Toward an Early-Phase Conceptual System Design Risk-Informed Decision Making Framework

Conference Paper · November 2012

DOI: 10.1115/IMECE2012-89639

6 authors, including:

Douglas Lee Van Bossuyt
Naval Postgraduate School

Christopher Hoyle
Oregon State University

Irem Y. Tumer
Oregon State University

Richard Malak
Texas A&M University

Proceedings of the ASME 2012 International Mechanical Engineering Congress & Exposition
IDETC/CIE 2012
November 9-15, 2012, Houston, TX, USA

IMECE2012-89639

TOWARD AN EARLY-PHASE CONCEPTUAL SYSTEM DESIGN RISK-INFORMED DECISION MAKING FRAMEWORK

Douglas Van Bossuyt*
Complex Engineered Systems
Design Laboratory
School of Mechanical, Industrial,
and Manufacturing Engineering
Oregon State University
Corvallis, OR 97331
Email: douglas.vanbossuyt@gmail.com

Chris Hoyle
Complex Engineered Systems
Design Laboratory
School of Mechanical, Industrial,
and Manufacturing Engineering
Oregon State University
Corvallis, OR 97331
Chris.Hoyle@oregonstate.edu

Irem Y. Tumer
Complex Engineered Systems
Design Laboratory
School of Mechanical, Industrial,
and Manufacturing Engineering
Oregon State University
Corvallis, OR 97331
Irem.Tumer@oregonstate.edu

Richard Malak
Design Systems Laboratory
Department of Mechanical Engineering
Texas A&M University
College Station, TX 77843
rmalak@tamu.edu

Toni Doolen
School of Mechanical, Industrial,
and Manufacturing Engineering
Oregon State University
Corvallis, OR 97331
Toni.Doolen@oregonstate.edu

Andy Dong
Faculty of Engineering and
Information Technologies
University of Sydney
Sydney, NSW, Australia
andy.dong@sydney.edu.au

ABSTRACT

Current methods of risk analysis conducted during the early phases of complex system design do not give a clear voice to the customer or design engineer when considering engineering risk attitude in the dynamic shaping of early-phase conceptual design trade study outcomes. The existing methods either collect risk information following the completion of a conceptual design thus treating risk as an afterthought during trade studies, make risk-informed decisions prior to the conduction of trade studies thus artificially constraining the design space, or do not consider risk at all. This paper proposes a risk-informed decision making framework that offers a new, meaningful way of accounting for risk during trade studies, informs design decisions during trade studies with pertinent risk information, and takes into account risk attitude of the design engineer or customer when risk-informed decisions are made. Risk is elevated to the same level of importance as other system level variables in trade studies and risk-based decisions are made by individual subsystem engineers through the lens of risk appetite. Several previously developed methods of risk trading, assessing engineering risk attitude, and making risk-informed decisions based upon engineering risk attitude using utility theory are synthesized into the risk-informed decision-making framework. Implementation methods for trade studies being performed by groups of people and automatically by computers are presented. Sensitivity of the framework to input variable variation is examined. A spacecraft example is employed to demonstrate the usefulness of the framework. This paper provides a novel framework for risk-informed design decisions made within trade studies that are based upon engineering risk attitudes in early phase conceptual design.

1 INTRODUCTION

This paper develops a framework to make risk-informed decisions during trade studies using risk models contained within

*Address all correspondence to this author.

subsystems and the lens of engineering risk attitude via a utility function method. By developing the framework, the voice of the customer is more accurately reflected in conceptual designs. Risk tolerant customers are given conceptual designs with high utility and high risk where innovation can occur to realize high profits. Risk averse customers receive conceptual designs with high utility and low risk where the risks that are present have more certainty. Collaborative Design Center (CDC) customers benefit from this framework by having conceptual designs created that more accurately reflect their risk appetites.

Initial verification and demonstration of the integrated Risk-Informed Decision Making Framework is presented in this paper. Verification and demonstration is done in a computer simulated CDC environment. The implementation of the framework into software is presented. Methods of implementing the framework into trade studies performed by groups of people in CDCs are presented. A sensitivity analysis of the framework is developed and discussed. The paper closes with a discussion of the framework and future work to continue development of the work presented below.

2 CONTRIBUTIONS

This paper makes a significant contribution to the literature. The framework brings together several areas of active research to contribute 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. While other methods partially address the issues covered by the framework, none comprehensively addresses the entire problem. Methods of implementing the framework in trade studies conducted by people and in automated trade studies generated by computers are presented. A preliminary validation of the framework in a simulated CDC environment is presented and discussed.

3 BACKGROUND

The Risk-Informed Decision Making Framework developed in this paper draws from several disparate bodies of research and knowledge. This section briefly reviews the most pertinent information that is necessary for the framework and objectives. Several previous papers cover the topics in greater depth [1–6].

3.1 Risk in Engineering

Risk in the engineering context is defined as the probability of occurrence of an event multiplied by the consequences of the outcome [7]. Thus a risk having a probability of occurrence over a given time period of 1% and a consequential cost of $-\$10,000$ is worth $-\$100$ to a decision maker. By examining the worth of several decision choice risks, decision makers can make risk-informed decisions in an engineering context. Most methods use an expected value choice paradigm where probability and cconsequential cost are directly multiplied. This can cause issues such as when analyzing between the previously presented risk and a risk with a probablility of occurrence of 0.1% and consequential cost of $-\$100,000$ where the risk is found to be worth $-\$100$. Both risks are worth the same using expected value and thus no direction is given to the decision maker over which risk is preferred.

Many methods have been developed to aid engineers in analyzing and accounting for risk in the design process. These include standard industry methods such as Reliability Block Diagram (RBD) [8], Probabilistic Risk Assessment (PRA) [9], Failure Modes and Effects Analysis (FMEA) [10], and Fault Tree Analysis (FTA) [11] among others. New methods are being actively developed in academia and are expected to see deployment in the future. These include Functional Failure Identification Propagation (FFIP) [12], Function Failure Design Method (FFDM) [13], and Risk in Early Design (RED) [14].

3.2 Design Trade Studies

Conceptual complex system design often uses design trade studies to generate design alternatives and compare between them. System-level parameters such as cost and mass are often traded in trade studies between subsystems in order to achieve higher utility [15–17]. Conceptual designs that result from trade studies are often then ranked according to appropriate selection rules [18, 19].

Trade studies are often performed in CDCs where teams of people are housed with detailed knowledge of individual subsystems commonly used in the creation of conceptual designs. For instance, National Aeronautics and Space Administration (NASA) Jet Propulsion Laboratory (JPL) houses Team X, a design team that develops conceptual spacecraft mission designs [20]. Individuals from all major subsystems such as propulsion, navigation, etc. work together over two or three days to complete trade studies that result in a conceptual spacecraft mission design [21, 22]. Other NASA research centers, government organizations, academic settings, and private industry have analogous groups [20, 23–31].

Risk information is occasionally captured and analyzed in trade studies but often risk-informed decisions are made either prior to or after trade studies have been conducted. Two tools have been developed by JPL to partially address this issue including Risk and Rationale Assessment Program (RAP) [32] and Defect Detection and Prevention (DDP) [33, 34] but for various reasons these tools have fallen short [35] as have other similar proposed methods [4, 5, 35–37]. Van Bossuyt et al. developed a novel risk trading method for use in trade studies [35]. The method encapsulates risk metrics from a variety of potential engineering risk methods such as FMEA, acFTA, and others into a vector notation structure called a "risk vector." The risk vector of each subsystem is then analyzed and traded at the system level as a system level parameter. Testing occurred in a simulated CDC with promising results.

3.3 Risk-Based Utility Theory in Engineering Design

Rather than analyze risk-based choice outcomes from an expected value perspective as many common engineering risk assessment methods do, risk-based utility theory allows the risk attitude of a decision-maker to influence the worth of a choice outcome. A risk tolerant decision maker's higher intrinsic value for riskier decisions skews the decision utility higher than a risk neutral or risk averse decision maker. A risk averse decision maker's utility skews toward more certain and lower value outcomes. A risk neutral decision maker assesses risk in the same manner as the expected value perspective. In other words, different utilities are found based upon a decision-maker's risk appetite [4, 5, 38].

Two methods of developing utility functions to support risk-based decisions using utility theory are available. The widely used lottery method presents a series of choice lotteries to an individual and uses the result to fit a utility function. Common functions include quadratic, logarithmic, and exponential functions [39]. Several issues have been identified with the lottery method that make it ill-suited for conceptual design [4, 5, 40]. Van Bossuyt et al. present a method of using results from the *E*ngineering-*Do*main-*Sp*ecific *R*isk-*T*aking (E-DOSPERT) survey to develop utility functions [4, 6] and use the functions to make risk-informed decisions using risk metrics from engineering risk methods such as FMEA viewed through the lens of risk appetite. The E-DOSPERT is a psychometric risk survey tool that can assess general engineering risk aversion or risk tolerance and follows in the tradition of well-respected psychology tools such as the *Do*main-*Spe*cific *R*isk-*T*aking (DOSPERT) [3]. The method presented in Van Bossuyt et al. is aspirational in nature and allows for design engineers to make risk-informed decisions that match the aspirational risk appetite of a stakeholder, customer, or design engineer [4, 6].

4 A RISK-INFORMED DECISION MAKING FRAMEWORK FOR EARLY-PHASE CONCEPUTAL DESIGN OF COMPLEX SYSTEMS

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 attitude 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 integrates the ability to trade risk as a system level parameter in trade studies developed by Van Bossuyt et al. [35], the E-DOSPERT engineering risk attitude psychometric survey developed by Van Bossuyt et al. [3, 5], and the engineering risk utility function method developed by Van Bossuyt et al [4, 6]. Figure 1 graphically demonstrates how the framework overlays the traditional trade study process. Decisions between several different options with varying risk profiles that take into account risk appetites will thus be able to be made during trade studies. The framework is implemented and demonstrated in software, and methods of using the framework with CDCs where people participate in trade studies are also presented. 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.

A typical trade study process conducted in a CDC starts with initial design parameters being assigned to subsystems. Then, 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 [35]. The resulting design is 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.

Initial Risk-Informed Decision Making Framework Step

The risk-informed decision making framework integrates into the trade study process 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 Van Bossuyt et al. [3] and Van Bossuyt [5] provides a critical piece of infor-

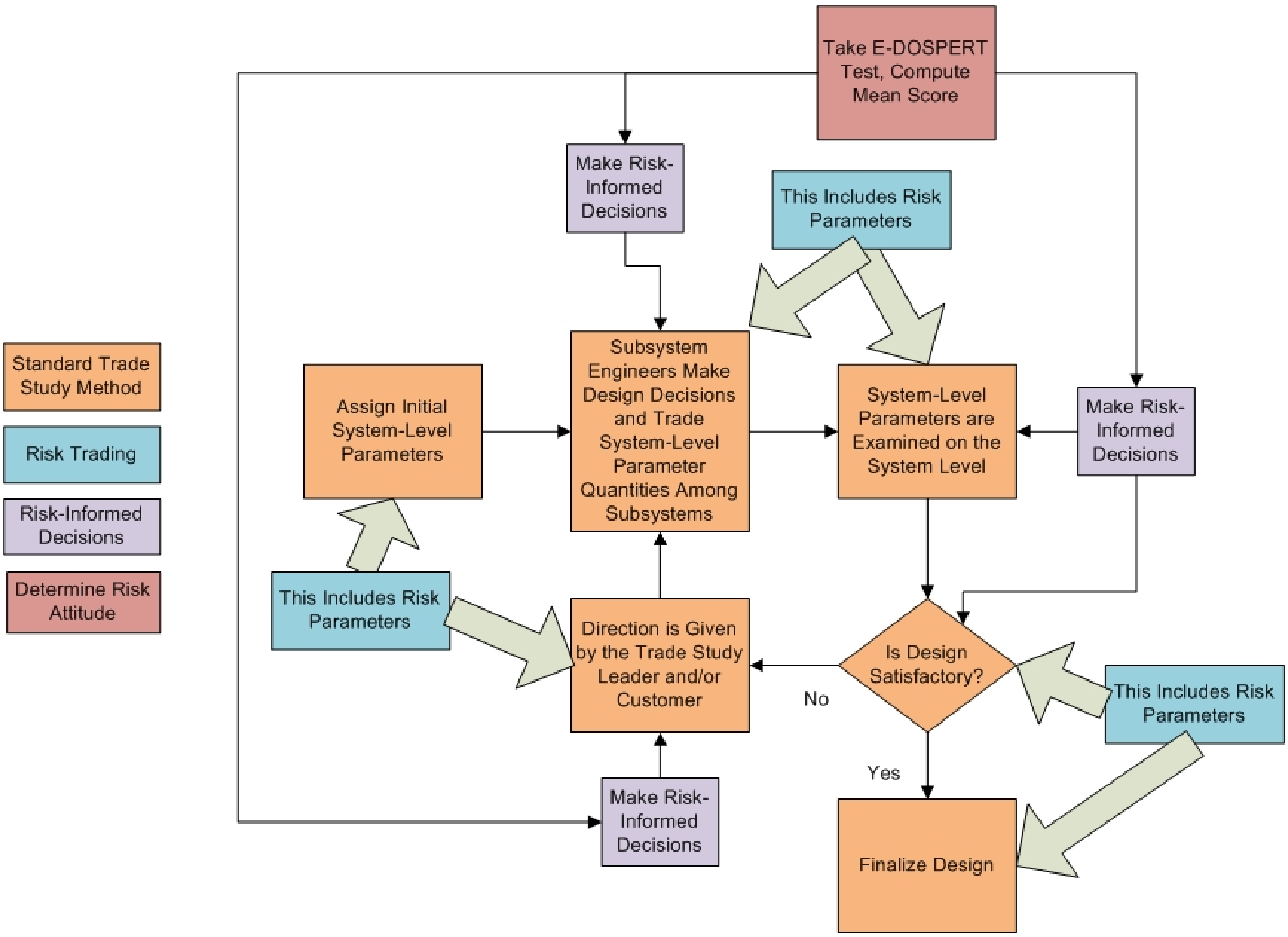

FIGURE 1. Risk-Informed Decision Making Framework.

mation necessary to create utility functions, as was done in Van Bossuyt et al. [4, 6]. Risk trading can then occur, as detailed in Van Bossuyt et al. [35]. 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 while the other method imposes a system-level risk appetite upon the entire trade study. Both methods are demonstrated in following sections of this paper.

Risk-Informed Decision Making Framework Iteration Loop

During the design decision and trading step of trade studies, 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 Van Bossuyt et al. [35]. Depending upon the style of risk-informed decision making framework implementation, methods described in Van Bossuyt et al. [3] and Van Bossuyt [5], and Van Bossuyt et al [4,6] and Van Bossuyt [5] are used to help inform the system-level decision-makers' risk-informed decision making process.

Risk-Informed Decision Making Framework Decision Process for Continued Iteration

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.

Risk-Informed Decision Making Framework Conceptual Design Finalization

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 [3–6, 35] 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 section details framework user interface development.

4.1 User Interfaces for 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. 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.

The first FMEA user interface method, shown in Figure 2, presents the user with three different potential design alternative FMEAs. The example shown in Figure 2 is drawn from the Data Handling subsystem, a component-based model that contains nine potential design alternatives, developed in Van Bossuyt and Tumer [2] and used subsequently in this paper. 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 Van Bossuyt et al. [35]. The consequential costs were developed previously in this paper. 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 $R_{SF} = 60$.

From Figure 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 2 as well as other important metrics.

The second user interface method, shown in Figure 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 3 is derived from Design Alternative 1 shown in Figure 2.

The user in Figure 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 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. The methods presented above can be implemented

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

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.

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

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	

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

FIGURE 2. FMEA Design Selection Interface

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 3. FMEA Risk Mitigation Selection Interface

into algorithms to automate much of the process for automated trade studies. The following section details specific aspects of the framework and provide examples of the framework in use.

5 CASE STUDY

This section presents several examples of the risk-informed decision making framework. The examples are implemented in a combination of MATLAB, Excel, and Phoenix Integration Incorporated's ModelCenter [41], a model-based design tool. First a model that includes four subsystems is examined in automated trade studies. Then a sensitivity analysis is performed on a simplified single subsystem model. Results are presented and analyzed.

Specifically, a simplified spacecraft model comprising of four subsystems was derived from Wertz and Larson [42] and implemented in both Excel and MATLAB. Details of the model are presented in [2]. The model was then brought into ModelCenter and integrated with E-DOSPERT risk utility function algorithms developed in [4, 5]. Following the steps outlined in Section 4, initial system-level parameters were assigned to the individual subsystems. During the conduction of the trade studies presented in this section, the steps shown in Section 4 were followed.

5.1 Subsystem Development, Expansion, and Implementation

In order to demonstrate the risk-informed decision making framework, a simplified spacecraft model was developed from Wertz and Larson [42] 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. In order to replicate CDC trade studies, three system level variables including power, mass, and cost were chosen to represent the overall spacecraft design. Further information on model development and subsystem model information is contained in Van Bossuyt and Tumer [2]. Additionally, this paper makes use of certainty equivalent values as described in Van Bossuyt et al. [4, 6]. Table 1 lists values for the corresponding FMEA entries.

The simplified spacecraft models developed from Wertz and Larson [42] 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.

The models detailed Van Bossuyt and Tumer [2] were implemented in ModelCenter [41]. For the purposes of this research, the models were integrated into a single ModelCenter instance rather than separate ModelCenter instances as was done in Van Bossuyt and Tumer [2]. 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 [2] and used in Van Bossuyt

TABLE 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

et. al. [35] 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 1.

5.2 Four Model Trade Studies Using the Risk-Informed Decision Making Framework

Following the implementation of the four subsystem models and payload subsystem into ModelCenter using the risk-informed decision making framework two different implementations of the framework were completed. The first implementation 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 second implementation 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. The EDS_{Mean} values are representative of values found during the development and testing of the E-DOSPERT scale.

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 [43]. The example in this section took a similar approach where initial cost allocation was performed prior to the start of the trade study. EDS_{Mean} values were set

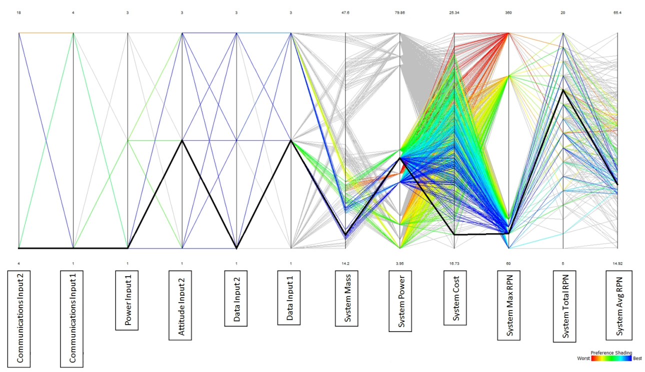

FIGURE 4. Weather Satellite Design Using Individual EDS_{Mean} Values Parameter Scan Parallel Axis Plot

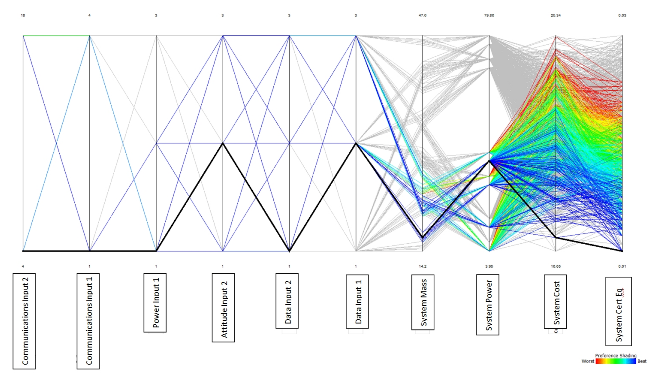

FIGURE 5. Weather Satellite Design Using a System-Level EDS_{Mean} Value Parameter Scan Parallel Axis Plot

at either 3.1 or 2.9 for the four subsystems. These values are representative of typical scores found in the E-DOSPERT literature [3, 6].

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 4 presents the results of a parameter scan of the trade study space of a weather satellite design problem described in Van Bossuyt and Tumer [2]. 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 Risk Priority Number (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.

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. A demonstration of how risk can be traded and mitigated at the system level when using a system-wide EDS_{Mean} value follows.

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 engineering risk utility function method developed in [4, 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 5 shows a parallel axis graph of pertinent data derived from a parameter scan of the weather satellite design problem 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 optimization could be performed to find the optimum design solution.

The method of implementing the risk-informed decision making framework presented above 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

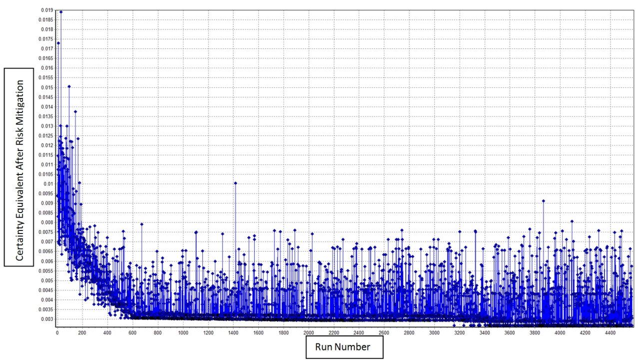

FIGURE 6. Weather Satellite Design Using a System-Level EDS_{Mean} Value Optimized for Minimized System-Level Certainty Equivalent

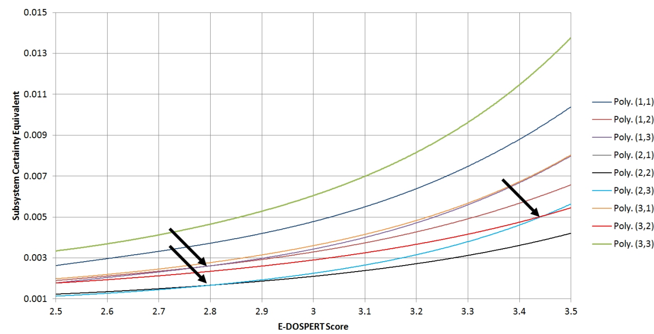

FIGURE 7. Data Handling Subsystem Model Subsystem Input Choice Combination Data

solution. Figure 6 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.

5.3 Benefits and Sensitivity Analysis of the Risk-Informed Decision Making Framework

A single subsystem model was 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.

A trade study was performed using the single subsystem model. The E-DOSPERT test statistic (EDS_{Mean}) 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 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 Van Bossuyt et. al. [4]. 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 Van Bossuyt et. al. [4].

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 engineering risk utility function method. The following text provides insight into the sensitivity of this part of the risk-informed decision making framework.

A sensitivity analysis of the utility risk curve method based upon the E-DOSPERT survey statistic EDS_{Mean} 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 as presented in Van Bossuyt et al. [4, 6] that is sized based upon practitioner experience and several rules of thumb [44–46], 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%.

A simple model was implemented in MATLAB and brought into ModelCenter. The model contained two representative FMEA entries including information on consequential costs. Table 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 Table 3. The table 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 Table 3, R_{SF} is shown to have

TABLE 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

TABLE 3. System-level Certainty Equivalent Response

Variable Name	Variance
EDS_{Mean}	41%
Higher Order Effects	12%
EDS_{Mean} Cons Cost 1	10%
Cons Cost 1 V_{Max}	6%
EDS_{Mean} V_{Max}	6%
Cons Cost 1	6%
V_{Max}	6%
EDS_{Mean} R_{SF}	4%
R_{SF}	3%
Cons Cost 1 R_{SF}	2%
V_{Min} R_{SF}	2%
Cons Cost 2	2%
EDS_{Mean} Cons Cost 2	1%
Other	0%

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}.

6 DISCUSSION

The risk-informed decision making framework presented in this paper has several benefits and limitations. There are also several interesting points to note. For instance, it is possible for the framework to be implemented in such a way that different levels of risk tolerance or aversion are used at different points during the creation and maturation of a conceptual design. For example, several subsystem engineers can make risk-informed design decisions based upon their own personal EDS_{Mean} values which may or may not be the same. At a later point in the design process while selecting between designs, a decision-maker can use yet a different EDS_{Mean} value.

The benefit of using a unified EDS_{Mean} value is that an organization can produce a design with a unified product-level risk attitude. This is especially useful when producing a design for a customer, such as the Principal Investigator (PI) on a scientific spacecraft, where the PI has a specific risk attitude that she wishes to maintain throughout the spacecraft. The benefit of allowing individual subsystem engineers and decision-makers to use their own personal EDS_{Mean} values comes from the individual engineers satisfying their personal risk attitudes and more fully justify decisions that int he past would have been justified primarily with gut instinct by expert judgment. The authors of this paper believe that the choice of using a unified EDS_{Mean} value or several different EDS_{Mean} values should be left up to the practitioner at this time. Future research will examine the benefits and drawbacks of each framework implementation in detail.

Another issue that can impact the framework as well as many other risk methods is a design that does not match the risk attitude of the customer, user, or society. A company that deems a product acceptably safe while a customer or the public finds it otherwise will quickly find that the product is not salable. The framework can only assist in risk-informed design. It remains the practitioner's duty to make sound engineering and business 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. A further limitation of the framework as currently implemented is the need for the creation of multiple FMEAs early in the design process. Some organizations may not be willing to invest the resources in generating such models. The authors believe that the benefits of using the framework will outweigh the extra initial resources invested. While limitations do currently exist within the framework, they are surmountable with further research.

The risk-informed decision making framework provides several benefits to the practitioner. The practitioner can now make risk-informed decisions that take into account risk attitude during conceptual design trade studies. The risk attitudes of the individual subsystem engineers, of the company, or of the customer can be used to make design decisions. In this way, resulting designs will more closely match the risk attitudes of engineers, the company, or the customer.

7 CONCLUSION AND FUTURE WORK

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

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.

ACKNOWLEDGMENT

This research was funded in part by the National Science Foundation (project number CMMI 1030060). The opinions, findings, conclusions, and recommendations expressed are those of the authors and do not necessarily reflect the views of the sponsors. Special thanks go to Jacob Postman and Zach Bailey for their MATLAB assistance.

REFERENCES

[1] Van Bossuyt, D. L., Wall, S. D., and Tumer, I. Y., 2010. "Implementation of risk consideration in complex system design trade studies". In ASME IDETC/CIE Conference. Forthcoming Publication.

[2] Van Bossuyt, D. L., and Tumer, I. Y., 2010. "Toward understanding collaborative design center trade study software upgrade and migration risks". In Proceedings of the ASME 2010 International Mechanical Engineering Congress and Exposition IMECE2010, ASME.

[3] Van Bossuyt, D. L., Carvalho, L., Dong, A., and Tumer, I. Y., 2011. "On measuring engineering risk attitudes". In Proceedings of the ASME 2011 International Design Engineering Technology Conferences and Computers in Information and Engineering Conference (IDETC/CIE2011).

[4] Van Bossuyt, D. L., Hoyle, C., Tumer, I. Y., and Dong, A., 2012. "Considering risk attitude using utility theory in risk-based design". *Artificial Intelligence for Engineering Design, Analysis and Manufacturing (AIEDAM),* ***26***(4).

[5] Van Bossuyt, D. L., 2012. "A risk-informed decision making framework accounting for early-phase conceptual design of complex systems". PhD thesis, Oregon Sate University.

[6] Van Bossuyt, D., Hoyle, C., Tumer, I. Y., Dong, A., Doolen, T., and Malak, R., 2012. "Toward considering risk attitudes in engineering organizations using utility theory". In Proceedings of the ASME 2012 International Design Engineering Technical Conferences and Computers and Information in Engineering Conference IDETC/CIE2012.

[7] Standards Australia, and Standards New Zealand, 2009. As/nzs iso 31000:2009 risk management - principles and guidelines.

[8] International Organization for Standardization, 1997. Iso 10628: Flow diagrams for process plants - general rules.

[9] Villemeur, A., 2000. *Reliability, Availability, Maintainability, and Safety Assessment*. John Willey and Sons.

[10] Department of Defense, 1980. Procedures for performing failure mode, effects, and criticality analsysis. MIL-STD-1629A.

[11] International Electrotechnical Commission, 1990. International standard iec 61025 fault tree analysis.

[12] Kurtoglu, T., and Tumer, I. Y., 2008. "A graph-based fault identification and propagation framework for functional design of complex systems". *Journal of Mechanical Design,* ***30***(5).

[13] Stone, R. B., Tumer, I. Y., and Wie, M. V., 2005. "The function-failure design method". *Journal of Mechanical Design,* ***127***(3), May, pp. 397–407.

[14] Grantham-Lough, K., Stone, R., and Tumer, I. Y., 2007. "The risk in early design method". *Journal of Engineering Design,* ***20***, Apr., pp. 155–173.

[15] NASA, 1995. *NASA Systems Engineering Handbook*. NASA.

[16] FAA, 2006. *National Airspace System System Engineering Manual*, 3.1 ed. Federal Aviation Administration ATO Operations Planning.

[17] Ross, A. M., Hastings, D. E., Warmkessel, J. M., and Diller, N. P., 2004. "Multi-attribute tradespace exploration as front end for effective space system design". *Journal of Spacecraft and Rockets,* ***41***(1), pp. 20–29.

[18] Russell, J. S., and Skibniewski, M. J., 1988. "Decision criteria in contractor prequalification". *Journal of Manage-*

ment in Engineering, ***4***(2), pp. 148–164.
[19] Ji, H., Yang, M. C., and Honda, T., 2007. "A probabalistic approach for extracting design preferences from design team discussion". In Proceedings of the ASME 2007 International Design Engineering Technology Conferences and Computers in Information and Engineering Conference (IDETC/CIE2007), IDETC/CIE.
[20] Shishko, R., 2000. "The proliferation of pdc-type environments in industry and universities". In Proceedings of the 2nd European Systems Engineering Conference, EuSEC.
[21] Deutsch, M.-J., and Nichols, J. S., 2000. "Advanced approach to concept and design studies for space missions". *Astrophysics and Space Science,* ***273***, pp. 201–206.
[22] Oberto, R. E., Nilsen, E., Cohen, R., Wheeler, R., DeFlorio, P., and Borden, C., 2005. "The NASA exploration design team: Blueprint for a new design paradigm". In Proceedings of the 2005 Aerospace Conference, no. 8957662 in IEEE Conferences, IEEE, pp. 4398–4405.
[23] Gough, K. M., Allen, B. D., and Amundsen, R. M., 2005. "Collaborative mission design at NASA Langley Research Center". In Space Systems Engineering Conference.
[24] Edelson, R. E., 2000. "Team Z, a rapid reaction approach to mission operations system design and costing". In The Proceedings of SpaceOps, AIAA.
[25] Oxnevad, K. I., 1998. "A concurrent design approach for designing space telescopes and instruments". In Space Telescopes and Instruments.
[26] Karpati, G., Martin., J., and Steiner, M., 2003. "The integrated mission design center (IMDC) at NASA Goddard Space Flight Center". In Aerospace Conference.
[27] Bandecchi, M., Melton, B., and Ongaro, F., 1999. "Concurrent engineering applied to space mission assessment and design". *ESA Bulletin,* ***99***.
[28] Osburg, J., and Mavris, D., 2005. "A collaborative design environment to support multidisciplinary conceptual systems design". *SAE Transactions,* ***114***, pp. 1508–1516.
[29] Finkel, S., Wilke, M., Metzger, H., and Wahnfried, M., 2002. "Design centers - transfering experience from astronautics to aeronautics". In Proceedings of the 12th Annual Symposium of the International Council on Systems Engineering, INCOSE.
[30] Masher, T. J., and Kwong, J., 2004. "The space systems analysis laboratory: Utah State University's new concurrent engineering facility". In Aerospace Conference.
[31] Aguilar, J. A., Dawdy, A. B., and Law, G. W., 1998. "The aerospace corporation's concept design center". In Proceedings of the 8th Annual International Symposium of the International Council on Systems Engineering.
[32] Meshkat, L., Weiss, K. A., Luna, M., and Leveson, N., 2006. "Supporting concurrent engineering in JPL's advanced project design team using a systems engineering development environment". In In the Proceedings of Virtual Concept.
[33] Cornford, S. L., Dunphy, J., and Feather, M. S., 2002. "Optimizing the design of spacecraft systems using risk as currency". In IEEE Aerospace Conference.
[34] Cornford, S. L., Feather, M. S., and Jenkins, J. S., 2006. "Intertwining risk insights and design decisions". In Eigth International Conference on Probabilistic Safety Assessment and Management.
[35] Van Bossuyt, D. L., Wall, S., and Tumer, I., 2010. "Towards risk as a tradeable parameters in complex systems design trades". In Proceedings of the ASME 2010 International Design Engineering Technology Conferences and Computers in Information and Engineering Conference (IDETC/CIE2010), ASME, ASME, pp. DETC2010–29016.
[36] Dezfuli, H., Youngblood, R., and Reinert, J., 2007. "Managing risk within a decision analysis framework". In Second International Association for the Advancement of Space Safety Conference, IAASS.
[37] Stamatelatos, M., Dezfuli, H., and Apostolakis, G., 2006. "A proposed risk-informed decision-making framework for nasa". In Eigth International Conference on Probabilistic Safety Assessment and Management.
[38] Kahneman, D., and Tversky, A., 1979. "Prospect theory: An analysis of decision under risk". *Econometrica,* ***47***(2), Mar., pp. 263–291.
[39] Keeney, R. L., and Raiffa, H., 1993. *Decisions with Multiple Objectives: Preferences and Value Tradeoffs*. Cambridge University Press.
[40] Pennings, J. M. E., and Smidts, A., 2000. "Assessing the construct validity of risk attitude". *Management Science,* ***46***(10), October, pp. 1337–1348.
[41] , 2009. Model center. Phoenix Integration Website. `http://www.phoenix-int.com/software/phx_software_suite.php`.
[42] Wertz, J. R., and Larson, W. J., 1999. *Space Mission Analysis and Design*. Springer.
[43] Wall, S. D., 2000. "Use of concurrent engineering in space mission design". In Proceedings of EuSEC.
[44] Howard, R. A., 1988. "Decision analysis: Practice and promise". *Management Science,* ***34***, pp. 679–695.
[45] Kirkwood, C. W., 1997. Notes on attitude toward risk taking and the exponential utility function. Department of Management, Arizona State University, January.
[46] McNamee, P., and Celona, J., 1990. *Decision Analysis with Supertree*, 2nd edition ed. Scientific Press, South San Francisco, CA.