AN ABSTRACT OF THE THESIS OF

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The ultimate goal of large-scale design organizations are mainly to reduce costs and improve reliability and performance of systems while assessing how much risk (cost, schedule, scope) they can take and still remain competitive. To achieve this goal they need to develop tools to reach the most preferred design product while reducing the time of decision making during the design process, time to market and total costs, as well as increasing reliability, safety, satisfactory, performance. In addition, they should understand attitudes toward risk; know where more information is needed and identify critical factors and assumptions underlying decisions to aid in the design and development cycle of complex systems.

To address these needs, this research introduces design organizations can capture, assess, and efficiently and effectively communicate uncertainty through their design processes, and as a result, improve their capacity for

delivering complex systems that meet cost, schedule, and performance objectives.

# Risk-Based Design for Multidisciplinary Complex Systems

by

Farzaneh Farhangmehr

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

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Farzaneh Farhangmehr, Author

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I dedicate this thesis to my family.

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# Nomenclature

| | |
|---|---|
| CACTUS | Capturing, Assessing and Communication Tool for Uncertainty Simulation |
| DRRAM | Design Requirement and Resource Allocation Management |
| ORBID | Optimal Risk-Based Integrated Design |
| FROD | Flexible Risk-based Optimal Decision making |
| NASA | National Aeronautics and Space Administration |
| JPL | Jet Propulsion Laboratory |

# DEDICATION

To my lovely and supportive family.

# 1. Introduction

The ultimate goal of large-scale design organizations are mainly to reduce costs and improving reliability and performance of system while assessing how much risk (cost, schedule, scope) they can take and still remain competitive. To achieve this goal they need to develop tools to reach the most preferred design performance while reducing design and decision time, time to market and total costs and increasing reliability, safety, satisfactory, performance and ease of design and decision making.

## 1.1. Motivation

One of the most challenging tasks of the design team during the design process and development of complex systems is to make decisions in risky and unambiguous environments to reach the most desirable products. To achieve this goal, they must obtain the most preferred design product satisfying all design constraints and requirements within risk and uncertainty constraints. This process can be divided into these main interconnected steps [76]:

- **Risk and uncertainty management:** The design and development cycle for complex systems is full of uncertainty, commonly recognized as the main source of risk in organizations engaged in design and development. One of the challenges for complex large organizations is to assess how much risk (cost, schedule, scope) they can take on and still remain competitive; to determine the probability and consequences of associated risks; and, to decide whether or not they should apply additional mitigation techniques to reduce risks and uncertainties with respect to associated costs.

Risk and uncertainty management techniques offer methodologies for dealing with uncertainties (qualitative or quantitative; controllable or uncontrollable) and satisfying critical challenges that design teams encounter. They provide answers for decision maker's critical questions: 1- Where is uncertainty from?; 2- What is its severity and importance?; 3- What are possible methods to assess, mitigate and dealt with risks in the design process; 4- How do uncertainties propagate and which model describes them the best?; 5- How might the sensitivity of the system performance to this uncertainty be reduced or controlled?   6- How can the performance of system be improved in spite of the existence of this uncertainty?

- **Design requirement management:** During the design and development of complex systems, the design team should be aware of properties of systems and subsystems such as associated tasks, requirements, criteria, issues, etc. This step includes modeling and defining the project; determining associated decisions and subsystems; identifying design requirements; allocating resources and generating alternatives. These issues not only define design constraints that should be satisfied to meet requirements, but also enable decision makers to predict system and subsystem properties so they can devote more effort (cost, schedule, additional safeguards) to subsystems with more importance with respect to certain issues. However; design requirements and information are unambiguous in early stages of design and they become clearer when the project progresses. As a result, techniques of design requirement management should be changeable and updatable with respect to new information.

- **Collaborative design environment**: Because of the complexity of multidisciplinary systems, the design process of complex systems is mainly based on team collaboration. However, decision making in collaborative team has its own challenges. The design team must be able to communicate and synchronize data and be aware of decisions made by others as the project goes forward. In recent years many efforts have been conducted to address challenges of collaborative decision-making. These challenges mostly include developing optimization tools [119, 126] or providing group decision making collaborative design with methods, such as Multi-Agent Architecture for collaboration [109], for eliminating communications barriers of design teams during design lifecycle.

## 1.2. Research Approach

As mentioned above, a methodology that can satisfy engineers', managers', stakeholders' and decision makers' needs must be able to satisfy the critical challenges of design teams by understanding the sources of uncertainties and risks and providing a means for managing them and making best decisions. To aim this goal, this research provides:

**Design Requirement and Resource Allocation Management (DRRAM):** This research provides techniques for Design Requirement and Resource Allocation Management (DRRAM) by analyzing and defining the project from the very early stages, associated tasks, issues and design requirements; dividing the system into subsystems, parallel decisions, decision nodes, alternatives; and generating the model. It enables designers, decision makers and stakeholders to predict system and subsystem properties and requirements and also devote more effort (cost, schedule, safety guard, etc.) to subsystems with more importance with respect to certain issues.

The design requirements can be adjusted as the design goes forward and new criteria are obtained. Prior research by Tumer et al, specifically, Function-Failure Design Method (FFDM) [149] and Risk and Uncertainty-Based Integrated Design (RUBIC) [150] are used by DRRAM to allocate resources. DRRAM's information sheet not only provides the necessary information for decision making, but also helps decision makers to change their decisions more effectively.

**Capture, Assessment and Communication tool for Uncertainty Simulation (CACTUS):** For dealing with risks and uncertainties during the multidisciplinary complex system's design process, this research introduces the "Capture, Assessment and Communication Tool for Uncertainty Simulation" (CACTUS). CACTUS monitors systems from the very early stages of design and as the project goes forward, identifies the sources, severity, boundaries and propagation of uncertainties and identifies and mitigate associated risks that should be analyzed by decision makers. In addition, since complex systems commonly rely on concurrent design teams, its collaborative environment for design teams enables to efficiently and effectively communicate uncertainty through the design process and as a result, improve their capacity for delivering complex systems that meet cost, schedule, and performance objectives.

**The excel-based environment:** This research addresses the communication issue by providing an updatable excel-based communication environment for design teams during the design life cycle. By applying this excel-based environment, design members would be able to update and synchronize data to be aware of decisions made by others as the project goes ahead. This concurrent environment also reduces the ambiguity uncertainty due to lack of communication or misunderstanding of the precise definitions of tasks and requirements and hence helps customers, stakeholders and decision makers to communicate more effectively and efficiently.

## 1.3. Terminology

To reduce the ambiguity in applying the methodologies offered by this research, in this section we define the terminology for terms used:

***Stage:*** The term “Stage” refers to the main steps of design determined by design teams. They mainly define stages in design by considering parameters such as timeline, design development, etc.

***Parallel decision****:* Parallel decisions refer to distinct decisions for each subsystem that have independent end points. In other words, each selected decision at the end is related to a parallel decision of a subsystem. The parallel decision number is defined by $m= \{1, 2,\ldots,M-1, M\}$ where $M$ is the total number of parallel decisions needed for the subsystem.

***Decision node****:* Decision nodes refer to points in parallel decisions of subsystems in the design and development of complex systems which where a decision must be made among many design alternatives to achieve the same task and satisfy the same issues.

***Phase:*** Since the design and development of complex systems can be represented as a decision tree, each decision node represents one phase of the associated parallel decision. Obviously, different phases of design can be located in the same or different stages. The phase number is defined by $n= \{1, 2,\ldots,N-1, N\}$ where $N$ is referred to the total number of phases in the design process.

***Alternative***: Each possible decision that can be made through decision-making in decision nodes is called an alternative. The number of alternatives is defined by $l= \{1, 2,\ldots,L-1, L\}$ where $L$ is the total number of alternative in the step. Each alternative is represented by the symbol of $X_{mnl}$ where $m$ is the number of parallel decisions, $n$ is the number of phase located in the $m$th parallel decision, and $l$ is the number of alternatives located in the $n$th step.

***Task and Issue***: Based on associated issues and tasks, decision makers make decisions among *alternatives* in decision nodes. Generally tasks introduce why and for what purpose we are making a decision while issues refer to constraints that should be satisfied for tasks to obtain the most preferred design product. Issues might not be equal in importance. In decision sheets, expert judgment scores qualify issues' importance and based on these scores, decision makers can give higher weight to more important issues. Tasks and issues represent design variables in the form of control factors, which designers can adjust to reach a desirable performance, and exogenous parameters in the form of noise factors which are difficult or impossible to control for designers.

***Decision sheet:*** A decision sheet, created for each decision node, is developed for alternatives that are considered actively in decision making. Types of decision sheets might vary based on the nature of issues and uncertainties that should be considered. For example, for considering qualitative aspects of uncertainties, a qualifier might be added to the decision sheets. As a result, decision sheets provide uncertainty assessing tools for combining qualitative and quantitative aspects of uncertainties. They also can be used to model degree of beliefs where only expert judgment is possible. Decision sheets also have columns showing the weight, distribution and type of issues associated with each decision node. The outcome of decision sheets is identifying alternatives that should be considered actively in the next decision node.

***Information sheet:*** Information sheets provide all necessary information for a design team to be able to evaluate criteria and manage design requirements and resource allocations. They help the design team to manage design resources and requirements. They enable decision makers at the system level to predict subsystems properties and requirements and devote more effort to subsystems with more importance with respect to certain issues. In other words they manage the system by identifying the amount of effort that should be done for each subsystem based on criteria that have been defined for the system before.

***Flow diagram:*** A flow diagram helps users to have a better understanding of active or passive alternatives in each parallel decision. Flow diagrams are generated for decision nodes and completed as the project goes forward. It shows both alternatives that are become passive (circles with dashed line) and active alternatives (circle with solid lines), which are sent to the next decision node for decision making.

***Model:*** The model shows a general scheme of the system, subsystem and their relations by modeling uncertainty propagation through the multidisciplinary system. It identifies exogenous parameters, design and linking variables and as a consequence, prepares the data for performing optimal decision making to reach the desirable product.

## 1.4. The Case Study

The case study applied in this research is the lunar lander mission design project, a conceptual mission design team at JPL's Project Design Center, borrowed from [33]. This design team, also known as Team X, is a concurrent engineering team that has the capability to design an entire mission in one week at the conceptual design stage. Their product is a conceptual design that includes the mission architecture, equipment lists, launch vehicle and estimates for cost and schedule. The team was formed in order to shorten the time required to develop a space mission proposal, a process that previously required months of work [34].

Figure 1 shows a portion of the decisions that occurred during the design process of a robotic lunar mission, based on the observations of the team over the course of a week as they worked on a robotic lunar lander mission design, initiated by an internal NASA customer [33].

This research uses this case study to show the structure and architecture of the proposed methodology, its processes, applicability and illustrates the techniques with more detail. The excel-based collaborative design environment, the decision and information sheets and other material covered in this research will be explained in more detail by applying them into this case study in the chapter five.

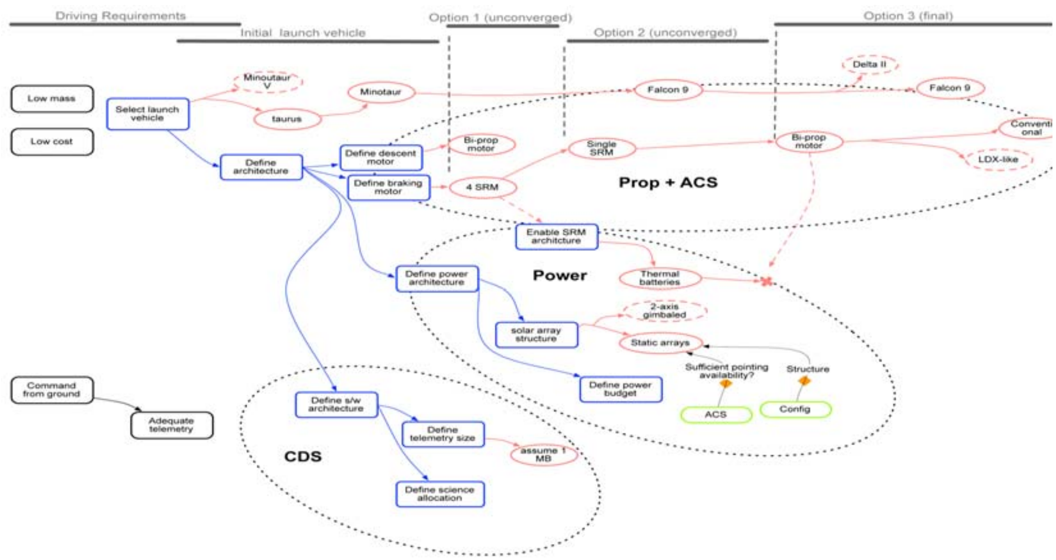


**Figure 1: Flow diagram of the lunar lander mission Team X design**

## 1.5. Structure of Thesis

In the first section of this chapter, an introduction to the thesis topic of Risk-Based Integrated Design for multidisciplinary complex systems was provided and research objectives and motivations were briefly described. Section 1.2 summarized achievements and the materials that will be covered in this research and Section 1.3 defined the terminology used in this methodology. Section 1.4 described the case study that will be used to clarify this methodology. The present section gives an overview of material that will be covered in upcoming chapters specifically:

- Chapter two reviews the literature and background of methodologies covered by this research. It provides definitions of complex systems and risks and uncertainties from various domains; techniques of dealing with systems' uncertainties by classifying, assessing and mitigating their sources, severity and consequences; design requirement management and resource allocation by functional decomposition methods; concepts of decision making in ambiguous and risky environments; collaborative decision making within the optimization domain and a brief overview of flexible alternative generating and decision making.

- Chapter three introduces the "Capture, Assessment and Communication Tool for Uncertainty Simulation" (CACTUS) as the proposed methodology for dealing with uncertainty to obtain the optimal risk-based design product. The CACTUS methodology, resulting sheets and future work will also be covered in this section.

- Chapter four proposes the Design Requirement and Resource Allocation Management (DRRAM) as one of the necessary tools for optimal risk-based design. The proposed methodology and optimization problem, information sheets and their properties and attributes to the design requirement management and resource allocation will be covered in this chapter.

- Chapter five shows CACTUS and DRRAM methodologies and processes with more details by applying them into the robotic lunar lander conceptual mission Team x design team case study at NASA

JPL's Project Design Center. The structure of the excel-based collaborative design environment, information sheets and decision sheets, flow diagrams, models and other covered material will be clarified with details for the case study in this chapter.

- Chapter six introduces complex system architecture for Optimal Risk-Based Integrated Design (ORBID) as a future work of this research. This chapter includes the goals, methodology and structure of ORBOD with respect to its components for design requirement management and resource allocation, uncertainty management and collaborative decision making.

  This chapter proposes a set of tools and techniques that should be incorporated into the system architecture of complex multidisciplinary systems in risky environments to obtain the most preferred products. The provided framework shows the process and associated methodologies' dependency with more details.

  This chapter also introduces Flexible Risk-based Optimal Decision making (FROD), as a decision making tool for generating flexible alternatives and making the best decisions among sets of optimal solutions with respect to costs and uncertainties. This chapter also provides a brief discussion for the properties of the proposed methodology and challenges of design teams to evaluate and apply flexibility in their consideration for the design projects.

- Chapter seven summarizes the results and contributions of this research to achieve its goal for risk-based design of complex systems. This chapter also offers recommendations to move forward this methodology and identifies research items for future work.

# 2. Background/Literature Review

This chapter reviews the literature background in related concepts associated with issues associated with design of complex systems in risky environments. First, it provides definitions of complex systems and their properties as a concurrent engineering design; next, it reviews the literature background of risk and uncertainty in addition to design requirement and resource allocation management.

## 2.1. Complex systems

Rechtin and Maier (2002) [162] defined a system as "A set of different elements so connected or related as to perform a unique function not performable by the element alone". In this context, two commonly accepted definitions for the complexity of a system includes:

"A measure of the numbers and types of interrelationships among system elements; Generally speaking the more complex a system, the more difficult it is to design, build, and use" Rechtin and Maier (2002) [162].

"Having many interrelated, interconnected or interwoven elements and interfaces...an absolute and quantifiable system property" Crawley (2005) [163].

Based on these definitions, the complexity can be characterized by the amount of information is necessary for the system to be described. As a result, a system with more complexity includes more stating information. However, the question is how much complex a system should be so that it can be defined as a complex system?

In 2005, Crawley [163] described the property of a complex system by “requires a great deal of information to specify” and then he classified systems based on their complexity by this rule:

- Simple systems: $(7 \pm 2)$ elements
- Medium systems: $(7 \pm 2)^2$ elements
- More Complex systems: $(7 \pm 2)^3$ elements

Architecture, as “rules to follow when creating a system” [163], is a way to design and manage complex systems. Here, some properties of complex systems affected by architecture are listed:

**- Robustness:** “the demonstrated or promised ability of a system to perform under a variety of circumstances, including the ability to deliver desired functions in spite of changes in the environment, uses, or internal variations that are either built-in or emergent” , (ESD 2002, [164]).

**- Adaptability**: “the ability of a system to change internally to fit changes in its environment,” (ESD 2002, [164]).

**- Flexibility:** “the property of a system that is capable of undergoing classes of changes with relative ease. Such changes can occur in several ways: a system of roads is flexible if it permits a driver to go from one point to another using several paths. Flexibility may indicate the ease of ‘programming’ the system to achieve a variety of functions. Flexibility may indicate the ease of changing the system's requirements with a relatively small increase in complexity and rework", (ESD 2002 [164]).

Maier and Rechtin (2000) [162] showed there are four quantities should be understood and traded off to achieve the design of a complex systems including: performance; time to market; cost, and risk. Trading off performance, time, cost and risks (as the most difficult part to be addressed), in addition to a variety of techniques to computerize, systematize, communicate, etc is the process need to be done to support the design of a complex system.

In the next section, this research provides a description about Integrated Concurrent Engineering (ICE) as one of the best examples of collaborative design environments to support the communication issue during the design of complex system.

### 2.1.1. Integrated Concurrent Engineering (ICE)

Team X was designed to enable JPL, NASA's lead center for robotic exploration of the solar system, to deal with the increasing number of conceptual-phase mission designs. The main purpose of Team X is to provide a study process to increase the quality and to decrease the time of mission concepts by dedicating facilities, equipments, procedures and tools [165].

To achieve this goal, Team X includes:

- 16 subsystem experts: Each expert has a computer workstation for his/her associated subsystem. These subsystems consist of: Attitude Control, Command Data Systems, Configuration, Cost, Ground Systems, Instruments, Mission Design, Power, Program Management, Propulsion, Science, Structures, System Engineering, Telecommunications-System, Telecommunications-Hardware and Thermal Control.

- The team leader: He/she leads the study and contact customers before and after and during the study.

- The documenatalist: The documenatalist is responsible to make sure the result of the study is documented properly. He/she also documents the study's technical discussion, electronic files etc.

As the following paragraph shows, to achieve this goal, the design process of complex systems needs to be provided with supportive tools to enable subsystems chairs to communicate.

Integrated Concurrent Engineering (ICE) that is an approach to facilitate and increase the productivity of complex system's design teams in conceptual stages is a collaborative process consists of five principles listed below [166, 167]:

1. Standard Information Products: Organizations should define their standard information product to systematize their process and determine benefits of applying ICE.

2. Network-Linked Tools: These tools such as Computer Aided Design (CAD) systems, spreadsheets, mathematical models and other types of software are used to facilitate instant quantitative engineering.

3. Procedures for real time collaboration: It is always important that design team members have a well understanding of the procedures for real time collaboration.

4. Standing Multidisciplinary Team: Team should be well-trained and skilled in the tools and methods by setting clear procedures, roles, standard information, etc.

5. Applicable Facility: Teams should be facilitated with environments that support hardware, software and human resources, such as networked computer workstations (either real or virtual).

To address these principles and increase the ease and speed of applying ICE, ICEMaker™ was designed. ICEMaker™ as an Excel based software tool that applied the ICE methodology and principles, has been adopted by JPL to implement the ICE to provide a faster and easier tool for team members to share, browse, send and receive data. In addition, its interface for inputting and outputting database from/to the model provides a faster send and request process.

ICEMaker™ facilities the communication between subsystems by providing a client-server architecture. Figure 2 shows this architecture.

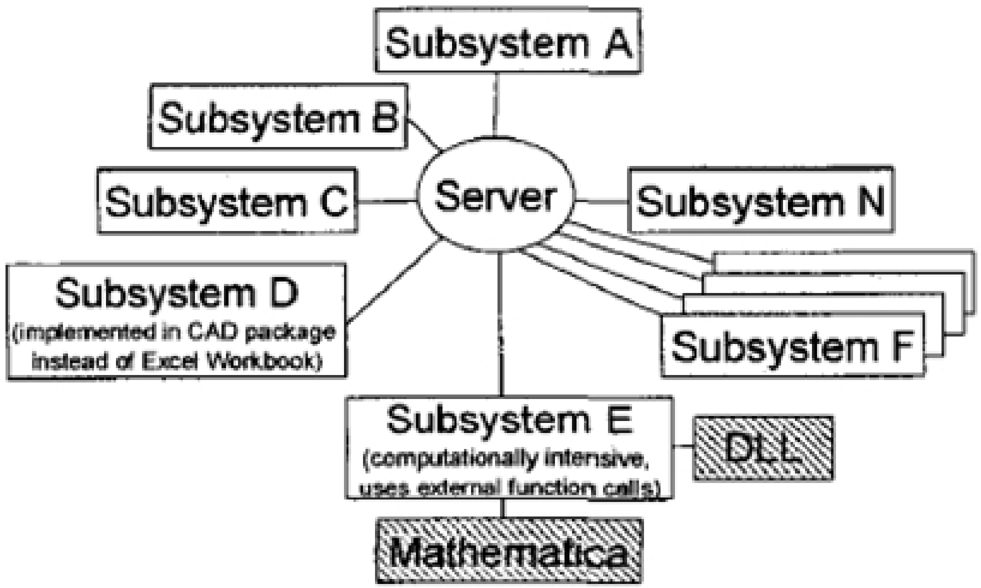


**Figure 2: The client-server Architecture of ICEMaker ™ borrowed from [32]**

ICEMaker™ server applies Visual Basic and Visual C++ and generates the client's excel workbooks that enable subsystems to communicate with each other via the server.

The workbook consists of four work sheets including: The main sheet (a summary sheet of calculation results); the input sheet (includes data from other subsystems as parameters); the output sheet (determines data calculated within the subsystem and is used by other subsystems) and the project Status sheet (an alternative menu-based method). Figure 3 shows the client major software routines.

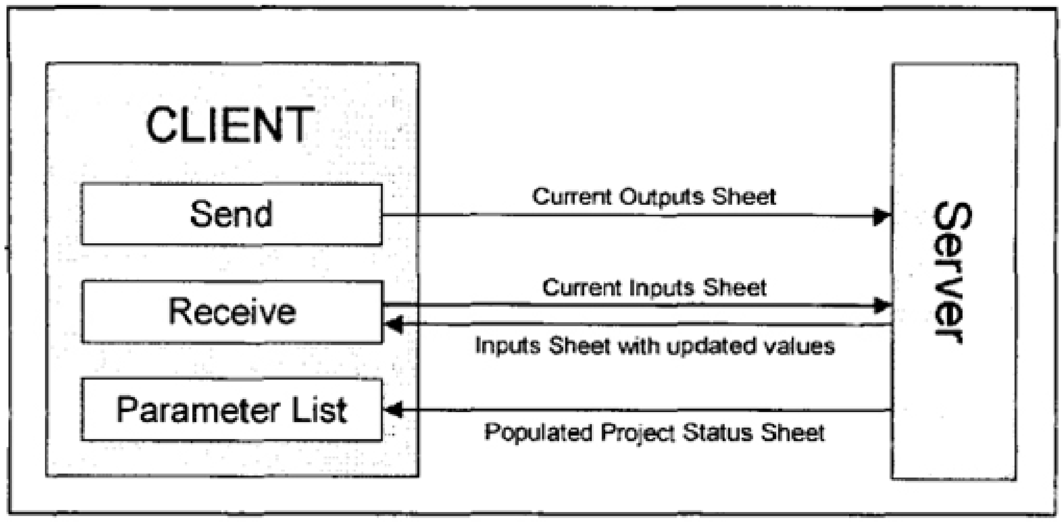


**Figure 3: Client Major Software Routines borrowed from [32]**

Figure 4 shows the ICEMaker™ folder structure. Project Chaos shown in this figure is the root folder consists of two sub folders: Client Subsystems (including all workbooks) and Project Server (the database associated with the server).

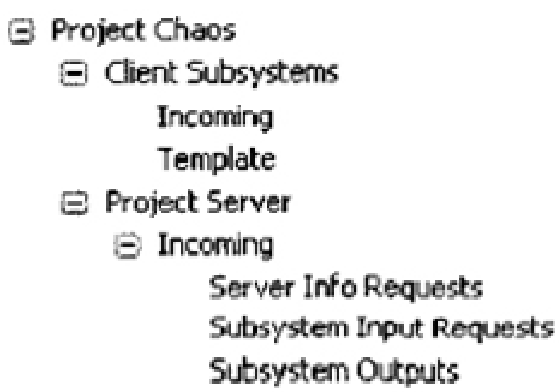


**Figure 4: The ICEMaker folder structure borrowed from [32]**

## 2.2. Risk and Uncertainty

In engineering design teams, decision makers encounter lots of uncertainties in each decision they make. The risk associated with the design of complex systems is fundamentally tied to these uncertainties commonly recognized as the main source of risk in organizations engaged in design and development. In fact, the design process includes consecutive decisions that start with high levels of uncertainties in the early stages of design, and lead to a final product at the end by reducing the overall uncertainty throughout the design cycle.

In the early stages of design, uncertainty is the highest since decisions have not yet been made and design alternatives to achieve the best design product have not yet been clearly and actively considered. To deal with the uncertainty in the design and development of a complex system, team members should be aware of consequences of their decisions while being aware of decisions made by others. In addition, different sources of uncertainty might not have the same importance as other sources. For example, when the number of design alternatives is increased, the uncertainty associated with that decision is also increased but obviously, offering more choices, especially in early stages of design is not as harmful as other types of uncertainty that cause poor or suboptimal performance, poor decisions and even failure.

Furthermore, selecting a poor or imperfect definition and classification for uncertainty might guide decision makers to account for uncertainty more or less than it is necessary. In addition, a well-established uncertainty management methodology has to be able to deal with all sources of uncertainty (technical or nontechnical; qualitative or quantitative). These show the importance of having a clear understanding of uncertainty, knowing its sources, severity, consequences and finding methods for mitigation and managing associated risks and their effects during the design process.

### 2.2.1. Definitions

Since uncertainty has been a concern in many diverse fields, including design, engineering analysis, project management, policy development, disaster recovery, there are several definitions for the term of "uncertainty" in existence. Selecting a poor or imperfect definition for uncertainty might guide decision makers to account for uncertainty more or less than necessary in the design process. So providing a detailed definition for the term "uncertainty" and its "sources", exclusively for complex systems, is critical. By using this definition, decision makers will be able to make more informed choices and reduce risks due to uncertainty by reallocating resources, adding safeguards, etc.

According to concerns from diverse fields, including design, engineering analysis, policy making, etc., there are several definitions for the term of "uncertainty", such as:

"The slack of certainty; A state of having limited knowledge where it is impossible to exactly describe existing state or future outcome, more than one possible outcome" [144].

In recent decades, several attempts to find the best description of uncertainty in the field of engineering design have been made but there is still no uniquely accepted definition for this term. In this research we will use the following definitions:

“Uncertainty is a characteristic of a stochastic process that describes the dispersion of its outcome over a certain domain” [27].

In this context, risk can be defined as:

“Risk is a state of uncertainty where some possible outcomes have an undesired effect of significant loss” [144].

### 2.2.2. Uncertainty classification

Uncertainty can be due to lack of knowledge, refers to Epistemic or Knowledge uncertainty, or due to randomness in nature, refers to Aleatory, Variability Random or Stochastic uncertainty. In the following paragraphs, a classification for sources of uncertainty during the design process and development of complex systems is introduced.

**Ambiguity:** One major source of uncertainty, ambiguity uncertainty [66-68], results from incomplete or unclear definitions, faulty expressions or poor communication. Ambiguity uncertainty should be reviewed from two aspects: First, as a lack of knowledge that can be reduced by clear definitions or linguistic conventions; and second, as an irreducible inherent uncertainty that is naturally associated with human behavior. Ambiguity uncertainty is also called imprecision [67] or uncertainty in context [29]. Ambiguity uncertainty shows itself from the beginning stages of design and has to be placed as a subcategory of both epistemic and aleatory uncertainty.

**Model Uncertainty:** Model (or process model) uncertainty includes uncertainties associated with using a process model or a mathematical model for the system. Model uncertainty is due to lack of knowledge (i.e., aleatory uncertainty) and appears in all stages of design. Model uncertainty might be a result of mathematical errors, programming errors, and statistical uncertainty.

Mathematical errors include approximation errors and numerical errors, where approximation errors are due to deficiencies in models for physical processes and numerical errors result from finite precision arithmetic [30].

Programming errors [60-63] are errors caused by hardware/software, such as bugs in software/hardware, errors in codes, inaccurate applied algorithms, etc.

Finally, statistical uncertainty comes from extrapolating data to select a statistical model or provide more extreme estimates [31].

**Behavioral Uncertainty:** Uncertainties associated with the behavior of individuals in design teams (designers, engineers, etc.), organizations, and customers are called behavioral uncertainty. Just as in ambiguity, behavioral uncertainty can be described as uncertainties due to lack of knowledge and uncertainties that are inherent in human behavior. Behavioral uncertainty arises from four sources: Human errors, decision uncertainty, volitional uncertainty and dynamic uncertainty.

*Volitional uncertainty* refers to unpredictable decisions of subjects during the stages of design [31]. The role of this uncertainty becomes more important in multidisciplinary design when several organizations are hired to develop the system. In this situation, individuals' decisions in dealing with other organizations cannot be anticipated [30].

*Human errors* [69-70] are uncertainties due to individuals' mistakes during the design process. Although human errors are inevitable in the system, they can be reduced by certain methods such as training or applying human factors criteria.

As its name indicates, *decision uncertainty* is when decision makers have a set of possible decisions and just one should be selected. To account for the role of decision uncertainty, a good methodology should be aware of the nature of the design process. For example, decision uncertainty has a more important role when the design process is not reversible or iterative.

The fourth major source of behavioral uncertainty is when changes in the organization or individuals' variables or unanticipated events (e.g., economic or social changes) contribute to a change in design parameters that had been determined initially. In this uncertainty classification, we refer to this as *dynamic uncertainty*.

Dynamic uncertainty also includes uncertainties resulted from degrees of beliefs (instead if knowledge) where just subjective judgments are possible and should be considered [41-49].

**Natural Randomness:** Uncertainties associated with the inherent nature of processes are called Natural Randomness uncertainty. This type of uncertainty is irreducible and decision makers are not be able to control it in the design process. Several sources refer to aleatory uncertainty in general as natural randomness. In this research we make distinction between Behavioral uncertainty that is related to individual's behaviors and Natural Randomness that is inherent in the nature of processes.

Table 1 shows sources of uncertainty associated with the complex system design process and the main categories in which they belong (Epistemic, Aleatory, or both).

**Table 1: Uncertainty sources in complex systems**

| Source of Uncertainty | Subcategories | Main Category |
|---|---|---|
| Model Uncertainty | Mathematical errors, Programming errors, Statistical uncertainty | Epistemic |
| Behavioral Uncertainty | Decision uncertainty, Volitional, Human errors, Dynamic uncertainty | Epistemic, Aleatory |
| Natural Randomness | N/A | Aleatory |
| Ambiguity | N/A | Epistemic, Aleatory |

Figure 5 is a general scheme of uncertainty classification based on Table 1. This research uses this classification to account for uncertainty in every stage of design.

Figure 6 shows the uncertainty Venn diagram for general understanding of uncertainty classification. As we can see, the inside of the two sets represents certain uncertainty referring to uncertainties where we know the sources, while the intersection of two sets includes Ambiguity and Behavioral uncertainty. The outside of the sets is unknown uncertainty, referring to what we don't know we don't know.

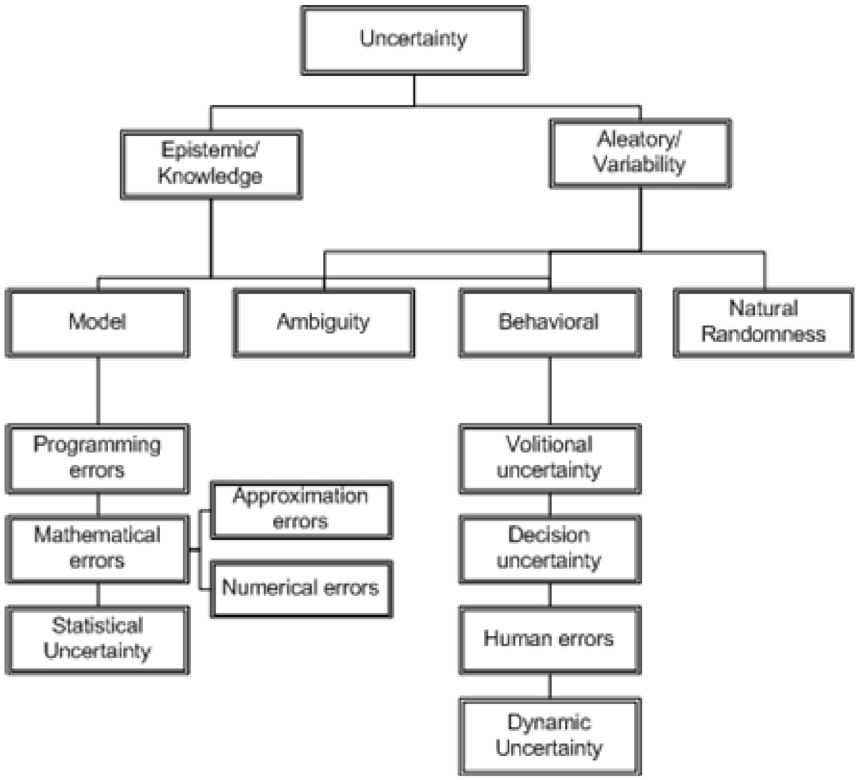


**Figure 5: Uncertainty classification**

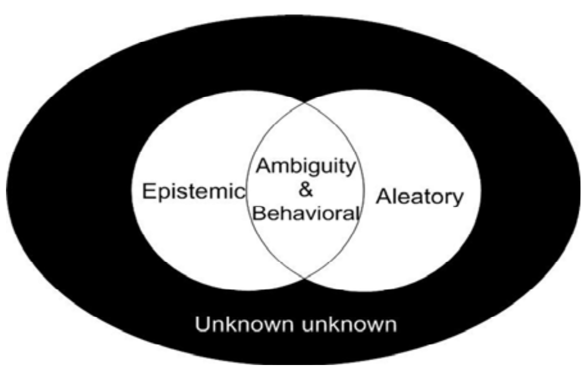


**Figure 6: The Uncertainty Venn diagram**

### 2.2.3. Uncertainty assessment methods

Design is by nature iterative and driven by decisions that are made under large amounts of uncertainty. Uncertainty studies typically involve methods for quantitative uncertainty analysis, including single and multi-variant sensitivity analysis, stochastic modeling with Monte Carlo techniques, etc. [1-6]. Attempts to quantify uncertainty during the design process have been published, but most focus on the quantitative aspects of uncertainty only [13-23]. These quantitative methods provide only a partial insight into a very complex set of uncertainties. As a result, these technical methods have to be complemented with qualitative methods of assessing uncertainties, including expert judgments. While there have been some attempts to accomplish this in various fields [7-12], methods to incorporate and propagate both types of uncertainties in a design process are less paid attention.

This research addresses this problem by combining both types and can be extended to include places where only expert judgment is possible and decision makers need to model degree of beliefs (instead of knowledge). Finally, even if the assessment of uncertainty is satisfactory, managing the uncertainty across multiple functions and across the entire design process is challenging and there is need for more research in this area [24-26]. This section provides a brief review of various uncertainty assessment methods, followed by a review of mitigating methods attempting to reduce sources which lead to these uncertainties.

Uncertainty assessment methods generally can be divided into four major approaches based on their characteristics in analyzing data and representing the output parameters. These approaches include probabilistic methods, Bayesian techniques, simulation methods and qualitative methods, which are generally combined with quantitative methods. Here we introduce these approaches in general and some of assessment methods which have been developed based on these approaches.

**Probabilistic methods:** A probabilistic approach is based on characterizing the probabilistic behavior of uncertainties in the model including a range of methods to quantify uncertainties in the model output with respect to the random variables of model inputs. These methods allow decision makers to study the impact of uncertainties in design variables on the probabilistic characteristics of the model. Probabilistic behavior may be represented in different ways.

One of the basic representations is the estimation of the mean value and standard deviation. Although this representation is the most commonly used results of the probability methods, it cannot provide us with a clear understanding of the probabilistic characteristics of uncertainties associated with the model. Another representation of probabilistic behavior is the probability density function (PDF) and the cumulative distribution functions (CDF), which provide the data that is necessary for analyzing the probabilistic characteristics of the model.

One of the useful methods is the probabilistic sensitivity analysis (PSA) [38-40]. This method determines the importance of input model variables in terms of their influence on the value of assigned output variables. Sensitivity analysis traditionally is used in the post-design stage to demonstrate the uncertainties associated with variables, and determine which variables should be controlled to improve the performance of the model. Sensitivity analysis also can be applied in the pre-design stage to determine the variables which can be eliminated without having a significant influence on the uncertainties of the model performance and hence improve the design efficiency.

**Bayesian techniques:** Although the classic statistical assessment approaches clarify the type and level of risk by assessing associated uncertainties, they cannot take past information into account. To address this problem, a Bayesian approach offers a wide range of methodologies based on Bayesian probability theory, assuming the posterior probability of an event is proportional to its prior probability [2], [41], [42].

The Bayesian approach has a variety of applications by itself, or in combination with other assessment methods, to quantify or qualify uncertainties in single or multi-objective problems of large scale systems. One of the applications of this approach used in this paper (see figure 7) is the third-level-Bayesian analysis for estimating the reliability of launch vehicles [35]. The first level of this method assumes nothing is known about the reliability before observing the launch attempts whereas the second and third levels consider the past experience. These three levels not only determine the probability density function of the future frequency of the launch success, but also yield the estimation of the future frequency of success where no launch attempts have been made yet.

The Bayesian logic can also be used to model degrees of beliefs (instead of knowledge) when just subjective judgments are possible (see dynamic uncertainty). The role of a Bayesian model for assessing degrees of beliefs is more important in large-scale multidisciplinary systems. However, this model can only be used when probability measures of values are known. ULP (the upper and lower probabilistic model) and TBM (the transferable belief model), which are obtained by generalizing Bayesian theory, address this problem and can be used when the probability measures of some of the values are unknown.

Another advantage of the Bayesian theory is its flexibility in being applied in the decision making process of multi-disciplinary systems by combining qualitative and quantitative aspects of uncertainties associated with systems. An example can be found in ACCORD®, a collaborative decision making method to manage the trade study process when decisions are a mix of quantitative and qualitative information, based on the Bayesian decision theory [48-49].

One example of the ULP method is the Dempster-Shafer model which is applied to assess degrees of belief, especially in multidisciplinary systems. The idea behind the Dempster-Shafer theory is simply to combine separate pieces of information to calculate the probability of an event [43-47].

In spite of a wide variety of applicability, applying the Bayesian approach has not been without criticism. Critics point out two main limitations for this approach: First, the Bayesian method ignores the chronological history of events (i.e., when systems mature over time) and second, it does not take into account the similarities of new and past events. More research in this area might be done to address limitations of the Bayesian methods by applying some methods such as decomposing data into certain intervals, devoting unequal weight to events, etc.

**Simulation methods:** Simulation methods analyze the model by generating random numbers and then observing changes in the output. In other words, a simulation approach is a statistical technique clarifying the uncertainties that should be considered by decision makers to reach to the desirable result. Simulation methods are generally applied when a problem cannot be solved analytically or there is no assumption on probability distributions or correlations of the input variables.

The most commonly used simulation-based methodology is the Monte Carlo Simulation (MCS) [50-54]. MCS includes a large number of repetitions, generally between hundreds and thousands. Each repetition simulates variables by their probability density distributions and then generates the probability distributions of the system parameters (output) by integrated probability distributions of variables through the system model. Although the model complexity is not a limiting factor in Monte Carlo simulation, this method can be computationally expensive or infeasible with models with long run time or when too many sources of uncertainty must be considered. To address the limitations of MCS, advanced sampling methods such as Latin Hypercube sampling have been developed to minimize the number of repetitions that is needed to obtain the necessary distributional information for the model. Even though these methods have advantages in efficiency in comparison to MCS, MCS is still the most preferable method when there is no limitation in run time or the model complexity.

Simulation methods can be used on their own or in combination with other methods. One example of this combination is Bayesian Monte Carlo applied in the robust design process [50].

**Qualitative methods:** The above three approaches generally provide only partial insight into a very complex set of uncertainties. As a result, these technical methods have to be complemented with qualitative methods of assessing uncertainties, including expert judgments. Methods which incorporate and propagate both qualitative and quantitative uncertainties in a design process are placed in the fourth category as qualitative approaches of uncertainty assessment. These methodologies may include combinations of two or more assessment methods.

One example is NUSAP [27] which can be used by itself or in combination with other assessment methods. The term of "NUSAP" is the acronym for "Numeral, Unit, Spread, Assessment and Pedigree", where the first three categories are quantitative measures and the two next categories are qualitative quantifiers which might be applied in combination of other assessment methods such as Monte Carlo, and sensitivity analysis.

The most significant shortcoming of NUSAP is its subjective judgment in the scoring of pedigree criteria. Furthermore, since no means of calculating, scoring and individually describing the qualitative components has been determined, communication with stakeholders, who are not familiar with this method, may be inefficient and time-consuming. In addition, as it has been mentioned above, some methodologies, such as ACCORD®, which is based on the Bayesian decision theory, combines both qualitative and quantitative uncertainties.

### 2.2.4. Uncertainty mitigation methods

Although being familiar with sources of uncertainty and methodologies for assessing them is the first step for dealing with uncertainties, still one challenge remains: how can we handle and mitigate the effects of these uncertainties in the systems? In addition, how can we diagnose these uncertainties before it's too late and they get out of control? To answer these questions, this research provides methodologies for uncertainty diagnosis and mitigation:

**Programming errors:** Uncertainties due to programming errors can be diagnosed by who committed it. Since programming errors may occur during input preparation, module design/coding and compilation stages [60, 61], it can be reduced by better communication, software quality assurance methods [62, 63], debugging computer codes and redundant executive protocols.

**Statistical and mathematical errors:** Applying higher precision hardware and software can mitigate the effect of mathematical uncertainties associated with the model due to numerical errors resulting from finite precision arithmetic. In addition it reduces the effect of statistical uncertainties by providing a better precision for the statistical model applied into the system. Statistical uncertainty also can be mitigated by selecting the best data sample in terms of both size and the similarity to the model.

Similar to the statistical uncertainty, approximation uncertainty is minimized when the best model with acceptable range of errors and the best assumption for variables, boundaries, etc., is selected. Simulation approaches might be applied to generate the best model. Generalized Likelihood Uncertainty Estimation (GLUE) [64-65] is an example of a methodology for mitigating the effect of model uncertainty by generating the best model by simulation. Providing a tool for modeling uncertainty, this research mitigates model uncertainty in design and development of large-scale complex systems.

**Ambiguity uncertainty:** Uncertainties associated with using incomplete or unclear definitions, faulty expressions or poor communication are naturally associated with human behavior; however they can be reduced by clear definitions, linguistic conventions or fuzzy sets theory [66-68].

This research attempts to reduce this uncertainty due to lack of communication or faulty expressions by providing an excel based communication tool.

**Volitional Uncertainty:** This type of uncertainty which results from unpredictable decisions especially in multidisciplinary design is diagnosed by other organizations or individuals and is mitigated by hiring better contractors, consultants and labor [30-31].

**Human errors:** Although Human errors and individuals' mistakes are inevitable in the system, they might be diagnosed and mitigated by applying human factors criteria such as inspection, self checking, external checking, etc., to diagnose this uncertainty and better personnel selection, education, etc., for reducing the effect [69-70].

**Dynamic Uncertainty:** As has been discussed before, when only subjective judgments are possible the effect of dynamic uncertainty can be mitigated by applying Bayesian approach (such as Demster-Shafer theory) by assessing degrees of beliefs (instead of knowledge) [41-49]. In addition this type of uncertainty can be reduced by applying design optimization methods to minimize the effect of changes in variables or unanticipated events which contribute changes to design parameters.

This research also addresses this uncertainty by enabling decision makers to combine both qualitative and quantitative aspects of uncertainty in their calculation and model degree of beliefs where just subjective judgment is possible.

**Decision Uncertainty:** Such as dynamic uncertainty, design optimization is useful for reducing the effect of uncertainty when a set of possible decisions are available. Methods based on Bayesian decision theory (such as ACCORD® [48-49]) also can be used to help decision makers to make more informed choices. Sensitivity analysis [38-40] and robust design are also be helpful by determining which variables should be controlled to improve the performance of the model and then considering them as critical factors in the decision making process to clarify which available choices are better in satisfying these criteria.

## 2.3. Design requirement management

It is important for design teams to have a clear understanding of assumptions, constraints, requirements, performance, parameters, and traceability into trades and decisions considered. Since the nature of design is iterative, in many phases of design decision makers may have to step back and change their decisions. Even in some cases it might be necessary to conduct a whole new team study to investigate a mission with slightly different requirements [117] and these iterations increase cost design. However, it is always possible that optimal solutions don't meet design requirements. So providing design requirement management techniques that help decision makers with these issues minimize costs of design and increase its speed.

### 2.3.1 Diversity of optimal solutions/Requirements Management

In recent decades, some attempts have been made to increase the diversity of optimal solutions so that they meet design requirements. The first attempts for increasing the diversity of solutions, have been made in 1975 by Holland [141] and 1989 by Goldberg [142] by applying genetic algorithms applications. M. L. Maher and S. Kundu, (1994) [96] conducted research on adaptive design using graph-based genetic algorithm; K. Abhari et al (1999) [97] applied genetic algorithms and artificial intelligence for designing of flexible manufacturing; Gunawan et al (2003) [143] developed methods for increasing the diversity of Pareto-Optimal Solution sets via the maximization of the entropy quality index. (Also see Pareto sets in decision-based design by Balling, 2000 [113]). They also extended their work (2004) to maximize solution diversities in a multi-objective multidisciplinary genetic algorithm for the design optimization [98].

Figure 7 shows adaptive design by genetic algorithms applications developed by M. L. Maher and S. Kundu in 1994. As this figure shows, in this methodology, the size of the population is increased until optimal genetic design solutions meet the design requirements and the most preferred design product is obtained.

On the other hand, design requirement management by M. W. Fu and W. F. Lu (2003) [105] brought models of modeling and management of design requirements in product development life cycle. Geoff Dromey (2005) [99] developed a perspective of genetic design for amplifying the ability to deal with the requirement complexity. V. Agouridas (2006) [103] reviewed early assignment of design requirements with stakeholder needs and David Baxter (2007) brought a framework to integrate design knowledge reuse and requirements managements in engineering design [104]. Figure 8 shows Baxter's framework for requirement management in engineering design.

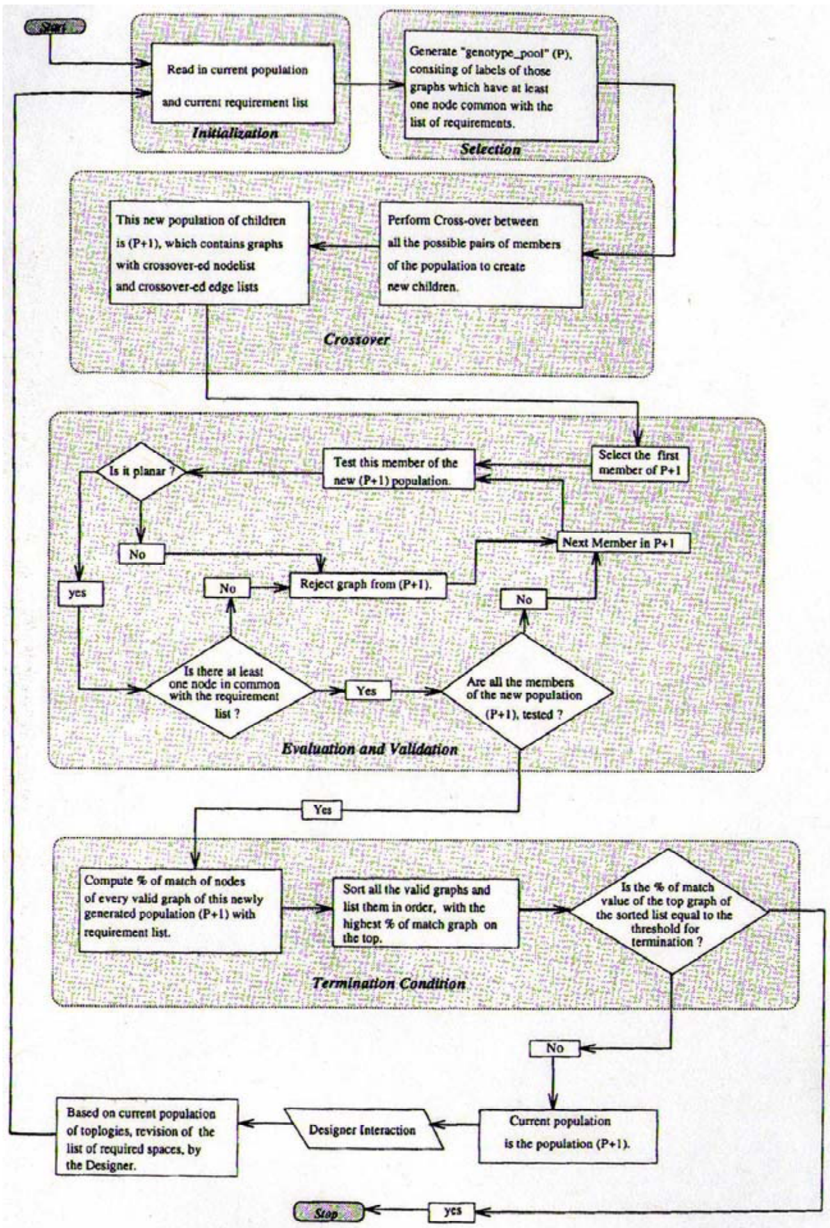


**Figure 7: Adaptive design by genetic algorithm application (Maher et al (1994))**

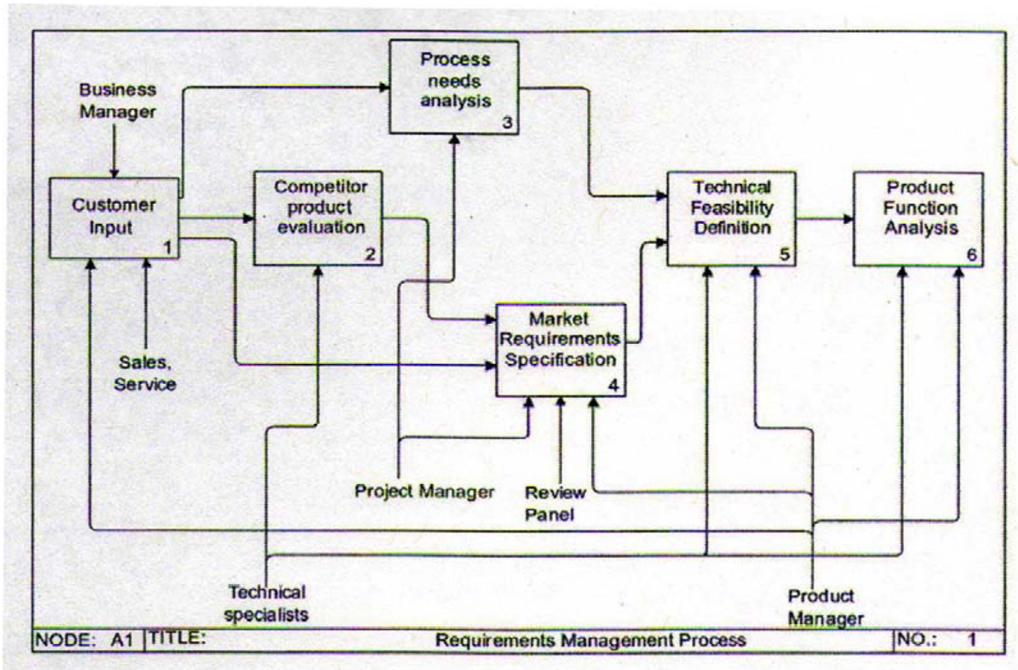


**Figure 8: Baxter's design requirement management framework for engineering design**

## 2.3.2. Resource Allocation

Functional models that are graphical representation of components functionality [160] have a variety of applications that represent the product or component functionality with respect to special needs. One application of functional models, used by the Function-Failure Design Method (FFDM) [150, 158, 159], is to map historical and potential failure modes to functions during component development to improve failure analysis in design. FFDM is based on the logic that failures modes can be correlated back to functions that a particular component addresses. FFDM has five steps:

1- Develop the functional model for the system. This step documents functional data.

2- Generate the function-component matrix. This matrix is called EC matrix whose columns (m) represents components and rows (n) represent components function. It correlates physical components of the system with the associated functional model. "1" for a given component corresponds to the function it performs. Other cells are filled with "0".

3- Extract information from historical data or expert elicitation about potential failure modes and their sources. This step documents the failure data.

4- Generate component-failure mode matrix. This matrix is called CF matrix whose columns (p) are failure modes and rows (n) represents components. "1" for a given component represents the associated failure mode. Other cells are filled with "0".

5- Obtain function-failure matrix (EF) by multiplying the function-component matrix (EC) and component-failure mode matrix (CF). This matrix shows the number of occurrences of a specific failure mode for a specific function.

The importance and applicability of FFDM for risk-based design can be reviewed from two aspects: First: generated matrices can be documented to obtain a large knowledge base of failure modes that can be reused by designers if it's populated. Second: it can track unknown unknowns in the very early stages of design where information is not available by comparing the functionality of similar systems with the same components.

In this context, the functional failure data can be applied by Risk and Uncertainty Based Integrated Concurrent Design (RUBIC) [151] to provide a real-time and evolving resource allocation vector that can be used to prevent failures, mitigate risk and account for uncertainty throughout the design process.

Resource allocation vectors are the percentages of resources to be spent on each functional risk elements. Based on this vector, designers can sort their priorities and allocate optimal amount of resources to reduce risk of each functional element. These are facts and assumption underlying the RUBIC methodology:

1- Each functional element in a complex system creates a risk premium. RUBIC allocates resources to either reduce the risk premium or balance risks against other elements.

2- Risk can be traded homogeneously between subsystems and elements. In this context, risk of an element is not independent of other elements in its subsystem and risk of failure can be reduced by allocating resources.

3- Risk can be traded for risk reduction resource. Risks of a certain function can be reduced by consuming risk reduction resources in the early stages of design, however, the actual amount of risk reduction is not known beforehand.

Applying these assumptions, RUBIC design methodology formulates the model to the following two-objective optimization problem:

Minimize F1= $W^T$□W

Maximize: F2= $W^T\mu$

Subject to W

Where $w=[w_1,...,w_n]^T$ is the risk reduction resource allocation vector which is defined as the percentages of resources to be spent on each functional risk element. $\mu$ is the vector of expected risk reduction for $b_i$ 's ($b_i$ is a random process) and □ is the covariance matrix where diagonal elements are the variance of $b_i$s and off-diagonal elements represent the covariance of risk elements.

$\mu$ and □ can be estimated by using FFDM in the early stages. $\mu$ is proportional to the failure rate and □ can be estimated by estimating $\mu$ and also from incidents where a malfunction in one functional element led to failure in another element.

The first objective function F1 represents the expected total benefit and the second function F2 shows the variance of total benefit. Hence, our optimization problem is to maximize the expected total benefit of risk reduction and to minimize the variance of total benefit subject to risk reduction resource allocation vector $w=[w_1,...,w_n]^T$.

RUBIC design provides a quantitative framework for considering risk and uncertainty during the conceptual design. It assumes hierarchical decomposition of a system, based on functional modeling of systems, whose functional models evolves as the design process moves forward. In addition, RUBIC considers both historical data and expert opinion and accounts for both individual risks as a result of failures due to each functional element and the correlation between multiple elements. Finally, it provides an evolving resource allocating methodology can be used to prevent failures and mitigate risks.

In this research, RUBIC design methodology is applied to allocate resources by functional-model decomposition of systems (chapter 4).

# 3. The Capture, Assessment and Communication Tool for Uncertainty Simulation

The task of decision makers during the design process and development cycle of complex systems is to make optimal decisions in risky environments. Their decisions should satisfy limitations due to constraints associated with systems. One of these limitations is risks that might lead to failure or suboptimal performance of systems. However, uncertainties associated with decisions have significant effects on critical factors and assumptions underlying each decision.

Having no plan for managing uncertainties increases costs of design and decision making by changing resources (market, time, etc). Planning for uncertainty not only prevents these costs but also might provide new opportunities by reformulating initial models and changing associated issues and their importance. As a result, uncertainty management changes resource allocation criteria.

Thos research offers a means for dealing with risk and uncertainty in complex multidisciplinary systems by introducing the "Capture, Assessment and Communication tool for Uncertainty Simulation" (CACTUS). CACTUS satisfies critical challenges that design teams might encounter by identifying sources of uncertainties, assessing and mitigating associated risks, modeling propagation of uncertainties and communicating uncertainty. These techniques are added to systems from the very early stages of design and while the project goes forward, help identify sources of uncertainties and their boundary which may lead to failure, help identify and mitigate associated risks, and models their propagation to be analyzed by decision makers. It provides answers to these questions:

1- Where is uncertainty from?
2- What is its severity and importance?
3- What are possible methods to assess mitigate and dealt with uncertainties?
4- How do uncertainties propagate and which model describes them the best?

In the following chapter, CACTUS provides a methodology to answer these questions.

## 3.1. Introduction

In a real engineering design team, especially in the early stages of conceptual design, decision makers encounter lots of uncertainties in each decision they make. In the early stages of conceptual design, uncertainty is high since many decisions have not yet been made and design alternatives to achieve the best design product have not yet been clearly and actively considered. If the whole design process is considered as a decision tree, each decision point with more than one alternative represents a decision node. To deal with the uncertainty in the design and development of a complex system, team members should be aware of consequences of their decisions in each decision node. To achieve this goal, they should be able to deal with uncertainties associated with each decision, while being aware of decisions made by others.

To address these needs, "Capture, Assessment and Communication Tool for Uncertainty Simulation" (CACTUS) offers a means for dealing with uncertainty in a complex system design process to satisfy critical challenges of design teams:

- **CACTUS by identifying sources of uncertainties,** classifies sources of uncertainties associated with systems in different stages of design of complex systems. Different sources of uncertainties are not the same with respect to their importance and types of treatments should be considered. In addition, selecting a poor or imperfect definition and classification for uncertainty might guide decision makers to account for uncertainty more or less than necessary in the design process. CACTUS provides a methodology for identifying and classifying sources of uncertainties associated with systems from early stages of design to the end.

  Figure 5 and Table 1 in chapter 2 have shown uncertainty classification used by CACTUS. This classification not only identifies sources of uncertainties, but also helps decision makers to choose the type of uncertainty treatment (mitigation, model, etc) that should be considered.

  One example of this classification will be shown in chapter 5 by applying it into the robotic lunar lander mission design case study to identify sources of uncertainties for alternatives in the decision sheet.

- **CACTUS, by providing both qualitative and quantitative uncertainty assessment method,** not only pays attention to quantifying uncertainty, but also addresses qualitative uncertainties associated with systems. It achieves this goal by introducing the qualifier and the importance number in the decision sheets. The importance score devotes unequal weighting from 1 (lowest) to 5 (highest) to uncertainties associated with decision nodes based on expert judgment. This number, after being normalized, can be used for weighting issues in places expert judgment is necessary. The qualifier is simply an expression of the qualitative judgments.

Since it divides the project into system level and associated subsystems that exchange data with each other in a collaborative excel-based environment, each team member either at the system level or subsystem, will have his/her own importance number and qualifier.

The importance number and the qualifier in combination with quantitative assessment representations of distribution of variables (such as mean and deviation) introduce CACTUS as an uncertainty assessment method with the power of combining both qualitative and quantitative methods. It also can be extended to model degree of beliefs (instead of knowledge) where just subjective expert judgment is possible (see descriptions of Bayesian techniques and Dempster-Shafer theory in section 2.2.3). One example of decision sheets will be provided by CACTUS for the robotic lunar lander mission design case study in Chapter 5.

In addition, this step provides design teams with risk boundaries that may lead to failure. These boundaries are considered as risk constraints. Techniques applied to obtain risk boundaries include simulation methods, PBA and Dempster-Shafer theory when only expert judgment is available.

- **CACTUS, by providing mitigating techniques with respect to associated sources of uncertainties**, offers solutions to manage all sources of uncertainty, whether controllable or uncontrollable, qualitative or quantitative. The excel-based environment, and hence the communication tool, reduces ambiguity uncertainty due to a lack of communication among team members, misunderstandings about customers requirements and the precise definition of design tasks and requirements. CACTUS provides techniques of reducing/eliminating uncertainties with respect to their sources. (See section 2.2.4 for more details of uncertainty mitigation techniques).

- **CACTUS, by modeling uncertainty propagation,** provides an uncertainty-based model for the project by identifying control factors, noise factors and linking variables. This model is applied for formulating the project to an optimization problem to obtain the most preferred design product. A simple example of this model will be shown in chapter 5 for the lunar robotic lander mission design case study.

In summary, CACTUS provides risk and uncertainty management techniques aimed to identify, assess and mitigate sources of uncertainties associated with systems and as a consequence, manage risks of suboptimal performance or system failures. In addition CACTUS provides uncertainty modeling methods for large-scale multidisciplinary systems. Modeling uncertainty propagation determines design variables and parameters and formulates the project as an optimization problem to reach the desirable design product.

The next section, describes the CACTUS methodology process.

## 3.2. Methodology

These are three major steps in the CACTUS methodology to obtain desirable outputs shown in this model:

***Step 1:*** The first step is to identify sources of uncertainties. CACTUS provides a classification for sources of uncertainties associated with design of complex systems (Figure 5 in section 2.2.2.).

Different sources of uncertainties are not the same in terms of importance and treatments that should be considered. For example, some sources of uncertainties (decision uncertainties) might be desirable to increase by decision makers by generating more alternatives or in cases where optimal solutions do not meet design requirement. On the other hand, other sources of uncertainties might be very harmful and cause failure or suboptimal performance of systems.

In addition, modeling techniques used by CACTUS depend on the sources of uncertainties. For example, techniques used for modeling behavioral uncertainties would be completely different from those used for modeling model uncertainties. As a result, the first step in CACTUS methodology would be identifying sources of uncertainties and classifying them regarding of their nature and their effects to the system.

***Step 2:*** The second step in CACTUS is to apply uncertainty assessment methods. CACTUS provides design teams with techniques of assessing uncertainties and their boundaries, severity, importance and consequence to the system. These criteria are used by Design Requirement and Resource Allocation Management (DRRAM) to weight uncertainties and allocate resources based on their severity and importance for the system.

In addition, CACTUS provides techniques of determining risk boundaries which may lead to failure or suboptimal performance.

***Step 3:*** The third step in CACTUS is to provide uncertainty mitigating techniques. Weighting uncertainties by DRRAM determines techniques that should be applied to manage associated uncertainties. These techniques have tremendous effects in managing risks and reducing costs of design.

Decision sheets which provide tools for making the best decision among sets of alternatives are generated in this step (See the previous section for properties of decision sheets). In Chapter 5, a decision sheet will be generated for the lunar lander mission design case study.

***Step 4:*** The fourth step is to model uncertainty. Applying uncertainty management techniques in the first three steps of CACTUS methodology provides the necessary information for design teams regarding the uncertainties, risks and their constraints that lead to failure. In this step, the uncertainty-based model for the project is obtained. This model not only gives a general understanding of the project with respect to variances from the predicted model, but also clarifies noise, control factors and linking variables.

In Chapter 5, this methodology will be clarified further by applying it into the case study.

## 3.3. Conclusions and Future Work

This chapter introduced the CACTUS methodology to help design teams to make more informed decisions in risky environment that are full of uncertainties during the design and development of complex system. CACTUS, as an excel-based environment, enables decision makers to identify, assess, mitigate, model and communicate uncertainty from early stages to the end. It creates decision sheets for alternatives in each decision node and help decision makers to select the optimal design product.

Although decision sheets provides a means for combining qualitative and quantitative uncertainties, future work is needed to develop this methodology so that it can assess, mitigate and model all sources of uncertainty, especially the qualitative aspects. Developing a decision tree to demonstrate criteria for selecting the best assessment methodology to capture uncertainties associated with issues is another work can be done to increase the speed of this process. This decision tree can be extended to include criteria for decision makers wherever expert judgment is needed and the scores that should be devoted to qualify issues.

In addition, future research for CACTUS should focus on developing techniques to obtain upper and lower margins of uncertainties. Since these margins define risk constraints,  critical factors underlying risk constraints include marginal distributions of the input variables in addition to their dependency. Future research is to extend this methodology to bounding approach to risk analysis so that it can address mentioned issues.

The bounding approach to risk analysis is the extension of traditional probabilistic analyses to determine four criteria in the risk model: precise parameter values for input distributions (i.e. minimum, maximum); marginal probability distributions for variables, the precise nature of dependencies of variables and the structure of the risk model. Probability Bounds Analysis (PBA) based on probability boxes (P-Box) (a class of distribution functions of epistemic uncertainties of a random variable defined by the upper and lower bound) and simulation-based methods for determining margins relied on Monte Carlo analysis are two approaches that would determine marginal distributions via probabilistic methods. In addition, Dempster-Shafer theory (or evidence theory) as a variant of probability theory in which elements of the sample space are sets (instead of single points) is applied to determine maximum and minimum margins of conceptual design where information is not available.

# 4. Design Requirement Management (DRRAM)

During the design and development of complex systems, design teams should be aware of properties of systems and subsystems and associated tasks, requirements, criteria, etc. These issues not only define design constraints that should be satisfied to meet requirements, but also enable decision makers to predict system and subsystem properties so they can devote more effort (cost, schedule, additional safeguards) to subsystems with more importance with respect to certain issues.

In this chapter, this research introduces Design Requirement and Resource Allocation Management (DRRAM).

## 4.1. Introduction

This research provides techniques for Design Requirement and Resource Allocation Management (DRRAM) by analyzing and defining the project, associated tasks, issues requirements and resources, dividing the system into subsystems, parallel decisions, decision nodes, alternatives and generating the model:

- The Design Requirements and Resource Allocation Management (DRRAM) framework defines the project and provides all necessary information for decision makers by generating information sheets.

Information sheets provide the necessary information especially from early stages of design, providing a useful tool for design teams to be able to evaluate criteria and manage the project and design requirements.

DRRAM's information sheets not only provide necessary information for making decisions, but also help design teams (including designers, stakeholders and customers) to communicate their needs during the design process and change their decisions more effectively as the design goes ahead and new criteria are obtained by providing an updatable excel-based collaborative environment.

In chapter 5, an example of information sheet will be shown for the lunar lander mission design case study.

- DRRAM also provides the project model to help decision makers to have a clearer understanding of the design platform in the early stages of design. This model used by decision makers to define the initial design platform and design alternatives.

- The Design Requirements and Resource Allocation Management (DRRAM) provides an evolving resource allocating methodology by hierarchical decomposition, based on functional modeling of systems, whose functional models evolve as the design process moves forward.

  As a result, it provides a methodology to allocate available resources (cost, schedule, safeguard, etc.) to functions with more importance with respect to certain issues and it can also be extended to prevent failures and mitigate risk.

- Design Requirements and Resource Allocation Managements (DRRAM) generates flow diagrams for each parallel decision, which helps design teams to have a better understanding of the active and passive alternatives in each decision node of the associated parallel decision.

  In chapter 5, a flow diagram will be shown for selecting the launch vehicle during the decision making process of the lunar lander mission design case study.

## 4.2. Methodology

Design Requirements and Resource Allocation Management (DRRAM) help the design team by these major steps:

***Step 1:*** The first step in DRRAM is to obtain the initial design project functional model to help decision makers to have an understanding and definition of the initial design platform from very early stages of design. This model also helps them to determine initial design alternatives.

This model is investigated by design teams (including designers, decision makers, stakeholders, customers, etc.) to determine the requirements of the project. Knowing these issues, decision makers can model the project at the early stages of design and predict systems' and subsystems' properties.

***Step 2:*** The second step in DRRAM is to generate the information sheet. For obtaining information sheets, the model created in step 1 is divided into subsystems and parallel decisions and associated issues, constraints, and the design requirements are determined by the design team.

Due to lack of information in early stages of design, generated information sheets are not complete and accurate at the beginning of a project, but they are matured as the project moves forward.

***Step 3:*** Decision makers should also determine decision nodes, where decisions are made and identify active items which are being actively investigated.

The third step in DRRAM helps them in developing decision sheets (For more information about decision sheets see chapter 4, the CACTUS methodology) for decision nodes.

In addition, flow diagrams are generated in this step that help the design team to have a better understanding of alternatives that are being investigated actively/passively in the decision nodes.

***Step 4:*** The fourth step in DRRAM is to allocate resources. DRRAM uses the Risk and Uncertainty Based Integrated Concurrent Design (RUBIC) design methodology (See chapter 2 for details) which provides a hierarchical decomposition, based on functional modeling of systems obtained in step 1, whose functional models evolve as the design process moves forward.

This step allocates resources to the model by mapping it into this optimization problem:

Minimize $F1= W^T□W$

Maximize: $F2= W^T\mu$

Subject to $W =[w_1,...,w_n]^T$

Where $w=[w_1,...,w_n]^T$ is the risk reduction resource allocation vector where $w_i$ is the percentages of resources to be spent on the $i^{th}$ functional risk element.

In this optimization problem, $\mu$ is the vector of expected risk reduction for $b_i$ 's ($b_i$ is a random process) and □ is the covariance matrix where diagonal elements are variance of $b_i$s and off-diagonal elements represents the covariance of risk elements.

The first objective function F1 represents the expected total benefit and the second function F2 shows the variance of total benefit.

The optimization problem provided in these steps is to maximize the expected total benefit of risk reduction and to minimize the variance of total benefit subject to risk reduction resource allocation vector $w=[w_1,...,w_n]^T$ as the percentages of resources should be spent for functional risk elements.

Figure 9 shows the four major steps of the methodology introduced by DRRAM. As this figure shows, decision sheets (developed by CACTUS) are developed after determining decision nodes by DRRAM. In addition, the investigated model and alternatives are used to determine possible design change to resolve defect modes.

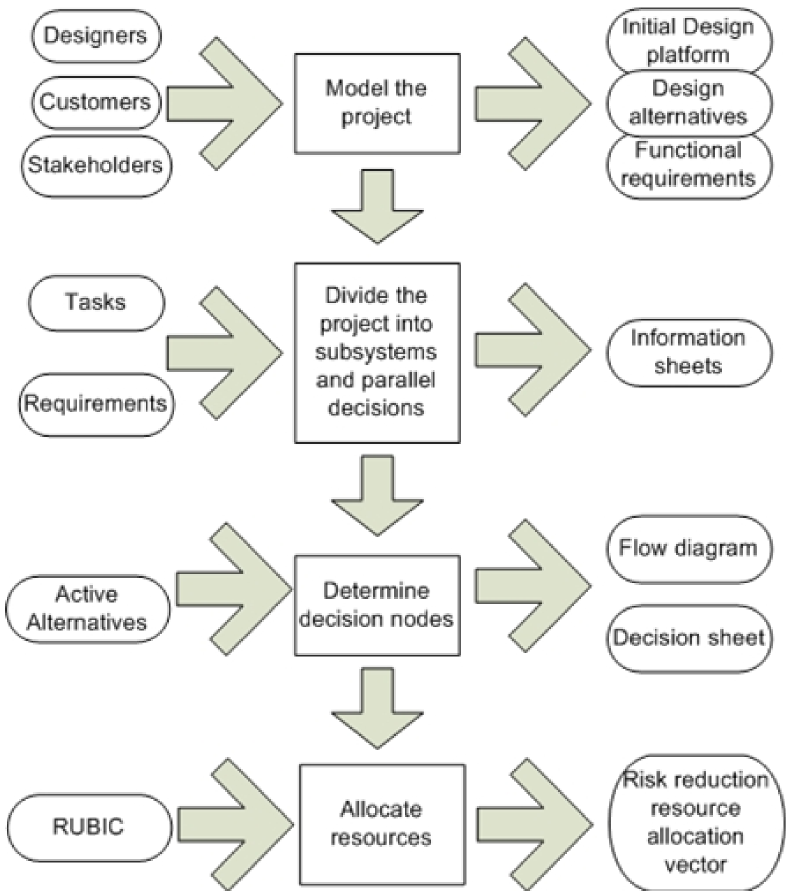


**Figure 9: Design Requirement and Resource Allocation Management (DRRAM)**

In chapter 5, this methodology is clarified by applying it into the lunar lander mission design case study.

## 4.3. Conclusions and Future Work

This chapter provided Design Requirement and Resource Allocation Management (DRRAM) as a management tool for design of complex systems. The benefits and process of this methodology was described and a figure showed its major steps schematically.

This method can be divided into design requirement management and resource allocation technique. The framework of design requirement management was provided by updatable excel-based information sheets that enable design teams to communicate and define design requirements and constraints in different stages of design concurrently. In addition, dividing the project into parallel decisions, decision nodes and alternatives helps them to manage the project more informed.

Future research to provide this method with techniques of design requirement management (See chapter 2) should be done so that it can address needs of design teams including designers, stakeholders and customers for trading off their requirements and design constraints.

On the other hand, as the other approach of DRRAM methodology, future work for the applied allocating resources technique should be done to extend the knowledge base that can support the applied RUBIC design tool. Future research is currently being carried by author of this research to improve the RUBIC design tool and address its limitations.

# 5. The Case study: Lunar lander mission design

In this section, this research presents a case study of the conceptual mission design team at JPL's Project Design Center, borrowed from [33].

Figure 10 shows a portion of the decisions that occurred during the design of a robotic lunar mission, based on the observations of the team over the course of a week as they worked on a robotic lunar lander mission design, initiated by an internal NASA customer [33].

The product of this Team X design is a conceptual design that includes the mission architecture, equipment lists, launch vehicle and estimates for cost and schedule. This team was formed in order to shorten the time required to develop a space mission proposal.

The ovals drawn with solid lines show these items were actively investigated and the ovals in dotted lines are items that were considered but not actively investigated.

As mentioned, for this case study, the methodology presented in this prepare provides an excel-based environment for clients to communicate throughout the design life cycle. Using this environment clients synchronize data (send/receive data to/from the server) and communicate with each other during the lifecycle.

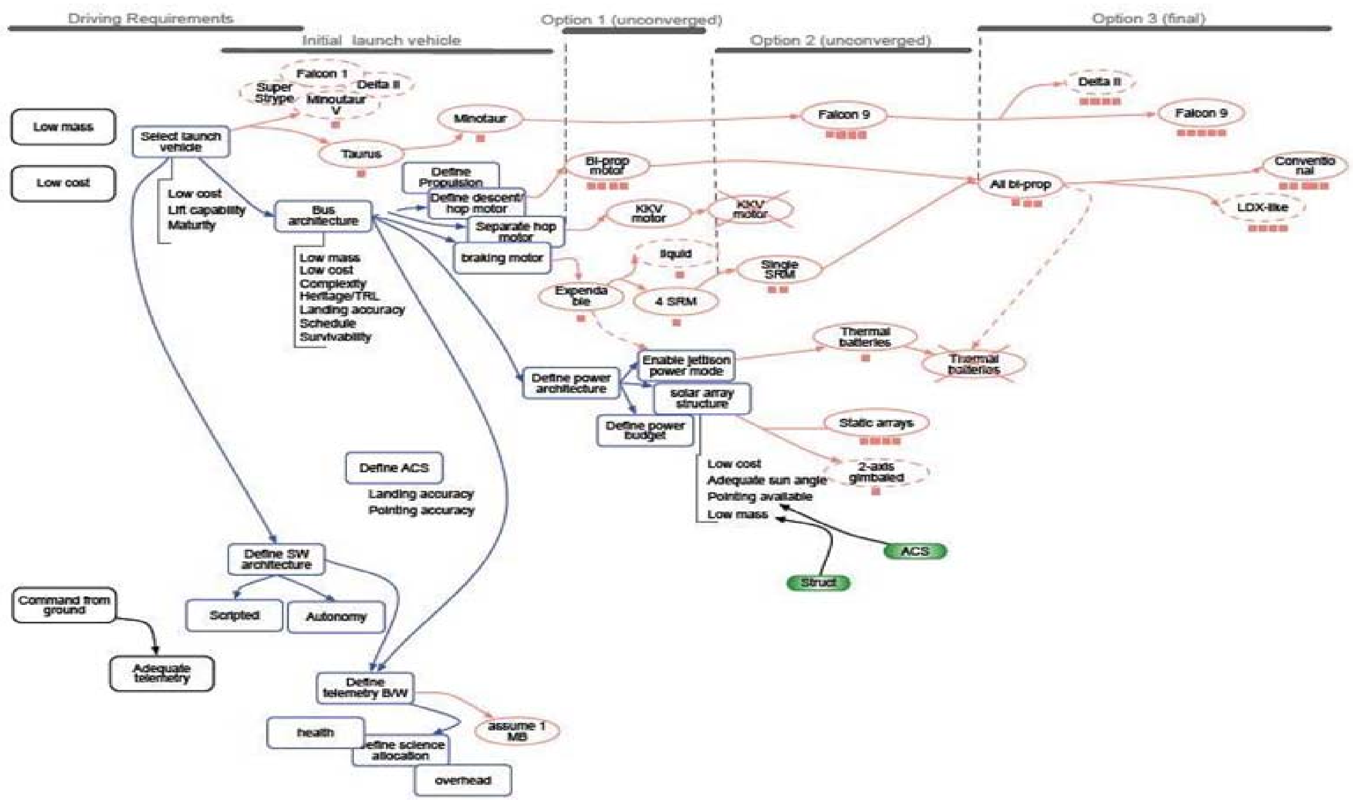


**Figure 10: The robotic lunar lander mission design**

Figure 11 shows the general structure of this excel-based environment provided by the proposed methodology. This environment might not be complete in the early stages of design. Here, we have generated a general scheme of this environment for stages of design where all necessary information (subsystems, parallel decisions, active items, etc.) has been captured by design team.

- TASKS
- REQUIEREMNTS
- MODEL
  - FLOW DIAGRAM
  - INFORMATION SHEET *
- PARALLEL DECISIONS
  - X1
    - TASKS
    - ISSUES
      - COST
      - RELIABILITY
      - MATURITY
      - LIFT CAPABILITY
    - DECISION NODES
      - X11
        - DECISION ITEMS
          - X111
          - X112
        - DECISION SHEET **
      - X12
      - X13
      - X14
    - FLOW DIAGRAM ***
  - X2
  - X3
  - X4
  - X5

**Figure 11: ORBID Excel-based environment for the robotic lunar mission design project.**

* Figure 13: Information sheet for the design process

** Figure 14: Decision sheet for the 2nd phase of X1

*** Figure 12: Flow diagram of the X1

The excel based environment provided in Figure 11 for this case study has been generated using the terminology (see section 1.3.) introduced by design requirement and resource allocation management (DRRAM) to divide the project into parallel decisions, decision nodes and alternatives:

The first step to develop such this structure is to identify parallel decisions should be made for the project. Estimating the necessary decisions in the very early stages of design helps decision makers to develop the project model and clarify decision nodes and alternatives in next steps as the project moves forward.

As Figure 10 showed, five selected alternatives including “Falcon 9”, ‘Bi-prop motor”, “Conventional”, “Static arrays”, and “Assume 1MB”, shown by solid lines, represent five associated parallel decisions that should be made by decision makers including: LAUNCH VEHICLE SELECTION, DEFINE DESCENT MOTOR, DEFINE BRAKING MOTOR, POWER and CDS. So, according to the terminology introduced by DRRAM, the set of parallel decisions would be:

$\{X_1, X_2, X_3, X_4, \text{and } X5\}$.

Where $X_1$ is the process of decision making for Launch vehicle selection, $X_2$ presents Define Descent Motor, $X_3$ includes Define Braking Motor, $X_4$ is the decision should be made for Power and finally $X_5$ is decisions for CDS.

Each of subsets in the above vector includes sets of associated decision nodes and each decision node contains a set of alternatives. An example of developing this division has been demonstrated in Figure 11 for $X_1$ for selecting launch vehicle. Figure 11 identifies four decision nodes for X1 and defines X1= $\{X_{11}, X_{12}, X_{13}, X_{14}\}$.

Here, it is helpful to mention that, in the early stages of design decision makers have no idea about the quality and numbers of possible decision making nodes they would have during the design process. The above set has been provided for the final stage of design; however this set is different at the beginning of the project and will be updated in the excel based collaborative environment when new information is obtained. Archiving the set of decision nodes not only archives the process of decision making that was done for the design to obtain the final product, but also it provides a knowledge-base that can be used by designers later.

Since decision nodes are places that a decision should be made among alternatives, each of the decision nodes in the above set is associated with alternatives. Figure 11 has been categorized alternatives of the first decision node, $X_{11}$, of $X_1$, Launch vehicle selection. This set is obtained by looking into the Figure 10:

$X_{11}= \{X_{111}, X_{112}\}$,

where $X_{111}$ and $X_{112}$ are Taurus and Minoutaur V, alternatives are actively considered in the first decision node of the selecting launch vehicle process.

In Chapter 4, this research has introduced the flow diagram as one approach of Design Requirement and Resource Allocation Management (DRRAM) that helps decision makers to have a better understanding of alternatives are being passively and actively investigated. Figure 12 shows the flow diagram of the parallel decision for selecting the launch vehicle.

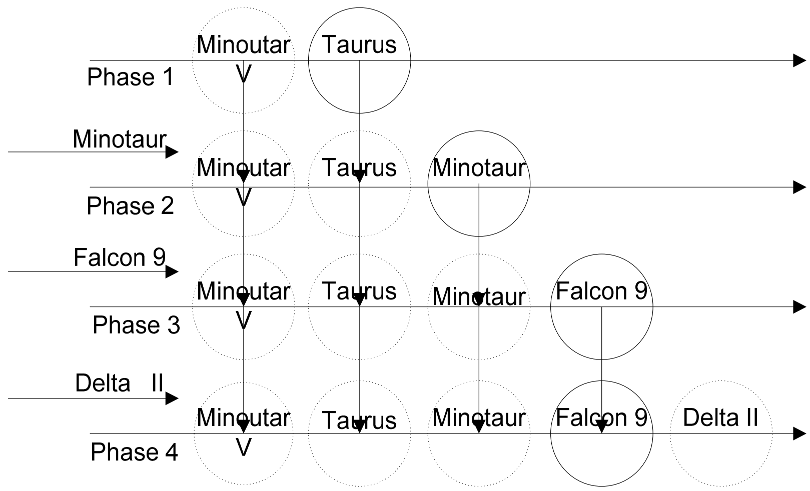


**Figure 12: An example of decision flow diagram**

This flow diagram starts from the first decision phase which is the decision node between Taurus and Minoutaur V and ends at the last phase in choosing the final decision. Each dotted circle shows the alternative which is not investigated actively and circles with solid lines show active items that take part in decisions. Arrows from left to right show alternatives which are added in each phase. So, the decision node in each phase is among active alternatives (circles with solid lines) in the previous phase and items that the arrows show (items which are added from the previous phase).

The selected alternatives in each decision node will be represented by circles with solid lines (Falcon 9 for this example in the last phase) that represent decisions made by decision makers at the end of the decision making process. As the excel-based structure in Figure 11 and the set of decision nodes, the flow diagram shown in the Figure 12 is not complete in the very early stages of design and be updated in the excel-based environment when the project goes ahead.

In the flow diagram shown in Figure 12, the first decision node for the launch vehicle selection parallel decision is a decision node between two launch vehicles: Minoutaur V and Taurus; where solid lines show Taurus was actively investigated and dotted lines show Minoutaur V was not actively investigated. In the next phase, we have the second decision node for this parallel decision where Minotaur is considered as an active item and Taurus is not investigated actively. As the design process develops, in phase 3 and 4, we have two more decision nodes.

As the flow diagram shows, Falcon 9 is added in the 3$^{rd}$ phase as an active item and Delta II is added to step 4. So, our final decision node is a selection between two launch vehicles Delta II and Falcon 9, which ends in the selection of Falcon 9.

As mentioned in Chapter 5, The Design Requirements and Resource Allocation Management (DRRAM) framework defines the project and provides all the necessary information for decision makers by generating information sheets. Information sheets provided by DRRAM enables decision makers to be aware of tasks and issues associated with the project and give all necessary information they need to manage design requirements and allocate resources. They determine the name/symbol and tasks and issues associated with parallel decision and decision nodes and describe each decision node in terms of its alternatives in addition to functional requirements and associated resource allocation vector.

| | A | B | C | D | E | F | G | H | I | J | K |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | Parallel decisions | | Tasks | Issues | Phase | Stage | Decision node | Decision Items | | Comments | Active Items |
| 2 | Symbol | Name | | | | | | Symbol | Name | | |
| 3 | X1 | Launch vehicle selection | Select launch vehicles | Low cost | 1 | Initial launch vehicle | X11 | X111 | Minoutaur V | | X112 |
| 4 | | | | Lift capability | | | | X112 | Taurus | | |
| 5 | | | | Maturity | 2 | Initial launch vehicle | X12 | X112 | | | X121 |
| 6 | | | | Reliability | | | | X121 | Minotaur | | |
| 7 | | | | | 3 | Option 2 | X13 | X121 | | | X131 |
| 8 | | | | | | | | X131 | Falcon | | |
| 9 | | | | | 4 | Option 3 | X14 | X131 | | | X131 |
| 10 | | | | | | | | X141 | Delta II | | |
| 11 | X2 | Descent motor defining | Define architecture | Low mass | 1 | Option 1 | X21 | X211 | Bi-prop motor | | X211 |
| 12 | | | Define descent motor | Low cost | | | | | | | |
| 13 | | | | Complexity | | | | | | | |
| 14 | | | | Landing accuracy | | | | | | | |
| 15 | | | | Shedule | | | | | | | |
| 16 | | | | Survivability | | | | | | | |
| 17 | X3 | Braking motor defining | Define architecture | Low mass | 1 | Option 1 | X31 | X311 | 4 SRM | | X311 |
| 18 | | | Define braking motor | Low cost | 2 | Option 2 | X32 | X311 | | | X321 |
| 19 | | | | Complexity | | | | X321 | Single SRM | | |
| 20 | | | | Landing accuracy | 3 | Option 3 | X33 | X321 | | | X331 |
| 21 | | | | Shedule | | | | X331 | Bi prop motor | | |
| 22 | | | | Survivability | 4 | Option 3 | X34 | X331 | | | X341 |
| 23 | | | | | | | | X341 | Conventional | | |
| 24 | | | | | | | | X342 | LDX-like | | |
| 25 | X4 | Power | Define power architecture | Low cost | 1 | Option 2 | X41 | X411 | 2-axis gimbaled | | X412 |
| 26 | | | | Adequate sun angle | | | | | | | |
| 27 | | | Solar array structure | pointing available | | | | X412 | Static array | | |
| 28 | | | | Low mass | | | | | | | |
| 29 | X5 | CDS | Define s/w architecture | | 1 | Option 1 | X51 | X511 | Assume 1MB | | X511 |
| 30 | | | Define telementry size | | | | | | | | |

**Figure 13: The information sheet provided by DRRAM for the case study**

Figure 13 shows the a simple version of an information sheet provided by DRRAM for the lunar lander mission design to show the general structure of body of information sheets excluding functional requirements and associated resource allocation vector. RUBIC design methodology, introduced in Chapter 5 can be applied at this point to obtain the correct resource allocation vectors.

One example of applying the FFDM methodology (introduced in chapter 5) for obtaining the functional requirement model of the project and one case study of applying RUBIC design methodology for the Satellite Reaction Wheel (borrowed from [151] has been attached in Appendix A and B).

As figure 13 shows, the information sheet provides the necessary information for the design team including task and issues associated with each decision. Tasks determine issues associated with parallel decisions and issues determine criteria that should be considered for the decision making process.

Determining tasks and issues enables CACTUS to develop the decision sheets for associated decision nodes. Decision sheets are developed from the earliest decision node to the end where the final decisions are made. Figure 14 illustrates one example of decision sheet made for one decision node of selecting launch vehicle provided by CACTUS for the robotic lunar lander mission design case study.

| | A | B | C | D | E | F | G | H | I | J | K | L | M | N |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | PARALLEL DECISION | | NODE | ACTIVE ITEMS | | ISSUES | DISTRIBUTION | | METHODOLOGY | SOURCES OF | ISSUE IMPORTANCE | | | |
| 2 | NAME | SYMBOL | | NAME | SYMBOL | | MINOUTAR | TAURUS | | UNCERTAINTY | 1 | 2 | 3 | 4 |
| 3 | Select launch vehicle | X1 | X12 | Minotaur | X112 | Reliability | (0.87,0.1331) | (0.82,0.1228) | Third-level Bayesian | Model uncertainty | 2 | | | |
| 4 | | | | Taurus | X121 | Cost | | | | | 4 | | | |
| 5 | | | | | | Maturity | | | | | 3 | | | |
| 6 | | | | | | Capability | | | | | 3 | | | |

**Figure 14: A simple example of decision sheet provided by CACTUS.**

As Figure 14 shows, the decision sheet has columns showing the distribution of issues. In addition, the importance numbers are devoted to show the importance of issues. They provide unequal weighting from 1 (lowest) to 5 (highest) to uncertainties associated with decision nodes based on expert judgment. This number, after being normalized, can be used for weighting issues in places only expert judgment is possible to model degree of beliefs. In addition, the qualifiers which are the expression of these qualitative judgments could be added to this information sheet to show the qualitative assessment of uncertainties.

It's beneficial to mention that since the CACTUS methodology divides the project into system level and associated subsystems that exchange data with each others in a collaborative excel-based environment, design team members either at the system level or subsystem level might use their own importance number and qualifier.

Figure 14 has provided a decision sheet for the second phase of the first parallel decision for the selecting launch vehicle process. As the sheet shows, for the second phase, our decision node is the selection among two launch vehicles: Taurus and Minotaur. Also, from the information sheet for the project model (Figure 13), our issues include: Reliability, Cost, Capability and Maturity. By giving the expert judgment score to these issues decision makers are able to rank them from the highest important issue to the lowest one.

In this figure the issue considered by this paper is the reliability issue. The reliability issue's distributions for two available active alternatives has been calculated by using the third-level Bayesian analysis method [35] (See Appendix C). Determining the weight (importance) and distribution of all issues (also see [36, 37]) helps decision makers to rank alternatives

Figure 15 shows a simple model for uncertainty propagation provided by CACTUS where:

$C_i$ = Control factors of subsystem i

$C_S$ = Sharing system control factors

$N_S$ = Sharing system noise factors

$N_i$ = Noise factors of subsystem i

$L_{ji}$ = Linking variables (from subsystem i to j)

$Z_i$ = $Z_i$ ($C_S$, $C_i$, $N_s$, $N_i$, $L_{ji}$) = output of subsystem i

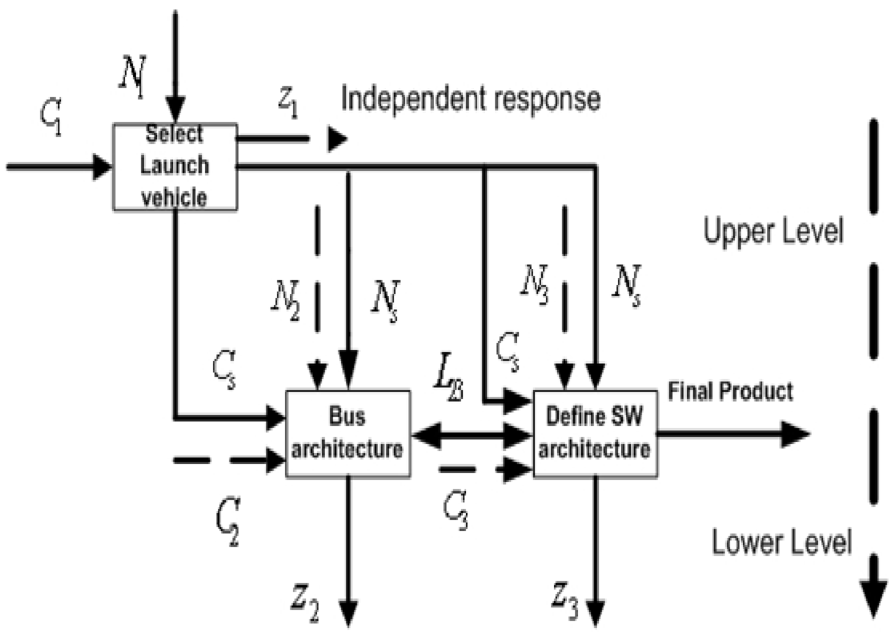


**Figure 15: A simple uncertainty propagation model for Lunar Lander Mission**

Multidisciplinary systems are defined by subsystems interacting with each others. In this model, control factors refer to design variables which designers have control over while noise factors refer to variations of systems during the design lifecycle which designers have no control or limited control over.

Linking variables shows this dependency of subsystems. Figure 15 shows the propagation of uncertainty in the form of noise and control factors and also linking variables for the three subsystems of the case study including selecting the launch vehicle, bus architecture and defining the software architecture. As this Figure shows, decisions made for each subsystem effects decisions made by other subsystems.

# 6. Future Vision: Optimal Risk-Based Integrated Design

As mentioned before (See Section 2.1.), The ultimate goal of large-scale design organizations are mainly to reduce costs and improving reliability and performance of system while assessing how much risk (cost, schedule, scope) they can take and still remain competitive. To achieve this goal they need to trade off performance, time, cost and risks (as the most difficult part to be addressed). In addition they should be provided with a variety of techniques to computerize, systematize, communicate, etc to support the design of a complex system.

In this chapter, this research introduces Optimal Risk Based Integrated Design (ORBID) [76] as a cumulative tool for dealing with these issues in complex systems. ORBID satisfies critical challenges that design teams might face and help them to obtain the highest performance of multidisciplinary systems within risk constraints while satisfying all limitations and requirements of design and development of large-scale complex systems. It addresses mentioned issues by identifying sources of uncertainty and available methods for assessing and mitigating them, developing methods for modeling, optimizing and decision making, providing a communication tool for the concurrent design team through the design life cycle and finally producing the desirable design performance at the final stage of design and development of multidisciplinary complex systems.

The proposed methodologies of the Capture, Assessment and Communication Tool for Uncertainty Simulation (CACTUS) (see Chapter 3) and Design Requirement and Resource Allocation Methodology (DRRAM) (see Chapter 4), in this research are applied in the ORBID methodology as tools and techniques for managing risks and requirements of complex systems. In addition, ORBID introduces Flexible Risk-based Optimal Decision making (FROD) to help decision makers to generate and select the most preferred design product.

This chapter focuses on the ORBID methodology as the future work of this research.

## 6.1. Motivation

Following paragraphs mentioned the importance of providing tools and techniques to trade off risks, requirements (cost, time resources) and performance of complex systems. During the design lifecycle, the design team must minimize risks while increasing performance considering costs constraints by allocating resources to the most critical areas. In this research CACTUS and DRRAM have been proposed as tools for dealing with these issues by managing risks and requirements; however these critical areas are associated with critical decisions for risky scenarios tending to cause failure if combined and can be prevented by decisions made by designers in risky environments.

Decision making process as a perspective of engineering design is generating and selecting of design alternatives. So, the outcome of the decision making process can be defined by two steps: 1- Generating all possible design alternatives and 2- Selecting the most preferred design alternative(s) among available alternatives. Based on this definition, many alternative selection methods have been developed and widely applied, such as Taguchi's robust decision [86-95], Clausing 's Quality function deployment [124] and Suh 's design Axiom Matrix [125]. The role of decision makers is to make decisions in the ambiguous, uncertain and risky phases of design [75]. These uncertainties are presented in all phases of design, such as model uncertainty (uncertainties associated with using a process model or a mathematical model for the system), dynamic uncertainty (when changes in the organization or individuals' variables or unanticipated events, such as economic or social changes, to a change in design parameters) [106], etc. As a consequence, in multidisciplinary complex systems decision makers should be aware of all independent and interdependent variables associated with each discipline. However, in the early stages of design, information about different aspects of design is not always available. For this reason, the design of such complex systems is iterative by the nature and designers might have to change decisions made in different phases of design many times. Therefore, flexibility is another important issue (in addition to risk, uncertainty and ambiguity mentioned above) that should be considered in the decision making process.

Optimal Risk-Based Integrated Design (ORBID), shown in Figure 16, as a cumulative tool to obtain the most preferred product within risks and design constraints by introducing Design Requirement and Resource Allocation Management (DRRAM) and the Capture, Assessment and Communication Tool for Uncertainty Simulation (CACTUS) in a collaborative excel-based design environment, also addresses the issue of decision making to help designers wherever a decision has to be made among many alternative choices and accounts for uncertainties due to having multiple choices in decision nodes of the design process by introducing ”Flexible Optimal Risk-based Decision-making” (FROD) as a technique for making decisions within the optimization domain and risk constraints while all design requirements are satisfied. FROD also addresses the challenge of increasing costs of design due to unavoidable decision making iterations under risk and uncertainty by providing updatable uncertainty-based decision sheets. It generates and optimizes flexible alternatives with respect to minimization of costs and then ranks options based on evaluated costs and associated uncertainties.

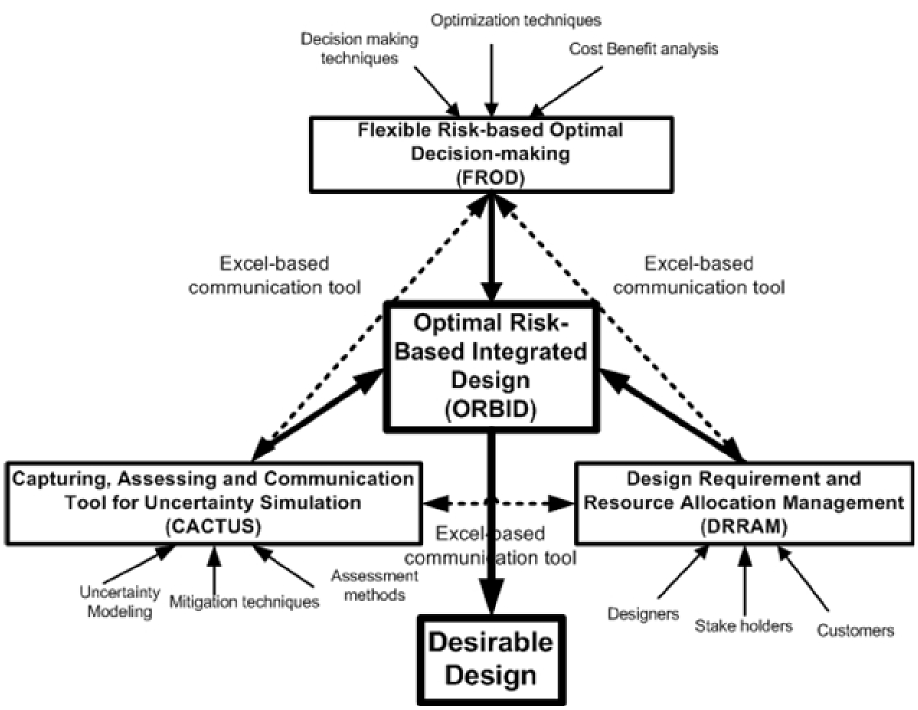


**Figure 16: A general scheme of Optimal Risk-Based Integrated Design**

Figure 16 shows the general scheme of Optimal Risk-Based Integrated Design (ORBID). It illustrates tools and techniques that are applied in this methodology to obtain the desirable design.

In the next sections, this research introduces ORBID with more details and describes its applied methodology.

## 6.2. Optimal Risk-Based Integrated Design (ORBID)

Large complex organizations not only should be protected from failures, degradations or any changes that may lead to negative consequences, but also be structured for a higher chance of success in the market by capturing associated risks and uncertainties. They need to optimize their performance in spite of the existence of risk to stay competitive in the market. Having a risk-based design plan to optimize system performance in risky environments reduces the costs of design and provides a successful risk-based design project.

### 6.2.1. Introduction

Optimal Risk-Based Integrated Design (ORBID) introduces a cumulative set of tools for decision making, managing risks and uncertainties and design requirements in an excel-based environment for design teams of multidisciplinary complex systems to obtain the most preferred optimal design performance within risk constraints while all design requirements and constraints are satisfied.

Specifically, three methods are introduced as part of ORBID: Design Requirements and Resource Allocation Management (DRAAM) introduced in Chapter 4 of this research analyzes data by defining the project, evaluating tasks, issues, requirements and dividing the system into disciplines, subsystems, parallel decisions, decision nodes and alternatives. In addition, in this step design team and their tasks should be determined. For example, while everyone is able to access information sheets, few of them at the system level might have the permission to modify some specific part of the information. We refer to this step as ‘evaluate criteria’. In this step, ORBID creates an information sheet for the system based on design requirements and resource allocations defined by designers, stakeholders and customers.

The previous process helps designers, customers and stakeholders to manage design sources and requirements. In addition, risk and uncertainties associated with decisions should be managed. Capturing, Assessing and Communication Tool for Uncertainty Simulation (CACTUS) introduced in Chapter 3 of this research achieves this goal by modeling uncertainty for the system and applying assessing and mitigating methods. Modeling uncertainty not only gives us a general understanding of the project, but also clarifies noise and control factors associated with systems and subsystems, determines the relationship of subsystems by identifying linking variables and as a consequence, prepares the information necessary for decision making to model the project as an optimization problem.

Managing uncertainty, defining risk constraints and identifying design requirements and resource allocation enable decision makers to model the design project as an optimization problem. Flexible Risk-based Optimal Decision-making (FROD) is used for this job where optimized results are analyzed to determine whether they satisfy all design requirements and constraints for the most preferred design product.

Figure 16 in Section 6.1 showed the general structure of ORBID with its components considered as black boxes showing the interaction with each other. Figure 17 shows this process as a flow diagram.

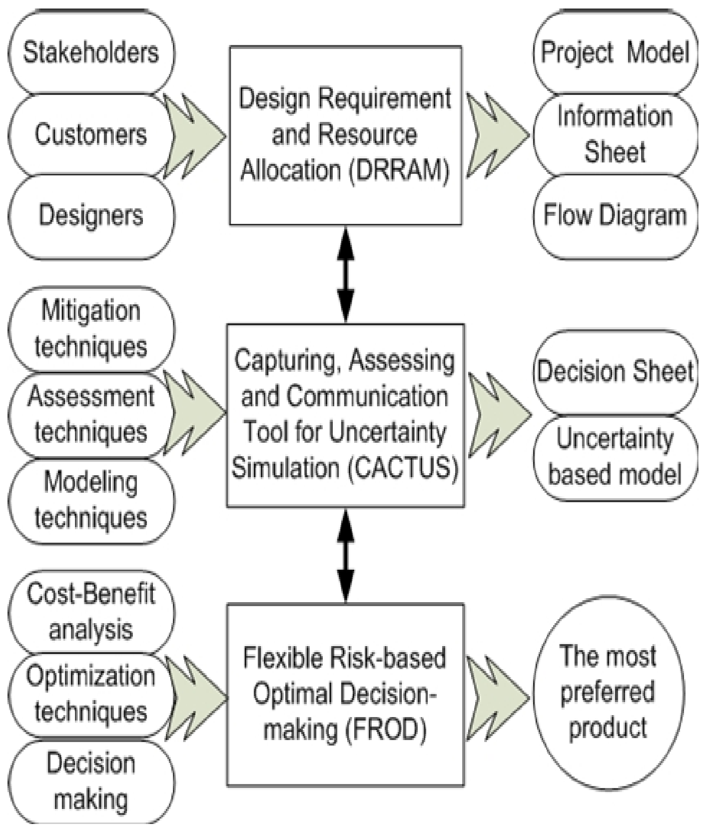


**Figure 17: ORBID's black-boxes.**

## 6.2.2. Methodology

Figure 18 shows the ORBID methodology. As shown this figure, applications of components are not separate from each other. For example, a small change in stakeholders' requirements leads to changes in the information sheet provided by DRRAM and as a consequence, information provided by CACTUS and

FROD might encounter many changes, which might in turn change DRRAM (and even Stakeholders requirements).

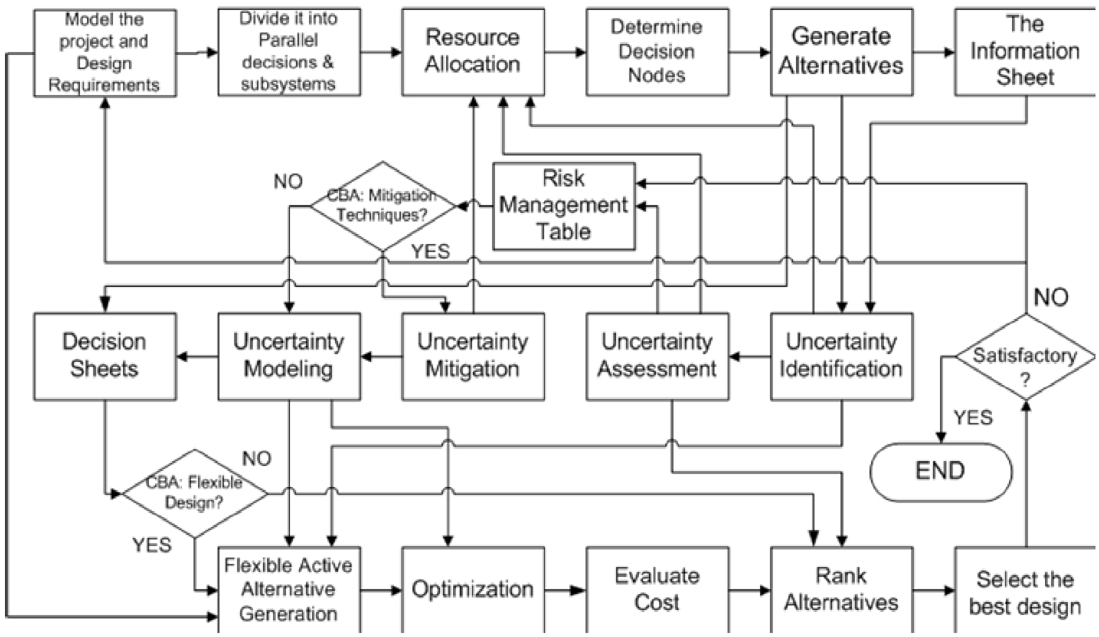


**Figure 18: The ORBID methodology**

ORBID’s components are linked through the excel-based environment. In such an environment, clients are able to communicate by sending/receiving data and be aware of decisions made by other clients. Sheets used in ORBID are updatable and criteria can be varied depending on the nature of project.

In this section, ORBID’s major steps are listed briefly:

**Step 1:** Design Requirements and Resource Allocation Managements (DRRAM) by designers, stakeholders and customers.

DRRAM, introduced in Chapter 4 of this research, provides the information sheet with all necessary information including requirements and resource allocations, as well as flow diagram for the whole design project to help design team in having a clear understanding of the project especially in the early stages of design.

This step clarifies h(x) which is the vector of design requirements that should be satisfied in the project's optimization problem. In addition, DRRAM provides a hierarchical decomposition, based on functional modeling of systems, whose functional models evolve as the design process moves forward. As a result, it provides an evolving resource allocating methodology that can be used to prevent failures and mitigate risks by modeling the project into the following optimization problem:

Minimize $F1= W^{T} \square W$
Maximize: $F2= W^{T}\mu$

Subject to $W =[w_1,...,w_n]^{T}$

**Step 2:** Capturing, Assessing and Communication Tool for Uncertainty Simulation (CACTUS).

This tool introduced in Section 3 of this research provides a means for managing risk and uncertainties by identifying sources of uncertainties, developing methods for assessing and mitigating associated risk, identifying risk constraints that may lead to failures under uncertainties and modeling uncertainty propagation which provides models of critical factors that should be considered by decision makers. CACTUS also provides decision sheets which enable decision makers to make more informed decisions among active available alternatives. This step provides g(x) which is the vector of risk constraints that should be satisfied in ORBID's optimization problem.

Figure 19 shows the methodology applied by CACTUS in the interaction with FROD and DRRAM to achieve goals of ORBID and Figure 20 illustrates it as a black box model.

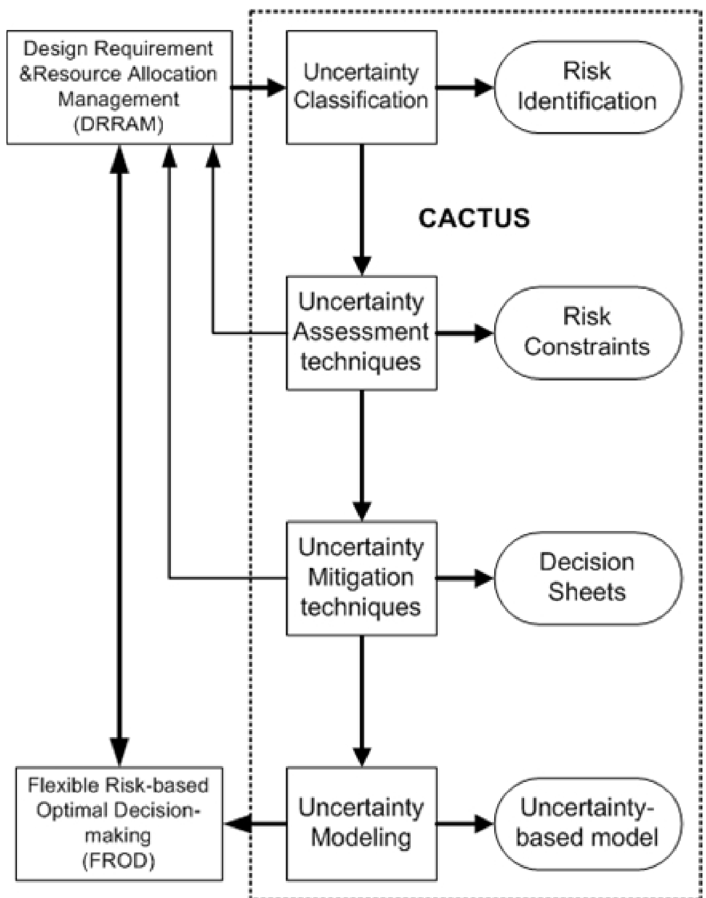


**Figure 19: CACTUS methodology**

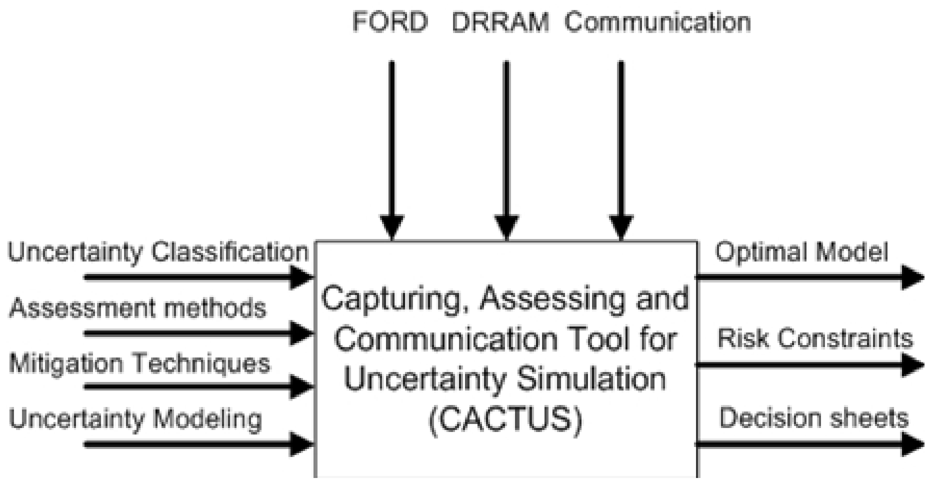


**Figure 20: CACTUS Black-box model**

**Step 3:** Flexible Optimal Risk-based Decision-making (FORD) which provides decision making tools by applying flexible decision techniques within the optimization domain. It gives us sets of optimal solutions that meet all design requirements by applying its flexibility techniques.

These three steps model the project into the following optimization problem:

*Objective Functions:* $F_{i,j}\,(x_{system}\,,\,x_j)$
*Objective Functions:* $f_j\,(x_{system},\,x_j)$

*Constraints:* $G_j\,(x_{system},\,x_j) \leq 0$
*Constraints:* $H\,(x_{system},\,x_j)$

*Subject to:* $X_j$

After each step, data are updated and criteria are re-evaluated and then new information is synchronized among systems and subsystems. Note that, the model is incomplete at the very early stages of design, but it is developed throughout the next stages when the project moves forward and decisions are made. In the next section, Flexible Risk-based Optimal Decision making (FROD) will be presented as the other future work of this research.

## 6.3. Flexible Risk-based Optimal Decision making (FROD)

This section aims to address the issue of decision making by introducing Flexible Risk-based Optimal Decision making (FROD) that provides a flexible framework for optimal decision-making under risks and uncertainties for the ORBID methodology. First, it provides a brief literature review for collaborative decision making and flexibility issue, next it describes the applied methodology.

### 6.3.1. Literature Review

Before talking about the FROD methodology, providing this section with a literature review can be helpful. For more details of decision making under risk see Appendix C.

#### 6.3.1.1. Collaborative Decision making

Following the complexity of multidisciplinary systems, the design process of such systems is mostly based on concurrent design teams. Decision making in design using collaborative teams has its own challenges.

The collaborative optimization strategy was first proposed in 1994 by Balling and Sobieszczanski-Sobieski [137] and Kroo et al [138]. Two years later, in 1996, Renaud and Tappeta [139] extended it for multi-objective optimization for non-hierarchic decisions.

In recent years many efforts tried conducted to address the challenges of Collaborative Decision-Based Design for eliminating communications barriers of design team during design lifecycle. Agent-based decision network [133-135], Multi-Agent architecture for collaboration [109] and decision-based design framework for collaborative optimization [136, 119, and 126] are examples of these approaches. (Also see decision-based software development: design and maintenance by Chris wild et al [110]).

Although these methods are not the same, they should be able to meet the requirements of making decisions by considering the fact that decisions might have different sources and disciplines [109]; they might be in conflict due to different criteria; the decision maker might be individual or group; decisions might be made sequentially or concurrently; designers might make decisions based on personal experiences and finally information might be uncertain and fuzzy. As a consequence, any structure for collaborative decision-based design has to address all these challenges.

#### 6.3.1.2. Decision making within optimization domain

Decision making in multidisciplinary complex systems is to select options that maximize the objective function while optimization methods (as automated decision making) minimizes the number of times an objective function is evaluated [112]. The decision making process within the optimization domain is applied for selecting the most preferred design options from the set of alternatives without evaluating all possible alternatives in details [121, 130-132]. As a result, optimization techniques increase the speed of design by automating decision making.

Generally the decision making process has three main elements: options identification; expectation determination of each option; and, finally, expression of values. The optimization problem of maximization or minimization of the objective function when all constraints are satisfied can be modeled as decision making tool [126, 119].

In this context, the option space can be modeled as a set of possible values of x in the feasible area; the expectation is modeled as F(x) and the preference is modeled by maximization or minimization. This is the key of decision-based design within an optimization domain. In this process, the optimizer is going to maximize the expected VN-M utility of the profit or net revenue.

The optimization of the design process also depends on the efficiency of the communication structure of collaborative decision making (See the previous section for collaborative decision making). Figure 21 shows the basic architecture of collaborative optimization developed by Barun et al [140].

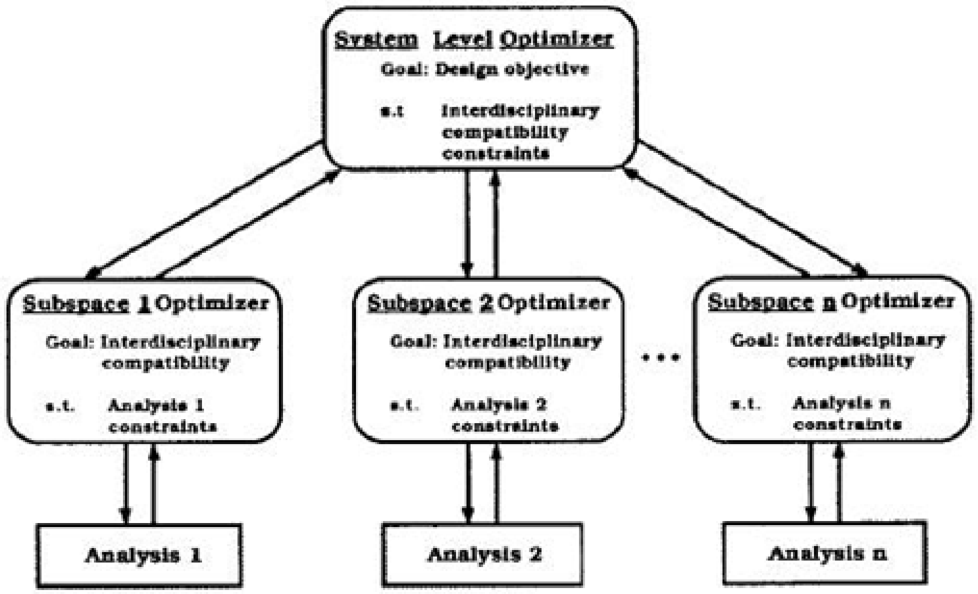


**Figure 21: Basic collaborative optimization architecture by Barun et al.**

### 6.3.1.4. Flexibility in decision making and design

In general, flexibility is defined as "The ease of changing the system's requirements with a relatively small increase in complexity (and rework)" [157]. However, many interpretations for flexibility have been introduced by researchers in different fields. For example, in 1986, Buzacott et al [152] developed a framework for flexible manufacturing systems to address the problem of changing demands of customers and Haubelt (2002) [153] introduced flexible systems for software applications. In the field of design methodology, Roser et al have introduced a flexible design methodology [146, 147] to minimize effects of risks and uncertainties in the design process [145]; Olewnik et al have proposed a framework for flexible system design [148-149] with the implementation of Hazelrigg's decision making framework [118] and

Suh et al have developed flexible product platform design [154] to address market uncertain change demand.

These methods address flexibility in design in places where designers choose fixed design variables before they select the design. However, Khire et al [155] proposed a methodology for designing flexible systems in changing operating conditions. It addresses the problem of flexibility design in changing environments such as aircrafts, cruises, etc. systems whose operating conditions and design requirements change during the operating life. The operational flexibility is an important issue for space systems since space missions are subjected to unanticipated changes. Since designing, manufacturing and launching space systems are highly costly processes, in recent years, flexibility in space systems has been the center of many research efforts. Nilchiani et al [156] have addressed both design and operation flexibility in space systems by introducing a Six-Element (6E) framework for measuring the value of flexibility in space systems.

### 6.3.2. Introduction

ORBID addresses the issue of decision making by introducing Flexible Risk-based Optimal Decision-making (FROD). FROD, by providing a flexible decision making framework in conjunction with design requirement and resource allocation management (DRRAM) techniques and the capture, assessment, and communication tool for uncertainty management (CACTUS), helps decision makers wherever a decision should be made among many alternatives and provides the most preferred product within the optimization domain and risk constraints while all design requirements are satisfied.

FROD gives us sets of optimal solutions that meet all design by modeling the design project into an optimization problem:

*Objective Functions:* $F_{i,j}\ (x_{system}\ ,\ x_j)$

*Objective Functions:* $f_j\ (x_{system},\ x_j)$

*Constraints:* $G_j\ (x_{system},\ x_{j)} \le 0$

*Constraints:* $H\ (x_{system},\ x_{j)=}\ 0$

*Subject to:* $X_j$

Where G(x) refers to risk constraints and H(x) refers to design requirement and constraints defined by design team (including decision making, stakeholders and customers).

## 6.3.3. Methodology

FROD's approach, as a decision making tool, is to help decision makers select the most preferred design among sets of possible design. To achieve this goal, it first identifies possible sets of alternatives associated with each design. Next it selects the optimized set of alternatives with respect to minimization of costs. Hence, the most preferred design is obtained by ranking possible designs in terms of costs of optimal alternatives and also associated uncertainties. This methodology provides a flexible framework for the decision making process.

To avoid the ambiguity associated with applying the FROD methodology, defining a terminology for two major terms is necessary. In this research, a set of design alternative refers to possible design alternatives that form a design platform. On the other hand, each possible design platform includes sets of possible design alternatives that satisfy the goals of the project.

The Flexible Risk-based Optimal Decision making (FROD) methodology includes listed nine major steps:

***Step 1:*** The first step of the FROD methodology is to investigate the initial design. The platform of the initial design is obtained by the initial model generated by Design Requirement and Resource Allocation Management (DRRAM). This initial design defines the system by identifying initial design variables and system responses to them; determining market, demands, initial alternatives and change options. It also provides an early estimation of costs and time associated with the selected design platform.

***Step 2:*** Uncertainties and variants of the investigated design should be identified in the second step. CACTUS's uncertainty identification techniques are applied in this step. These uncertainties might be due to changes in design or demands. This step defines the set of uncertain parameters U:

$U= \{u_1, \ldots, u_i\}$

where u is one of i individual uncertainties identified for the selected initial design platform.

***Step 3:*** The third step in FROD is to to identify defect modes and possible design change options. Identifying uncertainties and variants help to model uncertainties. This uncertainty-based model, which is obtained by CACTUS, investigates defect modes which occur when system responses cannot satisfy the upper and lower limits of allowable uncertainty.

***Step 4:*** The fourth step is to generate flexible alternatives. Identifying defect modes and possible design changes generates flexible component alternatives. These alternatives create the set of flexible design platform alternatives (A) includes m design alternatives:

$A = \{a_1, \ldots, a_m\}$

where a is one of m design alternatives identified for the selected initial design platform. Each alternative is a set of functional requirement (F) and cost requirements (C) obtained by Design Requirement and Resource Allocation management (DRRAM), so:

$a^k = [F^k, C^k]$ ; K= 1 to m

***Step 5:*** The next step is to optimize each design alternative. Alternatives should be optimized with respect to minimization of costs while all equality and inequality constraints are satisfied. This optimization includes:

*Objective Functions:* $C^k (x^k)$

*Constraints:* $G_j (x^k) \leq 0$

*Constraints:* $H (x^k) = 0$

*Subject to:* $x^k$

where the optimization problem is to minimize the objective function ($C^k (x^k)$ or all costs associated with each alternative) with respect to inequality constraints of functional requirement $F^k$ (upper bounds and lower bounds or $G_j (x^k) \leq 0$ ) and quality constraints of functional requirements subject to the set of component design variables or $x^k$.

***Step 6:*** The sixth step is to evaluate possible costs associated with all possible design alternatives ($C^k$) of optimized in Step 5. Associated costs constitute one of the critical decision making factors for selecting the best design platform.

***Step 7:*** The seventh step is to evaluate expected performance and costs of flexible design alternatives under uncertainties of the investigated design. Since flexibility becomes a more important issue as the severity of uncertainty is increased, in addition to costs, uncertainty is another critical facture for decision makers to select the design.

As we had mentioned in chapter 3, CACTUS provides techniques of identifying, assessing and determining upper bounds and lower bounds of uncertainties and as a result provides a clear understanding of uncertainties associated with the selected design and as we had mentioned in step 2, defines:

$U= \{u_1, \ldots, u_i\}$

where u is one of i individual uncertainties identified for the selected design.

In this step, the performance of alternatives under uncertainty should be evaluated economically.

***Step 8:*** Step eight is to select the best design from the set of design platform alternatives.

In this step, decision makers make decisions by ranking possible design. Decision makers' discipline for ranking designs depends on costs and uncertainties of associated design alternatives determined in steps seven and eight. They rank possible design platforms with respect to obtained expected value of their alternatives that is a function of costs ($C^k$ ($x^k$)) and uncertainties (U):

Expected Value= $EV = f(C^k (x^k), U)$

As decision makers evaluate expected values of alternatives of m possible designs in the set of $A= \{a_1, \ldots, a_m\}$, they can obtain the most preferred design.

***Step 9:*** It is always possible that the best design generated in Step 8 is not satisfactory or does not meet the design requirements. In this case, DRRAM is applied by designers, decision makers and stakeholders to modify design requirements and allocate resources again.

Figure 22 shows the process is done by the FROD methodology to help decision makers select the best design platform. As this figure shows, in this case previous eight steps are repeated until the best design platform is obtained so that meets all requirements and constraints of designers, stakeholders and customers.

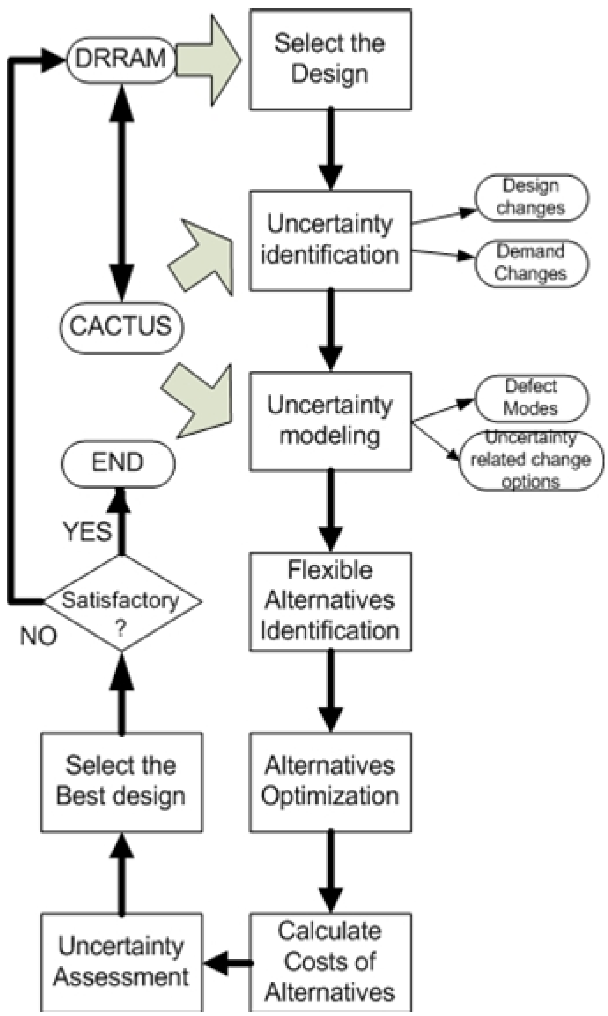


**Figure 22: The FROD methodology**

The other strategy in this case is to apply the uncertainty management techniques provided by the CACTUS methodology (See chapter 2). However applying these techniques brings additional costs that should be evaluated beforehand.

In the next section of this chapter, we provide a discussion for the further research and future work of the FROD methodology that are being carried out to provide a better framework and methodology that helps the Optimal Risk-Based Integrated Design (ORBID) to achieve its goals.

### 6.3.4. Conclusion and Future Work

This chapter has provided a flexible decision making process to obtain the most preferred optimal design in risky environments of multidisciplinary complex systems by introducing Flexible Risk-based Optimal Decision making (FROD).

The achievement of the FORD methodology is to decrease costs of design by reducing costs of design changes. It identifies possible design changes to generate flexible designs for resolving defects in the predicted model.

The FROD methodology analyzed each possible design by modeling associated sets of alternatives into the optimization problem of minimization of associated costs with respect to quality and inequality of design functional requirements in addition to evaluate associated uncertainties and then calculating expected value of each possible design. Ranking designs with respect to associated expected value clarified the most preferred design that should be selected by decision makers.

In this research, flexibility was defined as the ease of changing the system's requirements with a relatively small increase in complexity, opposite of the robust design that aims to increase the stability of systems with respect to a variety of possible changes so that they are less sensitive to variations. The flexible design identifies possible design alternatives to resolve the design change problem. It increases the ability of systems for being adopted with new technologies by reformulating issues and their importance, changing the methodology achievements and generating more flexible alternatives.

This research addresses flexibility in design in places where designers choose fixed design variables before they select the design. Future work should be done to develop this methodology so that it can be applied in operational conditions and address the flexibility issue in changing environments such as aircrafts, cruises, etc. or systems whose operating conditions and design requirements change during the operating life. The operational flexibility is a more important issue for space systems since they are subjected to unanticipated changes.

As mentioned before, the expected value is a function of costs and uncertainties. In steps 5 and 6, FORD provides an optimization technique for optimizing and evaluating costs of design alternatives. So, developing techniques to model and evaluate performance of systems under uncertainties economically is another important issue should be addressed by ORBID in the future.

In addition, more research will focus on the quality of providing this methodology with details and the process that should be followed to generate flexible design alternatives (Step 4 in the FROD methodology).  However, increasing systems' flexibility and generating flexible alternatives also increases associated uncertainties. This means that increasing the flexibility may not necessarily may result to the optimal performance. So, one of the most critical challenges is to provide techniques of measure the optimal flexibility. Decision makers should be aware of profits of being flexible and its associated costs. In this context, to develop cost benefit analysis techniques for measuring the value of flexibility in design is necessary for decision makers during the design process of multidisciplinary complex systems.

# 7. Conclusion

This research presented tools for uncertainty and design requirement management during the design process of complex systems by introducing Design Requirement and Resource Allocation Management (DRRAM) framework, the Capture and Assessment and Communication Tool for Uncertainty Simulation (CACTUS). The future work for each presented methodology was identified and a case study for the lunar lander mission design at NASA JPL's Project Design Center illustrated the processes with more details.

As the future work, this research presented Optimal Risk-based Integrated Design (ORBID) as a methodology for obtaining the highest performance within risk constraints while satisfying all constraints and requirements of the design and development of large-scale complex systems. ORBID as a cumulative tool for trading off risk, resources and performance of complex systems introduced Flexible Risk-based Optimal Decision-making (FROD) that provides a flexible framework for decision making in the ORBID's collaborative excel-based environment. The properties, methodology and hotspots of FROD has also identified and discussed.

Table 2 has listed the proposed methodology and the future work carrying out.

**Table 2: Future Work**

| | **Future Work** |
|---|---|
| | |
| Capture, Assessment and Communication Tool for Uncertainty Simulation (CACTUS) | - Developing techniques of assessing, mitigating and model all sources of uncertainty, especially qualitative aspects.<br>- Developing a decision tree to demonstrate criteria for selecting the best assessment methodology to capture uncertainties associated with issues to increase the speed of this process.<br>- Developing techniques to obtain upper and lower margins of uncertainties by bounding approach to risk analysis |
| Design Requirement and Resource Allocation Management (DRRAM) | - Providing this method with techniques of design requirement management so that it can address needs of design teams including designers, stakeholders and customers for trading off their requirements and design constraints. |

| | |
|---|---|
| | - Future work for extending the knowledge base that can support the applied RUBIC design tool.<br><br>- Improving the RUBIC design tool methodology and addressing its limitations in identifying the the efficient frountier by linearly and unlinearly utility functions. |
| Flexible Risk-based Optimal Decision making (FROD) | - future work should be done to develop this methodology so that it can be applied in operational conditions and address the flexibility issue in changing environments such as aircrafts, cruises, etc. or systems whose operating conditions and design requirements change during the operating life.<br><br>- Providing techniques to evaluate the value of flexibility and measure the optimal flexibility |

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# Appendices

# Appendix A: the application of Function-Failure Design Method (FFDM)

In this section we are going to apply the process of obtaining EF and EB matrix for a case study (borrowed from [161]). Consider a hardware/software system. Although such this system can be divided into different subsystems and each subsystem includes some other components and EF matrices should be generated for each component, for simplifying we divide it into 3 components:

C2=Software component

C3=Hardware component

C1=Interfaces which are responsible for importing and exporting data between users and machine.

Five functions can be considered for components including:

E1=import data

E2= Guide data

E3=Export data

E4=Convert data

E5=Store data

Determining components and functions provides the EC matrix. It enables designers to generate EC matrix. Now, the next step would be to generate CF matrix by identifying potential technical and dynamic failures mode. However for such this analysis, we have to determine our strategy beforehand so that we can categories behaviors, especially external factors. We have considered 6 failure modes due to technical and dynamic factors. These failure modes would be:

F11= input,

F12= information

F13=module

F21=culture

F22=economy

F23=society

CF matrix can be obtained by identifying failure modes. Figure A.1 shows the process of obtaining EF matrix by identifying components, their functions and possible failure modes for a simplified hardware/software system.

Components

Functions

| | C1 | C2 | C3 |
|---|---|---|---|
| E1 | 1 | 0 | 0 |
| E2 | 1 | 1 | 0 |
| E3 | 1 | 0 | 1 |
| E4 | 1 | 1 | 0 |
| E5 | 0 | 0 | 1 |

EC

×

Failures

**Technical | Dynamic**

| | F11 | F12 | F13 | F21 | F22 | F23 |
|---|---|---|---|---|---|---|
| C1 | 1 | 0 | 0 | 1 | 0 | 0 |
| C2 | 1 | 1 | 1 | 0 | 0 | 1 |
| C3 | 0 | 0 | 0 | 0 | 1 | 0 |

CF

=

| | F11 | F12 | F13 | F21 | F22 | F23 |
|---|---|---|---|---|---|---|
| E1 | 1 | 0 | 0 | 1 | 0 | 0 |
| E2 | 2 | 1 | 1 | 1 | 0 | 1 |
| E3 | 1 | 0 | 0 | 1 | 1 | 0 |
| E4 | 2 | 1 | 1 | 1 | 0 | 1 |
| E5 | 0 | 0 | 0 | 0 | 1 | 0 |

EF

**Figure A.1: Functional model for a simplified hardware/software system**

# Appendix B: The application of Risk and Uncertainty Based Integrated Design (RUBIC)

In this section, this research shows the applicability of RUBIC design methodology. This section has been borrowed from [151]. The case study is Motor Controller subsystem of a satellite reaction wheel (shown in Figure A.2). For thsi case study, 7 functional elements can be listed including:

- Import Electrical Energy
- Export Electrical Energy
- Guide Electrical Energy
- Regulate Electrical Energy
- Guide Electrical Energy
- Condition Electrical Energy
- Guide Electrical Energy

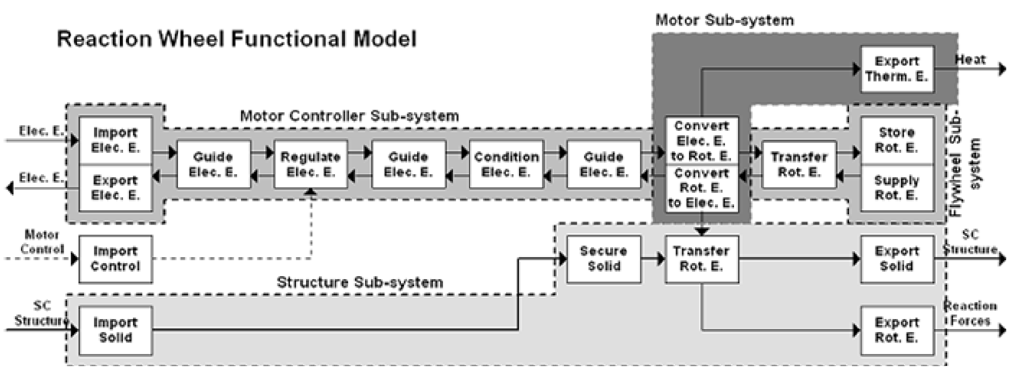


**Figure A.2: A high-level functional model of a satellite reaction wheel at some point in its conceptual design phase borrowed from [151].**

Using FFDM, $\boldsymbol{\mu}$ and $\boldsymbol{\Sigma}$ can be estimated at this stage. $\boldsymbol{\mu}$ is proportional to the failure rate and we can estimate $\sigma_{ii}$'s from $\mu_i$'s ($\sigma_i \approx 0.3\ \mu_i$), So:

$$\boldsymbol{\mu} = \begin{array}{c} \begin{bmatrix} 0.03 \\ 0.03 \\ 0.05 \\ 0.45 \\ 0.05 \\ 0.33 \\ 0.05 \end{bmatrix} \end{array} \begin{array}{l} \text{Import Elec. E.} \\ \text{Export Elec. E.} \\ \text{Guide Elec. E.} \\ \text{Regulate Elec. E.} \\ \text{Guide Elec. E.} \\ \text{Condition Elec. E.} \\ \text{Guide Elec. E.} \end{array}$$

and;

$$\Sigma = \begin{bmatrix} 9 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 9 & 0 & 1021 & 0 & 0 & 0 \\ 0 & 0 & 25 & 0 & 0 & 0 & 0 \\ 0 & 1021 & 0 & 2025 & 81 & 215 & 0 \\ 0 & 0 & 0 & 81 & 25 & 81 & 0 \\ 0 & 0 & 0 & 215 & 81 & 1089 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 25 \end{bmatrix} \times 10^{-4}$$

Now by applying the above formulation of risk reduction, the risk-efficient design frontier shown in Figure A.3 is obtained.

$$\begin{cases} \text{Minimize } \mathbf{w}^{\mathrm{T}}\Sigma\mathbf{w} \\ \text{Maximize } \mathbf{w}^{\mathrm{T}}\boldsymbol{\mu} \\ \\ \text{s.t. } \mathbf{w} \in F \end{cases}$$

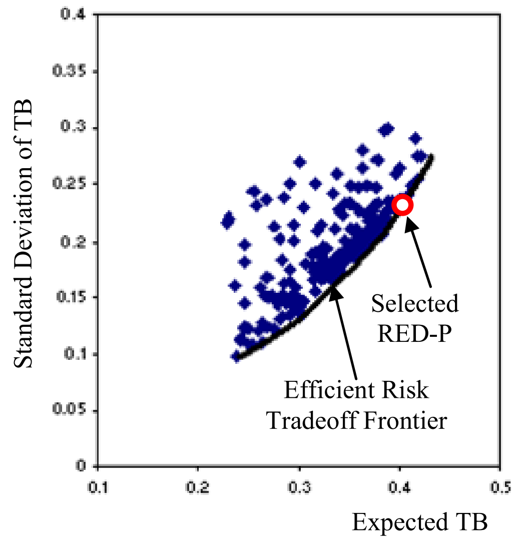


**Figure A.3: The efficient risk tradeoff frontier borrowed from [151]**

Now the question becomes which RED-P on the efficient frontier should be selected. To address this problem, RUBIC uses a linearly weighted utility function to assess the tradeoff between expected value and variance of the total benefit function two criteria:

u=E(TB)-0.3σ(TB).

Using this utility, u, the optimization problem represents a allocation vector (listed in table 3) that corresponds to the most preferred RED-P (the red circle in Figure A.3). For example Figure A.3 and A.4 shows that two functional elements of Regulate Elec. E. and Condition Elec. E. require the highest resources.

This was an example of the applicability of the RUBIC design methodology for allocation resources.

**Table 1: Optimal resource allocation borrowed from [151] that corresponds to the red circle in Figure 26.**

| Column # | Function | **Resource Allocation** |
|---|---|---|
| 1st | Import Electrical Energy | **<1%** |
| 2nd | Export Electrical Energy | **6%** |
| 3rd | Guide Electrical Energy | **<1%** |
| 4th | Regulate Electrical Energy | **57%** |
| 5th | Guide Electrical Energy | **10%** |
| 6th | Condition Electrical Energy | **26%** |
| 7th | Guide Electrical Energy | **<1%** |

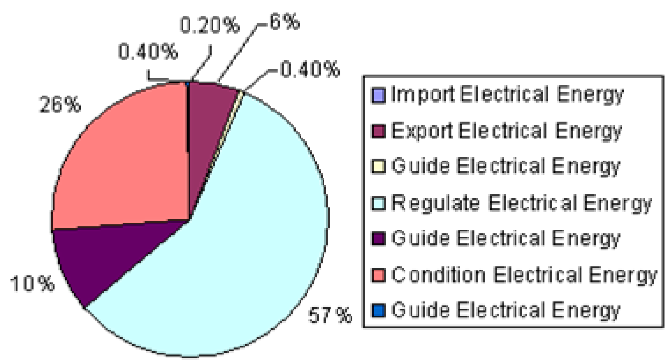


**Figure A.4 – Optimal Allocation**

# Appendix C: Decision making under risk: A Literature Review

The concept of decision making under risk extends back to Daniel Bernoulli, 1738 [127]. His solution to a problem under risk is known as Bernoulli's paradox. This problem, formulated by his cousin Nicholas, is to determine the amount of money that a person will be willing to enter a game with a prize of $\$2^n$ where a fair coin is tossed until on the nth flip it lands on heads. The expected monetary value (EMV) of this problem would be infinite since:

$$\sum_{n=1}^{\infty} \frac{1}{2^n} 2^n = \infty$$

Where, the probability of n flips is ($1/2^n$) and the expected prize for n trails is $2^n$.

Bernoulli showed that, in conflict with the outcome, people are not willing entering this game as a result of altering from risk associated with this game. Based on this fact, he introduced the definition of utility by formalizing this discrepancy between the EMV and the behavior of individuals. Then he presented his Expected Utility Hypothesis as: Individuals make decisions with respect to investments in order to maximize expected utility. The disciplines of decision analysis have been extracted based on Bernoulli's hypothesis.

In the framework of utility theory, the decision analysis discipline has three fundamental elements: 1) Options, which are design alternatives; 2) Expectations, which are range of possible outcome of a decision considering their probabilities of occurrence; and 3) values, whose purpose are to rank order alternatives. As a consequence decision analysis process includes options identification, expectation determination of each option and finally expression of values. The resulting of decision rule would be: The preferred decision is the option whose expectation has the highest value [118].

Since the purpose of values in decision making is to rank order of alternatives, (for example option A is preferred to B), this preference ordering requires the existence of a real scalar function such as u we had introduced as utility function, for this example $U_A > U_B$. Like other engineering design we tend to automate the process of rank ordering for two reasons: first; making an ad hoc assessment for relative merits of every design alternative versus every other design alternative doesn't sound feasible and second; this comparison would be too complex without the use of a mathematical value model. This mathematical requirement for a value function has been formalized by Von-Neumann (a mathematician) and Morgenstern (an economist) in 1944 [116]. It is referred to Von-Neumann and Morgenstern utility (VN-M utility).

As Figure A.5 shows, VN-M utility is based on the notion of a lottery where the utility of the more desired outcome is higher than the utility of the less desired outcome. Von-Neumann and Morgenstern claimed that if the probability of the more desired outcome occurrence tends to one, the utility of the lottery tends to the utility of the more desired outcome and in reverse, if the probability of the more desired outcome tends to zero; the utility of the lottery approaches the utility of the less desired outcome. Based on these two principles, Von-Neumann and Morgenstern concluded that the utility of the lottery always lies between the utilities of the less and the utility of more desired outcomes.

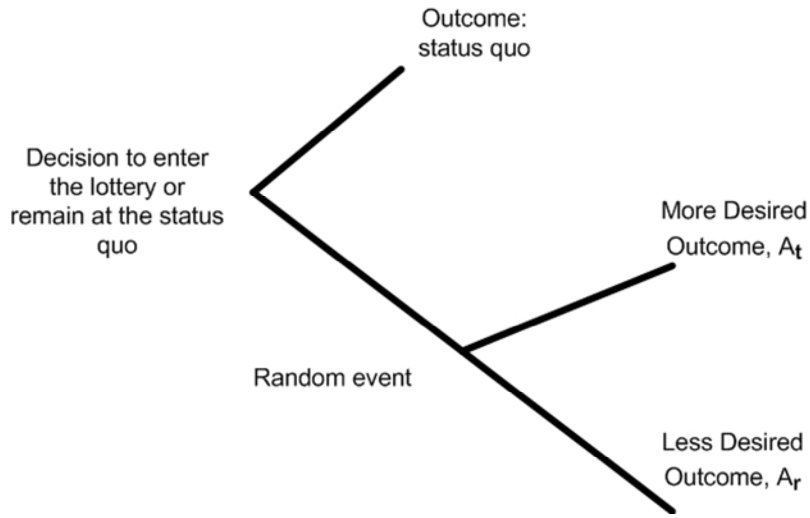


**Figure A.5:  A VN-M lottery**

In 1957, Luce and Raiffa [128] developed an interoperation of Von-Neumann and Morgenstern theory and concluded that:

*"If a person is able to express preferences between every pair of gambles, where gambles are taken over some basic set of alternatives, then one can introduce utility associations to the basic alternatives in such a manner that, if the person is guided solely by the utility expected value, he/she is acting in accord with his/her true tastes provided only that there is an element of consistency in his/her tastes."* [128].

Based on this interoperation, Luce and Raiffa extracted the Von-Neumann and Morgenstern axiom in engineering design, which is fundamentally the notion of utility within engineering design:

*"Suppose that one has to make a choice between a pair of lotteries that are each composed of complicated alternatives. Because of their complexity it may be*

*extremely difficult to decide which one is preferable [and this is usually the case in engineering design]. A natural procedure, then, is to analyze each lottery by decomposing it into simpler alternatives, to make decisions as to preference among these alternatives, and to agree upon some consistency rules that relate the simpler decisions to the more complicated ones. In this way, a consistent pattern is imposed upon the choices between complicated alternatives."* [128].

Luce and Raiffa [128] and Hazelrigg [118], summarized Von-Neumann and Morgenstern axioms, to six axioms which are the basis for decisions in utility theory:

1- All outcomes of a VN-M lottery can be ordered in terms of the decision maker's preferences and that ordering is transitive.

2- Any compound lottery, that is, any lottery that has been outcome another lottery, can be reduced to a simple lottery that has among its outcomes all the outcomes of the compound lottery with their associated probabilities of occurrence.

3- If the outcome of lottery, $A_1$, $A_2$ ,…, $A_r$ , are ordered from most desired to least desired, then there exists a number p, $0< p< 1$ , such that one is indifferent between an outcome $A_i$ , $1< i< r$, and the lottery $A_t$ with probability P and $A_r$ with probability p-1.

4- For any lottery such as that given in axiom 3, with $U_i$ specified, there exists an outcome $[u_iA_1, (1-u_i)A_r]$ that can be substituted for $A_i$, and the preferences of the decision maker will remain unchanged.

5- The decision makers's preferences and indifferences among lotteries are transitive.

6- Given two lotteries, each with only two outcomes, and which differ only in terms of the probabilities of the outcomes, the lottery in which the probability of the more desired outcome is larger is the proffered lottery.

Here, brief descriptions of terms are used in above six axioms sounds necessary. These terms are transitive/intransitive and rational/ irrational. Assume a decision maker should rank between three options A, B and C. where the symbol ">" means "is preferred to". If the ordering of preferences is necessary to be in the form of A >B >C > A, it means $U_A > U_B > U_C > U_A$. While we know U, utility function, is a real scalar function so it's not possible.

The preference ordering that causes this problem is said to be intransitive and the person who has such a preference order is called irrational. Such this person is not a good design engineer and decisions made by this person are not compatible with her/his preferences.

On the other hand, if A > B > C, then A > C. In this situation, the preference ordering is called transitive and the decision maker is said to be rational. In 1963, Arrow [129] proved that groups with rational individuals might have irrational preferences. This theory is called Arrow's impossibility theorem. Based on Arrow's theorem, any method that requires the formulation of a group utility to determine group preferences is likely to be fundamentally flawed.

After being familiar with VN-M axioms and definitions of transitive/intransitive and rational/ irrational, one can analyze VN-M's axioms with respect to their applications:

- First rule of this axioms, talking about ordering in terms of decision maker's preferences is necessary in order that rational decision making be possible.

- The second axiom; which explain reducing of any compound lottery to a simple lottery, equivalences compound and simple lotteries.

- The third axiom assures the continuity of preferences between outcomes $A_1$ and $A_r$.

- The fourth axiom shows that any lottery in axiom 3 can be reduced to an equivalent lottery that contains only the outcomes A1 and $A_{r.}$.
- The decision makers' preferences and indifferences among lotteries are transitive and it assures that rational preferences exist among lotteries. It is the base of the fifth axiom.

- Finally, the sixth axiom defines the statement of preference by showing that between two lotteries with two outcomes which are different in just probabilities of outcomes, the lottery in which the probability of the more desired outcome is higher is the preferred lottery.

Based on the notion of Von-Neumann and Morgenstern (that the utility of the lottery always lies between the utilities of the less and the utility of more desired outcomes) and these axioms (which are the basis of decisions in utility theory) VN-M utility basis in engineering design is build and Expected Utility Theorem can be described as:

*"If the preference or indifference relation (> or ~) satisfies assumption 1 through 6, there are numbers $U_i$ associated with the basic prizes $A_i$ such that for two lotteries L and L' the magnitude of the expected values ($P_1u_1+P_2u_2+\ldots+P_ru_r$) and ($P_1'u_1+P_2'u_2+\ldots+P_r'u_r$) reflect the preferences between the lotteries."* [128].

In other words, Expected utility theorem mentions that the utility of a lottery is the sum of utilities of all possible outcomes of the lottery if they are weighted by their probabilities of occurrence. Expected utility theorem provides measures of utility under condition of risk and uncertainty.

First time, in 1996, Hazelrigg [118] expressed the concepts of the six VN-M axioms and associated utility in the framework of systems design. This framework applies expected utility theory for selecting designs. It enables decision makers to assess the value of each design option so that options can be rationally compared and then the most preferred option is selected.

Figure A.6 shows Hazelrigg's framework for decision-based engineering design. The goal used in this framework is profit consisting of revenues less costs. Revenues are quantities of things sold times their prices. These Quantities depend upon the demand (q) of the product which is a function of the attributes of the product (things that determine the worth of the product in aspect of customers) (a), price (p) and time (t).

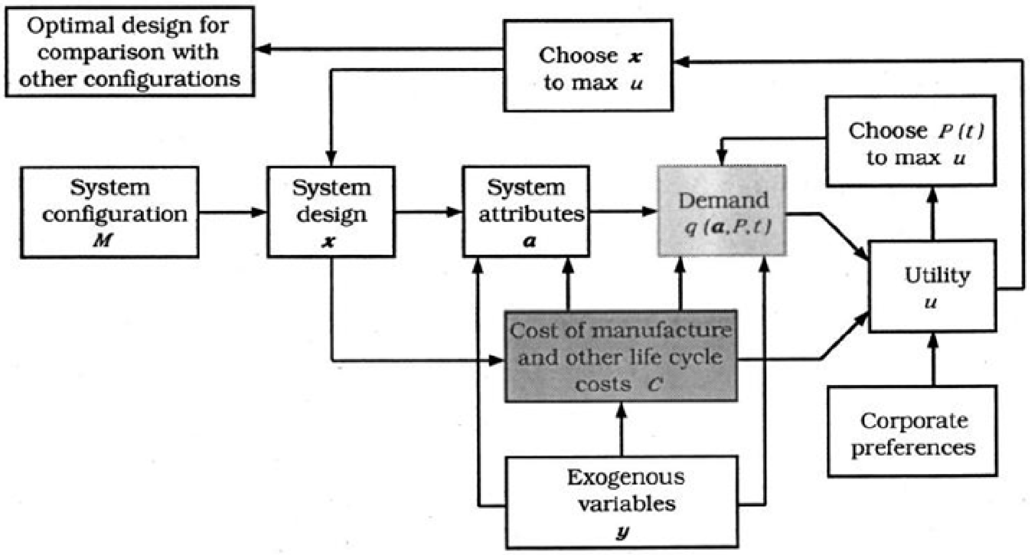


**Figure A.6: Hazelrigg's framework for decision-based design**

The variables which designers have control over them are design variables which have been shown as the design vector X, while variables which designers doesn't have control over them are referred to exogenous variables as vector Y. The ordered set of attributes is referred to vector **a.x**; **y** is transformed into **a** with uncertainty. The value of revenues is determined as the product of p and q properly discounted and integrated over time.

The framework then includes an optimization over p (p should be set to maximize the value of the particular design, **x** subject to **y)** with the purpose of maximizing utility (u) with respect to p with given **x** and **y**. It produces the utility measure for a design and then decision makers can compare alternative designs using this measure. In other word, it automates the process of alternative selection with an optimization scheme.

Hazelrigg's framework (Figure A.6) models design as a decision-making process aims to maximize the value of designed artifact. However, still there is a challenge of how decision-based design framework should be fitted into the engineering design or in the words, how the utility of a design should be formulated under a decision-based design framework. In recent years, many researches on decision-based design have been done. (As references used in the text demonstrated, Scott and Ontonsson (1999), Gu et al (2000), Azarm et al (2000), Wood (2000), Agogino et al(2005) , etc.).

Figure A.7 shows Von Neumann- Morgenstern utility framework for decision based design developed by Wei Chen et al (2001) [110- 111]. In this framework two different types of attributes are considered, engineering consideration (E) and the customer key attributes (A).

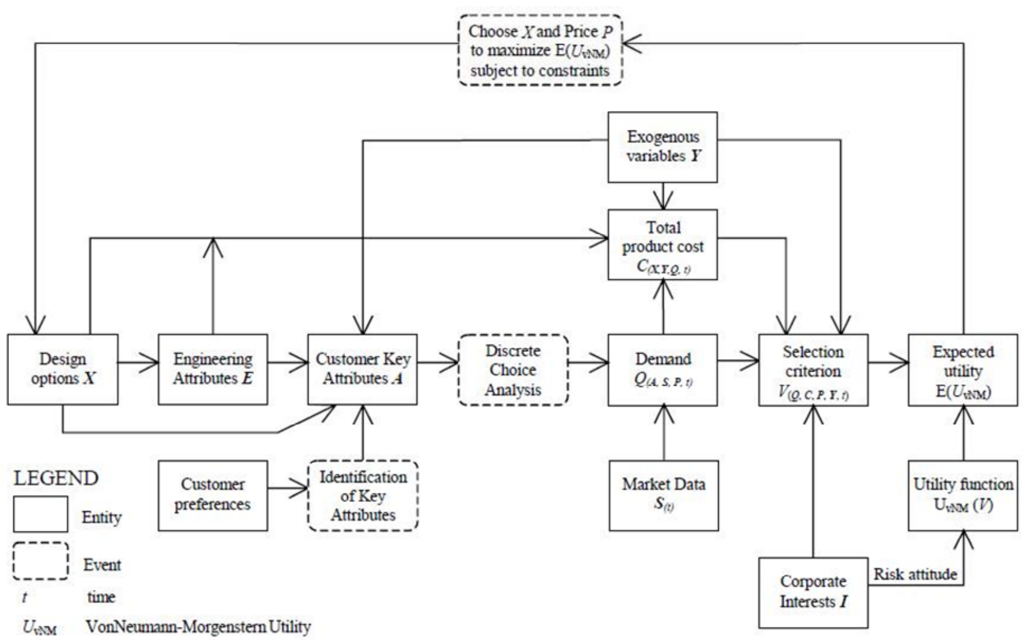


**Figure A.7: Chen's Decision-Based Design Framework**

The engineering attributes E are product properties of interest to a design engineer represented as functions of design variables **x**. the customer key attributes A are the product features a customer assess when purchases a product. The selection criterion V is expressed as a function of the demand (Q), Price (P), total product cost (C) [The time (t) is considered when discounting v to the net present value].

In addition, in this framework, corporate interests I acts as requirements (constraints) while Hazelrigg's framework is void of constraints. In this framework, optimal product design is determined by selecting the design options (**x**) and the price p while the expected utility E ($U_{VNM}$) of the selection criterion is maximized and the constraints are satisfied.

As mentioned before, the nature of complex systems are multidisciplinary design. However, the decision-based design framework of Hazelrigg [48] is a single level all-at-once optimization approach. Following this fact, building a framework for decision-based design in multidisciplinary systems needs specific efforts. X. Gu and J.E. Renaud (2000) [119], developed a framework for decision-based design of multidisciplinary systems by decomposing it into the multidisciplinary model.

This decomposed system includes two major organizations; the engineering disciplines and the business disciplines (while traditionally multidisciplinary design is focused on disciplines in the field of engineering analysis). The role of the business disciplines is providing targets for performance improvements in order to higher profit while the role of engineering disciplines is focusing on predicting the performance of product while satisfying the performance targets set in the business discipline.

Figure A.8 shows Gu and Renaud's framework for multidisciplinary systems. As this figure shows, engineering and business disciplines are coupled through attribute (**a**), total cost ($C_T$) and demand (q). Based on this model, the performance predictions obtained from a system analysis (SA) are referred to as states **y** in the contexts of multidisciplinary design. [126]. Contexts of decision making in aspect of multidisciplinary systems presents us with two new challenges: First, decision making in the domain of optimization; second, collaborative decision making.

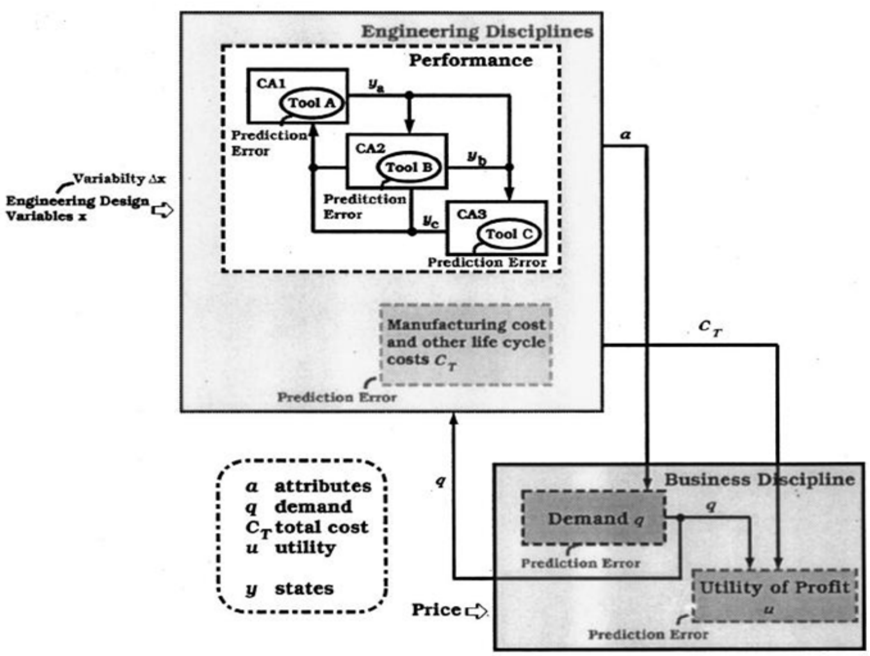


**Figure A.8: Gu and Renaud's decision-based design framework**