively straightforward. Probability can be derived from the occurrence metric. In the case of a purely linear occurrence metric scale, the percent chance of failure can be found by multiplying occurrence, Occ, by an appropriate factor, Oc_f. When the occurrence scale is not linear, an appropriate function can be used to translate the occurrence metric into a probability value. In the case of a linear occurrence metric scale, Oc_f should be determined by dividing 100 by the result of subtracting the low (Occ_{Min}) end of the occurrence metric scale from the high (Occ_{Max}) of the scale, as shown in Equation 6.13. Probability, P_0, can then be determined by Equation 6.14 where $P_{1 \to n}$ represents the complete set of probabilities under consideration.

$$Oc_f = \frac{100}{Occ_{Max} - Occ_{Min}} \tag{6.13}$$

$$P_0 = 1 - \frac{\frac{Occ * Oc_f}{100}}{\sum P_{1 \to n}} \tag{6.14}$$

Consequential cost, representing value, can be determined in a variety of manners. The authors suggest that consequential cost should be determined by the cost to return the system to a nominal state if the risk occurs. In the event that consequential cost cannot be directly determined, a summation of the severity and detection metrics can be used as an analogue metric to consequential cost.

Table 6.1 provides a simplified FMEA for a complex system design with three identified risks and the consequential cost of each risk. Decision-Maker A has been tasked with deciding which risk is the most important to fix. Decision-Maker A has a risk-averse appetite where EDS_{Mean} = 2.88. The generalized form of Equation 6.5 is used in this example by setting p_0 equal to Equation 6.14 where Occ_{Max} = 10, Occ_{Min} = 0, Oc_f = 0.1, X_{High} = 0, X_{Low} = $V(R_n)$, V_{Min} = \$250, V_{Max} = \$1,050, and R_{SF} = 20. Using a risk-averse utility function generated from Equation 6.8 and Equation 6.5 ,the risk-averse Decision-Maker A discovers that the most desirable certainty equivalent choice is $CE(R_1)$ = \$0.8909, while $CE(R_2)$ = \$1.1292, and $CE(R_3)$ = \$2.9184. Therefore, the risk-averse decision is to mitigate the R_1 risk as it has the lowest certainty equivalent value.

Table 6.1: Simplified FMEA Example for Decision-Maker A.

Risk	Function	Severity	Occurrence	Detection	RPN	Consequential Cost
R_1	Funct 1	7	3	4	84	\$450
R_2	Funct 2	4	5	8	160	\$300
R_3	Funct 3	2	8	3	48	\$650

This method can also be used to compare between different designs. For instance, using Table 6.1 as Design 1 and Table 6.2 as Design 2, a risk-tolerant person, Decision-Maker B, with an E-DOSPERT mean score of EDS_{Mean} = 3.15 can determine which design is more preferred. Using the monotonically decreasing exponential risk function of Equation 6.8 with V_{Max} = \$1,000, V_{Min} = \$0, Occ_{Max} = 10, Occ_{Min} = 0, Oc_f = 0.1, R_{SF} = 60, X_H = 0, and $X_L = V(R_n)$ the utilities of risks, probabilities, system utilities, and risk-adjusted values are found as shown in Table 6.3. Equation 6.15 is then used to find the overall certainty equivalents (CE) of the two designs where $CE_n(R_n)$ is the risk-adjusted value of the individual identified risk, R_n. Each of the risks identified in the FMEA presented in Tables 6.1 and 6.2 is an independent risk, and thus the total risk is simply the sum of the individual risks. Equation 6.15 is used rather than Equation 6.10 because each of the risks identified in the FMEA presented in Tables 6.1 and 6.2 is an independent risk. Applying Equations 6.8 and 6.15 shows that the risk-tolerant Decision-Maker B with an EDS_{Mean} = 3.15 would choose Design 1 as it has the smallest certainty equivalent. Decision-Maker C who has an expected value risk neutral decision making criteria would find Design 1 to have CE = \$8.05 and Design 2 to have CE = \$5.5000, and thus would choose Design 2 as it has a lower certainty equivalent than Design 1.

$$CE(R_{Total}) = CE_1(R_1) + \ldots + CE_n(R_n) \tag{6.15}$$

Table 6.2: Simplified FMEA for Design 2 for Decision-Maker B.

Risk	Function	Severity	Occurrence	Detection	RPN	Consequential Cost
R_1	Funct 1	5	4	4	80	\$400
R_2	Funct 2	6	5	7	210	\$700
R_3	Funct 3	3	2	3	18	\$200

6.5 Implementation and Testing

An illustrative case study is developed in the following section. The SuperNova /Acceleration Probe (SNAP) mission trade study [144] performed by Team-X provides the bulk of the background information necessary for this case study. Additional material comes from the Space Mission Analysis and Design book by Wertz and Larson [90]. Costing and risk data are simulated for illustrative purposes only and should not be used beyond this case study. The SNAP mission's purpose is inconsequential in

Table 6.3: Utility of Risk, Probability, and Risk-Adjusted Value Data for Design 1 and Design 2 Risks for Decision-Maker B.

Design 1				
Risk	Utility of Risk($u(X_L)$)	Probability (1-P_0)	System Utility ($U(s)$)	Certainty Equivalent ($CE(R_n)$)
R_{1_1}	0.0024	0.0030	0.9994	\$2.4885
R_{2_1}	0.0045	0.0050	0.9995	\$2.2278
R_{3_1}	0.0051	0.0080	0.9971	\$12.846
			Risk-Adjusted Value ($CE(R_{total})$)	Total: \$17.5623

Design 2				
Risk	Utility of Risk($u(X_L)$)	Probability (1-P_0)	System Utility ($U(s)$)	Certainty Equivalent ($CE(R_n)$)
R_{1_1}	0.0034	0.0040	0.9994	\$2.7398
R_{2_1}	0.0029	0.0050	0.9979	\$9.3979
R_{3_1}	0.0020	0.0019	0.9999	\$0.5186
			Risk-Adjusted Value ($CE(R_{total})$)	Total: \$12.6563

the demonstration of the method presented in this paper. Further information on the SNAP mission can be found in [144] for those interested.

The SNAP mission was intended to investigate the nature and origin of "Dark Energy" acceleration and expansion of the universe. The experiment was designed to precisely measure the history of the universe's expansion from the present day back to approximately 10 billion years in the past. Plans called for a satellite in a high earth orbit on a four year mission to study the brightness of la type supernovae and the redshift of la type supernova host galaxies [144].

Several risks were identified in the SNAP mission report. This paper makes use of and expands upon potential risks in the power and attitude control subsystems. Table 6.4 details several risks that will be used in the remainder of this paper.

During the course of the CDC trade study session, the risks outlined in Table 6.4 were identified. Risks R_1 and R_2 are potential threats to mission success. Risks $R_{3_{1-2}}$ and R_4 are threats to the level of science data that can be returned from the spacecraft but will not end the mission completely. The R_{3_1} and R_{3_2} risks identify the same risk and propose two different solutions. R_{3_2} also presents the same solution as the solution for R_4.

In order for the SNAP mission proposal to be considered for further development funding, it must meet a specific cost cap. In this fictitious example, the mission proposal is $40M away from reaching the cost cap. Not all of the identified risks can be mitigated under this cost cap. Based upon the RPNs of the four identified risks, R_2 should be addressed first. This however would not leave enough funds to address R_1, the next largest risk. Additionally, the customer believes that severity of R_1 is overstated and wants to take a more risk-tolerant stance on R_1 while addressing some of the science data concerns of R_3 and R_4 within the limited resources available.

Table 6.4: Simplified Case Study FMEA of SNAP Power and Attitude Control Subsystems.

Risk	Function	Failure Mode	Effects	Sev.	Occ.	Det.	RPN	Recommended Action	Cons. Cost
R_1	Spacecraft pointing	Excessive jitter	Long exposure photos are blurry	7	1	4	112	Increase reaction wheel size	\$30M
R_2	Energy storage	Ni-H2 battery cell fails	Degraded battery performance and possible loss of mission	9	2	7	126	Use redundant batteries or replace with Li-Ion battery	\$20M
R_{3_1}	Data storage	Insufficient storage space	Loss of science data if downlink is missed	5	5	2	30	Add second solid state recorder	\$15M
R_{3_2}	"	"	"	"	"	"	"	Add additional ground station	\$23M
R_4	Ground station	Missed downlink	Fail to receive data due to rain	4	5	4	80	Build additional ground station	\$25M

To help make risk mitigation decisions, the customer, represented by a single person, was given the E-DOSPERT test. The result, EDS_{Mean} = 3.17, was used with the monotonically decreasing exponential risk utility function in Equation 6.8 where V_{Max} = \$120M, V_{Min} = \$0, X_H = 0, $X_L = V(R_n)$, Occ_{Max} = 10, Occ_{Min} = 0, Oc_f = 0.1, and R_{SF} = 60. The consequential cost was used as potential outcome values while the occurrence values were used to determine probability of occurrence. Table 6.5 shows the resulting probability, and utility data. From this data, decision-makers can see that risks R_2 and R_{3_1} are the most preferred under a risk-tolerant decision process and will cost less than \$40M. A risk-neutral approach would have chosen risks R_1 and R_2. The two most preferred risks to mitigate also satisfy some of the questions surrounding mission success and science data return.

After a mission has been conceptually developed within Team-X, it is often placed into competition with other competing conceptual spacecraft mission designs for further funding. In this case study, the SNAP mission was put into competition against two other missions for funding after mitigating the risks identified above. Table 6.6 summarizes the relevant SNAP risk data and risk data for the other competing mission concepts. It is assumed that each mission has already mitigated as many risks as was possible under the budget cap.

The decision-maker who will choose which mission concept is awarded funding to continue development has decided to use a monotonically decreasing exponential risk utility function as shown in Equation 6.8 where V_{Max} = \$60M, V_{Min} = \$0, Occ_{Max} = 10, Occ_{Min} = 0, Oc_f = 10, and R_{SF} = 20. The decision-maker's E-DOSPERT test result is EDS = 3.10, making her risk-tolerant. Equation 6.10 is used to determine the certainty equivalent, CE, of each design. Table 6.7 shows the utility, probability, certainty equivalent.

Table 6.5: Probability and Risk Utility Data for Identified Risks in the SNAP Mission. The Certainty Equivalent is Derived Using the Customer's EDS_{Mean}.

Risk	Utility of Risk($u(X_L)$)	Probability (1-P_0)	System Utility ($U(s)$)	Certainty Equivalent ($CE(R_n)$)
R_1	0.0006	0.0001	1.0378	\$0.1681
R_2	0.0018	0.0020	1.0379	\$0.1182
R_{3_1}	0.0048	0.0050	1.0378	\$0.1641
R_{3_2}	0.0042	0.0050	1.0372	\$0.4040
R_4	0.0032	0.0040	1.0373	\$0.3991

Table 6.6: Simplified FMEA for the SNAP Mission and Other Competing Missions.

SNAP Mission						
Risk	Function	Sev.	Occ.	Det.	RPN	Cons. Cost
$R1_{SNAP}$	Funct 1	3	4	4	112	\$30M
$R4_{SNAP}$	Funct 4	2	5	4	80	\$25M

Competing Mission A						
Risk	Function	Sev.	Occ.	Det.	RPN	Cons. Cost
$R1_A$	Funct 1	4	5	3	84	\$25M
$R2_A$	Funct 2	3	2	8	48	\$20M
$R3_A$	Funct 3	5	3	4	60	\$35M

Competing Mission B						
Risk	Function	Sev.	Occ.	Det.	RPN	Cons. Cost
$R1_B$	Funct 1	6	1	4	72	\$40M
$R2_B$	Funct 2	8	3	5	120	\$30M

Table 6.7: Utility and Probability Data for Design 1 and Design 2 Risks.

SNAP Mission				
Risk	Utility of Risk($u(X_L)$)	Probability (1-P_0)	System Utility ($U(s)$)	Certainty Equivalent ($CE(R_n)$
$R1_{SNAP}$	0.0018	0.0030	0.9988	0.1542
$R2_{SNAP}$	0.0014	0.0020	0.0014	0.0780
		Risk-Adjusted Value ($CE(R_{total})$) Total: \$0.2322M		

Competing Mission A				
Risk	Utility of Risk($u(X_L)$)	Probability (1-P_0)	System Utility ($U(s)$)	Certainty Equivalent ($CE(R_n)$)
$R1_A$	0.0035	0.0050	0.9985	0.1945
$R2_A$	0.0016	0.0020	0.9996	0.0568
$R3_A$	0.0015	0.0030	0.9985	0.1984
		Risk-Adjusted Value ($CE(R_{total})$) Total: \$0.4497M		

Competing Mission B				
Risk	Utility of Risk($u(X_L)$)	Probability (1-P_0)	System Utility ($U(s)$)	Certainty Equivalent ($CE(R_n)$)
$R1_B$	0.0003	0.0001	0.9993	0.0837
$R2_B$	0.0018	0.0030	0.9988	0.1542
		Risk-Adjusted Value ($CE(R_{total})$) Total: \$0.2379M		

By using the risk appetite utility function method, the decision-makers see that the SNAP mission is the most preferred design in the case of risk tolerance. Therefore, assuming all other mission selection criteria are equal, the SNAP mission would be the preferred mission to receive continued funding. This selection would not have been made under a risk neutral, expected value decision making process and instead would have chosen Competing Mission A due to the lower certainty equivalent. In the case of a neutral risk appetite, $CE(SNAP)$ = \$0.1400, $CE(MissionA)$ = \$0.2700, and $CE(MissionB)$ = \$0.1300. A similar process to this would then be repeated at the next level of mission selection after further mission concept development.

6.6 Conclusion and Future Work

As seen in the case study, the risk appetite utility function method allows engineering risk methods which are in the expected value domain to be translated into an appropriate risk appetite domain for a specific enterprise or decision-maker. Viewing the risk information through the lens of risk appetite provides a decision-maker with a new, numerically based approach to select and justify selection of the most important risks to address under constrained resources. Rather than using "gut feeling" to try and explain risk decisions, this method gives stakeholders a way to rationalize their risk-based decisions.

Several limitations are present in the method. This method is only designed for individual stakeholders or enterprise-level usage where one consistent risk appetite function can be generated. Additional methods, such as the Accord decision support software package [145], could be useful in combining the inputs of multiple stakeholders into a unified risk appetite utility function.

Further expansion of this methodology will examine the benefit side of Equation 6.5 which can add an expected benefit if the risk outcome is not realized. This area of research could be especially fruitful for comparing multiple risks against one another for risk-tolerant enterprises. Large risks can have associated large benefits. This method does not currently account for the potential large return for taking a large risk.

Addition of a post-risk-realization cost to return the system to a nominal state is a promising area of future development for this method. Seven potential options for returning the system to a nominal state exist including repair, reconfiguration, replacement, redundancy, reconditioning, recovery, and resetting. Depending upon which option is chosen to return a system to its nominal state, the portion of Equation 6.5 that represents the beneficial outcome could change. This research only focuses upon the portion of Equation 6.5 that examines the costs of a risk. Additionally, future risk realizations could be limited from the initial risk event due to the option chosen to return the system to a nominal state. The definition of a nominal system state also could change to some form of a reduced system capacity but a capacity that still provides some value to the enterprise. This is exemplified with subsystems failures on satellites such as the failure of the high gain antenna and the tape recorder remote repair on the Galileo spacecraft [146].

Testing of this method should be conducted to determine user satisfaction levels between utility risk functions generated with lottery methods and with E-DOSPERT test results. For instance, surveys of user groups such as those conducted in [82] could be conducted. Choice determinations made with the help of risk functions generated from the E-DOSPERT test could be compared against choices made by individual respondents on risk decisions where a risk-averse person would decide differently than a risk-tolerant person. This would verify that risk appetite affects engineering risk decisions. The same population of respondents would also be provided data from the risk appetite utility function method using risk functions generated with lotteries to make risk decisions. In future work, this method will be tested and verified at Boeing in the Commercial Airplane division with production-level design engineers who work in or with a Team-X-like setting or equivalent under the auspices of a National Science Foundation (NSF) grant. This will include further testing and exploration of the creation of the scaling factor, R_{SF} with the intent of developing rules of thumb specific to the aerospace industry. Research is ongoing to investigate "gaming" the E-DOSPERT test which could adversely impact the method presented in this paper.

The risk appetite utility function method presented in this paper translates engineering risk data from the expected value domain into a risk appetite corrected domain using risk functions derived from E-DOSPERT test results using a single criterion decision based design approach. The resulting utility functions are aspirational in nature which is a departure from the predictive utility functions created using lottery methods. The method presented in this paper allows decisions to be made under risk-tolerant or risk-averse decision-making conditions rather than forcing decisions to be made using an expected value approach, as with engineering risk methods. Risk-averse industries such as nuclear power and aerospace will choose to view risk data through a risk-averse lens which emphasizes risks that are more certain. Risk-tolerant enterprises could have the appetite to accept riskier design choices that might result in larger payoffs if the risks are not realized.

The method has been shown to change risk-based decisions in certain situations where a risk-averse or risk-tolerant decision-maker would likely choose differently than the expected value approach suggests. As the E-DOSPERT test is further refined, the risk appetite utility function method could be more useful. Extensions of the method to examining the benefit side of the risk utility equation will provide further benefit to the practitioner. The risk appetite utility function method is a promising area of further research and practical application.

6.7 Acknowledgments

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Chapter 7 –Framework Example

This chapter presents several examples of the risk-informed decision making framework. The examples are implemented in a combination of MATLAB, Excel, and ModelCenter. First a simple single subsystem model is examined in an automated trade study and results are analyzed. Then a model that includes four subsystems is examined. Results are presented and analyzed.

Specifically, a simplified spacecraft model comprising of four subsystems was derived from Wertz and Larson [90] and implemented in both Excel and MATLAB. Details of the model are presented in [82]. A brief overview and additional relevant subsystem information is presented in Section 7.3. The model was then brought into ModelCenter and integrated with E-DOSPERT risk curve algorithms developed in [89] and presented in Chapter 6. (Note: Portions of this chapter are being prepared for submission as part of a journal article after this dissertation has been completed.)

7.1 Framework Deployment

Figure 7.1 shows a typical trade study process conducted in a CDC. After initial design parameters are assigned, individual subsystem chairs make design decisions and work with other subsystem chairs in order to trade system-level parameters such as mass, cost, power, and risk [83]. The resulting design is then examined based upon the system-level parameters and the ability of the design to achieve mission goals. If the design is found satisfactory by the trade study leader or customer, the trade study session is ended and the design is finalized. Otherwise, additional direction is given by the trade study leader or customer and the subsystem engineers iterate on subsystem design choices and intra-subsystem system-level parameter trading.

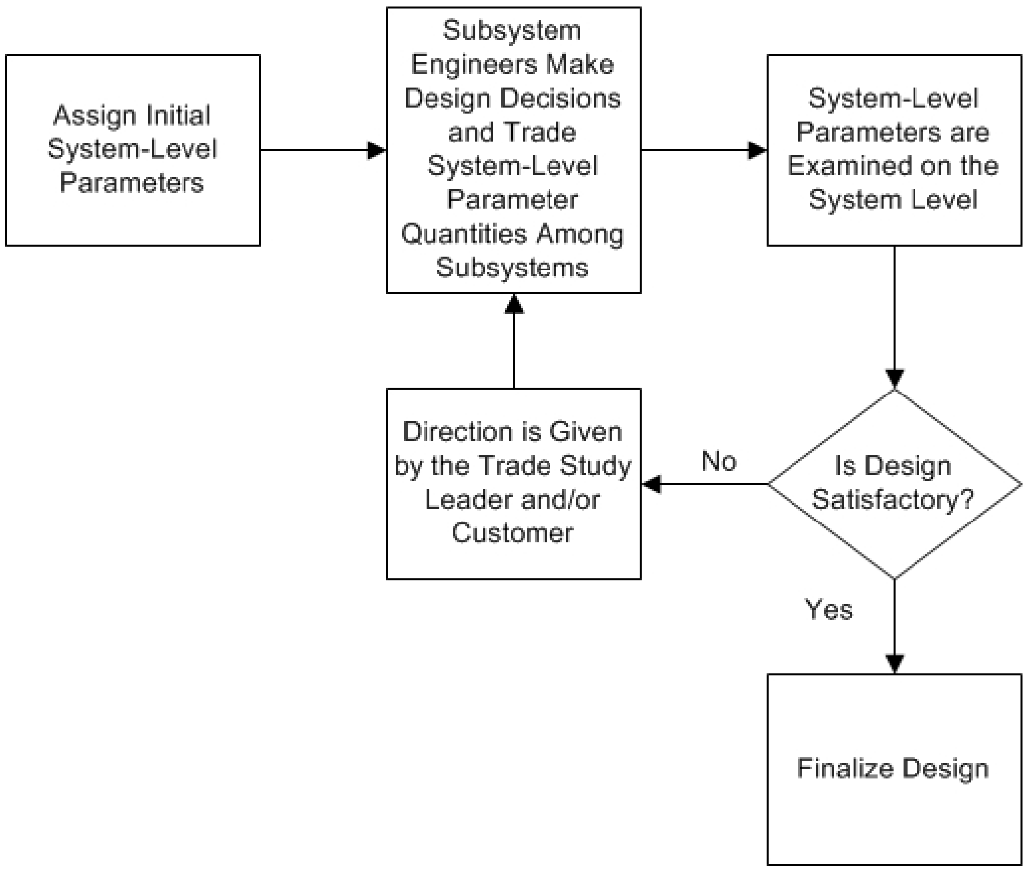

Figure 7.1: Typical Trade Study Process

The risk-informed decision making framework integrates into the trade study process shown in Figure 7.1 throughout the entire process. In the initial step of assigning system-level parameters to individual subsystems, the trade study leader specifies acceptable system-level and, when desired or appropriate, subsystem-level-specific risk parameters. The risk-informed decision making framework is used in assigning risk parameters at the system and subsystem level. In the next step where subsystem engineers make design decisions and trade with other subsystem engineers, the risk-informed decision making framework is used to provide risk-based decision-making support and to aid in risk trading. The E-DOSPERT mean score (EDS_{Mean}) derived from Chapter 5 provides a critical piece of information necessary to create utility risk curves, as was done in Chapter 6. Risk trading can then occur, as detailed in Chapter 4. It is important to note that there are two different ways of using the risk-informed decision making framework. One method allows each subsystem engineer to have individual risk appetites, shown in Section 7.7.1, while the other method imposes a system-level risk appetite upon the entire trade study, detailed in Section 7.7.2.

During the design decision and trading step of Figure 7.1, the subsystem engineers use the framework to analyze the risks present based upon either their own personal EDS_{Mean} values or a system-level EDS_{Mean} value, and make decisions regarding risk mitigation and system-level parameter trading, including risk metrics. The resulting system design and system parameter values are then examined at the system level. At this stage, the framework is used to bring together the subsystem risk metrics on the system level for analysis by the trade study leader or customer, as shown in Chapter 4. Depending upon the style of risk-informed decision making framework implementation, methods described in Chapters 5 and 6 are used to help inform the system-level decision-makers' risk-informed decision making process.

If the trade study leader and customer are satisfied with the design analyzed in the preceding step, the design is then finalized and sent on to the next step of the conceptual design process for the complex system under development. Otherwise, the trade study leader provides direction and guidance to the subsystem engineers and the system design is iterated upon using the preceding steps. As with the first iteration of the trade study process, the risk-informed decision making framework is used throughout the subsequent iterations of the trade study process.

During the design finalization process, key decision rationale is captured and recorded. This important step helps to inform engineers working on the later phases of the conceptual and physical complex system design process of the reasons that certain design decisions were made. The risk-informed decision making framework provides a wealth of information to engineers further along in the design process. Specifically, the information captured from the portions of the framework contained in Chapters 4, 5, and 6 provide the quantitative rationale behind risk-informed decisions that would either have not been considered or would have been an afterthought after a trade study design was finalized, or would have been justified based upon gut feeling or expert judgment. The risk-informed decision making framework gives a quantitative structure in which to determine risk appetites, make risk-informed decisions based upon risk appetites, and trade risk as a system-level parameter during trade studies. The following sections detail specific aspects of the framework and provide examples of the framework in use.

7.2 The Risk-Informed Decision Making Framework in a CDC Environment

This section presents two methods of using the risk-informed decision making framework with individual subsystems in a CDC environment. The methods presented here are specifically tailored to evaluation of risk using FMEA but can be expanded to be used with any other common risk method, as reviewed in Section 2.5. The first method provides the user with the opportunity to select between three different design alternatives based partially upon risk information and risk utility curves created with E-DOSPERT information. The second method provides the user with a method of selecting which risks to mitigate from a list of risks with the decision support of risk information and risk utility curves. Many additional permutations and expansions of the two presented methods of using an FMEA in the risk-informed decision making framework are possible. The methods presented here are not exhaustive but rather representative of potential user interfaces.

7.2.1 Choosing Between Design Alternatives

The first FMEA user interface method, shown in Figure 7.2, presents the user with three different potential design alternative FMEAs. The example shown in Figure 7.2 is drawn from the Data Handling subsystem, a component-based model that contains nine potential design alternatives, developed in Van Bossuyt and Tumer [82], presented in Section 4.5.2, and used in subsequent sections of this chapter. Design Alternative 1 represents a simple, one unit data handling subsystem. Design Alternative 2 represents a two unit, typical data handling subsystem. Design Alternative 3 represents a complex, integrated data handling subsystem. Further information about the possible subsystem combinations is available in Table 4.1. The consequential costs were developed as part of Section 7.3 and are presented fully in that section. The certainty equivalents were determined for a decision-maker with an EDS_{Mean} = 3.1, V_{Max} = 4, V_{Min} = 0, a monotonically decreasing exponential risk curve, and R_{SF} = 60.

Design Alternative 1

Risk Identifier	Function	Failure Mode	Effects of Failure	Severity	Occurrence	Detection Rating	RPN	Consequential Cost	Certainty Equivalent
DA1R1	F1	Data interface unit malfunction	end of mission	10	1	3	30	0.9	0.00109
DA1R2	F3	Backplane malfunction	end of mission	10	1	8	80	0.75	0.00088
DA1R3	F4	Central processor malfunction	degraded processing	7	3	5	105	0.6	0.00204
DA1R4	F5	Central processor malfunction	end of mission	10	1	5	50	0.6	0.00068
DA1R5	F9	Cable failure	degraded data throughput	10	1	1	10	0.25	0.00026
						Risk-Adjusted Value Total:			0.00495

Design Alternative 2

Risk Identifier	Function	Failure Mode	Effects of Failure	Severity	Occurrence	Detection Rating	RPN	Consequential Cost	Certainty Equivalent
DA2R1	F3	Backplane malfunction	end of mission	10	4	8	320	0.75	0.00088
DA2R2	F6	Command data interface malfunction	end of mission	10	6	4	240	0.6	0.00068
DA2R3	F9	Cable failure	degraded data throughput	3	2	4	24	0.25	0.00026
DA2R4	F10	Power Surge	end of missin	10	1	5	50	0.5	0.00056
						Risk-Adjusted Value Total:			0.00238

Design Alternative 3

Risk Identifier	Function	Failure Mode	Effects of Failure	Severity	Occurrence	Detection Rating	RPN	Consequential Cost	Certainty Equivalent
DA3R1	F1	Data interface unit malfunction	end of mission	10	1	3	30	0.9	0.00109
DA3R2	F2	Solid state recorder malfunction	degraded data storage	5	2	5	50	0.4	0.00087
DA3R3	F3	Backplane malfunction	end of mission	10	1	8	80	0.75	0.00088
DA3R4	F6	Command data interface malfunction	end of mission	10	1	4	40	0.6	0.0068
DA3R5	F7	Computer gains sentience	end of mission	10	3	10	300	0.8	0.00285
						Risk-Adjusted Value Total:			0.01249

Color Coding Guide

The most preferred design based upon the customer risk appetite data is highlighted in green while the least preferred design is highlighted in red. Intermediate colors indicate designs that are in between the two extremes.

Alternative Selection

Select the design alternative by placing an "X" next to the desired alternative below.

Design Alternative 1	
Design Alternative 2	X
Design Alternative 3	

Figure 7.2: FMEA Design Selection Interface

From Figure 7.2, it can be seen that the user selected Design Alternative 2 in the "Alternative Selection" box on the center right of the figure. The user is purposefully allowed to select any of the three design alternatives regardless of the consequential cost ranking. This implementation of the risk-informed decision making framework supports risk-informed decision making; it does not impose a decision upon the user. While Design Alternative 2 might be the most preferred design based upon risk, other criteria might be more important or more urgent in the decision maker's mind. Thus the decision maker is allowed to choose which design is preferred based upon the risk information presented in Figure 7.2 as well as other important metrics.

7.2.2 Choosing Which Risks to Mitigate

The second user interface method, shown in Figure 7.3, presents the user with an FMEA that includes certainty equivalent information for each of the identified risks. The user is also presented with consequential cost information and other information relevant to the amount of money available to support risk mitigation. The risk mitigation process works by the user selecting which risks to mitigate while staying within the cost cap. The user is free to select between different risks to mitigate. Risk-informed decision support is provided by the risk-informed decision making framework in the form of the certainty equivalent values and the consequential cost data. The user is free to consider the risk information provided by the risk-informed decision making framework in addition to any other information that the user believes to be pertinent. The data presented in Figure 7.3 is derived from Design Alternative 1 presented in Section 7.2.1.

The user in Figure 7.3 selected the two risks with the highest certainty equivalent that could be afforded together. The user's thought process was to mitigate the largest

Data Handling

Risk Identifier	Function	Failure Mode	Effects of Failure	Severity	Occurrence	Detection Rating	RPN	Consequential Cost	Certainty Equivalent	Mitigate? (Yes/No)
DA1R1	F1	Data interface unit malfunction	end of mission	10	1	3	30	0.9	0.00109	No
DA1R2	F3	Backplane malfunction	end of mission	10	1	8	80	0.75	0.00088	No
DA1R3	F4	Central processor malfunction	degraded processing	7	3	5	105	0.6	0.00204	Yes
DA1R4	F5	Central processor malfunction	end of mission	10	1	5	50	0.6	0.00068	No
DA1R5	F9	Cable failure	degraded data throughput	10	1	1	10	0.25	0.00026	Yes

Risk-Adjusted Value Total:	0.00495
Total Mitigation Cost:	0.85
Remaining Mitigation Money:	0.02

Figure 7.3: FMEA Risk Mitigation Selection Interface

certainty equivalent risk first and then mitigate the next largest risk that could be afforded with the remaining mitigation money. Many other decision methods could be used to make decisions based upon the figure including bringing in other outside information, weighting decision metrics, trading system-level parameters with other subsystems in order to achieve a higher level of utility, as partially defined by risk, for the subsystem, etc.

The two different user interfaces presented here to interact with FMEA risk data under the auspices of the risk-informed decision making process are not an exhaustive presentation of all possible user interfaces. These two examples are a starting point for the practitioner to create interfaces that are appropriate for the particular CDC in which the practitioner works. This type of interface can be adapted to work with the many different risk methods reviewed in Section 2.5. The methods presented above can be implemented into algorithms to automate much of the process for automated trade studies. The following sections present automated trade study case studies based upon the simplified spacecraft model presented in Chapter 4.

7.3 Subsystem Development and Expansion

In order to demonstrate the risk-informed decision making framework, a simplified spacecraft model was developed from Wertz and Larson [90] using Microsoft Excel and MATLAB for typical satellite missions. Four representative subsystems were chosen to represent the spacecraft including Communication, Data Handling, Attitude Control, and Power. Each subsystem model was programmed to have two inputs and three function or component-driven outputs. The inputs were user-driven in Excel and automated in MATLAB. The inputs were specific to each subsystem.

Table 7.1: Consequential Cost Subsystems Data

	Consequential Cost			
FMEA Entry #	Data	Attitude	Comms.	Power
# 1	0.9	0.7	0.75	0.1
# 2	0.4	0.3	0.4	0.4
# 3	0.75	0.5	0.4	0.3
# 4	0.6	0.9	0.3	0.2
# 5	0.6	0.2	0.9	0.15
# 6	0.6	0.9	0.8	0.6
# 7	0.8	0.19	0.75	0.35
# 8	0.2	0.4	0.3	0.425
# 9	0.25	0.25	0.2	0.3
# 10	0.5	0.7	0.2	0.6

To replicate actual CDC trade studies, three outputs were chosen to represent spacecraft output data from all of the subsystems including Subsystem Power Requirements, Subsystem Mass, and Subsystem Cost. Additionally, all formulas and other numeric information was altered to only generally correspond to real-world spacecraft systems. This is intentional. No part of the models used in this dissertation are meant for industrial CDC environments and are only suited to be used in research.

Subsystem model information is contained in Van Bossuyt and Tumer [82] and Sections 4.5.2 and 4.5.3. Additionally, this research makes use of certainty equivalent values. Table 7.1 lists values for the corresponding FMEA entries.

The simplified spacecraft models developed from Wertz and Larson [90] outlined in this section and presented elsewhere were used to simulate the conceptual spacecraft design trade study process. All unit information was intentionally expunged from the models. Constants used in the functional equations and output numbers from component models were intentionally altered to keep from closely resembling any real conceptual spacecraft designs. The subsystem models described here are the basis of the experiments described below.

7.4 ModelCenter Implementation

The models outlined in Section 7.3, detailed in Sections 4.5.2 and 4.5.3, and in Van Bossuyt and Tumer [82] were implemented in Phoenix Integration's ModelCenter [147]. For the purposes of this chapter, the models were integrated into a single ModelCenter instance rather than separate ModelCenter instances as was done in Van Bossuyt and Tumer [82].

Model integration was achieved via the built-in ModelCenter MATLAB plug-in. The choice to move away from Excel where the models had originally been implemented in Van Bossuyt and Tumer [82] and used in Van Bossuyt et. al. [83] and Chapter 4 was made in order to increase computational efficiency and data collection efficacy. Beyond the implementation software package, nothing has been changed between the models previous developed and used in Excel and the models implemented in MATLAB save for the addition of consequential cost values shown in Table 7.1.

7.5 Single Model Trade Study Using the Risk-Informed Decision Making Framework

A single subsystem model was initially implemented and a trade study was performed in order to highlight the benefits of the risk-informed decision making framework. The Data Handling subsystem was selected at random out of the four modeled spacecraft subsystems. Figure 7.4 portrays a graphical representation of the ModelCenter analysis view showing the various models used in implementing the risk-informed decision making framework and Data Handling subsystem model.

A trade study was performed using the single subsystem model. The E-DOSPERT test statistic (EDS_{Mean}) used in Equations 6.8 and 6.9 and the subsystem model inputs were allowed to vary in a trade space exploration consisting of approximately 3000 data points. EDS_{Mean} ranged from 2.5 to 3.5 while the two subsystem inputs varied between the three discrete choices each of the inputs were configured to accept. V_{Max} was set equal to 4 while $V_{Min} = 0$, and $R_{SF} = 60$.

Figure 7.5 shows a plot of the nine different subsystem input choice combinations with EDS_{Mean} on the X axis and the subsystem certainty equivalent on the Y axis. The subsystem certainty equivalent was found after risks were mitigated as outlined in Section 6.5 and Van Bossuyt et. al. [89]. The black arrows indicate places where two choice combinations intersect and cross over one another. This indicates places where a person with an EDS_{Mean} equal to the crossover point value would be indifferent between the two subsystem input choice combinations. On either side of the crossover point EDS_{Mean} value, a decision-maker with a higher or lower EDS_{Mean} value would make a different design selection as compared to a decision-maker with an EDS_{Mean} value on the other side of the crossover point. This is also replicated in the ordering of risks by mitigation preference as shown in Section 6.5 and Van Bossuyt et. al. [89].

In summary, there are clear crossover points where the preference between one design choice and another change based upon the EDS_{Mean} value of the decision-maker and the system certainty equivalence. An interesting investigation to make is the sensitivity of the various parameters that go into the utility risk curve models as presented in Chapter 6. The following section provides insight into the sensitivity of this part of the risk-informed decision making framework.

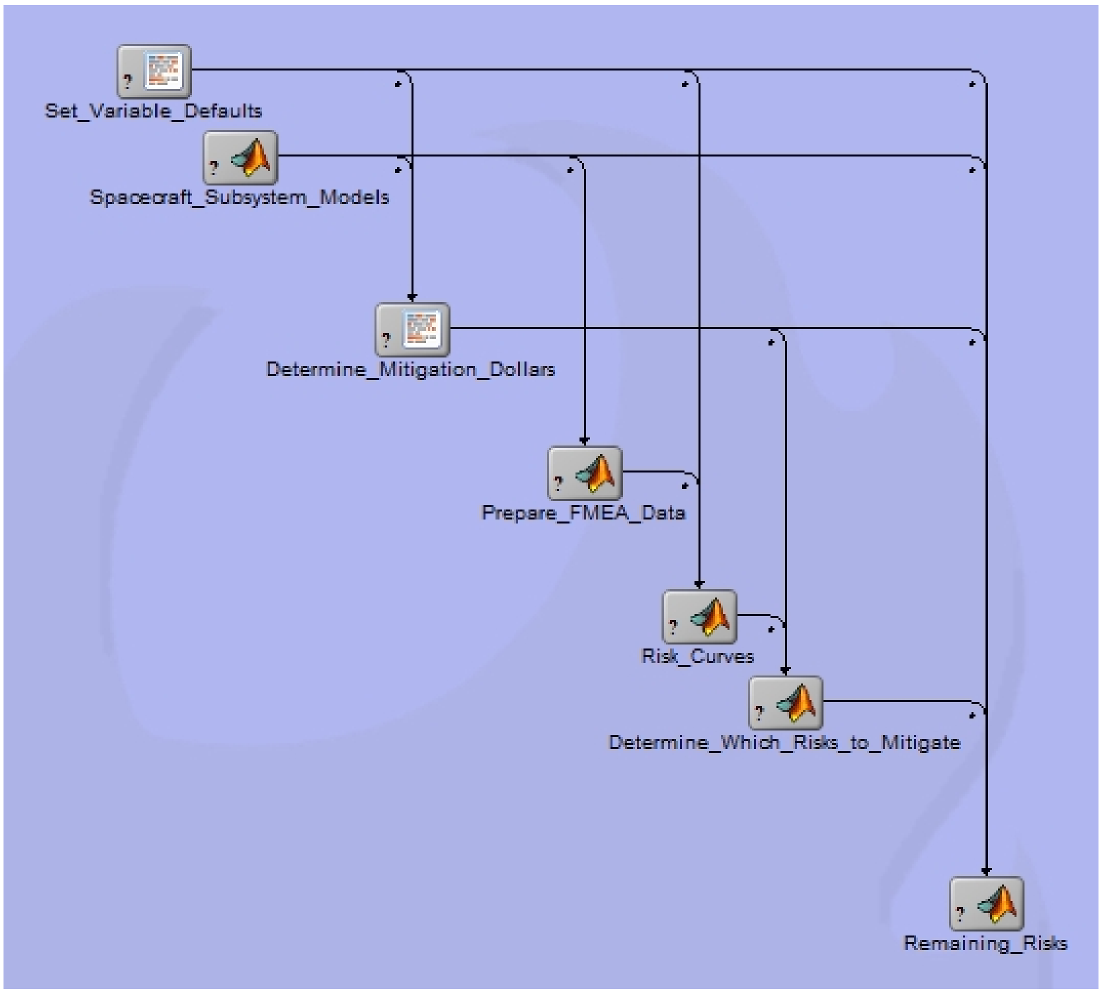

Figure 7.4: ModelCenter Analysis View of Data Handling Subsystem Model Integrated into the Framework

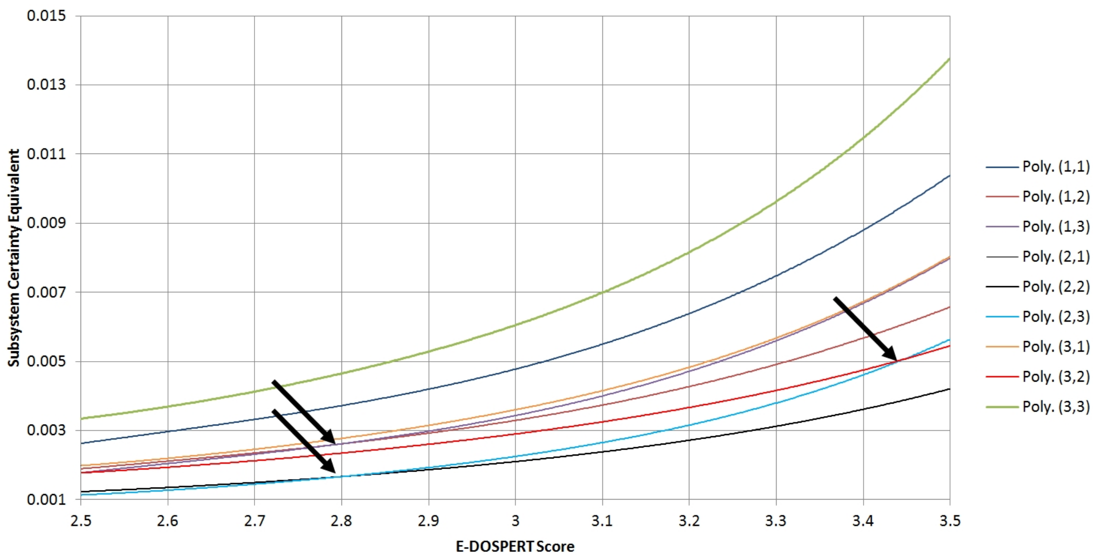

Figure 7.5: Data Handling Subsystem Model Subsystem Input Choice Combination Data

7.6 Sensitivity Analysis of Risk Appetite-Generated Utility Curves

A sensitivity analysis of the utility risk curve method based upon the E-DOSPERT survey statistic EDS_{Mean} presented in Chapter 7 was performed. The goal of the analysis was to determine the sensitivity of the utility risk curve method to changes in EDS_{Mean}, the R_{SF} scaling factor from Equation 6.9 that is sized based upon practitioner experience and several rules of thumb [142, 88, 143], FMEA occurrence, (Occ), the lowest point on the utility risk curve (V_{Min}), and the highest point on the utility risk curve (V_{Max}). Through a sensitivity analysis of a simple model, it was found that EDS_{Mean} contains 41% of the variance while other individual variables contain between 2% and 6%.

Table 7.2: Sensitivity Analysis Setup Data

Variable	Low	High
EDS_{Mean}	2.5	3.5
Occ Risk 1	1	9
Occ Risk 2	1	9
Cons. Cost Risk 1	10	90
Cons. Cost Risk 2	10	90
V_{Max}	90	100
V_{Min}	0	10
R_{SF}	30	100

A simple model was implemented in MATLAB and brought into ModelCenter. The model contained two representative FMEA entries including information on consequential costs. Table 7.2 provides details on the ranges over which EDS_{Mean}, Occ, consequential cost, V_{Max} and V_{Min}, and R_{SF} were varied. Constants in the model were the selection of a monotonically decreasing exponential function and $Oc_f = 0.1$. A sensitivity analysis was then performed. The system-level certainty equivalent response can be seen in Figure 7.6. The figure shows that the largest effect on the system-level certainty equivalent comes from EDS_{Mean} at 41%. Higher order effects make up 12% of the variance, interaction effects between several variables make up between 6 and 10% of the variance, and consequential cost and V_{Max} make up 6% of the variance each. The scaling factor, R_{SF}, makes up only 3% of the variance.

From the data presented in Figure 7.6, R_{SF} is shown to have a much smaller effect on the system-level certainty equivalent value than EDS_{Mean}. This demonstrates that risk appetite has a bigger effect on the results of a design trade study conducted using the risk-informed decision making framework than other factors such as R_{SF}.

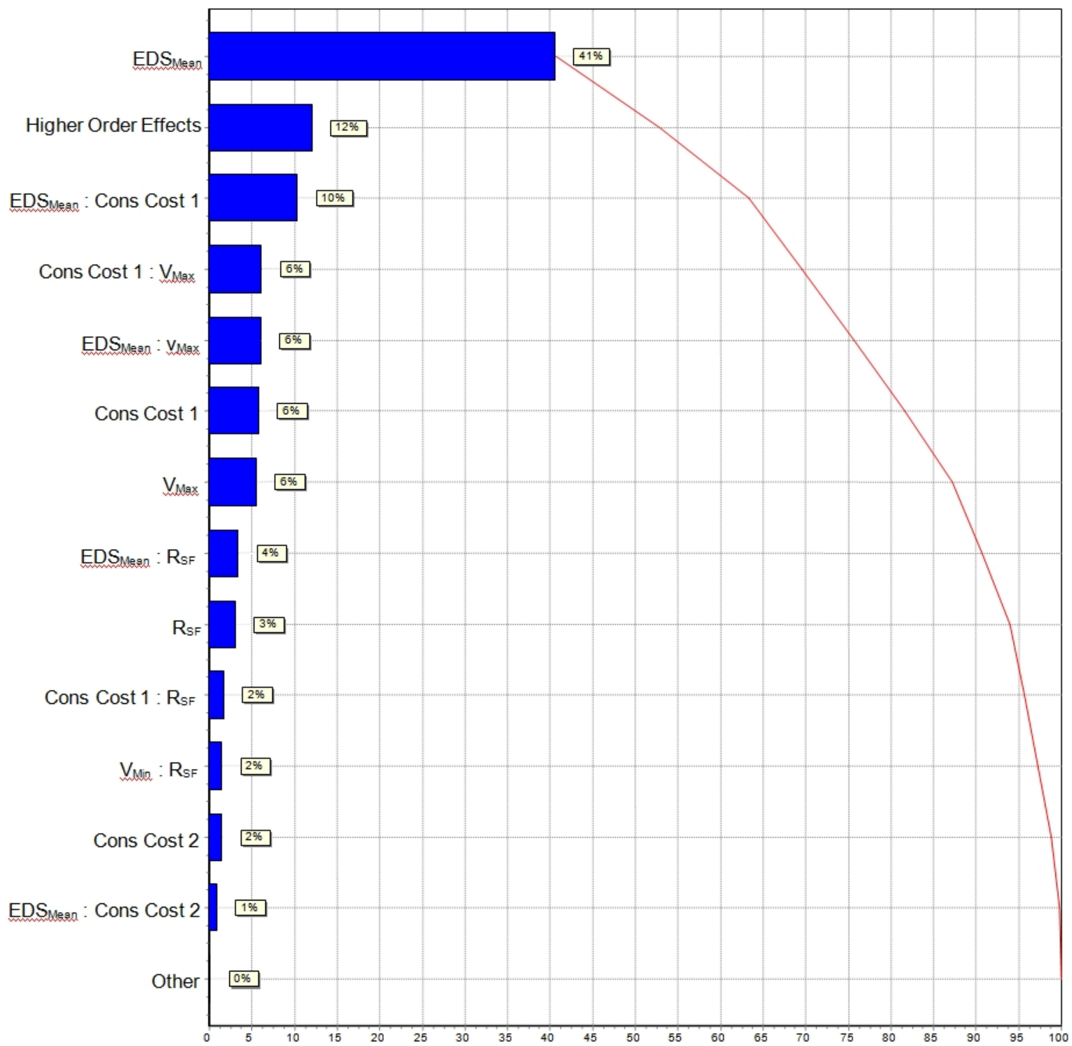

Figure 7.6: System-level Certainty Equivalent Response

7.7 Four Model Trade Study Using the Risk-Informed Decision Making Framework

The four subsystem models and payload subsystem outlined in Section 7.3 were implemented into ModelCenter using the risk-informed decision making framework as was done in the single model example in Section 7.5. Two different implementations of the framework were completed. The implementation detailed in Section 7.7.1 represents a situation where a CDC is using the risk-informed decision making framework to support the decisions of each subsystem chair based upon each subsystem chair's EDS_{Mean} value. The implementation detailed in Section 7.7.2 demonstrates a situation where an entire CDC is using a key stakeholder's EDS_{Mean} value to aid in decision-making. Each implementation uses risk as a tradeable parameter as detailed in Chapter 4. The EDS_{Mean} values are representative of values found during the development and testing of the E-DOSPERT scale as detailed in Chapter 6. Figure 7.7 graphically demonstrates the ModelCenter analysis view of the implemented four subsystem model simplified spacecraft.

7.7.1 Individual EDS_{Mean} Value Decision-Making

In the case where a CDC does not have a unified EDS_{Mean}, the risk-informed decision making framework can be implemented to support the decisions of each subsystem chair based upon the individual chairs' EDS_{Mean} values. CDCs such as JPL's Team-X often perform an initial allocation of system-level parameters such as cost, mass, and power, to the subsystems prior to the start of a trade study [148]. The example in this section took a similar approach where initial cost allocation was performed prior to the start of

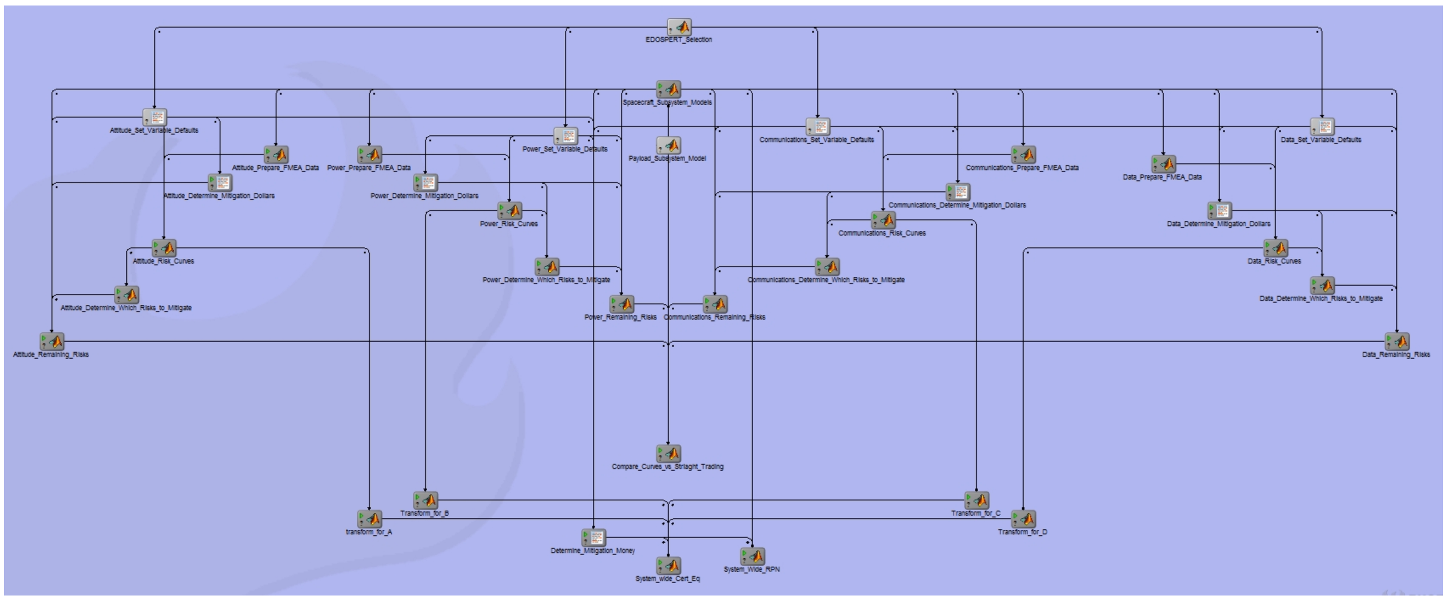

Figure 7.7: Four Subsystem Simplified Spacecraft ModelCenter Implementation

the trade study. EDS_{Mean} values were set at either 3.1 or 2.9 for the four subsystems. These values are representative of typical scores found in the E-DOSPERT research presented in Chapter 6.

As with Section 7.2.2, each subsystem is initially assigned a specific amount of money with which to mitigate risks. Two different means of assigning mitigation money are available including assigning a total amount of money to both the subsystem design and construction, and risk mitigation; and assigning separate pools of money for subsystem design and construction, and risk mitigation. The prior method of assigning mitigation money was used in the example in this section.

Regardless of using individual EDS_{Mean} values in automated trade studies or trade studies performed with people making iterative design decisions, two options are present for trading risk at the system level. Either risk can be traded between subsystems in its original risk-neutral form or it can be traded in a global EDS_{Mean}-adjusted form. The prior case is useful for when individual subsystem engineers wish to make risk-informed decisions based upon their own EDS_{Mean} values but there is no one unified EDS_{Mean} presented by the customer or other important stakeholder. The later case is useful for when subsystem engineers desire to retain the ability to make risk-informed decisions based upon their own EDS_{Mean} values and also trade risk at the system level based upon a key stakeholder's EDS_{Mean} value.

Figure 7.8 presents the results of a parameter scan of the trade study space of a weather satellite design problem described in Section 4.5.5. The design preference parameters within ModelCenter were set to identify the most preferred design by a combination of minimizing cost, mass, and power while also minimizing average system RPN and maximum system RPN. The black line indicates the most preferred design out of the trade study parameter scan design set. After ascertaining the design trade space, a design optimization could be performed to find an optimal design solution. This is done on a similar model in Section 7.7.3 below.

In the case where EDS_{Mean} values are allowed to differ between subsystems and risk mitigation is performed at the subsystem level, two methods of trading risk at the system level are available including trading using risk-neutral risk metric values or a unified EDS_{Mean} system-level value. The example in this section used risk-neutral risk metric values to enable a system-level view of risk. The next section demonstrates how risk can be traded and mitigated at the system level when using a system-wide EDS_{Mean} value.

7.7.2 Unified EDS_{Mean} Value Decision-Making

In the case where a CDC has a unified EDS_{Mean} value supplied by a key stakeholder or customer, the risk-informed decision making framework can be implemented to support the decisions of the subsystem chairs using the key stakeholder or customer's EDS_{Mean} value. This allows for risk mitigation to occur at the system level rather than the subsystem level if desired or for risks to be compared across subsystems while using the utility risk curves method developed in Chapter 6. A case where this method of implementing the risk-informed decision making framework would find use is in a CDC where a customer wishes for the conceptual design resulting from a trade study to reflect their risk appetite and not the individual risk appetites of the subsystem engineers.

Figure 7.9 shows a parallel axis graph of pertinent data derived from a parameter scan of the weather satellite design problem used in Section 7.7.1 but with a unified EDS_{Mean} = 3.1. The black line indicates the most preferred design as defined by minimizing mass, cost, and system-level certainty equivalent. At this point, a design

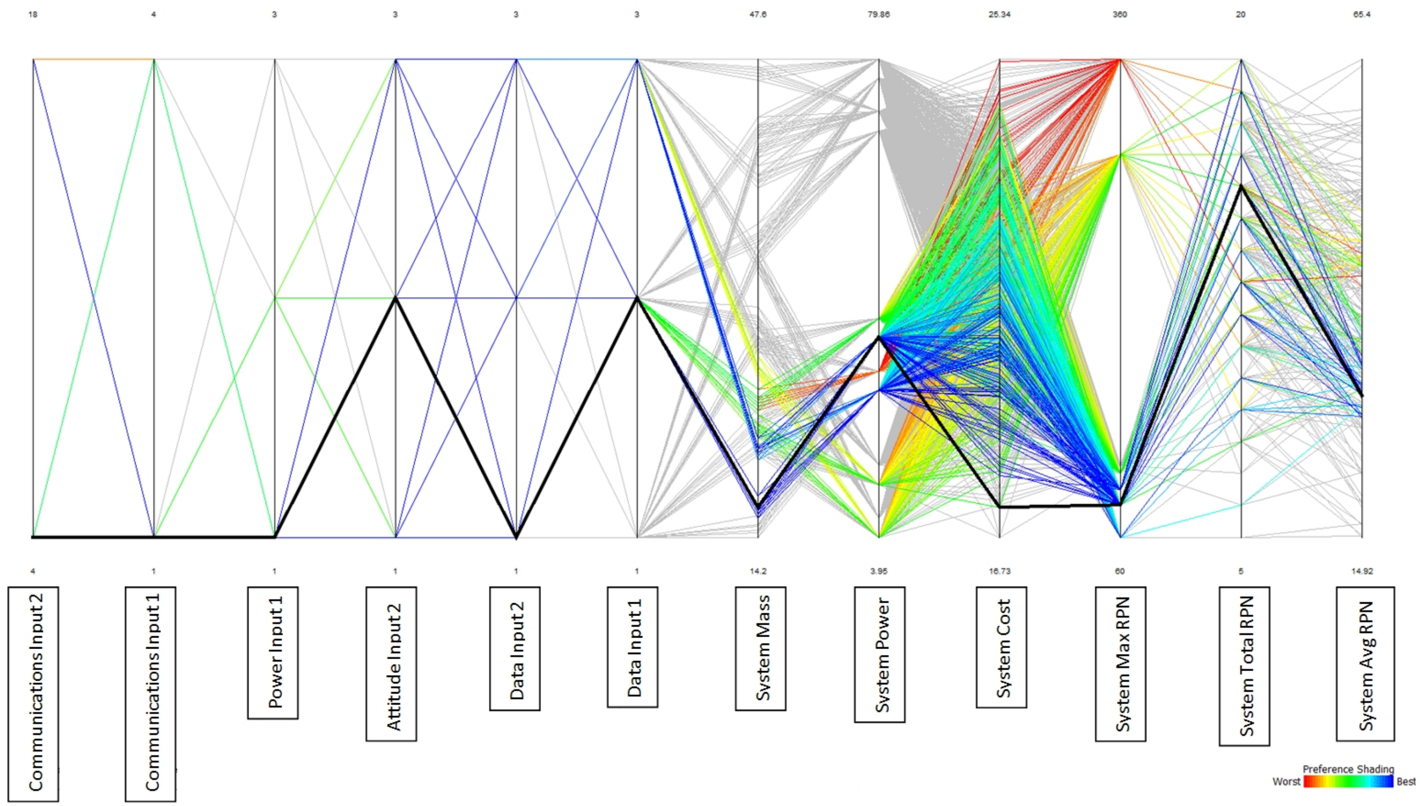

Figure 7.8: Weather Satellite Design Using Individual EDS_{Mean} Values Parameter Scan Parallel Axis Plot

optimization could be performed to find the optimum design solution. Section 7.7.3 demonstrates an optimum design solution process below.

7.7.3 Optimization of Satellite Design Using the Risk-Informed Decision Making Framework

The method of implementing the risk-informed decision making framework presented in Section 7.7.2 was used in a system optimization process performed in ModelCenter. The weather satellite example used in previous sections in this chapter was optimized using a Darwin algorithm that was set to specifically seek a design that minimized the system-level certainty equivalent. 4572 runs were needed in order to find an optimum design solution. Figure 7.10 shows the progression of the system-level certainty equivalent as the optimization was run.

In conclusion, the various methods of implementing the risk-informed decision making framework can be used with optimizer packages in order to find optimum designs.

7.8 Conclusion

This chapter presented several methods and examples of the implementation of the risk-informed decision making framework. The examples are implemented in a combination of ModelCenter, Excel, and MATLAB. The places in which the risk-informed decision making framework are implemented in the trade study process were outlined and demonstrated. Elements of this framework can be used in other places throughout the complex conceptual system design process and are not limited only to trade studies.

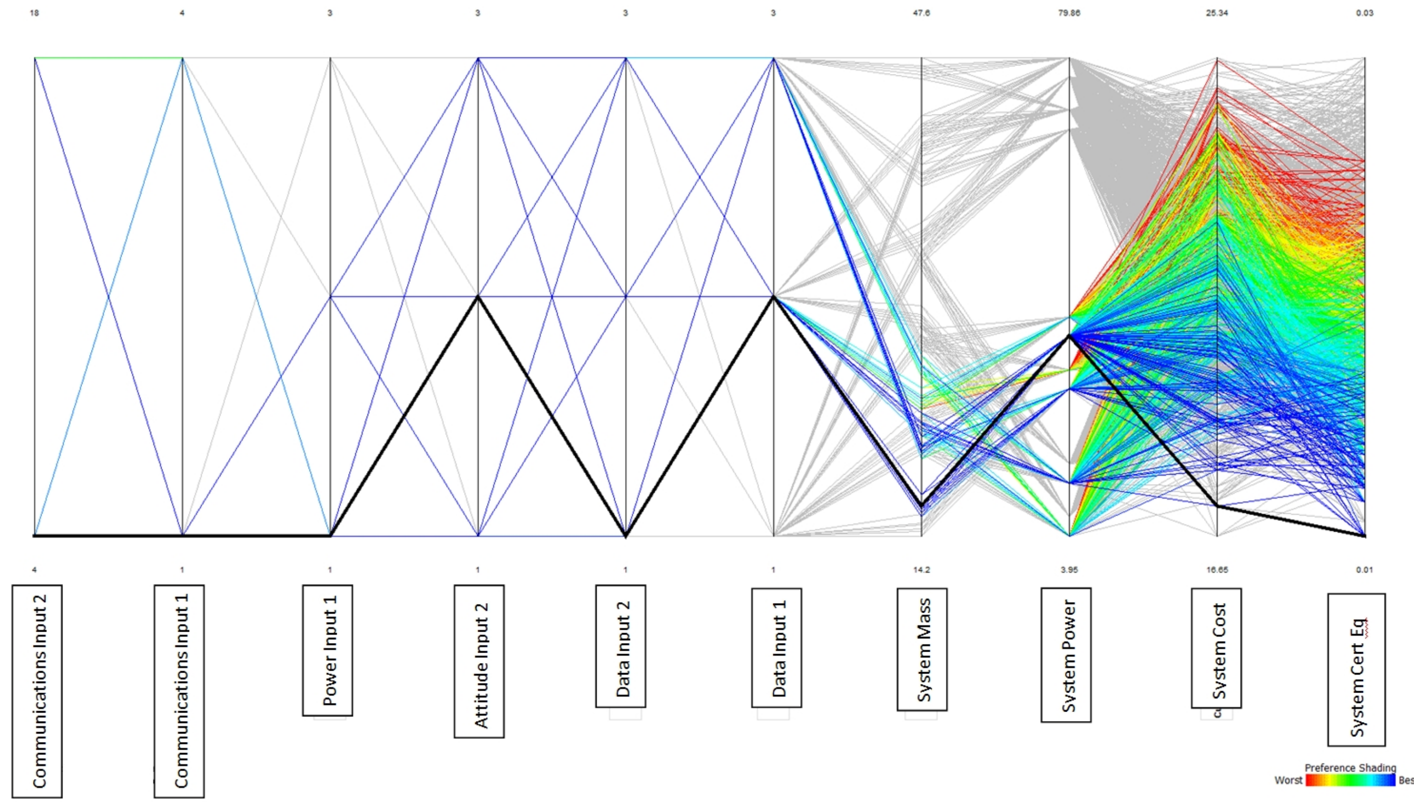

Figure 7.9: Weather Satellite Design Using a System-Level EDS_{Mean} Value Parameter Scan Parallel Axis Plot

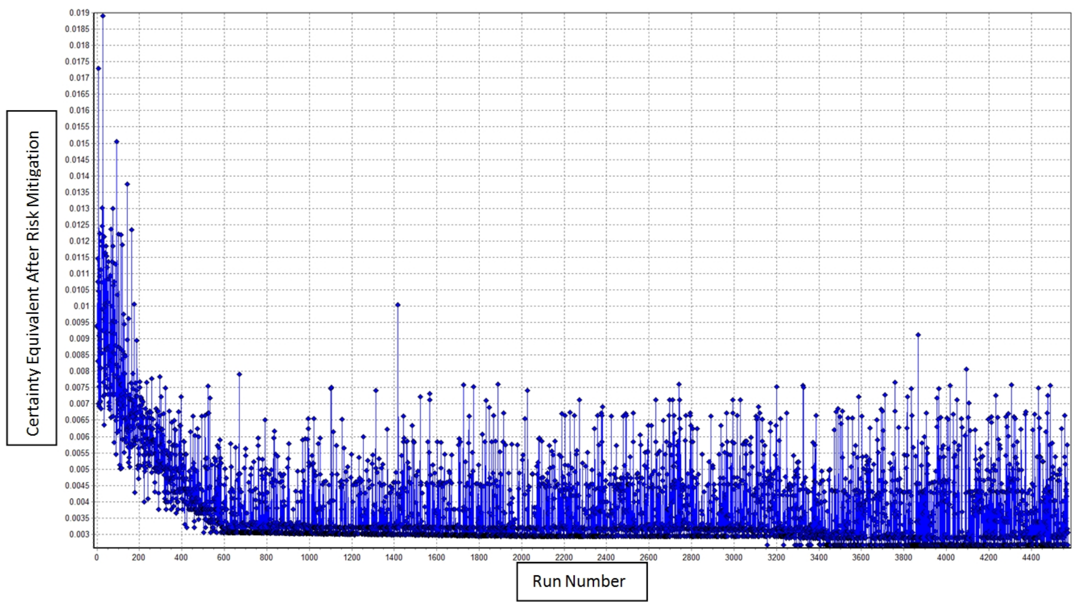

Figure 7.10: Weather Satellite Design Using a System-Level EDS_{Mean} Value Optimized for Minimized System-Level Certainty Equivalent

The methods presented in this chapter can be used both in automated trade studies and in trade studies where subsystem engineers make design decisions.

Several limitations exist within the framework. For instance, the choice of an R_{SF} is left up to the practitioner with several broad rules of thumb provided in the literature. Creation of specific guidelines for the appropriate selection of R_{SF} throughout a wide array of industries is needed. Another limitation of the framework is the assumption that there are no interaction effects between risks. This limitation can be addressed through the implementation of more advanced risk methods into the framework that can account for interaction effects. While limitations do currently exist within the framework, they are surmountable with further research. Chapter 8 goes into more detail on additional areas of future research.

The risk-informed decision making framework enables practitioners to account for and make decisions based upon risk information within conceptual complex system design trade studies. A meaningful integration of the consideration of risk into trade studies is achieved thus elevating risk consideration in trade studies to the level of consideration as other important system-level metrics, parameters, and design choices. Design decisions and design trade-offs are explicitly allowed based upon the risk preference of individual engineers, and the risk preference of individual customers. The framework has the potential to change the outcome of, and bolster trade studies with additional validity via a more thorough and rigorous consideration of risk and risk appetite during trade studies.

Chapter 8 –Future Work

This chapter contains information on future research directions spawned from the risk-informed decision making framework. An ongoing comparison of E-DOSPERT and lottery methods is discussed in Section 8.1. Section 8.2 discusses user testing of the risk-informed decision making framework. The addition of common engineering risk methods is outlined in Section 8.3. Potential methods of considering the benefits of choice outcomes and of considering multiple choice outcomes are presented and discussed in Section 8.4. Section 8.5 lays out further case study development and the rationale for presenting the risk-informed decision making framework in different industrial contexts. Section 8.6 discusses the additional research needed in order for the E-DOSPERT to be as respected as other psychometric risk surveys such as the DOSPERT. Finally, the chapter concludes with a discussion of ongoing research, expected publications, and other relevant information.

8.1 A Comparison of E-DOSPERT and Lottery Methods

Chapter 6 postulates that using E-DOSPERT to generate utility risk curves is more appropriate than lottery methods for early phase conceptual design. This postulation is based upon lottery-based risk curves only being valid over the range of values used in the initial lotteries. In the case of early phase conceptual design, the range of values over which a design might be developed is not always fully known or can change during the design process. Re-running lotteries in order to expand risk curves would quickly become burdensome to the practitioner. Further in the case where utility risk curves are developed based upon client or customer risk appetites, as was the case in Section 6, conducting multiple lottery sessions is impractical. Finally, evidence exists in the literature that lotteries do not closely match what individuals believe they will do [77]. However, actions that individuals take more closely align with the predictions of lotteries than they do to self-reporting methods. This can be interpreted as evidence that psychometric risk surveys are more appropriate to test for aspiration than for actual future performance.

Based upon this information, a comparison between the E-DOSPERT survey and lottery methods needs to be performed in order to confirm the postulation. At the time of writing, this work is underway in conjunction with a colleague at the USyd and Texas A & M. A survey instrument has been created that compares two of the identified engineering risk domains in Chapter 5 between lottery methods and the E-DOSPERT. Institutional Review Board (IRB) approval was recently obtained to conduct the survey with undergraduate and graduate participant pools. Survey administration shall begin shortly. A total participant population of 60 to 80 people is needed in order to perform a logistic regression.

Following analysis of the initial E-DOSPERT and lottery method comparison, the survey instrument will be expanded to encompass all five identified E-DOSPERT sub domains. The comparison will be validated initially using university students. Following satisfactory results at the university level, professional engineers will be administered the comparison survey in order to verify that results are consistent between student and professional populations. Based upon the results of Pennings and Smidts' research [77], it is expected and desired that the E-DOSPERT will be found to predict aspirations while lottery methods will predict future actions.

8.2 User Testing of the Risk-Informed Decision Making Framework

While individual elements of the risk-informed decision making framework have been tested with user groups [82, 85], the full framework has yet to be tested outside of computer simulations and small-scale pilot tests. The framework must be tested in several stages prior to industrial CDCs adoption. First, the framework shall be tested upon a university student participant pool in a simulated CDC similar to what was done in Van Bossuyt and Tumer [82] and similar to what was described in Chapter 4. Next, a limited trial of the method shall be performed with CDC design engineers. Finally, the framework will be trialled in an industrial CDC.

Based upon the results of each stage of user testing, the framework and its constituent parts shall be modified as necessary to better realize the goals of this research. This shall include additional user interface development. For instance, improvements to the graphical displays used to present risk information in CDC environments is needed. The interfaces presented in this dissertation are research quality and will need to be refined further for industrial use. An example of this is Figure 4.3 which was used to display risk information during testing of the risk trading methodology presented in Chapter 4. While the graphical display in Figure 4.3 was sufficient for the auspices of the research, it is not expected to be found sufficiently pleasing by design engineers in industry.

Further development and refinement of the framework and constituent methods will continue until the framework is sufficiently progressed in order to be commercially implemented. Commercial implementation shall be conducted outside of the auspices of this research.

8.3 Adding Risk Methods to the Risk-Informed Decision Making Framework

While FMEA and FTA have been demonstrated in the risk-informed decision making framework and the risk trading methodology respectively, many other common engineering risk methods can and should be implemented into the framework. Section 2.5 presents a brief overview of some of the many methods available to the practitioner. Common methods such as RBD, ETA, and fever charts shall be initially targeted for integration into the risk-informed decision making framework. Other methods such as FFIP and FFDM shall be investigated for integration after successful user testing of the framework.

8.4 Considering Benefits and Multiple Outcomes Using Utility Theory in Risk-Based Design

While the consequence side of Equation 8.1 has been examined in Chapter 6 and implemented in the risk-informed decision making framework, the benefits side of the equation has not been explored fully in this research. The risk and consequential cost sides of the formula are represented by B_{m+x} and A_{q+y} where B_{m+x} = *probability of benefit* × *outcome of benefit* and A_{q+y} = *probability of risk*$_{q+y}$× *outcome of risk*$_{m+x}$. The benefit and risk probabilities all sum to 100%. Additionally, multiple outcomes beyond a strictly nominal or failed state have not been considered. Equation 8.1 is able to account for multiple outcomes with multiple benefits and consequences.

$$R_n = B_m + B_{m+1} + \ldots + B_{m+x} + A_q + A_{q+1} + \ldots + A_{q+y} \tag{8.1}$$

This research has only examined the costs associated with mitigating risks and not the benefits of unrealized risks. For instance, a power system might be chosen for a spacecraft that has a very large consequential cost but in turn has a very large monetary yield. Initial testing of experimental MATLAB code has been conducted to examine the benefit side of Equation 6.1 using modified FMEA data. Results are promising that a modification of existing risk methods and functional modeling techniques will yield an expansion to the risk-informed decision making framework.

The methods implemented in the risk-informed decision making framework currently are demonstrated with binary event outcomes where the system or subsystem will either be in a nominal or failed state depending upon if the risk is realized. It is often the case in practice that systems can fail into a variety of non-nominal states. Equation 8.1 has the ability to account for more risk and benefit outcomes than only a single binary pair. Experimental testing has been conducted to investigate integrating existing risk methods such as FMEA and FTA into a modified risk-informed decision making framework that can account for multiple event outcomes. The results are promising although much work remains to be done in this area.

In order for the benefits side of Equation 8.1 and multiple event outcomes to be realized as part off the risk-informed decision making framework, additional research and development of the constituent methods must be undertaken. Future research and publications will be focused upon this topic. This is expected to be a very fruitful area of further research.

8.5 Additional Case Studies

While the case studies presented throughout this dissertation are sufficient to show the benefits and nuances of the risk-informed decision making framework, additional case studies are needed in order to gain a wider acceptance of the framework. The case studies that implement the framework or its constituent parts are all based upon simplified spacecraft models. This is useful for aerospace organizations such as JPL and Space-X but is less informative for companies such as Boeing Commercial Airplanes or Airbus.

Future case studies shall be developed as part of ongoing publication efforts that will replicate the simplified spacecraft model used throughout this dissertation in complexity. Of particular interest is a commercial aircraft model. Initial work has already been performed to model several relevant aircraft subsystems. Further development will be performed and a simplified commercial aircraft model will be implemented in the framework in the near future.

Additional case studies of future interest include a nuclear power plant model, a hydroelectric power plant model, an automotive example derived from freight trucks, and a 3-D rapid prototype printer example. As future work is conducted with further developing different components of the risk-informed decision making framework, additional case studies will be created and implemented. Through the use of additional case studies, industrial sectors beyond aerospace are expected to become aware of the risk-informed decision making framework.

8.6 Further Validation of the E-DOSPERT

As discussed in Chapter 5, two engineering risk sub-domains have been strongly identified through factor analysis. Strong evidence exists that there are two additional sub-domains and evidence exists that a fifth sub-domain might also be present. In order to thoroughly validate all five sub-domains, further user testing must be conducted and the E-DOSPERT survey instrument should be further revised.

Achieving a stable, well-respected psychometric risk scale will require testing of the E-DOSPERT upon several thousand participants. The well-respected DOSPERT scale was developed over several years and was tested upon thousands of undergraduate students and the general population. An initial version of the DOSPERT scale was released in 2002 [40] while a shortened version of the scale was released in 2006 [47]. Additional testing and validation was conducted in multiple languages and cultures. In order for the E-DOSPERT survey to take on the prominence in the engineering community that the DOSPERT test has taken on in the psychology community, a similar effort will be needed.

Long-term development and validation of the E-DOSPERT test shall continue beyond the completion of this dissertation. Research partners in Australia will continue to work with the author of this dissertation to realize the goal of understanding engineering risk appetite.

8.7 Conclusion

This chapter reviewed several avenues of future research based upon the research presented in this dissertation. Several of the areas are expected to yield many high quality conference papers and journal articles both in the short term and over a longer time-frame. Several research areas could easily be converted into masters-level theses and a solid starting point for dissertations. Some areas, such as developing new models to be examined using the risk-informed decision making framework, would make good projects for undergraduate research assistants.

In the short term, research will be completed and a journal paper will be prepared examining the differences between E-DOSPERT and lottery methods as outlined in Section 8.1. A journal paper will also be developed based upon the risk-informed decision making framework presented in this dissertation. Further investigation of the benefit side of Equation 8.1 and multiple choice outcomes, as discussed in Section 8.4, will also be conducted in the short term with a journal publication resulting. The other sections of this chapter are expected to yield high quality publications over a longer time scale.

Chapter 9 –Conclusion

In the introductory and background chapters (Chapters 1 and 2) of this dissertation a gap was identified in industry and academia wherein customers and engineers do not have a voice when considering risk appetite in the in the dynamic shaping of the outcome of early-phase conceptual design trade studies. Existing methods either do not capture risk information during conceptual design trade studies or consider risk information after a design has been created and chosen. A risk-informed decision making framework was developed in this dissertation that fills the gap in existing academic and industry methods which allows the risk preferences of the customer or engineer to dynamically shape the outcome of early-phase conceptual design trade studies.

9.1 Research Objectives and Contributions

In order to meet the goal of allowing customer or engineer risk preferences to dynamically shape the outcome of early-phase conceptual design trade studies, a risk-informed decision making framework was developed. Three key objectives necessary for the framework's success were defined, developed, and demonstrated. This section reviews the objectives, how they were developed and demonstrated, the status of the research into each objective, and the contributions each objective makes to the literature and professional practice.

9.1.1 Risk-Informed Decision Making Framework

Currently, trade studies conducted in the early phases of conceptual complex system design do not allow individual subsystem engineers to dynamically assess risk during the trade study process. Further, when risk is considered, it is analyzed using a risk-neutral risk appetite that does not support decisions based upon individual risk appetite. The risk-informed decision making framework addresses these issues by integrating the methods developed in Objectives #1-3. This is achieved by trading traditional engineering risk method metrics in trade studies as a system-level parameter, as shown in Objective #1. In order to capture the risk appetite of an individual customer or engineer, an engineering psychometric risk survey is developed in Objective #2. A method of using the aspirational information attained through the E-DOSPERT test developed in Objective #2 was developed using utility functions in Objective #3 that provides risk-informed decision support to engineers wishing to make decisions supported on the risk-related aspirations of the E-DOSPERT test taker. Together these three objectives allow the risk-informed decision making framework to succeed at providing a method of making risk-informed decisions and trades during trade studies that is based upon risk appetite.

The methods of framework deployment presented in Chapter 7 will appear in a forthcoming journal article. Additional research is in progress with USyd and Texas A & M to further develop the framework.

9.1.2 Objective #1: Trade Risk as a System-Level Parameter

The goal of Objective #1 is to allow risk to be traded as a system-level parameter on par with other important system-level parameters in trade studies. For example, in space system design important parameters such as cost, power, and mass are routinely traded but at present risk metrics are not. The risk trading methodology developed in Chapter 4 presents a method of trading risk as a system-level parameter equal to other important parameters such as cost, power, and mass.

The method presented in Chapter 4 has appeared in a well received conference paper at the ASME 2010 IDETC and CIE in the Systems Engineering, Information and Knowledge Management track of the CIE conference as paper number DETC2010-29016 [82] and is at the time of writing submitted to RIED. The risk trading method was developed in collaboration with JPL and was well received by key staff related to Team-X, the JPL CDC. Research for this objective spawned auxiliary research that investigated the risks and obstacles associated with upgrading from CDC trade study collaboration and optimization tools currently in use in many CDCs to a more modern tool such as ModelCenter. A conference paper was published in the proceedings of the ASME 2010 International Mechanical Engineering Congress and Exposition (IMECE) in the Risk Analysis track as paper number IMECE2010-39213 [82] on the risks upgrading and migrating to new trade study software.

9.1.3 Objective #2: Determine Engineering Risk Appetite

In order to better understand the risk appetite of engineers, Objective #2 developed the E-DOSPERT, a psychometric risk survey designed specifically for engineers. The

E-DOSPERT was modeled after the well regarded DOSPERT survey that examines risk appetite in peoples' personal lives. The development of the E-DOSPERT was conducted in close collaboration with USyd and is ongoing. The results of the research into strongly point to five domains of engineering risk appetite including Processes, Procedures, and Practices; Engineering Ethics; Training; Product Functionality and Design; and Legal Issues. The E-DOSPERT instrument was found to be statistically reliable in measuring engineering risk aversion and risk seeking, and to measure engineering risk aversion and risk seeking in the Processes, Procedures, and Practices; and Engineering Ethics domains. Factor analysis strongly points toward the other three sub-domains being present.

A well received conference version of the journal manuscript presented in Chapter 5 appeared in the ASME 2011 IDETC and CIE in the Uncertainty and Risk in Design track of the Design Theory and Methodology conference as paper number DETC2011-47106 [85]. A journal manuscript has been submitted to JMD.

9.1.4 Objective #3: Account for Risk Appetite in Decision Making

Existing methods of using utility functions to make risk appetite-based decisions utilize lottery methods which are predictive in nature. Psychometric risk surveys have been found to be predictors of aspiration rather than future performance. Psychological research has shown that stakeholders and decision-makers hold domain-specific risk attitudes that often vary between individuals. Current engineering risk methods and tools assume a risk-neutral risk appetite. Therefore, Objective #3 combined E-DOSPERT metrics with monotonic exponential utility functions in order to form a risk-informed decision support tool that allows decision-makers to make decisions based in part upon risk information as viewed through the lens of risk appetite. The method developed in Objective #3 is shown to change risk-based decisions in certain situations where a risk-averse or risk-tolerant decision-maker would likely choose differently than a decision-maker with a risk neutral risk appetite.

The journal manuscript presented in Chapter 6 will appear in AIEDAM in the Fall 2012 Vol. 26, No. 4 special issue on intelligent decision support and modeling [89]. A conference version of the article will appear in the ASME 2012 IDETC and CIE in the Uncertainty and Risk in Design track of the Design Theory and Methodology conference as paper number DTM-70399 [85]. Research and development of the methods developed in Objective #3 are ongoing and in partnership with USyd and Texas A & M.

9.2 Broader Impact

The success of the research efforts detailed in this dissertation yield benefits for a variety of sectors including education, industrial and government customers of CDCs, and for CDCs themselves. A CDC using the risk-informed decision making framework developed in this dissertation will benefit by creating conceptual designs that quantitatively take into account risk appetite when making risk-based design decisions. Rather than make risk-informed decisions prior to or after a conceptual design has been created, those decisions will be made during the trade study process and with risk metrics elevated to the same level as other system-level tradeable parameters.

Industrial and government customers of CDCs will be the beneficiaries of conceptual designs that more closely match their desired risk appetites. The conceptual designs generated using the risk-informed decision making framework are quantitatively generated and the risk-based decisions made as part of the trade study process are made based in part upon the risk appetites of the customers. In academia, undergraduate education is already benefiting from the risk appetite component of this research being integrated into design curricula as has been done with the Meyers Briggs Personality Type test. At the graduate level, courses on complex system design will benefit from the framework developed in this research being taught along side other important conceptual design methods.

9.3 Closing Thoughts

The risk-informed decision making framework and supporting methods developed in this dissertation provide a means to produce conceptual designs that align more closely with the risk appetites of stakeholders and customers. To date, no other method or framework encompasses the ability to trade risk in trade studies as a system level parameter, the determination of engineering risk appetite, and the ability to make risk-informed decisions based upon risk appetite in an aspirational context. If implemented widely, the risk-informed decision making framework promises to radically alter the way in which CDCs perform trade studies. Rather than consider risk only as an afterthought or ignore risk all together, risk and risk appetite will be considered and acted upon throughout the trade study process. The end result will be conceptual designs that are more in line with customer and stakeholder risk appetites. This is expected to increase satisfaction in conceptual designs; and increase the knowledge of what risks are present, how they are to be dealt with, and the rationale behind risk-based decisions.

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APPENDIX

Acronyms

ATSV Advanced Trade Space Visualization

CDC Collaborative Design Center

ESA European Space Agency

ETA Event Tree Analysis

FFDM Function Failure Design Method

FFIP Functional Failure Identification Propagation

FMEA Failure Modes and Effects Analysis

FMECA Failure Modes and Effects Criticality Analysis

FTA Fault Tree Analysis

ISHM Integrated System Health Management

JPL Jet Propulsion Laboratory

NASA National Aeronautics and Space Administration

PRA Probabilistic Risk Assessment

QRA Qualitative Risk Assessment

RBD Reliability Block Diagram

RED Risk in Early Design

RUBIC Risk and Uncertainty Based Integrated and Concurrent design methodology

RPN Risk Priority Number

RAP Risk and Rationale Assessment Program

DDP Defect Detection and Prevention

CRM Continuous Risk Management

PDC Project Design Center

EU Expected Utility

DOSPERT *Do*main-*Spe*cific *R*isk-*T*aking

EV Expected Value

E-DOSPERT *E*ngineering-*Do*main-*Sp*ecific *R*isk-*T*aking

OSU Oregon State University

USyd University of Sydney

NSR Non-Substantive Response

SNAP SuperNova /Acceleration Probe

DBD Decision-Based Design

ISHM Integrated Systems Health Management

NSF National Science Foundation

MLE Maximum Likelihood Extraction

KMO Kaiser-Meyer-Olkin

MBTI Meyers-Briggs Type Indicator

DBD Decision-Based Design

RCDM Robust Concept Design Methodology

SOS Subjective Objective System

QFD Quality Function Deployment

ASME American Society of Mechanical Engineers

AIEDAM Artificial Intelligence for Engineering Design, Analysis, and Manufacturing

RIED Research in Engineering Design

JMD Journal of Mechanical Design

IMECE International Mechanical Engineering Congress and Exposition

CIE Computers and Information in Engineering

IDETC and CIE International Design Engineering Technical Conferences and Computers and Information in Engineering Conference

IRB Institutional Review Board

CESD Complex Engineered Systems Design Laboratory