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OPTIMAL RISK-BASED INTEGRATED DESIGN (ORBID) FOR MULTIDISCIPLINARY COMPLEX SYSTEMS

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ABSTRACT
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 address these needs, this paper introduces Optimal Risk-Based Integrated Design (ORBID) for multidisciplinary complex systems that offers a methodology for obtaining the highest performance within risk constraints while satisfying all constraints of the design and development of large-scale complex systems. ORBID offers a cumulative tool for dealing with these issues by introducing techniques for Design Requirement and Resource Allocation Management (DRRAM), Capturing, Assessing and Communication Tool for Uncertainty Simulation (CACTUS) and Flexible Risk-based Optimal Decision-making (FROD) in an EXCEL-based design environment.

Keywords: Optimal Risk-Based design, Risk and Uncertainty, Decision making, Flexible design

1 INTRODUCTION
One of the most challenging tasks of the design team during the design and development cycle of complex systems is to make decisions to obtain the most preferred design product that satisfy all design constraints and requirements within risk and uncertainty constraints. They have to assess how much risk (cost, schedule, scope) they can take on and still remain competitive; understand attitudes toward risk; 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 paper introduces Optimal Risk-Based Integrated Design (ORBID) shown in Figure 1 and Figure 2. ORBID offers a cumulative tool for dealing with these issues by introducing techniques of design requirement and resource management, risk and uncertainty management and decision-making in a collaborative excel-based design environment:

- **Design requirement management and resource allocation:** 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. 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 resources (cost, schedule, time, etc) to subsystems. However; design requirements are not so clear in early stages of design and they become clearer when the project moves ahead. ORBID provides techniques for Design Requirement and Resource Allocation Management (DRRAM) by defining the project from very early stages, determining associated tasks, issues and design requirements; dividing the system into subsystems, parallel decisions, decision nodes, alternatives; and generating the model. The Risk and Uncertainty-Based Integrated Design (RUBIC) [1] is used by DRRAM to allocate resources to subsystems. In addition, DRRAM generates information sheet that provides necessary information for design teams and helps them to change decisions more effectively.

- **Risk and uncertainty management:** The design and development cycle of complex systems is full of uncertainty, commonly recognized as the main source of risk. One of the challenges for such organizations is to assess how much risk (cost, schedule, scope) they can take on and still remain competitive. 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 deal with risks in the design process; 4- How do uncertainties propagates and what model describes it the best? To address these needs, ORBID introduces the "Capture, Assessment and Communication tool for Uncertainty Simulation" (CACTUS) [2]. CACTUS monitors systems from 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. In addition, its collaborative environment enables design teams to efficiently and effectively communicate uncertainty through the design process and improve their capacity for delivering complex systems that meet cost, schedule, and performance objectives.
- **Decision-making:** During the design lifecycle, design teams trade off among risks, costs and performance. They must minimize risks and increase performance of systems by considering all requirements and constraints and allocating resources to the most critical areas. These critical areas are associated with critical decisions for risky scenarios that can cause failure if combined. However, the design of complex systems is iterative by nature and decision makers might have to change their decisions many times. This highlights the importance of decision-making techniques having the ability of adapting to design changes while minimizing the associated costs and time. ORBID addresses this issue by introducing the framework and techniques for Flexible Risk-based Optimal Decision-making (FROD). FROD helps decision makers wherever a decision should be made among many alternatives. It provides techniques for selecting the most preferred product within the optimization domain and risk constraints while design requirements are satisfied. It generates and optimizes flexible alternatives with respect to minimization of costs and then ranks options based on evaluated costs and associated uncertainties.
- **Communication in collaborative design environments:** Because of the complexity of multidisciplinary systems, the design process of such systems is mostly based on team collaboration. The design teams must be able to communicate and be aware of decisions made by others as the project goes forward. ORBID addresses this issue by providing an updatable excel-based environment. In this environment, they are able to update and synchronize data and be aware of decisions made by others as the project goes forward. This environment also reduces the ambiguity uncertainty due to lack of communication or misunderstanding of the precise definitions of tasks and requirements and helps customers, stakeholders and decision makers to communicate effectively and efficiently.

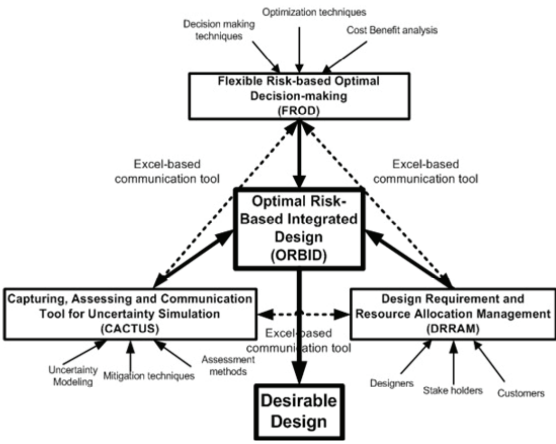

Figure 1: The general scheme of Optimal Risk-Based Integrated Design

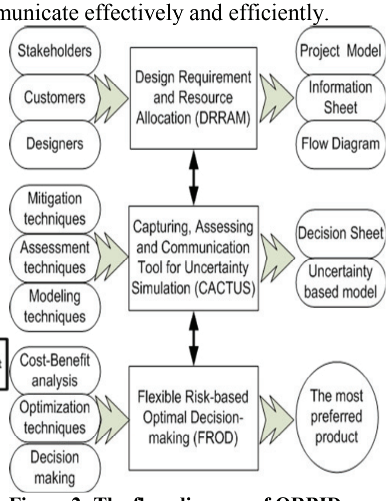

Figure 2: The flow diagram of ORBID

1.1. Terminology

Using the terminology below, ORBID is able to create sheets, diagrams and communication tools:

Stage: The term "Stage" refers to 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. The parallel decision number is defined by $m= \{1, 2,...,M-1, M\}$ where M is the total number of parallel decisions needed for the subsystem.
Decision node*:* Decision nodes refer to points in parallel decisions which decision makers should make a decision among many design alternatives.
Phase: Each decision node represents one phase of the associated parallel decision. The phase number is defined by $n= \{1, 2,...,N-1, N\}$ where N is the total number of phases.
Alternative*:* Each possible decision in decision nodes is called an alternative. The number of alternatives is defined by $l= \{1, 2,...,L-1, L\}$ where L is the total number of alternatives in the step. So, each alternative is represented by the symbol of X_{mnl} where m is the number of parallel decisions, n is the number of the phase located in the mth parallel decision, and l is the number of alternative located in the nth step.
Task and Issue*:* Generally tasks introduce why and for what purpose we are making a decision while issues refer to constraints that should be satisfied. 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 impossible or very difficult to control for designers.

2 DESIGN REQUIREMENT AND RESOURCE ALLOCATION MANAGEMENT

Since the design process is iterative by nature and these iterations increase cost design, it is important for design teams to have a clear understanding of assumptions, constraints, requirements, performance, and traceability into trades and decisions considered from early stages of design. Providing design requirement management techniques minimize costs and increase the speed of design. To address this issue, ORBID 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.

Design Requirements and Resource Allocation Management (DRRAM), by generating information sheets, defines the project and **provides all necessary information** from early stages of design. Information sheets are updatable sheets that enable design teams to evaluate criteria and communicate and manage the project and design requirements. DRRAM also **allocates resources to subsystems** by applying the RUBIC design methodology [1]. The logic of RUBIC design is the hierarchical decomposition, based on functional modeling of systems, whose functional models evolve as the design process moves forward. Furthermore, 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. Finally, it 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 helps decision makers to select the initial model that defines the initial selected design platform and design alternatives.

2.2 DRRAM Methodology

A specific process should be followed in Design Requirements and Resource Allocation Management (DRRAM) to help the design team reach the objectives of ORBID (Figure 3):

- Step 1: The first step in DRRAM is to obtain the initial design project functional model to help decision makers to have an understanding 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 and identify active alternatives. The third step in DRRAM helps them in developing decision sheets 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 is to allocate resources. DRRAM uses the Risk and Uncertainty Based Integrated Concurrent Design (RUBIC) [1] design methodology, 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. RUBIC allocates resources to the model by mapping it into this optimization problem: ($w=[w_1,...,w_n]^T$ is the risk reduction resource allocation vector and w_i is the percentages of resources to be spent on the i^{th} functional risk element)

Minimize $F1= W^T\Sigma W$
Maximize: $F2= W^T\mu$
Subject to $W =[w_1,...,w_n]^T$

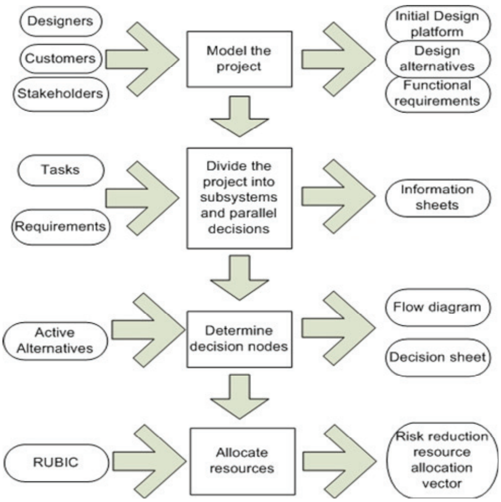

Figure 3: The DRRAM methodology

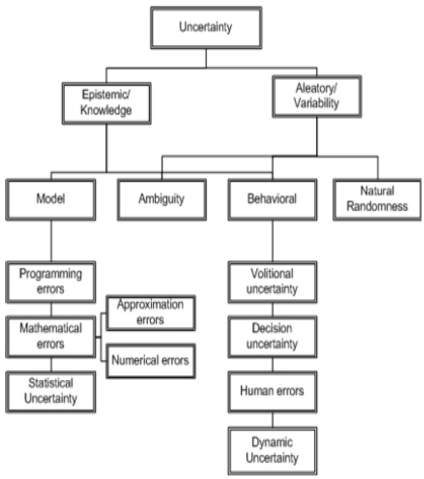

Figure 4: Uncertainty classification

3 CAPTURE, ASSESSMENT AND COMUNICATION TOOL FOR UNCERTAINTY SIMULATION (CACTUS)

Decisions must satisfy limitations due to constraints associated with systems. One of these limitations is uncertainty associated with systems that might lead to failure or suboptimal performance of systems. Decision makers encounter lots of uncertainties in each decision they make. Having no plan for managing uncertainties increases costs of design and decision-making. 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 alternatives is increased, the uncertainty associated with that decision is also increased; however offering more choices is not as harmful as other types of uncertainty that cause suboptimal performance and even failure. Furthermore, selecting a poor or imperfect definition and classification of uncertainty might guide designers to account for it more or less than necessary. These highlight the importance of having a clear understanding of uncertainty, knowing its sources, severity and effects. To address these needs, ORBID introduces the "Capture, Assessment and Communication Tool for Uncertainty Simulation" (CACTUS) [2].

CACTUS, by identifying sources of uncertainties, classifies uncertainties associated with systems in different stages of design. Different sources of uncertainties are not the same in importance and the types of treatments that should be considered. In addition, **CACTUS, by providing an 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 decision sheets. The importance score devotes unequal weighting from 1 (lowest) to 4 (highest) to uncertainties associated with alternatives based on expert judgment. The qualifier is simply an expression of the qualitative judgment. The importance number and the qualifier provide decision sheets with an uncertainty assessment technique, which combines both qualitative and quantitative methods. They can be extended to model degrees of belief where only expert judgment is possible. Decision sheets also determine alternatives that are considered actively in decision-making nodes. Furthermore, **CACTUS, by providing uncertainty mitigating techniques**, offers techniques to manage all sources of uncertainty; (controllable or uncontrollable, qualitative or quantitative). **The excel-based environment** reduces ambiguity due to lack of communication among team members, misunderstanding about customers' requirements and misunderstanding of the precise definition of design tasks and requirements. Finally, **CACTUS, by modeling uncertainty propagation** provides a model for propagation of uncertainty. This model gives us a general understanding of the project with respect to variances from the predicted model and clarifies noise, control factors and linking variables.

3.1 Uncertainty identification and classification

Since uncertainty has been a concern in many diverse fields, including design, engineering analysis, policy-making, etc., there are several definitions for the term of "uncertainty". Selecting an imperfect definition might guide decision makers to account for uncertainty incorrectly. In recent years, several attempts to find a description of uncertainty in the field of complex systems have been made but there is still no uniquely accepted definition. In this paper we use the following definitions: "Uncertainty is a characteristic of a stochastic process that describes the dispersion of its outcome over a certain domain", [3], and the following definition for risk (Doug Hubbard): "Risk is a state of uncertainty where some possible outcomes have an undesired effect of significant loss." [4]. 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). Figure 4 shows the uncertainty classification associated with complex systems introduced by CACTUS [2]. Here we describe these sources briefly:

One source of uncertainty, **ambiguity uncertainty** [5], results from incomplete or unclear definitions, faulty expressions or poor communication. **Model uncertainty** includes uncertainties associated with using a process model or a mathematical model. 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 [6]. Programming errors are errors caused by hardware/software [7, 8], 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 [9]. Uncertainties associated with the behavior of individuals in design teams (designers, engineers, etc.), organizations, and customers are called **behavioral uncertainty**. 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 [9]. Human errors are uncertainties due to individuals' mistakes. Decision uncertainty [10] is when decision makers have a set of possible decisions and just one should be selected. The fourth major source of behavioral uncertainty, dynamic 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. Dynamic uncertainty also includes uncertainties resulted from degrees of beliefs where only subjective judgment is possible. Finally, uncertainties associated with the inherent nature of processes are called **Natural Randomness.** This type of uncertainty is irreducible and decision makers are not be able to control it in the design process.

3.2 Uncertainty assessment

Attempts to quantify uncertainty during the design process have been published, but most focus on the quantitative aspects of uncertainty only [11]. These technical methods have to be complemented with qualitative methods, including expert judgments. While there have been attempts to accomplish this in various fields [12], methods to incorporate both types of uncertainties in a design process are not addressed. CACTUS addresses this issue by combining both types and can be extended to include places where only expert judgment is possible. Uncertainty assessment methods generally are divided into four major approaches based on their characteristics in analyzing data and representing the outputs:

A **probabilistic approach** is based on characterizing the probabilistic behavior of uncertainties in the model and includes 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 result of the probability methods, it cannot provide us with a clear understanding of the probabilistic characteristics of uncertainties. 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. 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 [13, 14]. The Bayesian logic can also be used to model degrees of beliefs. **Simulation methods** analyze the model by generating random numbers and then observe changes in the output. In other words, a simulation approach is a statistical technique that clarifies uncertainties that should be considered to reach the desirable result. Generally, simulation methods are 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) [15]. MCS includes a large number of repetitions. Simulation methods can be used on their own or in combination with other methods. Methods which incorporate both qualitative and quantitative uncertainty are placed in the fourth category as **qualitative approaches**. One example is NUSAP [12], which stands 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. Another example is ACCORD® [16], which is based on the Bayesian theory.

3.3 Uncertainty mitigating and diagnosing methods

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

Uncertainties due to **programming errors** can be diagnosed by those who have committed them. Since programming errors may occur during input preparation, module design/coding and compilation stages [17], it can be reduced by better communication, software quality assurance methods [8], debugging computer codes and redundant executive protocols. 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**. Statistical uncertainty also can be mitigated by selecting the best data sample for the size and 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. **Ambiguity uncertainty** is naturally associated with human behavior; however it can be reduced by clear definitions, linguistic conventions or fuzzy sets theory [5, 18]. **Volitional 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 [6, 9]. 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. When only subjective judgment is possible, the effect of **dynamic uncertainty** can be mitigated by applying the Bayesian approach [13, 14]. 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. Such as dynamic uncertainty, design optimization is useful for reducing the effect of **decision uncertainty**. Methods based on Bayesian decision theory also can be used to make more informed choices. Sensitivity analysis [19] and robust design [20] are also helpful to understand which variables should be controlled to improve the performance of the system.

3.4 CACTUS Methodology

Figure 5 shows the CACTUS methodology in the interactions with Flexible Risk-based Optimal Decision-making (FROD) and Design Requirement and Resource Allocation Management (DRRAM):

Step 1: The first step is to identify sources of uncertainties. Since sources of uncertainty are not the same in terms of importance and also modeling techniques, CACTUS provides a classification for sources of uncertainties associated with design of complex systems (Figure 4).
Step 2: The second step in CACTUS is to assess uncertainty. CACTUS provides 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) method to weight uncertainties and allocate resources. CACTUS provides techniques of determining risk boundaries, which may lead to failure or suboptimal performance. These boundaries are considered as risk constraints.
Step 3: The third step is to provide uncertainty mitigating techniques. Weighting uncertainties by DRRAM determines techniques and efforts that should be applied to manage uncertainties. Decision sheets which provide tools for making decision among sets of alternatives are generated in this step.
Step 4: The first three steps provide the necessary information for design teams regarding uncertainties. In this step, the uncertainty-based model for the project is obtained. This model not only gives us a general understanding of the project with respect to variances from the predicted model, but also clarifies noise, control factors and linking variables applied in formulating the project to an optimization problem.

4 FLEXIBLE RISK-BASED OPTIMAL DECISION-MAKING (FROD)

The decision making process in engineering design can be defined as the process of generating and selecting of design alternatives and the role of decision makers is to make decisions in the ambiguous, uncertain and risky phases of design [21]. As a consequence, in multidisciplinary complex systems, decision makers should be aware of all independent and interdependent variables associated with each discipline. This process is associated with costs, especially in the early stages of design where design teams' knowledge about the projects is incomplete. For example, decisions made during early stages of design costs 80% of total costs of the design life cycle [22]. In addition, iterations increase costs of decision-making and design. So, developing a flexible design methodology for making decisions under uncertainty plays a critical role in minimizing costs of design.

In general, flexibility is defined as "The ease of changing the system's requirements with a relatively small increase in complexity (and rework)" [23]. However, many interpretations for flexibility have been introduced by researchers in different fields. For example, in 1986, Buzacott et al [24] developed a framework for flexible manufacturing systems to address the problem of changing demands of customers and Haubelt (2002) [25] introduced flexible systems for software applications. In the field of design methodology, Roser et al have introduced a flexible design methodology [26] to minimize effects of risks and uncertainties in the design process; Olewnik et al have proposed a framework for flexible system design [27] with the implementation of Hazelrigg's decision making framework [28] and Suh et al have developed flexible product platform design [29] to address market uncertain change demand. These methods address flexibility in design in places that designers choose fixed design variables before they select the design. Khire et al [30] proposed a methodology for designing flexible systems in changing operating conditions. It addresses the problem of flexibility design in changing environments 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. Nilchiani et al [31] have addressed both design and operational flexibility in space systems by introducing a Six-Element (6E) framework for measuring the value of flexibility in space systems. ORBID addresses the issue of decision-making by introducing Flexible Risk-based Optimal Decision-making (FROD) framework. FROD, by providing a flexible framework for optimal decision making 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.

4.3 FROD Methodology

Figure 6 shows the process should be done in FROD methodology. Here we describe these steps briefly:

Step 1: The first step is to investigate the initial design. The platform of the initial design is obtained by the initial model generated by DRRAM. The 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 initial investigated design are identified in the second step. These uncertainties might be due to changes in design or demands.
Step 3: Identifying uncertainties and variants help to model uncertainties. This uncertainty-based model, which is obtained by CACTUS, investigates defect modes that occur when system responses cannot satisfy the upper and lower limit of allowed uncertainty. By identifying defect modes, possible design change options can be produced to resolve the defect.
Step 4: The fourth step is to generate flexible alternatives. Identifying defect modes and possible design changes generates flexible design alternatives.
Step 5: In the fourth step, alternatives should be optimized with respect to minimization of costs while all equality and inequality constraints are satisfied.
Step 6: Since cost is one important factor in selecting the design platform, costs associated with optimized design alternatives in step 5 are evaluated in this step.
Step 7: Uncertainty is another critical facture for decision makers to select the design. The seventh step is to evaluate expected performance and costs of flexible design alternatives under uncertainties.
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 six and seven. They rank possible design platforms with respect to expected value of their alternatives.
Step 9: It is always possible that the generated best design in Step 8 is not satisfactory or does not meet the design requirements. In this case, DRRAM is applied to modify design requirements and allocate resources again. As Figure 6 shows, in this case previous 8 steps are repeated until the best design platform is found that is satisfactory to designers, stakeholders and customers and meets all requirements and constraints. Another strategy is to apply the uncertainty mitigation techniques by CACTUS. However applying these techniques brings additional costs that should be evaluated beforehand.

In the next section, this paper clarifies some steps of Optimal Risk-Based Integrated Design (ORBID) very briefly by applying it to NASA's lunar lander mission case study and generating simple examples of decision sheets and information sheets obtained by DRRAM and CACTUS. In addition, an example of the excel-based environment is provided. Further research for developing FROD and applying it to a case study is being carried out by authors.

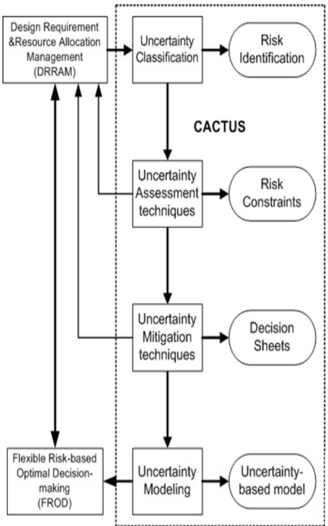

Figure 5: CACTUS methodology

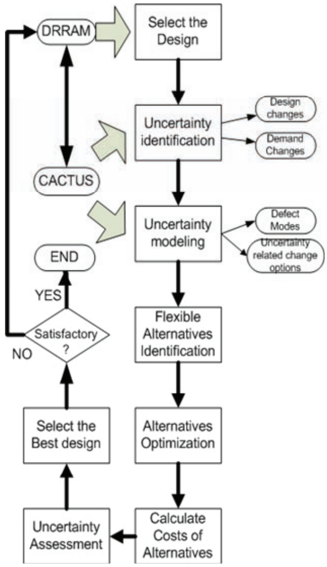

Figure 6: FROD methodology

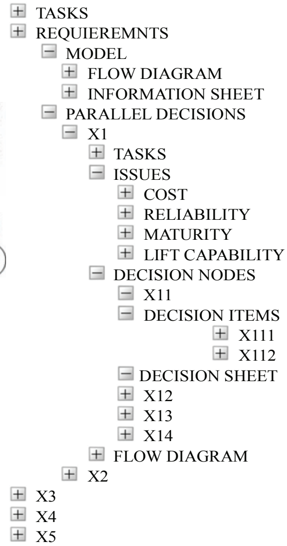

Figure 8: ORBID Environment

5 CASE STUDY

In this section, we present a case study of a conceptual mission design team at JPL's Project Design Center, borrowed from [32]. 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. Figure 7 shows a portion of decisions that occurred during the design of a robotic lunar mission, based on the observations of the team over the course of a week, initiated by an internal NASA customer [32]. ORBID prepares an excel-based environment for clients to communicate throughout the design life cycle. Figure 8 shows this concurrent collaborative environment. As we had mentioned, DRRAM manages design requirements and allocates resources to subsystems by providing flow diagrams and information sheets. Figure 9 shows the flow diagram for selecting the launch vehicle. Each dotted circle shows the item which is not investigated actively and circles with solid lines show active items that take part in decisions. Arrows from left to right show items which are added in each phase. Figure 10 shows the information sheet provided by DRRAM. It determines the name/symbol; tasks and issues of each parallel decision; divides them into decision nodes and describes each decision node in terms of its alternatives. It also provides the project model to help designers obtain a clear understanding of the project. Figure 11 shows a general scheme of this model. In addition, CACTUS develops decision sheets for decision nodes. Decision sheets have columns showing the distribution of issues and the methodology used. The expert judgment score has been devoted to show the importance of issues. Figure 12 is the decision sheet for the second phase of the first parallel decision (selecting launch vehicle). In this decision sheet, we only considered the reliability issue as an example and calculated its distribution by using the third-level Bayesian analysis method [33].

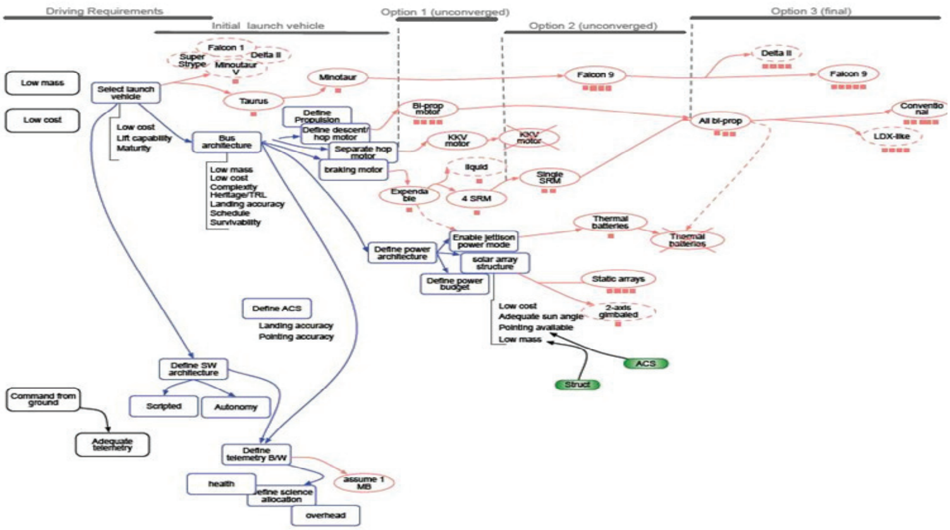

Figure 7: The robotic lunar lander mission design

	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 10: The information sheet provided by DRRAM for the lunar lander mission design

	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 12: Decision sheet

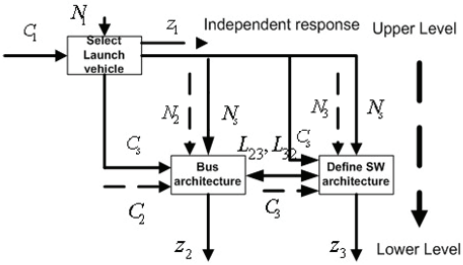

Figure 11: The project model

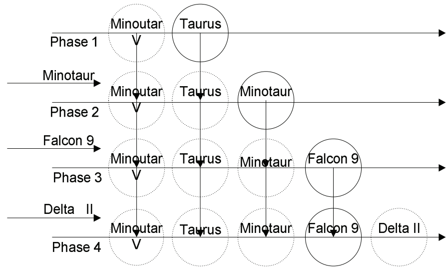

Figure 9: An example of decision flow diagram

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

6 CONCLUSION

This paper presented Optimal Risk-based Integrated Design (ORBID) for multidisciplinary complex systems 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 offers a cumulative tool for dealing with these issues by introducing: Design Requirement and Resource Allocation Management (DRRAM) framework, the Capture, Assessment and Communication Tool for Uncertainty Simulation (CACTUS), and the Flexible Risk-based Optimal Decision-making (FROD) framework in a collaborative excel-based design environment. These techniques were applied in a mission design team case study at NASA JPL's Project Design Center. Future research will focus on developing the FROD methodology and techniques to apply flexibility during design and operational conditions.

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