Propagating and Mitigating Uncertainty in the Design of Complex Multidisciplinary Systems

Thesis by
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Abstract

As humanity has developed increasingly ingenious and complicated systems, it has not been able to accurately predict the performance, development time, reliability, or cost of such systems. This inability to accurately predict parameters of interest in the design of complex multidisciplinary systems such as automobiles, aircraft, or spacecraft is due in great part to uncertainty. Uncertainty in complex multidisciplinary system design is currently mitigated through the use of heuristic margins. The use of these heuristic margins can result in a system being overdesigned during development or failing during operation.

This thesis proposes a formal method to propagate and mitigate uncertainty in the design of complex multidisciplinary systems. Specifically, applying the proposed method produces a rigorous foundation for determining design margins. The method comprises five distinct steps: identifying tradable parameters; generating analysis models; classifying and addressing uncertainties; quantifying interaction uncertainty; and determining margins, analyzing the design, and trading parameters. The five steps of the proposed method are defined in detail. Margins are now a function of risk tolerance and are measured relative to mean expected system performance, not variations in design parameters measured relative to heuristic values.

As an example, the proposed method is applied to the preliminary design of a spacecraft attitude determination and control system. In particular, the design of the attitude control system on the Mars Exploration Rover spacecraft cruise stage is used. Use of the proposed method for the example presented yields significant differences between the calculated design margins and the values assumed by the Mars Exploration Rover project.

In addition to providing a formal and rigorous method for determining design margins, this thesis provides three other principal contributions. The first is an uncertainty taxonomy for use in the design of complex multidisciplinary systems with detailed definitions for each uncertainty type. The second is the modification of two simulation techniques, the mean value method and subset simulation, that can significantly reduce the computational burden in applying the proposed method. The third is a set of diverse application examples and various simulation techniques that demonstrate the generality and benefit of the proposed method.

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Glossary and Nomenclature

A glossary is presented to familiarize the reader with some of the terminology that is introduced and subsequently used throughout the course of this thesis. The terms are consistent with the literature, *where the literature itself is consistent*.

aleatory uncertainty. Inherent variation associated with a physical system or environment under consideration.

ambiguity. Imprecise terms and expressions used in general communication.

approximation errors. Deficiencies in models where the phenomena or processes are relatively well understood.

asymmetric information. Information available to only a subset of a group and not all the parties involved.

Bayesian techniques. Formal mathematical methods that start with an existing belief and update that belief based on new data.

behavioral uncertainty. Uncertainty in how individuals or organizations act.

complex multidisciplinary system. A combination of two or more subsystems (disciplines) that result in a total system. The complexity is due primarily to the number of subsystems and their interactions with each other; individual subsystem complexity is secondary.

component. A functional item that is viewed as a complete and separate entity for purposes of manufacturing, maintenance, or record keeping. Examples in space systems design include a star tracker, thruster, and an electrical heater.

conceptual design. A short study period on the order of weeks or months to turn an idea into a concept and secure additional funding.

contingency. A synonym of margin or reserve. In some fields contingency is used specifically in design.

cumulative distribution function (CDF). A monotonically increasing mathematical expression that gives the probability that an uncertain quantity is less than or equal to a specific value.

decision maker. One or more individuals or organizations responsible for making final decisions in a project. In this thesis, the singular is used although the decision maker may consist of more than one individual or organization (e.g., the board of directors and the chief executive officer in a private corporation).

design uncertainty. A choice among alternatives over which an individual or individuals exercises direct control but has not yet decided upon. An example is the choice an engineer has in selecting a given component among a set of possible components.

deterministic. A state that does not include or involve uncertainty.

discipline. A synonym for subsystem.

epistemic uncertainty. Any lack of knowledge or information in any phase or activity of the modeling process.

errors. The accuracy of a mathematical model to describe an actual physical system of interest.

human errors. Blunders or mistakes by an individual or individuals during design.

interaction uncertainty. Uncertainty arising from unanticipated interaction of many events and/or disciplines, each of which might, in principle, be or should have been foreseeable.

margin. Variations in parameters (or resources) measured relative to best-estimate values.

mean. Expected value of a random variable.

median. A value of a random variable such that there is a 0.5 probability that the actual value of the variable is less than that value: $P[X \leq X_{0.5}] \equiv 0.5$.

mode. The value or values of a random variable that have maximal probability density.

model uncertainty. Accuracy of a mathematical model to describe an actual physical system of interest

numerical errors. Errors that arise due to finite precision arithmetic in a numerical model.

percentile. A value in percent such that there is a probability p that the actual value of a random variable, X, will be less than that value: $P[X \leq X_p] \equiv p$. Also known as a fractile or quantile when expressed as a fraction.

phenomenological uncertainty. Uncertainty that cannot be imagined. Also referred to as "unknown unknowns."

preliminary design. A more rigorous extension of conceptual design where the development of other options; the creation of risk management strategies; and the refining of previously performed trades, analyses, and cost estimates are performed.

probabilistic. A state that involves uncertainty represented by random variables instead of fixed and (assumed) known deterministic values.

probability density function (PDF). A mathematical expression that provides the probability of an event for each possible outcome.

programming errors. Mistakes or blunders by a programmer during development of a mathematical model.

random variable. An empirical quantity which is uncertain. Specifically, a real valued function defined on a sample space.

requirement uncertainty. Parameters of interest to and determined by the stake holder, independent of the engineer or designer.

reserve. A synonym for margin or contingency, typically used with respect to cost.

sample. A grouped number of observed random variables.

standard deviation. The square root of the variance. The standard deviation (variance) reflects the amount of spread or dispersion in the distribution.

space system. An integrated set of subsystems and components capable of supporting an operational role in space. Examples in the field of space systems design include an Earth-orbiting satellite, an interplanetary spacecraft, and a space station.

stake holder. One or more individuals or organizations who own a portion or the entirety of a project or is directly impacted by its outcome. In this thesis, the singular is used although the stake holder may consist of more than one individual or organization (e.g., the stake holder for a government mission is both the government and that country's citizens).

subsystem. An assembly of functionally related components (e.g., attitude control, propulsion, and thermal control). Also referred to as discipline.

tradable parameter. A quantifiable property that provides a performance measure of the complex multidisciplinary system that can be traded during design against one or more other quantifiable properties (e.g., mass, cost, schedule, and risk).

risk. The likelihood of failure.

uncertainty. The difference between an anticipated or predicted value (behavior) and a future actual value (behavior).

variance. The second central moment of a random variable.

volitional uncertainty. Uncertainty about what a subject him/herself will decide.

Acronyms and abbreviations used throughout the course of this thesis are summarized here:

ADCS	= attitude determination and control system
A/F	= analyst/facilitator
BWR	= Benedict-Webb-Rubin
CBE	= current best estimate
CDF	= cumulative distribution function
c.o.v.	= coefficient of variation
DoD	= Department of Defense
DS	= descriptive sampling
FP	= fault protection
FY2002$K	= fiscal year 2002 dollars in thousands (K)

FY2003$M	= fiscal year 2003 dollars in millions (M)
INCOSE	= International Council on Systems Engineering
JPL	= Jet Propulsion Laboratory
LHS	= Latin hypercube sampling
MCS	= Monte Carlo simulation
MCMC	= Markov chain Monte Carlo
MER	= Mars Exploration Rover
MMVM	= modified mean value method
MoM	= method of moments
MPF	= Mars Pathfinder
MVM	= mean value method
NASA	= National Aeronautics and Space Administration
PDF	= probability density function
PDR	= preliminary design review
PRA	= probabilistic risk analysis
REM	= rover electronics module
SDST	= small deep space transponder
SS	= subset simulation
SSPA	= solid state power amplifier
USAF	= United States Air Force
WCE	= worst case estimate

Symbols used throughout the course of this thesis are defined here (some have multiple definitions; their context should make it clear what the relevant definition is):

A	cross-sectional area, m^2
$\underline{A}$	two column array; first column ($\underline{A}_1$) is the choice ($\underline{A}_1 \in$ integer), second column ($\underline{A}_2$) is the probability of that choice being selected ($0 \leq \underline{A}_2 \leq 1$)
A_0, a, B_0, b, c_0	Beattie-Bridgeman constants

a, b	van der Waals constants
A_0, a, B_0, b, C_0, c, α, γ	Benedict-Webb-Rubin constants
$B(n,p)$	binomial distribution with parameters n (number of trials) and p (constant probability of success for each trial)
C_i	boundary value of "failure region" for simulation level i
$C_d(\underline{\underline{A}})$	discrete custom distribution with parameters listed in the array $\underline{\underline{A}}$
c	engine exhaust velocity, m/s
c_0	speed of light in a vacuum, 299792458 m/s
D	data
d	distance from the spacecraft to the sun, AU
F	thrust, N
F_i	failure region i
F_x	x^{th} fractal value (P_x /100)
f	mathematical function or friction factor; flux, W/m^2
$\underline{G}$	vector function that determines the tradable parameters based on the input variables; may be a computationally expensive function
g_s	solar constant at 1 AU, W/m^2
H	hypothesis; angular momentum, kg-m^2/s
h	step size
I	impulse, N-s
I_F	indicator function (I_F = 1 if true, I_F = 0 if false)
$I_{jj,k}(i)$	indicator function for the k^{th} Markov chain sample in the jj^{th} Markov chain at simulation level i
i	subset simulation level
J	moment of inertia, kg-m^2
j	input variable number
jj	Markov chain number
k	Markov chain sample number

k_1, k_2	thrust constants for a given engine
k_3, k_4	exhaust velocity constants for a given engine
$L(\mu,\sigma)$	lognormal distribution with parameters μ and σ
m	number of conditional levels (indexed with i = 1, …, m); mass, kg
N	total number of Monte Carlo simulation (MCS) samples; total number of MCS samples for initial run through (i = 1) subset simulation; total number of Markov chain samples across all chains for subsequent simulation levels (i > 1)
$N(\mu,\sigma_j)$	normal distribution with parameters μ and σ_j
N/N_c	number of samples in each Markov chain (Markov chain samples starting from a seed; indexed with k = 1, …, N/N_c)
N_c	number of Markov chain seeds ($N_c = p_0 \cdot N$; indexed with jj = 1, …, N_c)
n	number of input variables (indexed with j = 1, …, n); number or quantity
P	probability
P_f	specified probability of interest at distribution tail (e.g., $P_f = 0.01$ corresponds to 99th percentile, $P_f = 0.001$ to 99.9th percentile, etc.)
P_i	specified probability of failure at simulation level i; $P_i = P(F_i \| F_{i-1})$, i = 2, …, m
P_x	x^{th} percentile value
P_i^*	actual probability of failure at simulation level i
p	pressure, Pa
p_j^*	proposal probability density function (PDF) for input variable j
p_0	conditional probability specified for subset simulation; $p_0 \in (0,1)$
Q_j	one-dimensional cumulative distribution function (CDF) for input variable $\theta(j)$
Q_j^{-1}	inverse CDF for input variable $\theta(j)$
q	spacecraft surface reflectivity
$\underline{q}$	vector of one-dimensional PDFs
q_j	one-dimensional PDF for input variable $\theta(j)$

R	engine moment arm, m
R_{det}	deterministic result value
$R_i(k)$	covariance sequence for subset simulation level i at Markov chain sample number k
Re_D	Reynolds number based on diameter
r	effective engine moment arm, m
r_j	ratio used in Metropolis-Hastings algorithm for input variable j
s	number of Latin hypercube segments and repetitions
T	temperature, K
t	number of tradable parameters; time, s
U	(continuous) uniform random variable on the interval 0 to 1
U(min,max)	(continuous) uniform distribution with parameters “min” and “max”
U_d(min,max)	discrete uniform distribution with (integer) parameters “min” and “max”
X	general random variable
x	fraction
$\underline{Y}$	vector of probabilistic tradable parameters
y	dependent variable or tradable parameter
$\underline{y}$	vector of tradable parameters, vector of tradable parameter values at a subset simulation level of interest
α	rotational control acceleration, rad/s^2
$\beta(a,b)$	beta distribution with parameters a and b
$\Gamma(A,B)$	gamma distribution with parameters A and B
γ	pointing control, rad
γ_i	correlation factor at subset simulation level i
Δ_{c}(peak,minus,plus)	continuous triangle distribution with parameters peak, minus, plus
Δ_{d}(peak,minus,plus)	discrete triangle distribution with parameters peak, minus, plus
ΔF_x	x^{th} fractal difference value (ΔP_x /100)

ΔI_{torque}	change in impulse torque, N-m-s
$\Delta\tau$	change in torque, N-m
$\Delta\phi$	angle through which engine(s) are fired, rad
$\Delta\omega$	change in spin rate, rad/s
δ	engine misalignment angle, rad
δ_i	coefficient of variation (c.o.v.) of *Pi**
δ_i^*	total c.o.v. up to and including simulation level *i*
η	engine duty cycle
θ_i	sunlight angle of incidence, rad
θ_k	vector of uncertain input variables at Markov chain sample number *k*
$\theta_k(j)$	(potentially uncertain) input variable *j* at Markov chain sample number *k*
θ_k^*	vector of input variable candidate states at Markov chain sample number *k*
$\theta_k^*(j)$	candidate state for input variable *j* at Markov chain sample number *k*
κ	distance from the center of pressure to the center of mass, m
λ	confidence deviation parameter calculated via the inverse of $N(0,1)$; nutation frequency, Hz
μ	mean
ν	specific volume, m^3/kmol
ξ_j	simulated value generated from proposal PDF for input variable *j*
$\rho_i(k)$	correlation coefficient at lag *k* of the stationary sequence $\{I_{jk}(i): k = 1, \ldots, N/N_c\}$
σ_i	standard deviation of P_i^*
σ_j	standard deviation of one-dimensional PDF q_j
τ	torque, N-m
χ	fraction used in calculating proposal PDF width; specific impulse efficiency parameter

ψ	slew angle, rad
ω	spin rate, rad/s
$\Im$	force, N
$\Re$	set of all real numbers or universal gas constant, 8314.51 J/kmol-K
$\lfloor \sim \rfloor$	round down to nearest integer
$\lceil \sim \rceil$	round up to nearest integer
$\varnothing$	empty set
$\cup$	union
$\cap$	intersection

Subscripts:

act_tot	total actual
f	final desired
half_rev	half a revolution of the spacecraft about the spin axis
i	initial
ideal_tot	total ideal
inlet	at the engine inlet
j	input variable uncertainty number
max	maximum
min_on	engine minimum on per pulse
on	engine on per pulse
p_slew	propellant required for slewing
p_spin	propellant required for (de)spinning
req	required
s	solar
sd	scaled down
slew_tot	total for a slew maneuver

xx	axis orthogonal to spin axis
zz	spin axis

Superscripts:

i	engine number
j	thrust maneuver number
k	pulse maneuver number, tradable parameter number
t	true value
*	optimal

Chapter 1 Introduction

This chapter introduces the research presented in this thesis. The chapter begins with motivation and background concerning uncertainty in engineering design and, specifically, in complex multidisciplinary systems. An overview of space systems, the complex multidisciplinary system consistently referred to as an example throughout this thesis, follows. Methods of space systems design and uncertainty mitigation in space systems design are then presented. The current method of uncertainty mitigation through the use of heuristic design margins is discussed with an entire section dedicated to design margin examples. Particular attention is paid to the impact the current method of determining these margins has had on space systems design, development, and the aerospace industry in general. The mathematical problem statement this thesis addresses is then described. The chapter ends with a summary of the key thesis contributions and an overview of the remainder of the thesis.

1.1 Motivation and Background

Humans have developed as the dominant species on Earth (with respect to altering lives and the environment). Foremost among the reasons for this is the ability of humans to develop, build, and master instruments and tools. Although many species alter their surroundings for habitation, only a handful of other species use tools (e.g., otters use rocks to open clams, apes use sticks for food gathering). Development of increasingly complex tools by humans followed from similar humble beginnings, an activity that continues to this day. One of the reasons tools have become increasingly complex is uncertainty. Tools (systems) have become complex to reduce uncertainty and allow for reliable predictability. An example which illustrates this well is the missile.

A missile is defined as "an object (as a weapon) thrown or projected usually so as to strike something at a distance" [*Webster's Ninth New Collegiate Dictionary*, 1990]. The first missiles were simply rocks hurled by early man to kill animals and other humans. As humankind evolved from hunter gathers to city-states around 8000 BC, the missile evolved from a rock being thrown by man to one shot by a sling and, by c400 BC, one propelled by a catapult. This modest evolution (and increase in complexity) occurred because early man had two goals. The first goal was to increase the destructive power of the missile (i.e., to counter uncertainties in the strength of the target). The second goal was to improve the accuracy of hitting the target (i.e., to counter uncertainties in throwing the rock). These goals drove the evolution of the catapult to become the Chinese rocket (c1200 AD), cannon (c1350 AD), artillery (c1800 AD), howitzer (c1850 AD), and flying bomb (c1940 AD). Throughout this evolution, uncertainty has been intertwined with the design of complex systems. Today cruise and ballistic missiles are highly complex systems capable of quickly delivering enormous ordinances over thousands of kilometers while requiring little to no human assistance. The transition from flying bombs to missiles included the addition of sensors, actuators, and computers to counter uncertainties in atmospheric conditions, release conditions, and target movement.

As humanity has developed increasingly ingenious and complicated systems to reduce uncertainties and allow for reliable predictability, humanity has not been able to accurately predict other parameters of interest such as the performance, development time, reliability, or cost of such systems. This inability to accurately predict parameters of interest in the design of complex systems is due in great part to uncertainty. Uncertainty has repeatedly been treated as a supplemental piece of information during design. It is often considered after decisions have been made and sometimes ignored completely. This thesis addresses this issue by proposing a formal method to propagate and mitigate uncertainty in the design of complex systems. One of the goals of this proposed method is to make uncertainty a central concept in the design of these systems. This thesis illustrates the intimate relationship and importance uncertainty has to the entire design, development, and decision-making process.

Uncertainty can result in a system being overdesigned during development or failing during operation. Addressing uncertainty can thus reduce the effort in designing (redesigning) complex systems. It is not always possible to remove uncertainties or even obtain the information necessary to predict them. Hence, the need remains for a repeatable and mathematically rigorous approach for quantifying these uncertainties to assist a decision maker. A decision maker is one or more individuals or organizations responsible for making final decisions in a project. In this thesis, the singular is used although the decision maker may consist of more than one individual or organization. Probabilistic methods are the cornerstone of this mathematical rigor presented in this thesis and offer a viable approach to mange uncertainties that confront the decision maker. Probability theory is well-known to provide a rational and consistent framework for treating uncertainties and plausible reasoning [Cox, 1961; Papoulis, 1965; Jaynes 1983]. In short, the method proposed in this thesis attempts to improve how complex systems are designed, which remains one of the major contemporary engineering research challenges.

1.1.1 Engineering Design

Engineering design is the process by which systems and products are built to satisfy the needs of customers in a safe, efficient, and reliable manner. Design involves the conception of something new to satisfy a need. All design involves creativity (the generation of alternative solutions) and decision (choice among those alternatives). Engineering design distinguishes itself from other fields of design by its use of calculation and analysis. An integral part of this process is using limited resources to manage uncertainties in the development process and to improve the performance of the system, itself an uncertainty during the design process, once it is placed in service. The engineering design process consists of a number of steps to find a good solution to a specific problem. First there is the statement of a need and a specification of the requirements for the system. This is followed by an exploration of possible forms of solutions to the stated problem, leading to a conceptual design. This conceptual design, a specification of the general type of solution but not of the details of the design itself, then becomes a detailed design, recorded in working drawings and other documentation, through analysis and optimization of its characteristics. The detailed design is then implemented through the process of building, testing, and finally placing in service the resulting system. Throughout this process there is considerable feedback and iteration as shown in Fig. 1.1.

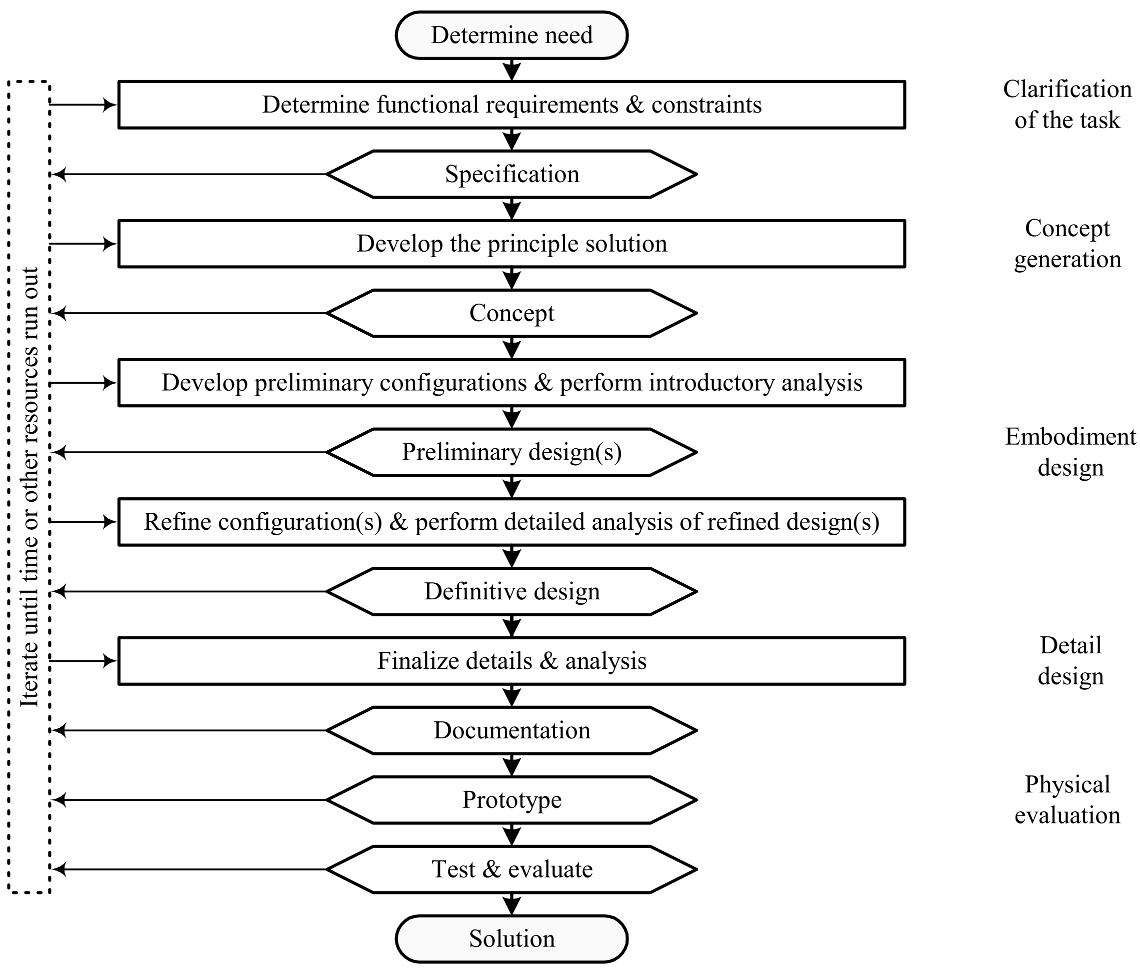

Fig. 1.1 The design process; adapted from Pahl and Beitz (1996).

Engineering design research seeks both a strong mathematical foundation and real-world applicability. The two are often connected: a rigorous mathematical foundation helps guarantee the success of an application, while the desire to solve particular problems uncovers needs of the theory. Complex multidisciplinary systems represent the application used in applying the method and theory developed in this thesis.

1.1.2 Complex Multidisciplinary Systems

The major engineering projects of the last half a century and those planned for the current century dwarf those of previous centuries in complexity. The development of the ballistic missile and space programs in the 1960s helped to usher in a new level of complexity in design and building multidisciplinary systems. The fields of systems engineering and project management were formalized during these two programs to assist in their successful development [Sapolsky, 1972]. This formalization is significant in that methods to propagate and mitigate uncertainty in design of complex systems must include and be compatible with these two fields. Missiles, automobiles, aircraft, power plants, submarines, and space systems are all examples of complex multidisciplinary systems. This thesis uses space systems as the archetypal complex multidisciplinary system in applying formal uncertainty techniques.

Complex multidisciplinary systems require dozens of different specialists to design and significant resources to build. These systems are usually designed by a team of engineers, each with responsibility for a different portion (subsystem) of the design. This design team could be arranged in a number of ways such as traditional (or pyramid) organization, a task-force organization, or a matrix organization. The design team aspect means that there are often asymmetries in information and differing incentives among the team members. Complex multidisciplinary systems are often built by more than one organization since a single organization rarely has the expertise in all the subsystems required in the design. When multiple organizations are involved, the complexity and informational asymmetries often increase further as interaction among specialists is more difficult.

Complex multidisciplinary systems are also characterized by severe uncertainty in design. They often have hundreds of independent variables that uniquely define a design. A large number of interdependent components must all come together for the complex multidisciplinary system to work. These systems are intrinsically difficult to model and understand because no single person has the detailed knowledge in all discipline areas, all variables, and all components that is required to comprehend or predict the performance of the final total system. Furthermore, it is important to predict the performance of several (perhaps many) design alternatives that may be significantly different from existing similar designs to allow well-informed design decisions to be made. If the environment is defined as everything outside the complex multidisciplinary system, an increase in complexity of these systems shifts uncertainty from the environment to the subsystems (assemblies, components, etc.) and to the system as a whole. This is a significant system benefit if the subsystems are sufficiently reliable. However, to realize this benefit, explicit models of subsystem uncertainties and the ability to quantify and propagate these uncertainties through the system is critical. Moreover, complex multidisciplinary systems often have a tightly constrained set of resources that further complicates asset allocation and risk management among the various subsystems during design. Hence, the "complex" in complex multidisciplinary systems refers primarily to the complexity in the number and interaction of disciplines (subsystems). The actual "complexity" of an individual subsystem is secondary.

The development of a complex system is characterized by distinct phases: conceptual design; preliminary design; detailed design; manufacturing design; system integration and verification; and operations. Conceptual and preliminary design of complex multidisciplinary systems are characterized by decision making that is separated far from the consequences of such decisions. Hence, although both conceptual and preliminary design entails a relatively low allocation of resources and effort, the decisions made during this stage of the design have significant ramifications. This is shown in Fig. 1.2.

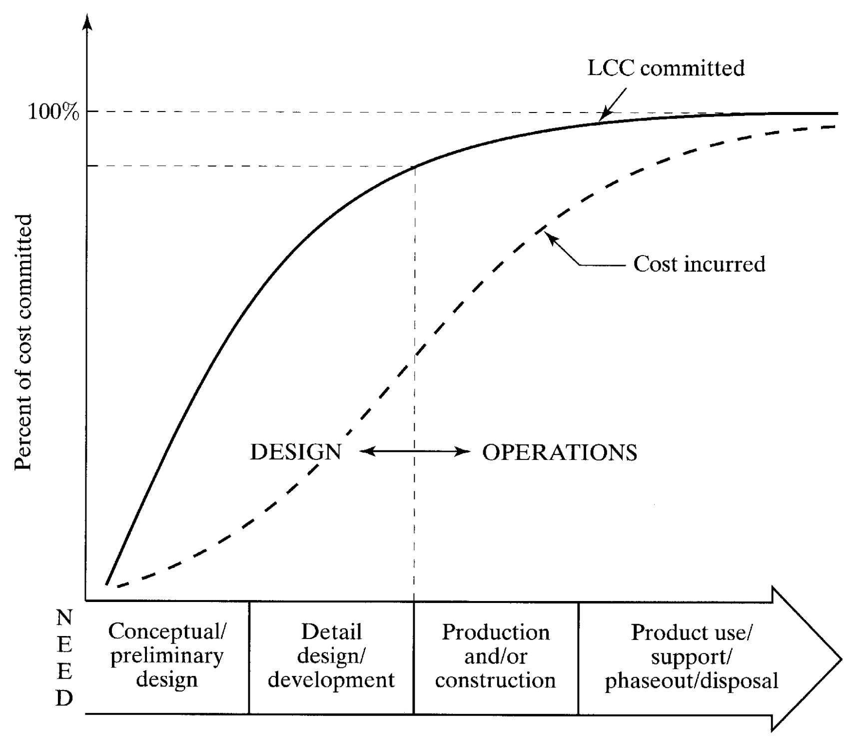

Fig. 1.2 Decisions made early in design have a significant impact [Symon & Dangerfield, 1980; Thuesen & Fabrycky, 2001].

Finally, complex multidisciplinary systems are often designed concurrently, as opposed to sequentially. Concurrent engineering reduces the time of manufacturing and total cost provided the individuals involved in the design process are properly trained and communicate [Burghardt, 1999]. The formal methods to propagate and mitigate uncertainty described in this thesis were developed with concurrent engineering in mind for maximum applicability.

1.2 Space Systems

A space system is an integrated set of subsystems and components capable of supporting an operational role in space. Space systems range widely from an Earth-orbiting space station to an interplanetary spacecraft. Space systems, specifically spacecraft, are used as examples in applying the method developed in this thesis. Spacecraft differ from other space systems in that they are robotic (i.e., unmanned) systems on the order of tens to a few thousand kilograms. Spacecraft are built by one or more organizations that must have a significant knowledge base in a multitude of disciplines such as structures, thermal control, and propulsion. One or more designer/decision maker represents each of these spacecraft subsystems (disciplines). These subsystems must be integrated together which requires competent systems engineering and management. A summary of typical spacecraft subsystems and their definitions are provided in Table 1.1. More detailed descriptions of spacecraft subsystems are provided in Griffin and French (2004) and Larson and Wertz (1999).

Table 1.1 Typical spacecraft subsystems

Subsystem (Discipline)	Definition
Attitude, determination, and control (ADCS)	Orients and stabilizes the spacecraft countering external and internal disturbances that act upon it
Command and data handling (C&DH)	Stores and processes commands and data
Management	Oversees all other subsystems and disciplines and acts as the liaison to the mission stake-holders
Mission design	Selects launch vehicle(s), analyzes trajectories, and determines orbital characteristics for all mission phases
Payload	Instruments and devices used to achieve the overall spacecraft/mission goals
Power	Generates, conditions, regulates, stores, and distributes power throughout the spacecraft
Propulsion	Provides the changes in velocity needed to translate the center of mass of a spacecraft and/or to provide a torque to rotate a vehicle about its center of mass
Structures & mechanisms	Supports and protects all other subsystems for all operating modes of the spacecraft and in all of the expected mission phases; deploys components and/or separates from other elements during the mission
Systems engineering	Oversees integration and interaction between subsystems
Telecommunications	Receives and transmits signals between the spacecraft and ground stations on earth or other spacecraft

Subsystem (Discipline)	Definition
Thermal control	Maintains all components of a spacecraft within their allowable temperature limits for all operating modes of the spacecraft and in all of the expected thermal environments

The definitions provided in Table 1.1 illustrate many of the uncertainties a spacecraft encounters in operation that must be accounted for in design. Each of the subsystems listed in Table 1.1 have developed significantly in capability and complexity to handle such uncertainties since the first successful spacecraft (Sputnik) was designed and built in 1957. A recent trend in space systems design is towards spacecraft constellations which are designed to counter uncertainties in the location where a signal, such as a phone call or missile launch, may be generated. Although built upon relatively established fields of mechanical and aeronautical engineering, aerospace engineering is nascent. Furthermore, much of the aerospace experience is either classified or competition sensitive and not available for analysis. The aerospace industry does not have the benefit of centuries of experience and highly visible and public applications that other engineering fields boast (e.g., civil, mechanical, naval). In short, the statistical base readily available to the aerospace industry is small.

1.2.1 Space Systems Design

Conceptual design; preliminary design; detailed design; manufacturing design; system integration and verification; and operations for space systems are often abbreviated using National Aeronautics and Space Administration (NASA) terminology [*INCOSE Systems Engineering Handbook*, 2000]. Conceptual design, referred to as "Pre-phase A," is a short study period on the order of weeks or months to turn an idea into a concept and secure additional funding. Initial requirements are defined; evaluation criteria are determined; risks are identified; and preliminary trades, analyses, and cost estimates are made. Pre-phase A is typically unstructured with engineers and designers pursuing a single concept or modifying an existing design [Mosher, 1999]. Preliminary design, referred to a "Phase A," is a more rigorous analysis of the concept and includes development of other options; creation of risk management strategies; and refining of previously performed trades, analyses, and cost estimates. Detailed design, referred to as "Phase B," converts the preliminary design into a baseline technical solution. A more detailed look at the design and tasks performed previously is undertaken. Phase B is where much of the detailed planning and ordering of parts for the actual construction and flight of the space system is performed. The transition from conceptual to detailed design for space systems often occurs at different times for different subsystems. Phase A/B is on the order of months to years. Manufacturing design and system integration & verification, referred to as "Phase C/D," is where design is finalized, the spacecraft is developed, integrated, tested, and launched. Phase C/D is on the order of months to years. Finally, operations, referred to as "Phase E," is the actual period in time of the mission to which the space system was designed. Phase E is on the order of minutes to years depending on the type of mission.

Space systems design durations and costs have changed dramatically in the 50 years they have been built. Early spacecraft were designed and built in months (e.g., early Explorer, Pioneer, and Mariner series spacecraft) and cost on the order of hundreds of millions of current year dollars [Koppas, 1982]. As space system designs became more complex and methods and technologies improved, this time frame became years and billions of current year dollars for many missions (e.g., Space Shuttle; NASA's Chandra and Cassini; ESA's Envisat; USAF's Milstar). Recently, the design time has begun to move back towards the order of months and the cost to hundreds of millions of current year dollars (e.g., NASA's Mars Pathfinder and Genesis, commercial satellites), due in part to a return to simpler spacecraft designs stressed in NASA's "faster, better, cheaper" effort of the 1990s. The typical contemporary spacecraft development programs do not typically have the luxury of long times or large budgets for extensive technology development, full system testing, and redesign. Aerospace design has gone from maximizing performance under technology constraints to minimizing cost under performance constraints [Mosher, 1999] and addressing affordability in conceptual design shifts the fundamental question from "can it be built" to "should it be built" [DeLaurentis, 1998]. Space systems today continue to be unique and high unit costs are not amortized in building subsequent models of that design. Upgrading and extending the capability of space systems in orbit is prohibitively expensive and difficult while software upgrades take time on the ground in testing and delay possible revenue-generating operations in space. All these ongoing issues provide opportunities and impetus for research in improving how these systems are designed and built [Thunnissen, 2004a].

1.2.2 Uncertainty Mitigation

Despite the great uncertainties in space systems design, formal methods to propagate and mitigate uncertainty are scarce. Reasons for this may include the difficulty in characterizing uncertainty in a design and propagating it through such a complex system. Another reason may be that engineers dislike having to address uncertainty. Many engineers have a belief that displaying and discussing uncertainty is displaying a lack of understanding [Seife, 2003]. Uncertainty mitigation in conceptual and preliminary design at present can be characterized as qualitative, expert driven, and point based. Uncertainties are evaluated individually, assessed and addressed as unique, and any calculations of these uncertainties are typically *a posteriori* and are not embedded in the end model [Walton, 2002]. Moreover, current methods are not amenable to trading resources and parameters of interest such as mass, cost, and time under conditions of uncertainty. The three formal methods currently used to propagate and mitigate uncertainty in space systems design are probabilistic risk analysis (PRA), factors of safety, and design margins. Each is discussed in detail in this section.

1.2.2.1 Probabilistic Risk Analysis

Probabilistic risk analysis (PRA) provides a method to define and measure quantitatively the technical failure risks of engineering systems. PRA was developed in the decades following the Second World War in analyzing the risks of failure of, and the risks imposed on, society by increasingly complex systems. The purpose of a technical PRA is to examine all potential damage states and the frequency of each state as uncertain variables. Early work in PRA focused on simple electronic circuits, leading to the development of fault trees, a tool that has become an integral part of current PRA. The first major program to apply PRA was the Minuteman Missile program. PRA was applied by NASA in estimating catastrophic probabilities for the Apollo program in the late 1960s. This PRA effort yielded such controversial results that it left the aerospace industry reluctant to apply PRA for the following two decades [Seife, 2003].

As the aerospace industry discarded PRA in the 1970s for more traditional methods, PRA developed significantly in the fields of structural engineering, nuclear power plant safety, and chemical processing. The more robust and rigorous PRA that resulted was reintroduced to the field of aerospace engineering following the Challenger accident in 1986 [Feynman, 1986; Paté-Cornell & Fischbeck, 1993]. PRA today uses probabilistic methods, statistical methods, and event trees in addition to fault trees. The quantification of uncertainty with PRA for design is based on a combination of statistical data from past experiences with systems similar to the one being designed, interpretations of test results, and expert opinions. Since appropriate statistical data are often not available, especially in the relatively nascent and competition-sensitive field of aerospace engineering, PRA must frequently rely on expert opinion. PRA has traditionally been used in space systems design to support established design decisions with the goal of justifying a low probability of a technical failure of the system and not a method used for actual design.*
However, when applied during design, PRA techniques provide an extremely powerful tool for discovering design errors, inconsistencies, and incompatibilities. Increasingly PRA has been used

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*"Sentence first, verdict afterwards, facts sooner or later forgotten." - Queen of Hearts in *Alice in Wonderland* by Lewis Carroll

in conjunction with other methods such as safety factors and design margins in addressing uncertainty. Dillon (1999) and Guikema (2003) describes PRA in detail.

1.2.2.2 Factors of Safety

Safety factors are one of the simplest and most widely used methods of addressing uncertainty. The use of a safety factor is a design philosophy which addresses uncertainty through conservatism in tolerances and operational limits [DeLaurentis, 1998]. This approach, deterministic in nature, seeks to identify the worst possible conditions a product may encounter, and then design the product to perform adequately under such conditions. Factors of safety are often even greater than this union of worst possible conditions to account for "unknown unknowns."[†] For example, a factor of safety of 1.5 is often used in pressure vessel design to account for uncertainties in material properties, storage conditions, and operating conditions. Factors of safety in solid mechanics account for uncertainties in static and dynamic loadings. The primary drawback of safety factors is their conservatism. Performance is sacrificed over the range of typical operating conditions for performance guarantees at unlikely or impossible conditions. A design's true factor of safety can never be known if the ultimate failure mode is unknown. Thus the design that succeeds (i.e., does not fail) can actually provide less reliable information about how or how not to extrapolate from that design than one that fails. It is this observation that has long motivated reflective designers to study failures even more assiduously than successes [Petroski, 1994]. From a pedagogical point of view, the safety factor approach generates no new information about the behavior of the design space which can be exploited in future designs [DeLaurentis, 1998].

1.2.2.3 Design Margins

Conceptual and preliminary design is generally done deterministically, operating as though all quantities of the design are known with complete certainty. Design margins are applied *ex post facto* to account for the uncertainties in the design because rigorous techniques for uncertainty mitigation and propagation are not available. Design margins are defined as variations in parameters (or resources) measured relative to best-estimate values. The definition often differs from resource to resource and organization to organization. Design margins are also known as "margins," "contingencies," and "reserves." Margin is often employed when referring to operational resource values, contingencies when referring to design resource values, and reserves when referring specifically to cost. The word *margin*, not contingency or reserve, is

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[†]Factors of safety are sometimes disparagingly referred to as "factors of ignorance" [Petroski, 1994]

used in this thesis. Many margins for parameters are expressed as percentages, using worst-case estimate (WCE) and current best estimate (CBE) parameter values:

$$\%\ \text{margin}\Big|_{\text{current}} = \frac{\text{WCE} - \text{CBE}}{\text{CBE}} \cdot 100 \tag{1.1}$$

CBE values can be viewed as deterministic since they represent a best guess point value based on some combination of data, analysis, and technical judgment. However, the basis for many assumptions and the scope of thought that went into estimating CBEs are often not explicitly documented. On their own, CBEs have no degree of confidence associated with them. Furthermore, CBEs are often biased away from the mean values of the uncertainties they represent. WCE values can be viewed as some combination (perhaps the union) of worst possible conditions. Hence, the "worst" in WCE is subjective.

This definition of design margin appears similar to the definition of factor of safety provided in the previous section. But while factors of safety are typically static during design, design margins vary throughout the development and their allocation range from being capricious to "hope oriented" to overly conservative. Design margins are implemented to allow the various elements of a design team to work in parallel as much as possible. By providing numbers with margin ("holding margin"), a team of a given subsystem or discipline is more insulated from changes occurring in other subsystems or disciplines and can proceed with their design. Design margins are chosen to be robust enough to accommodate uncertainties and enable design changes with minimal system-wide "ripple effects." Margins maintained vary not only from organization-to-organization, but from individual-to-individual (e.g., project manager-to-chief engineer, chief engineer-to-flight systems engineer) within an organization based on the risk tolerance of that organization or individual or both. The choice in these margins is typically an afterthought and attempts to account for all uncertainties that engineers encounter by lumping these uncertainties into one value with little or no analysis.

For space systems in general, margins not based on a WCE are allocated heuristically, based on historical data, or in a crudely quantitative manner, based on such concepts as design maturity and mission environment. Heuristic is defined as "involving or serving as an aid to learning, discovery, or problem-solving by experimental and especially trial-and-error methods" [*Webster's Ninth New Collegiate Dictionary*, 1990]. For space systems design, the "experimental and especially trail-and-error methods" correspond to previous historical experience by an organization or set of organizations. Heuristics suffer from cognitive biases including *representativeness*; *availability*; and *anchoring and adjusting* [Tversky & Kahneman, 1974]. The *representativeness* heuristic is a judgment that is made by comparing the information known about the item (or variable or quantity) with the stereotypical member of the category. *Availability* occurs when judgment about the characteristics of an item is based on the ease with which similar items from memory are recalled. Finally, *anchoring and adjusting* refers to the notion that in making estimates of an item an initial "anchor" is chosen. That anchor is subsequently adjusted based on knowledge of the specific item. Heuristic-based design margins tend to be simple, easy to apply, but often lead to severe and systematic errors. The following section provides actual examples that illustrate the current heuristic method of applying design margins in space systems design and their impact.

1.2.3 Design Margin Examples and Impact

As the design of a space system progresses, CBEs of resources typically rise using up the margin that is being held. Significant design and management problems can occur when the rise in the CBEs is greater than the margin being held ("blown margins"). Such systems may have to be redesigned which may result in the system being over budget, delivered late, descoped, or cancelled. On the other hand, holding too much margin early in project design may cause the system to be overdesigned, uncompetitive, and/or poorly managed. Determining the correct margin at various stages of the development is critical in determining the likelihood of success in designing a spacecraft. Examples of applying heuristic and/or historical based methods to determine design margins in space systems design are numerous. Unfortunately, obtaining best estimate and margin values for space system that can be referenced is more difficult. Reasons for this include competition sensitivity, insufficient tracking and recording of values, and reluctance on the part of space system designers to document missions in which margin values have exceeded or missions in which too much margin was held. The following section provides examples of the current method of applying margins to NASA, Department of Defense (DoD), and commercial missions. The section concludes with some examples of margin application in other fields. All examples are referenced.

1.2.3.1 NASA Spacecraft

NASA has been at the forefront of space systems development since it was founded in 1958. The Jet Propulsion Laboratory (JPL) in Pasadena, California, has been NASA's primary center responsible for robotic space exploration. JPL missions typically follow an institutional design principles document [Yarnell, 2003] regarding margin levels at various stages of the design. Historical data collected by JPL suggest that total mass and power growth due to uncertainties ranged from 20% to 48%, with most in the range of 25% to 40%. Factors affecting growth included mission/system design changes, design complexity, amount of inheritance, amount of new technology/concepts, quality/fidelity of early estimates, and funding available [Yarnell, 2003]. Such analyses resulted in the recommended margins (relative to a preliminary mission system review) for hardware mass and power using a maturity-based approach as shown in Table 1.2.

Table 1.2 Recommended hardware mass and power margins [Yarnell, 2003]

Hardware	Recommended Margin (%)
New design	30
Inherited design	15
Inherited hardware	10
Inherited “use as is”	2

Recommended margins (relative to preliminary mission system review) for cost (reserves) are based on the current phase of the design as shown in Table 1.3.

Table 1.3 Recommended cost margins [Yarnell, 2003]

Design Phase	Recommended Margin (%)
Proposal and/or Phase A to B transition	30
Project PDR[a] and/or B-to-C/D Transition	25
Project CDR[b]	20
Start of ATLO[c]	20
Ship to Launch Site	10

[a]PDR = preliminary design review; [b]CDR = critical design review; [c]ATLO = assembly, test, & launch operations

Similar time-phased margins exist for schedule and other parameters [Yarnell, 2003]. Individual missions are typically free, subject to reviews, to choose different margin levels. Whether the margins selected follow the design principles document or are chosen specifically for a given mission, these margin levels are heuristically and/or historically determined. For example, in the design of the recent JPL Mars Exploration Rover (MER) missions, margins were time phased and determined on the basis of organizational (JPL) policy, the experience of the flight system manager, and experience of MER team members. The many margins held throughout design of MER pertained to the spacecraft itself (e.g., mass, flash memory) and to the operation of the spacecraft (e.g., telecom link strength). Table 1.4 lists margins assumed for several flight system parameters.

Table 1.4 MER flight system margins [Welch, 2001]

Resource	PDR (10/00)	CDR (8/01)	ATLO start (2/02)	Ship to Cape (1/03)
[a]Mass[b]	15/5%	10/2.5%	5/1%	2/0%
[a]Energy/Power[c]	10/10/10%	10/5/5%	10/0/5%	10/0/0%
Power switches	30%	20%	10%	10%
Pyro Switches	30%	20%	10%	10%
[a]CPU utilization[d]	50%	50%	50%	40%
Memory				
DRAM[d]	50%	40%	25%	25%
Flash	30%	25%	20%	10%
[a]EEPROM[d]	50%	50%	50%	40%
Electronics				
Chassis Margin (VME slots)	1	1	0	0
PWB Margin (spare real-estate)[d]	50%	30%	10%	10%
Analog signals (e.g. temp sensors)	30%	15%	5%	5%
Telecom (link margin)	3 db	3 db	3 db	3 db
Propellant (tank margin)	30%	20%	10%	10%

[a]Critical technical margins required by project manager
[b]mass margin is specified in terms of X/Y% where X is total above CBE and Y is above CBE+uncertainty.
[c]updated based on three margins X/Y/Z, X% operation margin, Y% flight system margin, and Z% project manager reserve. These are added together for total power/energy margins required at each phase.
[d]these resources are managed at the subsystem level and allocations changes; as long as margins are met, do not require ECRs.
PDR = preliminary design review; CDR = critical design review; ATLO = assembly, test, & launch operations; CPU = central processing unit; DRAM = dynamic random access memory; EEPROM = electrically erasable programmable read-only memory; VME = VersaModule Eurocard; PWB = printed wiring board; CBE = current best estimate; ECR = engineering change request

MER also held margins on cost and schedule (reserves) as well as ΔV and launch vehicle capability that are not listed in Table 1.4. The mass history of MER during its development is plotted in Fig. 1.3.

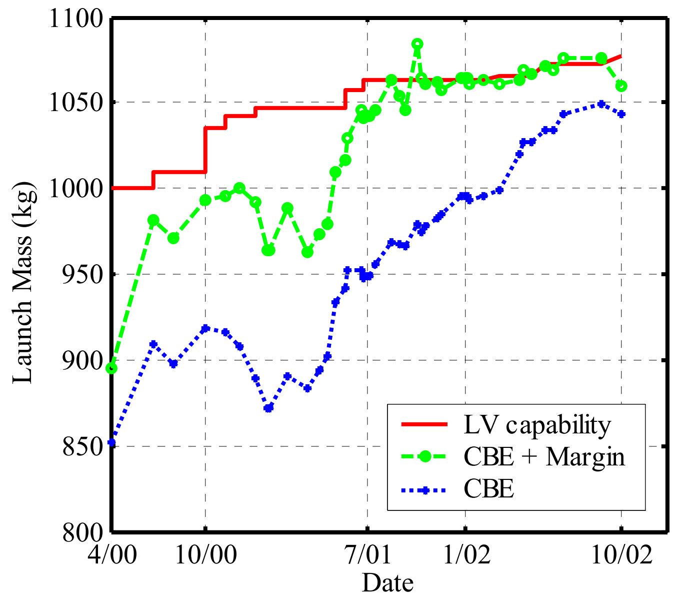

Fig. 1.3 MER mass history.

Fig. 1.3 plots the CBE and CBE plus margin for the launch mass (injected mass) as well as the injected mass capability of the Boeing Delta II 7925 launch vehicle (LV), the launch vehicle used by MER-A (MER-B used a Boeing Delta II 7925H which provides a slightly greater injected capability). In Fig. 1.3, the first six months or so (April to October 2000) were devoted to conceptual/preliminary design. Detailed design and fabrication were carried out from about October 2000 to January 2002. Finally, the period from February 2002 until June 2003 was dedicated to assembly, test, and launch operations. MER had a tight project schedule and mass growth was a problem during development. Cost and schedule were used to reduce mass. For example, additional launch vehicle and trajectory analyses were performed eight times during development to increase the estimate of the injected capability of the launch vehicle (solid line in Fig. 1.3). Additional mass reduction exercises at almost $100K/kg (in FY2002 dollars) were also performed. These activities were critical since the launch mass of MER approached 1072 kg by October 2002 which is considerably greater than the original maximum mass estimates of 900 to 1000 kg that were assumed early in the project and only slightly less than the 1077 kg injected mass capability of the lower capability launch vehicle [Thunnissen & Nakazono, 2003].

The mass margin for the MER mission assumed early in design was exceeded by mid-2001. Additional launch vehicle and trajectory analyses as well as expensive mass reduction exercises were performed to reduce the total mass. These efforts, if not successful would have resulted in MER switching to a more powerful launch vehicle. Such a late change in the launch vehicle would have significantly increased the total mission cost and possibly might have resulted in the mission missing its launch opportunity (which in the case of Mars missions occurs only every 26 months). Fortunately for the MER mission, these efforts were successful and MER launched on time (schedule margin was sufficient) although the final cost of MER was significantly greater than original estimates. These margins for MER and actual and assumed design margins for several other recent NASA projects are provided in Table 1.5 [NASA, 1997; NASA, 1998a; NASA, 1998b; NASA, 2004; Thunnissen, 2004a].

Table 1.5 Design margins for several recent NASA projects

	Value		Margin		
	Predicted	Actual	Allocated (%)	Actual (%)	Difference (%)
Mars Pathfinder (MPF)[a]					
Entry mass	390 kg	580 kg	28.2	48.7	+20.5
Cost	$100M	$171M	50.0	71.0	+21.0
Clark[b]					
Schedule	1.8 years	3.6 years	11.1	100.0	+88.9
Cost	$44M	$55M	11.3	25.00	+13.7
Deep Space 1 (DS1)[c]					
Schedule	2.3 years	3.1 years	17.3	34.7	+17.4
Cost	$128M	$152.3M	10.1	19.0	+8.9
Mars Exploration Rover (MER)[d]					
Mass	918 kg	1062 kg	8.2	15.7	+7.5
Cost	630$M	$820M	20.0	30.0	+10.0

[a]predicted values and margin allocation at 1/1994, costs in FY1992$s; [b]costs in FY1998$s; [c]costs in FY1997$s; [d]predicted values and margin allocation at 10/2000; costs in FY2003$s

It is apparent from the examples listed in Table 1.5 that the current heuristic method has failed in properly accounting for uncertainties in design. Perhaps the consummate example of exceeded margins for NASA missions is Clark, the second spacecraft listed in Table 1.5. Clark was a NASA earth science mission built by CTA Systems (now part of Orbital Sciences Corporation in Dulles, VA). Clark originally scheduled for a mid-1996 launch at a cost of $49M (including margin). In February 1998, NASA terminated Clark "due to mission costs, launch schedule delays, and concerns over the on-orbit capabilities the mission might provide" [NASA, 1998]. Termination is the extreme case of poor margin estimation and management. Deep Space 1 (DS1) exceeded its schedule margin and was forced to launch more than a year later than planned (October 1998 vs. July 1997). This delay resulted in a redesign of the mission. For DS1 this was not catastrophic as it was a technological demonstration mission. For science missions with limited launch opportunities or national security assets, a schedule delay in the spacecraft development can be devastating. Table 1.5 lists just a few of NASA's many missions which have exceeded one or more important margins. A stake holder is defined as one or more individuals or organizations who own a portion or the entirety of a project or is directly impacted by its outcome. In this thesis, the singular is used although the stake holder may consist of more than one individual or organization. Poor margin determination and management has led NASA's stake holder (the government and taxpayers) to lose confidence in NASA's capability and competence and has jeopardized NASA's ability to achieve its short- and long-term goals.

1.2.3.2 Department of Defense Spacecraft

Poor uncertainty mitigation also undermines program stability and stake holder confidence in funding new projects. Perhaps this is best seen by several recent Department of Defense (DoD) projects which have had significant cost and technical problems. One of the most glaring examples is the Space-Based Infrared System – High (SBIRS-High), a high-orbiting infrared constellation designed to detect and track ballistic missiles of all sizes. SBIRS-High is the replacement for the Defense Support Program (DSP) spacecraft which have provided early missile warning information for more than 30 years. SBIRS-High recently had two recent high-profile cost overruns. The first in 2001 topped 25% and the most recent in July 2004 indicated costs would be greater by an additional 15%. Since the program's inception, costs have tripled. The USAF now projects $9.9B for the life of the project [Wall, 2004]. Although requirements of SBIRS-High have changed somewhat since its inception, the cost overrun updates have exemplified the Pentagon and their contractors' poor job in anticipating these uncertainties.

The poor uncertainty mitigation and management in DoD projects is not new. The Nunn-McCurdy Amendment passed by Congress in 1982 attempts to force projects to improve management practices. This legislation stipulates a mandatory review when a program exceeds its cost by 15% and sets requirements that must be met by the program in order to continue development. Projects with a cost growth of 25% are subject to cancellation [Wall, 2004]. Problems with SBIRS-High and other space projects have begun to jeopardize next-generation programs because lawmakers are increasingly skeptical about the Pentagon's performance, schedule, and cost assessments. Skepticism for these DoD projects includes both uncertainty mitigation techniques, competency of program management, and concerns that contractors building these systems are defrauding the government. In response, the U.S. government has attempted a variety of cost- and risk-sharing methods to motivate contractors to improve their estimates and management. The skepticism and distrust has grown to such a level that government lawmakers recently cut funding to several DoD high-profile projects, including space-based radar (SBR) and transformational communications system (TCS), and threatened future funding cuts or cancellation for several other DoD projects. At best, these examples of poor margin determination and management by the DoD are a nuisance and poor use of tax payer dollars. At worst, exceeded margins are a threat to national security by diverting resources from one set of critical projects to shore up one or two other (potentially less critical) projects.

1.2.3.3 Commercial Spacecraft

Design margin application and examples in commercial spacecraft are difficult to obtain. Whereas NASA and DoD missions have some level of accountability to their stake holder (i.e., the general public) that results in certain margin estimations and actual results being available, commercial missions do not. Commercial missions are accountable to their stake holder (service providers and possibly insurance carriers) who have, due to competition reasons, incentives not to release uncertainty mitigation techniques or actual results. Although it is generally known that a variety of commercial missions have exceeded margins in mass, schedule, and cost, it is difficult to obtain values that can be documented. However, most commercial missions cannot suppress the revenue generating (operations) portion of their missions since the stake holder now includes service provider share holders who follow the performance of their investments. Several recent commercial ventures have turned into colossal operational failures. Perhaps the two that best exemplify this are the $5B Iridium and $3B Globalstar systems [Cáceras, 2002]. Both were mobile telephony systems developed and deployed around the turn of the 21st century. Both were engineering successes yet both projects (and several others) badly miscalculated the potential market and national/international regulatory changes in mobile telephony. Poor uncertainty estimation of the potential market doomed these missions and funding for several others. These two examples illustrate that uncertainty mitigation techniques are not only critical during design but also during the revenue generating phase of a mission. The huge loss incurred in these failures has been devastating to commercial spacecraft developers. One of the primary stake holders and primary funding source of such projects is investment houses and venture capitalists (i.e., Wall Street). These highly publicized failures have undermined confidence Wall Street has in commercial aerospace and has been devastating to commercial spacecraft developers. For example, only five new commercial spacecraft were ordered in 2002 *worldwide* and Space Systems Loral, a major satellite manufacturer, filed for bankruptcy protection in 2003. Worldwide launches of commercial spacecraft payloads were at ten year lows in 2001, 2002, and 2003 which in turn impacted the launch services sector [Cáceras, 2004]. Poor margin determination and management by commercial developers has arguably hindered the growth for the entire commercial aerospace industry.

1.2.3.4 Other Fields

Poor uncertainty mitigation and propagation is a problem in a wide variety of complex multidisciplinary systems beyond space systems. The F/A-22 Raptor fighter, V/A-22 Osprey, and Patriot missile defense system all resulted in final per unit costs two to three times original estimates and delayed deployments [Edwards, 2003]. A number of high profile large civil engineering projects have exceeded margins on schedule and cost (e.g., Sydney opera house in Australia, the Chunnel between the United Kingdom and France, "Big Dig" in Boston, Massachusetts) [Flyvbjerg, Bruzelius, & Rothengatter, 2003]. A study by RAND specifically investigated over 80 of these "megaprojects" and reported that most projects meet their performance goals, many their schedule goals, but few their cost goals [Merrow, 1988]. Indeed, the problem of poor uncertainty mitigation in complex system or large projects may be more pervasive than is even known since failures in a wide variety of fields, by governments, and by organizations are often not publicized; only the success are.[‡] Undoubtedly another reason why complex multidisciplinary systems and megaprojects exceed margins repeatedly is political. Often, government agencies and contractors specify overtly optimistic cost estimates to gain initial funding approval. Cost increases are often revealed only when a system or project is far enough long that it cannot easily be terminated or descoped. The current method of determining margins allows a lack of accountability to the stake holder on the part of the participants. Lastly, it should be noted that even small underestimates of margins on the order of a percent in multi-billion dollar projects can lead to large dollar sums that, when taken out of context, can be embarrassing and potentially detrimental to participants and the stake holder alike.

1.3 Problem Statement

The examples provided in the preceding section vividly illustrate the detrimental impacts of poor margin estimation and management on individual missions and the aerospace industry as a whole. This thesis is dedicated to developing a formal method to determine margins in design based on the uncertainties that exist and the risk tolerance of the decision maker. Specifically, consider:

$$\underline{y} = \underline{G}(\underline{\theta}) \tag{1.2}$$

Equation (1.2) represents a general expression for design where a vector $\underline{\theta}$ of input parameters (variables) is mapped to a vector $\underline{y}$ of output parameters (tradable parameters) via one or more transformation (response) functions $\underline{G}$. The response function(s) may be complicated

[‡] "Victory has a hundred fathers but defeat is an orphan" – Galeazzo Ciano (1942)

(e.g., closed-form equations, computational algorithms, "black box" functions) requiring significant expense in time and resources to calculate values. Whereas, the current heuristic-based method assumes all these input variables are deterministic and margins are placed on the evaluated tradable parameters *ex-post facto*, the proposed method determines the appropriate margin levels to place on the tradable parameters $\underline{y}$ by accounting for all the uncertainties in the $\underline{\theta}$ input variables themselves.

The proposed method transforms this deterministic vector θ into a vector of random variables $\underline{\Theta}$:

$$\underline{Y} = \underline{G}(\underline{\Theta}) \tag{1.3}$$

This vector $\underline{\Theta}$ may include discrete random variables, continuous random variables, constant values, and discrete choices among options. By assuming random variables for the inputs, the vector of discrete tradable parameters becomes a vector of random variables via the response function. The result is that each tradable parameter can then be represented by a unique cumulative distribution function (CDF). A CDF value P_x, selected based on the risk tolerance of the decision maker, is used along with the deterministic result in calculating margins in the proposed definition:

$$\%\ \text{margin}\Big|_{\text{proposed}} = \left[\left(P_x - R_{\text{det}}\right)/R_{\text{det}}\right]\cdot 100 \tag{1.4}$$

The proposed margin definition relies on probabilistic methods and innovative sampling techniques to accurately determine CDF values of interest while minimizing the amount of response function calculations (i.e., minimize the total computation cost of applying the method).

The design of complex multidisciplinary systems, space systems in particular, is characterized by several subsystems, dozens to hundreds of input variables, and several tradable parameters. The design space is neither smooth nor unimodal [Mosher, 1999]. The response function may be several physics-based models with both linear and nonlinear relationships. Depending on the input variables, nonlinear relationships result in significant multiplication factors in the tradable parameters. Input variables may be integers or real numbers, static or dynamic, certain or uncertain. The uncertain quantities may be represented best by discrete random variables or continuous random variables. Space systems design also involves selecting discrete choices among options (e.g., existing off the shelf components, readily available materials) as well as among multiple configurations. The resulting tradable parameter space may have discontinuities, multiple viable solutions, or no solutions. Finally, the design of complex multidisciplinary systems is not a single-loop input/output process. The process of evaluating Eqns. (1.3) and (1.4) and revising assumptions, goals, methods, information, and preferences is constantly occurring. Representing all the input variables, evaluating the response function(s), calculating the values of tradable parameters, and determining the appropriate margin values via a formal method is a task of significant complexity that this research addresses.

1.4 Key Contributions and Organization of Thesis

The principal contribution of this thesis is a formal method to propagate and mitigate uncertainty in the design of complex multidisciplinary systems. Specifically, applying the proposed method produces a rigorous foundation for determining design margins. This introductory chapter provides the motivation and background for this research. Prior to this chapter, preliminary sections include a table of contents, list of figures, and list of tables in addition to glossary. In particular, the glossary includes the definitions of commonly used terms, expressions, acronyms, and symbols used repeatedly in the thesis.

Chapter 2 discusses and defines uncertainty in a wide variety of fields culminating with a detailed definition and classification of uncertainty for complex multidisciplinary systems. Chapter 3 summarizes the proposed method and lists the qualitative benefits and quantitative results of its application. The method comprises five distinct steps: identifying tradable parameters; generating analysis models; classifying and addressing uncertainties; quantifying interaction uncertainty; and determining margins, analyzing the design, and trading parameters. Chapter 4 through Chapter 8 develop and discuss each of these steps in detail. Margins are now a function of risk tolerance and are measured relative to mean expected system performance, not variations in design parameters measured relative to heuristic values or worst-case estimates. The proposed method is applied in its entirety to a single example application, a spacecraft attitude determination and control system, in Chapter 9. Finally, Chapter 10 summarizes concerns about the proposed method, thoughts on how this method can transform the process of preliminary design, and provides recommendations for future research direction.

In addition to providing a formal and rigorous method for determining design margins, this thesis provides three other contributions. The first is an uncertainty taxonomy for use in the design of complex multidisciplinary systems with detailed definitions for each uncertainty type. This is provided in Chapter 2. The second is the modification of two simulation techniques, the mean value method and subset simulation, that can significantly reduce the computational burden in applying the proposed method. These modifications are discussed in Chapter 7. The third is a set of diverse application examples and various simulation techniques that demonstrate the generality and benefit of the proposed method. These example applications are provided in Chapter 9 and Appendix B. Elaborations and explanations of the major mathematical techniques used are deferred to Appendix A. Appendix C provides a recommended implementation strategy for applying this method in an organization. References and an index are found at the end of this thesis.

Chapter 2 Uncertainty Classifications and Types

Uncertainty plays a critical role in analysis for a wide and diverse set of fields from economics to engineering. Ideas and concepts of uncertainty have long been associated with gambling and games. The earliest-known form of gambling was a kind of dice game played with an astragalus (knuckle-bone) in 3500 BC Egypt [Bernstein, 1998]. Gambling has developed considerably in the centuries that followed but the underlying form of this type of uncertainty is unchanged. Pure games of chance, such as the astragalus, roulette, or craps, deal with aleatory uncertainty, essentially inherent randomness. These games are distinct from games such as poker or horse racing in which skill or knowledge makes a difference. Formally addressing this type of uncertainty in games of chance began in the Renaissance and culminated in the theory of probability during the 17th century [Hacking, 1984].

The Greeks of the 4th century BC were the first recorded civilization to have considered uncertainty explicitly, primarily in the context of epistemology. The word epistemology is derived from the Greek episteme, meaning "knowledge," and logos, which has several meanings, including "theory." Epistemology deals with the possibilities and limits of human knowledge. Basically it tries to arrive at a knowledge of knowledge itself. Aristotle suggested that people should make decisions on the basis of "desire and reasoning to some end" but offered no guidance to the likelihood of a successful outcome. Despite their explicit consideration of uncertainty, when the Greeks wanted a prediction of what the future might hold they turned to the oracles instead of consulting their wisest philosophers [Bernstein, 1998].

Bernstein (1998) and Hacking (1984) provide an extensive history of uncertainty in the context of risk management and probability theory, respectively. Ideas about aleatory and epistemic uncertainty have developed significantly since the early Egyptians and Greeks but the distinction has persisted almost unchanged until the 20th century and only recently has the impact of uncertainty been analyzed and understood. Uncertainty influences decisions, designs, and behavior in a wide variety of fields from economics to engineering. Reducing uncertainty has been and continues to be a costly business in time and resources. Efforts to classify and define uncertainty, propagate it through an analysis, and devise methods to mitigate its impact have been the objective of research efforts.

This chapter first summarizes uncertainty taxonomies and definitions in the fields of social sciences, physical sciences, and engineering. A new classification for uncertainty in the design of complex multidisciplinary systems follows. The classification delineates ambiguity, epistemic, aleatory, and interaction uncertainty. Epistemic uncertainty is further subdivided into model-form, phenomenological, and behavioral uncertainty. Each of these uncertainties is described in detail. The chapter ends with a summary.

2.1 Uncertainty and Its Classification in Other Fields

The term 'uncertainty' has come to encompass a multiplicity of concepts. A fundamental definition of uncertainty is "liability to chance or accident," "doubtfulness or vagueness," "want of assurance or confidence; hesitation, irresolution," and "something not definitely known or knowable" [Murray, 1961]. This definition has motivated a wide variety of classifications of uncertainty in a variegated set of fields. Many of the uncertainty classifications that follow have similarities and most have an emphasis on one aspect of uncertainty which most impacts that particular field. Hence, these classifications are often more of a practical than theoretical significance. Unfortunately, many of these taxonomies have different definitions for the same words. The following section describes classifications and definitions for uncertainty in the fields of social sciences, physical sciences, and engineering that were most influential in the development of the classification introduced in the second half of this thesis chapter. Fields that were less influential in the development of the classification are summarized in Thunnissen (2003). It should be noted that the classifications and definitions provided are not exhaustive nor universally agreed upon but are representative of the general areas for each field.

2.1.1 Social Sciences

Research into uncertainty in the field of social sciences has a rich history. The following section summarizes this research in economics and the field of policy and risk analysis. The field of decision making, management, and system analysis is provided in Thunnissen (2003).

2.1.1.1 <u>Economics</u>

Classical economic theory had no room for uncertainty. The theory assumed that people decide how to consume, produce, and invest with full knowledge of what the outcome of their decisions will be. Uncertainty was either ignored or explicitly "assumed away." The resulting theory was neither realistic nor useful [Borch, 1968]. To develop a realistic theory, economists began studying uncertainty extensively starting in the early 20th century. The American economist Frank Knight wrote in 1921, "Uncertainty must be taken in a sense radically distinct from the familiar notion of Risk, from which it has never been properly separated" [Knight, 1921]. Knight refers to "risk" as situations where the decision-maker can assign mathematical probabilities to the randomness with which he is faced. In contrast, "uncertainty" refers to situations when this randomness "cannot" be expressed in terms of specific mathematical probabilities. As the English economist, journalist, and financier John Maynard Keynes was later to express it:

> By 'uncertain' knowledge, let me explain, I do not mean merely to distinguish what is known for certain from what is only probable. The game of roulette is not subject, in this sense, to uncertainty ... The sense in which I am using the term is that in which the prospect of a European war is uncertain, or the price of copper and the rate of interest twenty years hence ... About these matters there is no scientific basis on which to form any calculable probability whatever. We simply do not know. [Keynes, 1937]

A distinction in this classification arrived in the mid-20th century, influenced by pioneering work in the creation and development of game theory by von Neumann and Morgenstern; Nash; and others [von Neumann & Morgenstern, 1953; Nash, 1951]. Uncertainty and information about the environment was viewed as distinct from that of uncertainty and information about others' behavior or the outcome of as yet unperformed computations [Radner, 1968]. Building on the mid-20th century work, economists have recently gone a step further arguing that Knightian risk and uncertainty are one and the same thing. In Knightian uncertainty the problem is not that the agent cannot assign probabilities but in fact that the agent does not assign probabilities. That is to say, that uncertainty is really an epistemological and not an ontological problem, a problem of "knowledge" of the relevant probabilities and not of their "existence." Uncertainty has recently been classified as fundamental uncertainty or ambiguity. Fundamental uncertainty is not merely that there is not enough information to reliably attach probabilities to a given number of events but that in fact, an event which cannot be imagined may occur in the future. This implies that some relevant information cannot be known, not even in principle, and that something unimaginable may happen [Dequech, 2000]. Ambiguity is defined as "uncertainty about probability, created by missing information that is relevant and could be known" [Camerer & Weber, 1992]. It should be noted that some economists argue in the opposite direction: that there are actually no probabilities out there to be "known" because probabilities are really only "beliefs." In other words, probabilities are merely subjectively-assigned expressions of beliefs and have no necessary connection to the true randomness of the world (if it is random at all) [Fonseca & Ussher, 2004]. The evolution in economic uncertainty belief is illustrated in Fig. 2.1.

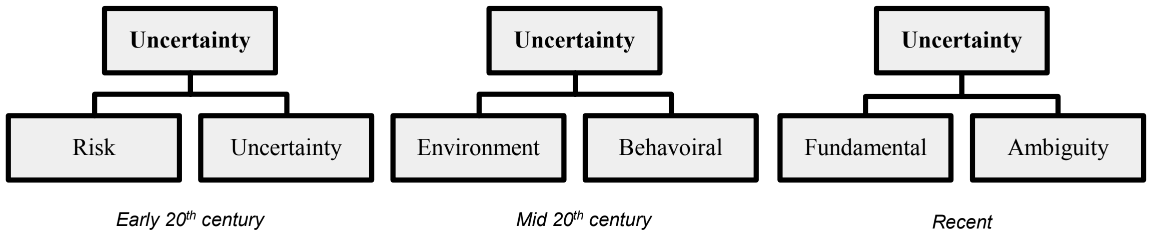

Fig. 2.1 Uncertainty classifications in economics.

2.1.1.2 Policy and Risk Analysis

The policy and risk analysis community has classified uncertainty into quantity and model form uncertainty [Morgan & Henrion, 1990]. Fig. 2.2 illustrates this classification.

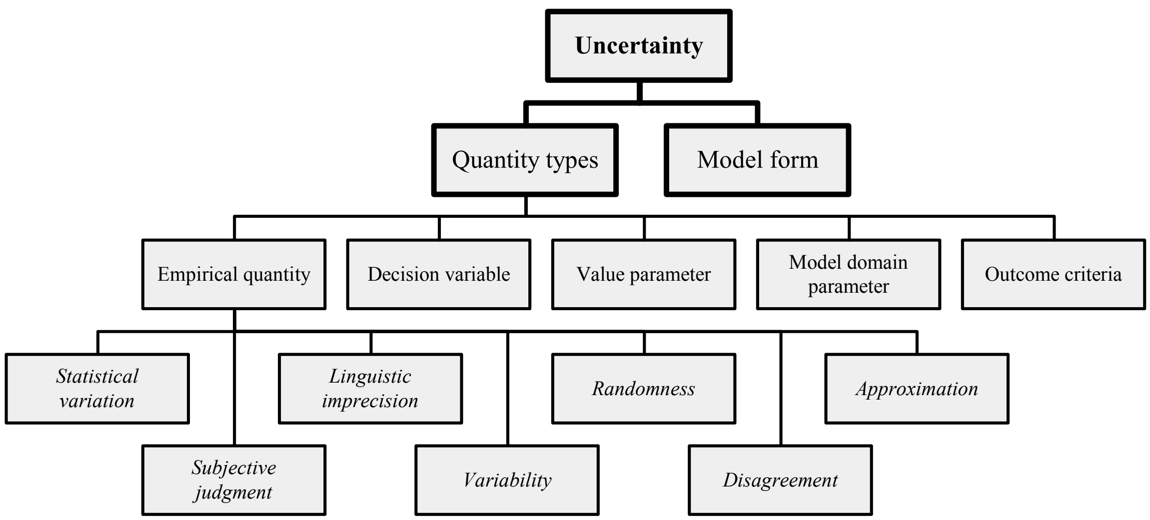

Fig. 2.2 Uncertainty classification in policy & risk analysis [Morgan & Henrion, 1990].

Quantity type uncertainty is defined in Table 2.1.

Table 2.1 Quantity type uncertainty definitions in policy & risk analysis [Morgan & Henrion, 1990]

Uncertainty	Subclassification	Definition/Explanation
Empirical quantity	Statistical variation	arises from random error in direct measurements of a quantity
	Subjective judgment	teamed with systematic error as the difference between the true value of a quantity of interest and the value to which the mean of the measurements converges as more measurements are taken
	Linguistic imprecision	refers to quantities that are not well-specified and could not be empirically measured in principle
	Variability	refers to quantities that are variable over time and space
	Randomness	uncertainty that is irreducible even in principle
	Disagreement	refers to differences of opinion between informed experts about a quantity
	Approximation	difference between the assumed quantity value and the real-world value
Decision variable	n/a	quantity over which the decision maker exercises direct control
Value	n/a	parameter that represents aspects of the preferences of the decision

Uncertainty	Subclassification	Definition/Explanation
parameter		maker or the people they represent
Model domain parameter	n/a	specifies the domain or scope of the system being modeled
Outcome criteria	n/a	variable used to rank or measure the desirability of possible outcomes

Model form uncertainty refers to the approximations that a model provides to a real-world system. Model form uncertainty is differentiated here from (quantity type) model domain parameter uncertainty by referring to the actual model itself as opposed to the quantities assumed in the model. Any model is unavoidably (and by definition) a simplification of reality. A real-world system contains phenomena or behaviors that cannot be produced by even the most detailed model. The difference between the real-world system and such a model is “model form uncertainty.”

2.1.2 Physical Sciences

Uncertainty in the physical sciences has primarily concentrated on error analysis and quantum physics. Error analysis uncertainty often goes by the name measurement uncertainty and represents the difference between a measured value and the actual value. This uncertainty impacts a wide range of fields in the physical sciences and engineering. Much has been made of Werner Heisenberg’s uncertainty principle that was first proposed in 1927. Heisenberg introduced the notion that it is impossible to determine simultaneously with unlimited precision the position and movement of a particle. Heisenberg was careful to point out that the inescapable uncertainties in momentum and position do not arise from imperfections in practical measuring instruments but rather from the quantum structure of matter itself [Serway, 1989]. This uncertainty in quantum physics is analogous to the inherent randomness in policy and risk analysis described by Morgan and Henrion (1990). It has been argued that this indeterminacy is not a matter of principle but simply a result of the limited (current human) understanding of the world (an epistemological issue). There may be hidden variables and causal mechanisms that, if discovered and understood, would resolve the apparent inherent randomness. This difference of opinion is similar to the notion of risk and uncertainty discussed in the fields of economics and decision making.

2.1.3 Engineering

Research into uncertainty in the field of engineering has been significant, particularly in the last two decades. This section briefly summarizes uncertainty research that has been completed in the engineering fields of civil, structural, and environmental; computational methods and simulation; mechanical; and aerospace. Uncertainty research in the fields of control and dynamical systems and management science are described in Thunnissen (2003).

2.1.3.1 Systems Engineering

System engineering provides two distinct definitions/classifications for uncertainty: one that is rigorous and somewhat theoretical, the other which is more relaxed and practical. The rigorous definition classifies uncertainty as either vagueness or ambiguity. Vagueness is associated with the difficulty of making sharp or precise distinctions in the world; that is, some domain of interest is vague if it cannot be delimited by sharp boundaries. Ambiguity is associated with one-to-many relations, that is, situations in which the choice between two or more alternatives is left unspecified. Ambiguity is further separated into nonspecificity of evidence, dissonance in evidence, and confusion in evidence [Klir & Folger, 1988].

The practical definition characterizes uncertainty by a distribution of outcomes with various likelihoods of both occurrence and severity. It intertwines the definition with that of risk. Risk is defined as a measure of the uncertainty of attaining a goal, objective, or requirement pertaining to technical performance, cost, and schedule. Risk level is categorized by the probability of occurrence and the consequences of occurrence. Risk is classified into technical (e.g., feasibility, operability, producibility, testability, and systems effectiveness), cost (e.g., estimates, goals), schedule (e.g., technology/material availability, technical achievements, milestones), and programmatic (e.g., resources, contractual) [*INCOSE Systems Engineering Handbook*, 2000]. This classification is similar to the management classification of Browning (1998). The two distinct classifications are provided in Fig. 2.3.

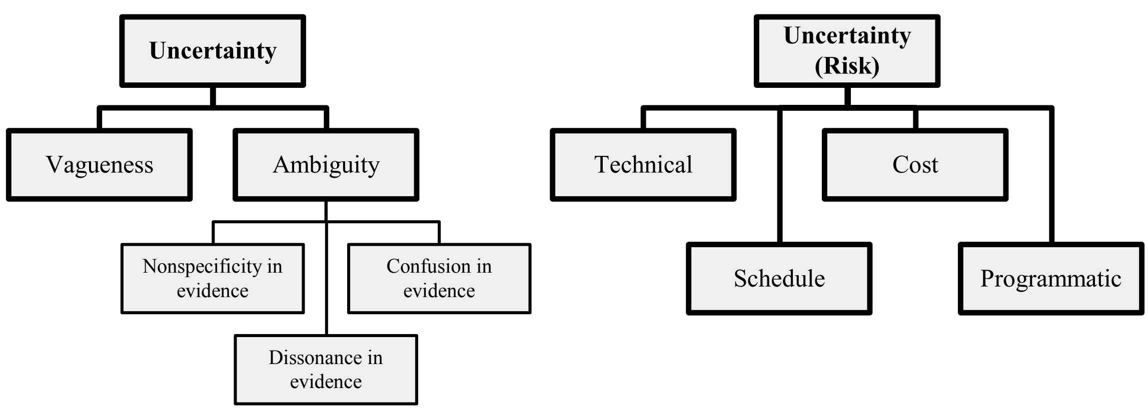

Fig. 2.3 Uncertainty classification in systems engineering [Klir & Folger, 1988; *INCOSE Systems Engineering Handbook*, 2000].

2.1.3.2 Civil, Structural, and Environmental

Although the fields of civil, structural, and environmental engineering are often grouped together, the classifications for uncertainty that each assume is different. The leading classification of uncertainty for civil engineering is provided in Fig. 2.4 [Ayyub & Chao, 1998].

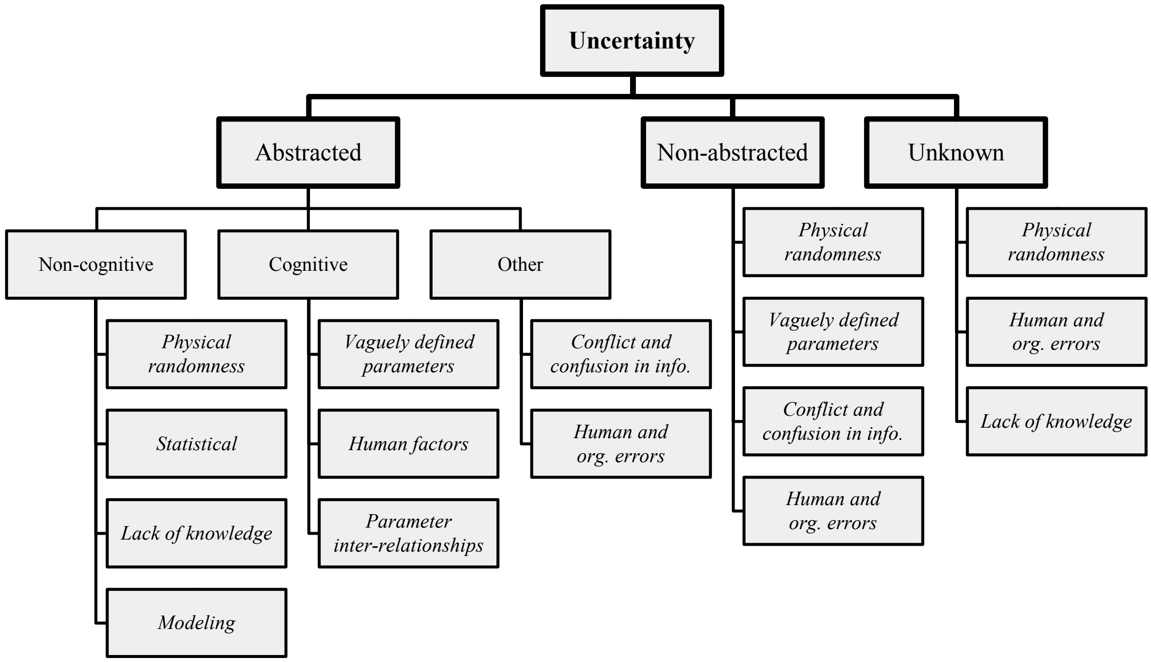

Fig. 2.4 Uncertainty classification in civil engineering [Ayyub & Chao, 1998].

Ayyub and Chao (1998) specialize the rigorous uncertainty classification provided by Klir and Folger (1988) in systems engineering to civil engineering. Abstracted uncertainties arise from elements of a real system that are represented by a model. Unknown uncertainties are due to the nature, sources, contents, and impact on the system that are not known. Cognitive uncertainties arise from mind-based (subjective) abstractions of reality. Uncertainties that are neither non-cognitive nor cognitive are called 'other uncertainties' and include conflict in information as well as human and organizational errors. Ayyub and Chao (1998) state that the division between abstracted and non-abstracted aspects may not be rigid but in fact a convenience that is driven by objectives of the system modeling.

Structural engineering follows a somewhat analogous classification [Melchers, 1999]. The classification and definitions of for structural engineering are provided in Fig. 2.5 and Table **2.2**, respectively.

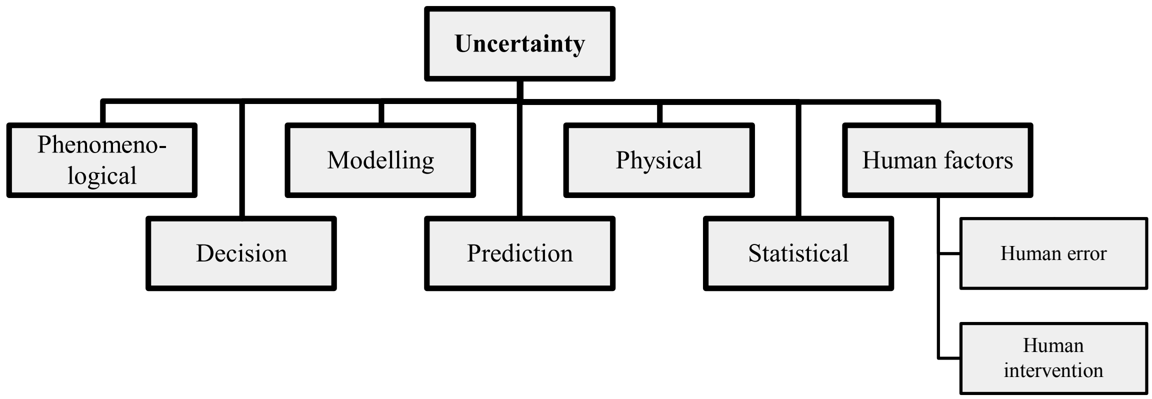

Fig. 2.5 Uncertainty classification in structural engineering [Melchers, 1999].

Table 2.2 Uncertainty definitions in structural engineering [Melchers, 1999]

Uncertainty	Definition/Explanation
Phenomenological	arises whenever the form of construction or the design technique generates uncertainty about any aspect of the possible behavior of the structure under construction, service, and extreme conditions
Decision	arises in connection with the decision as to whether a particular phenomena has occurred
Modelling	associated with the use of one (or more) simplified relationships between the basic variables to represent the 'real' relationship or phenomenon of interest
Prediction	associated with the prediction of some future state of affairs
Physical	inherent random nature of a basic variable
Statistical	arises in the associated parameters when a simplified probability density function is implemented
Human factors	
Human error	due to natural variation in task performance and gross errors
Human intervention	associated with the intervention in the process of design, documentation, and construction and, to some extent, also in the use of a structure

Melchers (1999) stresses the importance of uncertainty in human factors: the uncertainties resulting from human involvement in the design, construction, use, etc., of structures. Environmental engineering (e.g., [Frey, 1998]) follows closely the policy and risk analysis classification and definitions provided by Morgan and Henrion (1990) that was introduced earlier.

2.1.3.3 Computational Modeling & Simulation

One of the more extensive efforts to classify and define uncertainty has been done by the computational modeling and simulation community. Oberkampf et al. (1999) are clear to distinguish variability, uncertainty, and error as shown in Fig. 2.6.

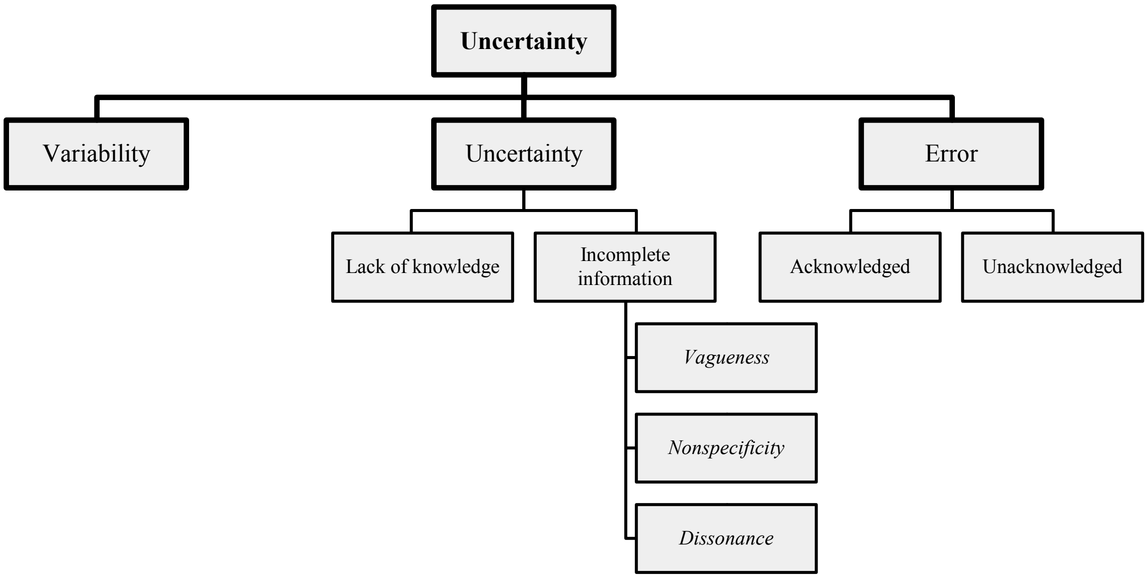

Fig. 2.6 Uncertainty classification in computational modeling & simulation [Oberkampf et al., 1999].

Variability is defined as the inherent variation associated with the physical system or the environment under consideration. Uncertainty is defined as a potential deficiency in any phase or activity of the modeling process due to a lack of knowledge or incomplete information. Sources of incomplete information are summarized in Table 2.3 and follow closely the rigorous systems engineering definitions provided by Klir and Folger (1988).

Table 2.3 Incomplete information definitions in computational modeling & simulation

Type	Definition
Vagueness	Characterizes information that is imprecisely defined, unclear, or indistinct (characteristic of communication by language)
Nonspecificity	Refers to the variety of alternatives in a given situation that are all possible, i.e., not specified
Dissonance	Refers to the existence of totally or partially conflicting evidence

Error is defined as a recognizable deficiency in any phase or activity of the modeling and simulation that is not due to a lack of knowledge. Error is further subclassified into acknowledged error (such as finite precision arithmetic on a computer or approximations made to simplify the modeling of a physical process) and unacknowledged error (such as blunders and mistakes). The classification of uncertainty in Oberkampf et al. (1999) is based on the mathematical type and information content of the uncertain quantity. A different perspective of uncertainty by the same group of researchers has also been formulated. It is based on how uncertainty appears in the mathematical model, that is to say, it is a parametric or model-form uncertainty [Oberkampf, Helton, & Sentz, 2001]. This classification and definitions for uncertainty is provided in Fig. 2.7 and Table 2.4, respectively.

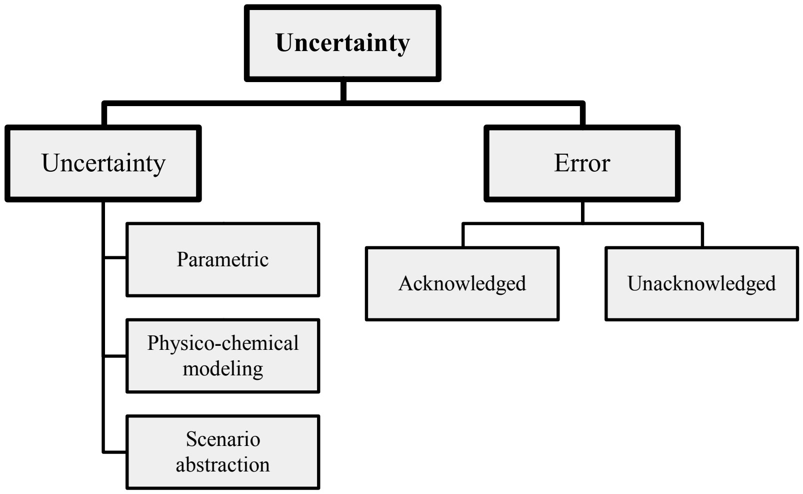

Fig. 2.7 Uncertainty classification in computational modeling & simulation (mathematical model) [Oberkampf, Helton, & Sentz, 2001].

Table 2.4 Uncertainty definitions in computational modeling & simulation (mathematical model) [Oberkampf, Helton, & Sentz, 2001]

Uncertainty	Definition
Parametric	Uncertainty in the occurrence in parameters contained in the mathematical models of a system and its environment
Physico-chemical modeling	Limited knowledge or understanding of a physical process or interactions of processes in a system
Scenario abstraction	Limited knowledge for the estimation of likelihood of event scenarios of a system

Error definitions in Fig. 2.7 remain unchanged from that of Oberkampf et al. (1999). Oberkampf et al. (1999) and Oberkampf, Helton, and Sentz (2001) provide two different perspectives of uncertainty. A difference classification in the same field is presented in Fig. 2.8 [Du & Chen, 2000].

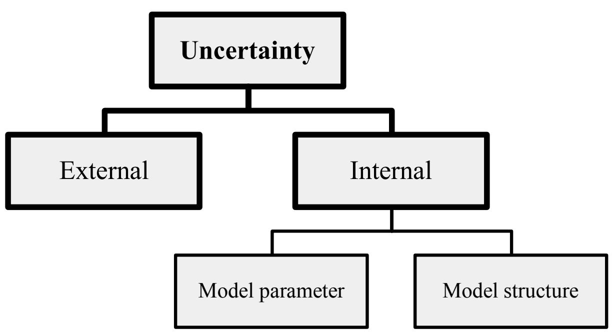

Fig. 2.8 Alternate uncertainty classification in computational modeling & simulation [Du & Chen, 2000].

External uncertainty is variability in model prediction arising from plausible alternatives for input values (also known as input parameter uncertainty). Internal uncertainty arises from two sources. One is due to both limited information in estimating the characteristics of model parameters for a given fixed model structure (model parameter uncertainty). The other is the model structure itself, including uncertainty in the validity of the assumptions underlying the model.

2.1.3.4 Mechanical

Over a decade of research into uncertainty occurred in the field of mechanical engineering beginning in the late 1980s. Antonsson and Otto (1995); Otto and Antonsson (1994); Otto and Antonsson (1993) combine to define uncertainty as imprecision (design imprecision), probabilistic uncertainty (noise, stochastic uncertainty), and possibility. Imprecision is the representation of an incomplete design description. That is to say, ranges of possibilities resulting from choices not yet made (uncertainty in choice). Probabilistic uncertainty is a random (stochastic) uncertainty. Possibility is the uncertainty in the limits in capacity within a formal model (uncertainty due to freedom). Fig. 2.9 summarizes this classification for mechanical engineering.

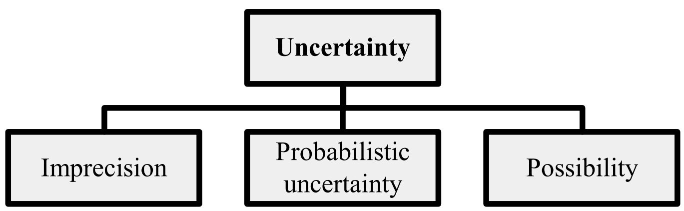

Fig. 2.9 Uncertainty classification in mechanical engineering [Otto & Antonsson, 1993].

2.1.3.5 Aerospace

Only recently has an effort been made of classifying and defining uncertainty in aerospace engineering. DeLaurentis and Mavris (2000) define uncertainty as "the incompleteness in knowledge (either in information or context), that causes model-based predictions to differ from reality in a manner described by some distribution function." Using an analogy to a control system problem, uncertainty for aerospace vehicle synthesis and design is classified into input, model parameter, measurement, and operational/environmental. This classification is illustrated in Fig. 2.10.

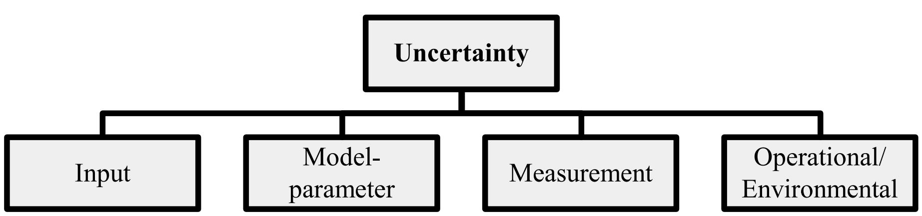

Fig. 2.10 Uncertainty classification in aerospace vehicle synthesis and design [DeLaurentis & Mavris, 2000].

Input uncertainty arises when the requirements that define a design problem are imprecise, ambiguous, or not defined. Model parameter uncertainty refers to error present in all mathematical models that attempt to represent a physical system. Measurement uncertainty is present when the response of interest is not directly computable from the mathematical model. Finally, operational/environmental uncertainty is due to unknown/uncontrollable external disturbances. This classification is redefined somewhat for the specific field of aircraft system design where uncertainty is now delineated into operational/environmental, system-level, and discipline-level uncertainty [DeLaurentis, 1998]. This classification is presented in Fig. 2.11.

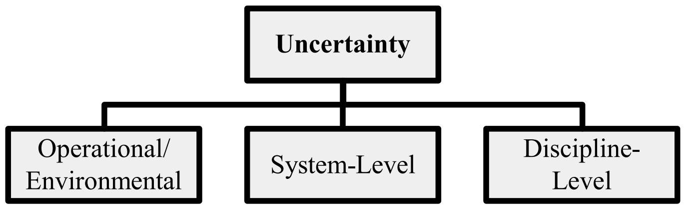

Fig. 2.11 Uncertainty classification in aircraft systems design [DeLaurentis, 1998].

Operational/environmental uncertainty is concerned with modeling how a vehicle or fleet of vehicles will be utilized over its useful life. System-level uncertainty is concerned with the requirements, synthesis, and predicted performance of a vehicle. Finally, discipline-level uncertainty is concerned with the various contributing analyses that are required to synthesize vehicle alternatives.

Uncertainty research in space system design is even more recent. Walton (2002) defines uncertainty as "inability to quantify precisely; a distribution that reflects potential outcome." Uncertainty is classified into development, operational, and model. Fig. 2.12 illustrates this classification and Table 2.5 defines these uncertainties.

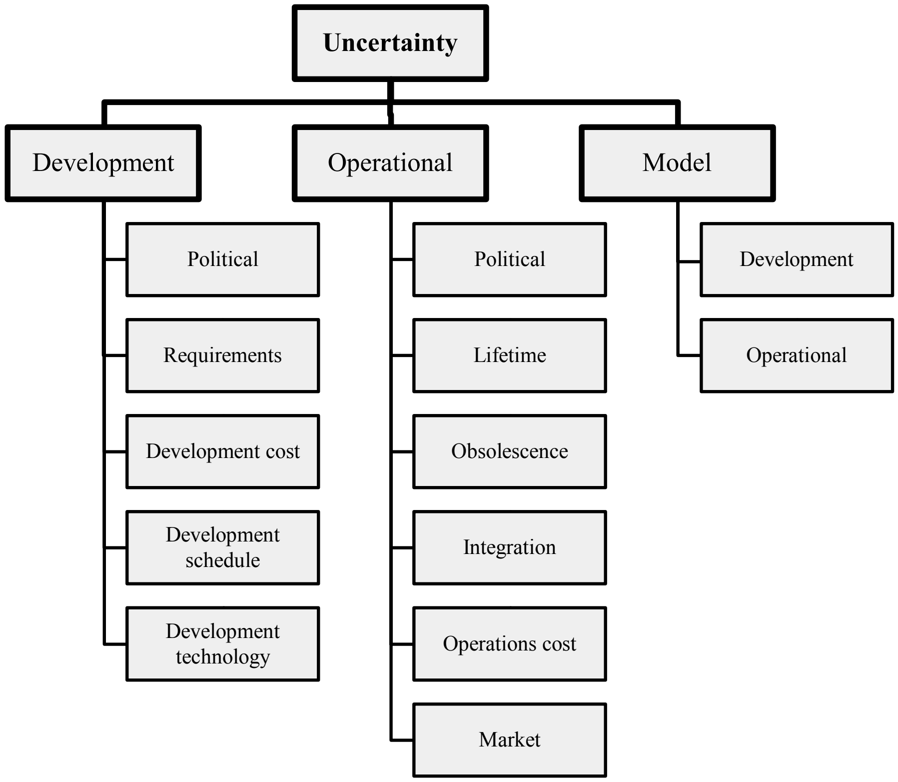

Fig. 2.12 Uncertainty classification in space architectures [Walton, 2002].

Table 2.5 Uncertainty definitions in space architectures [Walton, 2002]

Uncertainty	Subclassification	Uncertainty of …
Development	Political	development funding instability
	Requirements	requirements stability
	Cost	developing within a given budget
	Schedule	developing within a given schedule profile
	Technology	technology to provide performance benefits
Operational	Political	operational funding instability
	Lifetime	performing to requirements in a given lifetime
	Obsolescence	performing to evolving expectation in a given lifetime
	Integration	operating within other necessary systems
	Cost	meeting operations cost targets
	Market	meeting demands of an unknown market
Model	n/a	*no formal definition*

This classification and associated definitions appears to build on the management classification provided by Browning (1998). Walton (2002) does not provide significant details on uncertainty types beyond these definitions.

2.2 Uncertainty Types

The various classifications described provide both common and distinct classifications and definitions for uncertainty. Unfortunately, none of the previous classifications seem applicable exactly to the design of complex multidisciplinary systems. Although the classifications provided in the computational modeling and aerospace engineering fields are thorough (e.g., [Oberkampf et al., 1999; Oberkampf, Helton, & Sentz, 2001; DeLaurentis & Mavris, 2000; Walton, 2002]) they still lack important uncertainty types. The definition and classifications of uncertainty from the various fields provided in the first half of the chapter motivate a new classification for the design of complex systems: ambiguity, epistemic, aleatory, and interaction. This new classification is provided in Fig. 2.13.

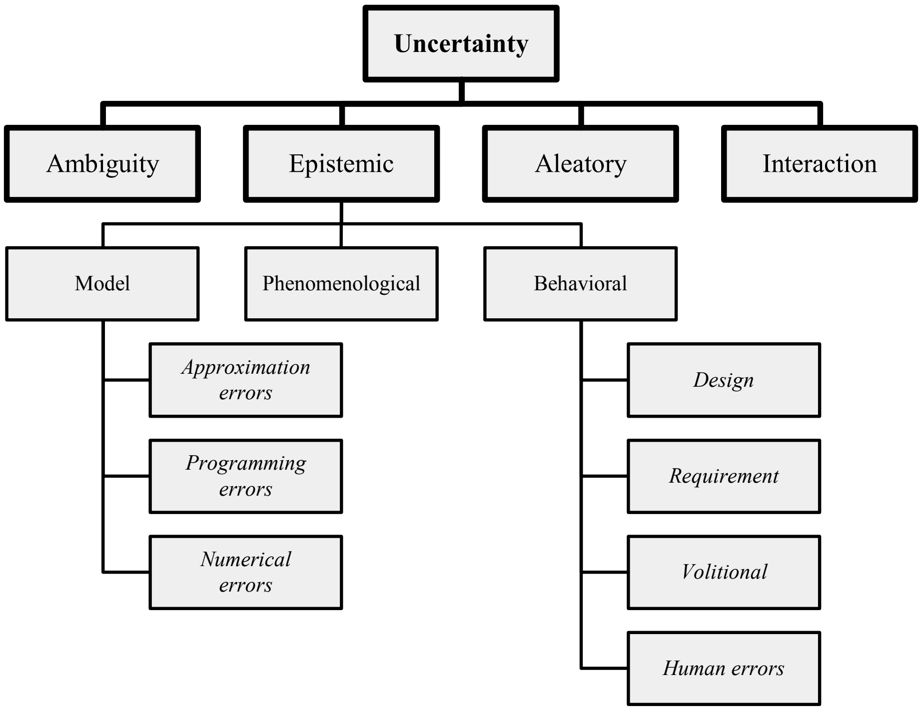

Fig. 2.13 Uncertainty classification for the design of complex systems.

This classification stresses that uncertainty is a condition of not knowing. This thesis formally defines uncertainty as the difference between an anticipated or predicted value (behavior) and a future actual value (behavior). A definition for each type of uncertainty follows. Although some of the definitions were provided earlier for a given field, these definitions are repeated in full in this section for clarity.

2.2.1 Epistemic

Epistemic uncertainty is any lack of knowledge or information in any phase or activity of the modeling process. The key feature that this definition stresses is that the fundamental cause is incomplete information or incomplete knowledge of some characteristic of the system or the environment. Epistemic uncertainty also goes by the names: reducible uncertainty, subjective uncertainty, model form uncertainty, state of knowledge, type B uncertainty, and *de dicto*

[Oberkampf, Helton, & Sentz, 2001; Bedford & Cooke, 2001; Hacking, 1984]. Epistemic uncertainty can be further classified into model, phenomenological, and behavioral uncertainty.

2.2.1.1 Model

Model uncertainty is the accuracy of a mathematical model to describe an actual physical system of interest. Model uncertainty, also known as model-form, structural, or prediction-error uncertainty, is a form of epistemic uncertainty. That is to say, model uncertainty is often due to a lack of knowledge. Model uncertainty is associated with the use of one or more simplified relationships between the basic variables used in representing the 'real' relationship or phenomenon of interest [Melchers, 1999]. All models are unavoidably simplifications of the reality which leads to a disturbing conclusion: every model is false, at least in part. However, some models are better than others. Model uncertainty arises from approximation, numerical, and programming errors.

2.2.1.1.1 Approximation Errors

For physical processes that are relatively well understood, deficiencies in certain models are often called approximation errors rather than model uncertainty. For example, in the modeling of the specific volume of a gas, four models can be ordered in terms of increasing accuracy (decreasing model uncertainty) as follows: ideal-gas law, van der Waals equation, Beattie-Bridgeman equation, and Benedict-Webb-Rubin (BWR) equation. The ideal gas law neglects intermolecular forces between molecules and uses only one constant. The van der Waals equation uses two constants to allow for interaction and volume effects. The Beattie-Bridgeman equation uses five constants and is accurate over a much larger range. The BWR equation uses eight constants and is even more versatile. In general, this ordering is appropriate, but for individual gases there is no guarantee that any one model will be more accurate than any other because even the ideal gas law can be accurate for specific conditions such as low pressures and high temperatures.

2.2.1.1.2 Numerical and Programming Errors

Model uncertainty also includes numerical and programming error. Numerical error can arise due to finite precision arithmetic while programming error occurs during development of the model due to mistakes or blunders by the programmer.

2.2.1.2 Phenomenological

Phenomenological uncertainty follows the definition of fundamental uncertainty provided earlier in the chapter for the field of economics. Phenomenological uncertainty arises whenever the design technique or form of development generates uncertainty about any aspect of the possible behavior of the system under development, operation, and extreme conditions. Some relevant information cannot be known, not even principle, at the time of making decisions during design. Phenomenological uncertainty is particularly important for novel projects or those which attempt to extend the 'state of the art.' Often these projects fail due to an apparently 'unimaginable' phenomenon (so called "unknown unknowns").

2.2.1.3 Behavioral

Behavioral uncertainty is uncertainty in how individuals or organizations act. Behavioral uncertainty arises from four sources: design uncertainty, requirement uncertainty, volitional uncertainty, and human errors.

2.2.1.3.1 Design

A design uncertainty is a choice among alternatives over which an individual or individuals exercises direct control over but has not yet decided upon. An example is the choice an engineer has in selecting a given component among a set of possible components. Design uncertainty is eliminated when a system is complete as all choices have been implemented.

2.2.1.3.2 Requirement

Requirement uncertainty includes parameters of interest to and determined by the stake holder, independent of the engineer or designer. An example may be the orbit of a satellite that is explicitly specified by the customer. The question of whether an uncertain variable is a design or requirement depends on the context and intent of the model it is being used in and who the decision maker is. For example, a spacecraft may have requirements specified by the stake holder on the orbit to achieve but leave the orbit insertion design to the mission designer making the change in velocity of the spacecraft a design variable. The change in velocity of the spacecraft, however, would likely place a requirement on the propulsion system.

2.2.1.3.3 Volitional

Volitional uncertainty is uncertainty about what the subject him/herself will decide [Bedford & Cooke, 2001]. Other people's future actions and conduct are not entirely predictable, particularly in dealing with other organizations. As was mentioned in Chapter 1, multiple organizations are often required to design and develop complex multidisciplinary systems. The lead organization hires contractors and/or consultants to help in development. These contractors and consultants may provide full assemblies, components, analysis, and/or labor. Estimates for products and resources provided by the contractors/consultants are often underestimated (sometimes deliberately) to the lead organization and result in potentially significant engineering and management problems. Although an individual or organization cannot quantify their own volitional uncertainty, one individual or organization could do it for another.

2.2.1.3.4 Human Errors

Human errors occur during development of a system or project due to blunders or mistakes by an individual or individuals.

2.2.2 Aleatory

Aleatory uncertainty is inherent variation associated with a physical system or environment under consideration. Aleatory uncertainty goes by many names: variability, irreducible uncertainty, inherent uncertainty, stochastic uncertainty, intrinsic uncertainty, underlying uncertainty, physical uncertainty, probabilistic uncertainty, noise, risk, type A uncertainty, uncontrolled variations, and *de re* [Oberkampf, Helton, & Sentz, 2001; Otto & Antonsson, 1994; Bedford & Cooke, 2001; Luce & Raiffa, 1957; Hacking, 1984] Aleatory uncertainties can typically be singled out from other uncertainties by their representation as distributed quantities that can take on values in an established or known range, but for which the exact value will vary by chance from unit to unit or time to time. The mathematical representation most commonly used for aleatory uncertainty is a probability distribution [Oberkampf et al., 1999].

As discussed in the first half of this chapter, there is much disagreement about the distinction between aleatory and epistemic uncertainty. It has been argued that all uncertainty is epistemic: that aleatory uncertainties, represented by distributions, are used purely because of our lack of knowledge or understanding of a fundamental underlying process or because we choose not to learn about that underlying process. As an example, consider the tossing of a fair coin. This activity is represented by the discrete binomial (Bernoulli) distribution: either it lands heads (1, true, yes, etc.) or tails (0, false, no, etc.). However, flipping a coin is not truly a random activity. In theory, a sophisticated model based on which side of the coin is initially facing up, the strength and angle of the coin flip, the wind resistance, gravity, and so on could be created to accurately determine whether the coin lands heads or tails. Although this sophisticated model would likely be influenced by minute differences in initial conditions, the remaining uncertainty in the coin flip would now be epistemic. Likewise, a quantity may legitimately be random to one person, but deterministic to another who knows and understands the underlying model or process. For example, a random number generated by a computer does indeed appear random to the vast majority of people but completely predictable to those who know the algorithm being used to generate the value. Depending on the model being used and the criticality of the variable, it may not be worth developing sophisticated models such as the coin-flip model described and instead represent that variable as an aleatory uncertainty with a specified probability distribution.

2.2.3 Ambiguity

Because little precision is required for general communication, individuals often fall into the habit of using imprecise terms and expressions. When used with others who are not familiar with the intended meanings or in a setting where exactitude is important, this imprecision may result in ambiguity. Ambiguity has also been called imprecision, design imprecision, linguistic imprecision, and vagueness [Antonsson & Otto, 1995; Morgan & Henrion, 1990; Klir & Folger, 1988]. Although it can be reduced by linguistic conventions and careful definitions, ambiguity remains an unavoidable aspect of human discourse. Ambiguity in a quantity or parameter is characterized by an inability to empirically measure it. A clarity test has been proposed as a conceptual way to sharpen up the notion of well-specifiedness [Howard & Matheson, 1984]. Imagine a clairvoyant who could know all facts about the universe, past, present, and future. Given the description of the event or quantity, could the clairvoyant say unambiguously whether the event will occur (or had occurred)? Could the clairvoyant give the exact numerical value of the quantity? If so, the description of the event or quantity is well-specified. A statement such as the "rocket engine is heavy" would not pass the clarity test. However, "the Aerojet model #MR-111C weighs 331.1 grams" would pass the clarity test. There is some debate as to whether ambiguity is a form of uncertainty [Bedford & Cooke, 2001]. Although in theory it is possible to reduce any given ambiguity to any desired level, this is often not done because of the effort required. Fuzzy logic has been used as a formal method to represent ambiguity [Zadeh, 1984].

2.2.4 Interaction

Interaction uncertainty arises from unanticipated interaction of many events and/or disciplines, each of which might, in principle, be or should have been foreseeable. Interaction uncertainty can also arise due to disagreement between informed experts about a given uncertainty (such as a design or requirement) when only subjective estimates are possible or when new data are discovered that can update previous estimates. Interaction uncertainty is significant in complex multidisciplinary systems such as spacecraft which may have many subsystems, variables, and experts involved in the design.

2.3 Summary

This chapter summarizes efforts to classify and define uncertainty in a wide variety of fields. In particular, the efforts in the fields of social sciences, physical sciences, and engineering heavily influenced the classification and definition of uncertainty for complex multidisciplinary systems that is introduced. This classification separates uncertainty into four types: epistemic, aleatory, ambiguity, and interaction. Epistemic uncertainty is further broken out into model, phenomenological, and behavioral uncertainty. The next chapter begins by summarizing efforts by various researchers to address uncertainty, in particular efforts that significantly influenced the development of the method proposed in this thesis.

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Chapter 3 Method Development and Overview

The previous chapter defined and classified uncertainty in the fields of social sciences, physical sciences, and engineering. Many researchers in these fields went on to develop methods of varying formality to address these different uncertainty types. This chapter summarizes these research efforts in the fields that most influenced the method proposed in this thesis. A summary of the five steps that comprise the proposed method follow. Each of these steps is described in detail in chapters that follow. The qualitative benefits of the proposed method are then summarized. The key quantitative results of the method when applied to an example application are then provided.

3.1 Previous Work

Methods to classify and define uncertainty are discussed in the previous chapter and in Thunnissen (2003). The efforts of several of the researchers to develop methods to address uncertainty for a variety of applications are elaborated upon in this section. Although none of the research efforts described in this section investigated design margins in particular and many were at an abstract level for different applications, all dealt with one or more types of uncertainty that were discussed in Chapter 2 and all were influential in one or more ways in the direction of this research, development of the theory, and the creation of the method proposed in this thesis.

3.1.1 von Neumann and Morgenstern

von Neumann and Morgenstern (1953) provided the first formal definition of basic games and developed game theory for cooperative, two-person, zero-sum games (games in which there are only two players and the players have diametrically opposing interests). Game theory is a method for modeling the interactions between cooperating or competing individuals engaged in economic transactions. The name "game theory" is unfortunate, for it suggests that the theory deals with only the socially unimportant conflicts found in parlor games, whereas it is far more general. Nash (1951) extended game theory by developing the basic theory of competitive two-person games (games in which players do not cooperate or negotiate the outcome) and the two-player framework to model games with an arbitrarily large number of players. Game theory uses utility theory to represent player's values and it examines the "utilities" players would realize if they followed a certain course of action (called a "strategy" in game theory) and their opponents chose each of their other possible courses of action. Utility theory is based on seven axioms: ordering and transitivity; reduction of compound uncertain events; continuity; substitutability; monotonicity; invariance; and finiteness [Clemen, 1996]. Game theory assumes each player knows and can mathematically represent their beliefs by a "utility function." Each player's strategy in games attempts to maximize this utility function obeying the seven axioms listed. Three simple utility functions for different risk tolerances are shown in Fig. 3.1.

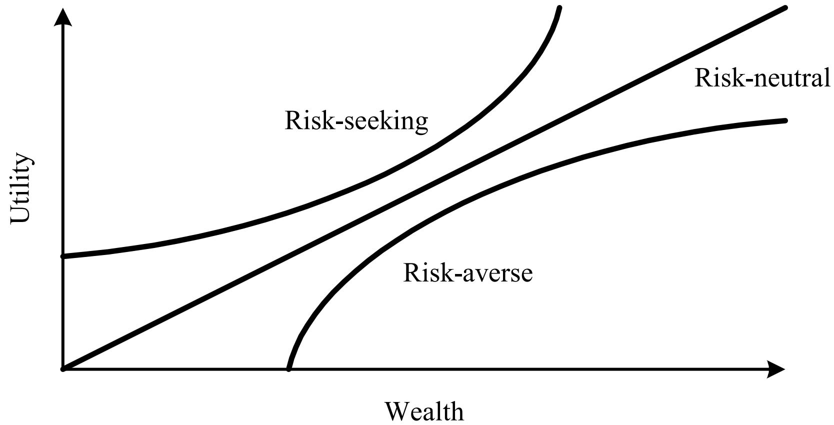

Fig. 3.1 Example utility functions.

The risk-neutral utility function implies that increased utility is linearly related to increased wealth. The risk-averse utility function implies that significant increases in wealth achieve only modest increases in utility. Conversely, the risk-seeking utility function implies that modest increases in wealth achieve significant increases in utility.

Another key aspect in game theory is the concept of information. Games of "complete information" assume each of the players knows the preference patterns (utility functions) of all the other players. Games of "incomplete information" assume not all the players know the utility functions of all of their opponents. Games of "perfect information" assume all the players know everything else that the other players know throughout the game while games of "imperfect information" allows a player to possess private information (i.e., they know things that the other players do not know). Engineering design is most closely modeled as a game of imperfect information because different individuals involved in the design know things which others do not [Guikema, 2003]. The individuals may be part of the same organization or different organizations. They may be willing to share this information or not. Asymmetric information is an important aspect in the design of space systems.

Unfortunately, although simple to implement in theory, both utility and game theory are difficult to implement in practice. Some of the axioms utility theory is based on, such as transitivity, appear to be violated in experiments and paradoxes [von Winterfeldt & Edwards, 1986]. Utility functions are rarely a function of one variable nor smooth as those shown in Fig. 3.1. They can also be constantly changing for individuals and organizations. Hence, utility functions are difficult to determine and generate, especially for others, and extremely difficult to represent and convey to others. Utility curves are in fact hypersurfaces, possibly with discontinuities, when they are functions of several variables. Utility theory also assumes one parameter can always be traded off for more or less of another parameter since everything reduces to equivalent utilities. This is not true in engineering design. Finally, utility functions are entirely individual and not comparable from person to person (or organization to organization). Although utility theory is implicit in all decision-making endeavors, using it explicitly in a practical yet nontrivial application, such as the design of space systems, without significant simplification is not possible.

3.1.2 Raiffa

Raiffa (1968) is generally credited with formalizing decision theory. Decision theory is the product of the joint efforts of economists, mathematicians, philosophers, social scientists, and statisticians toward making sense of how individuals and groups make decisions [Resnik, 1987]. "Decision theory" as Hacking (1984) describes it, "is the theory of deciding what to do when it is uncertain what will happen." Decision theory, like game theory, relies on utility theory and risk-tolerance behavior. Therefore, decision theory shares many of the same benefits and drawbacks as game theory in applying it to practical tasks. Nonetheless, the process and themes of decision theory are valid and applicable to decision-making in engineering design. Decision theory provides a systematic framework for choosing among alternative actions when consequences of these alternatives are uncertain. The decision theory process structures a problem and helps the decision maker understand the problem better, possibly leading to the recognition of new alternatives. The basic steps in a decision analysis process [Covello, 1987] are

1. Define decision objectives.
2. Identify decision alternatives and all consequences that relate to the decision alternatives.
3. Define performance measures or variables for quantifying decision objectives (attributes).
4. Identify critical uncertain variables.
5. Assess probabilities for uncertain variables and scenarios.
6. Specify value judgments, preferences, and tradeoffs.
7. Evaluate alternative actions or policies.
8. Conduct sensitivity analyses and value of information analyses.

The general theme of decision analysis and these eight steps in particular are applicable to decision making in engineering design, especially the design of complex multidisciplinary systems.

3.1.3 Engineering Design Imprecision

Efforts to develop a formal decision-making method specifically for engineering design occurred at the Caltech Engineering Design Research Laboratory in the 1990s. Professor Antonsson and four of his doctoral students (Wood, Otto, Law, and Scott) devised and subsequently developed the Method of Imprecision (MoI). Wood (1990) describes the initial MoI whose purpose was to assist designers in decision making in preliminary engineering design by generating information on the performance of design alternatives. Otto (1992) extended the MoI and presented an axiom-based method to formalize decisions. Law (1996) provided a clearer interpretation of the elements of MoI and a more efficient computational implementation. Scott (1998) investigated formalizing negotiation in engineering design and the set-based design (instead of point-based design which is typically done). These researchers developed the first formal quantitative method to manage imprecision in engineering design through the use of fuzzy logic. Fuzzy logic is a more general case of classical crisp sets. Developed by Zadeh beginning in 1965, fuzzy logic provided an alternative to probability theory in representing imprecision. Despite all their differences, probability theory and fuzzy logic share a similarity of form. Both quantify uncertainties with normalized mathematical functions: the probability density or the membership function. Although fuzzy logic can provide conceptual and practical benefits in representing uncertainty, probability theory remains a more well known, understood, and accepted mathematical approach. The MoI, with its underlying fuzzy mathematics, represents and manipulates design and customer preferences. Portions of a modified version of the MoI are used at General Motors in the design of automobiles [Mourelatos, Kloess, & Nayak, 2005].

3.1.4 DeLaurentis and Mavris

Research into formal methods to address uncertainty occurred by DeLaurentis and Mavris at the Georgia Institute of Technology in the 1990s. DeLaurentis (1998) took the analogy that the aerospace system design process could be modeled as a control system problem as detailed in Chapter 2. By using control theory, methods to quantify design process robustness and sensitivities to uncertainty were obtained through feedback and error models. The method was developed specifically for aircraft design yet is general enough to be valid for many other complex multidisciplinary systems. The research led by DeLaurentis is based on the premise that design is a decision-making activity and that deterministic analysis and synthesis can lead to poor, or misguided decision making. By transforming design from a deterministic activity to a probabilistic one, DeLaurentis extended the state of the art of formally addressing uncertainty. Probabilistic methods encompass a wide range of techniques that are based on random variables instead of fixed and (assumed) known deterministic values. The application of probabilistic methods offers the ability to quantify parameters of interest to a decision maker in a way that they can select the level and type of risk to accept. In particular, DeLaurentis leveraged response surface methods and Monte Carlo simulation as powerful techniques in the robust design framework that was developed. DeLaurentis also concludes that the cumulative distribution function (CDF) obtained by probabilistic analysis is the key decision function in design. Perhaps the greatest strength in the method proposed by DeLaurentis, Mavris, and others at Georgia Tech was the use of realistic and nontrivial example applications.

3.1.5 Sandia National Laboratories

Research into formal methods to propagate and mitigate uncertainty in the area of modeling and simulation has occurred at the Sandia National Laboratories in Albuquerque, New Mexico since the late 1990s. Oberkampf et al. (1999) proposes a comprehensive structure composed of six phases: conceptual modeling of the physical system; mathematical modeling of the conceptual model; discretization and algorithm selection for the mathematical model; computer programming of the discrete model; numerical solution of the computer program model; and representation of the numerical solution. Sandia researchers also investigated using different mathematical techniques for different uncertainties including probability theory to represent aleatory uncertainty and information theories such as Dempster-Shafer (evidence) theory to represent epistemic uncertainty [Oberkampf, Helton, & Sentz, 2001]. Although the structure and techniques developed by Oberkampf and others at Sandia address issues and concerns faced by the operations research, risk assessment, and computational physics communities, much of the work is applicable to the design of space systems.

3.1.6 Au and Beck

Research into computationally efficient algorithms to assess the impact of uncertainty occurred in the field of civil engineering around the turn of the 21st century by Au and Beck at Caltech. In particular, two methods developed by Au and Beck provided significant computational benefit, sometimes orders of magnitude benefits, compared to traditional methods. The first method, importance sampling using elementary events (ISEE), was applied in estimating the reliability of linear dynamical systems [Au & Beck, 2001b]. The second method, subset simulation (SS) based on a modified version of Markov chain Monte Carlo (MCMC) gains its efficiency by expressing a small failure probability as a product of larger conditional failure probabilities, thereby turning the problem of simulating a rare failure event into several problems that involve the conditional simulation of more frequent events. SS via MCMC was successfully applied in estimating small failure probabilities in high dimensions [Au & Beck, 2001a]. The structural engineering application, to which SS was successfully applied to, shares many of the characteristics to the design of space systems.

3.1.7 Walton

Walton (2002) made a substantial impact on investigating uncertainty in space systems design. His research at MIT, which was funded by the same sponsor as this research, investigated uncertainty specifically in space system architectures. Although space system architectures are at a slightly higher level of application, many of his research goals are applicable to the design of complex multidisciplinary systems. Likewise, much of the method presented in this thesis would likely be applicable to space system architectures. Walton investigated using portfolio theory and carrying sets of designs, to propagate and mitigate uncertainty in space system architecture preliminary design. Portfolio theory, a financial technique, was developed by Markowitz (1952).* The underlying goals of portfolio theory are to recommend investment strategies that balance the needs of an individual investor to achieve the maximum return on their investment and for this return to be subject to as little uncertainty as possible. Set-based design was developed by Toyota in the 1980s [Ward et al., 1995] and Scott (1998) used it in the method of imprecision (MoI) discussed earlier. Walton's application of set-based design in conjunction with uncertainty is a significant departure from current preliminary space systems design techniques. The application of portfolio theory to tackle uncertainty issues in aerospace engineering distinguished and captured the upside as well as the downside of uncertainty. Walton concluded that aspects of uncertainty may in fact be positive. The upside and downside of uncertainty can be separated as reward and risk. Walton's research stresses exploring potential space system architectures through the "lens of uncertainty" and offers a new way to think about early conceptual design and the selection of designs to pursue [Walton, 2002].

3.2 Method Steps and Key Concepts

The following section introduces the method for propagating and mitigating the effect of uncertainty in conceptual-level design proposed in this thesis. Application of this method produces a rigorous foundation for determining design margins in complex multidisciplinary systems, specifically space systems. The actual reduction of uncertainty in design is of secondary

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*Markowitz shared the 1990 Nobel Prize in Economic Sciences for his development of portfolio theory.

importance in applying this method. Reduction of uncertainty constitutes an action or set of actions that may result from applying the method. It is ultimately the actions or inactions of the participants in applying this method which determine the impact uncertainty will have on the design of the complex multidisciplinary system of interest. The method comprises five distinct steps: identifying tradable parameters; generating analysis models; classifying and addressing uncertainties; quantifying interaction uncertainty; and determining margins, analyzing the design, and trading parameters. Each step is briefly described in this section. A detailed description of each of the five steps is provided in following five chapters. Aspects of work done by researchers discussed earlier are seen in many of the method steps and their subsequent description.

3.2.1 Identifying Tradable Parameters

Identifying tradable parameters is motivated by the overarching requirements of the complex system being investigated. It is the decision maker who must understand the overall complex multidisciplinary system being analyzed to determine which parameters are truly important in satisfying the overarching requirements and associated sub-requirements that will be placed on the complex system. Engineering parameters will necessarily result from this analysis. Parameters such as schedule duration, total cost, and risk, must usually be considered as well. This set of parameters is "tradable" in a sense that one or more of these parameters could be expended in an effort to improve or reduce another. Identifying tradable parameters is discussed in depth in Chapter 4.

3.2.2 Generating Analysis Models

With tradable parameters identified, analytic models must be generated to calculate each of these parameters. A model might include dozens or hundreds of equations and relations. These equations and relations in turn require input variables. Determining how accurate models need to be to effectively determine the margin levels in conceptual design is a critical issue and is addressed via model uncertainty. Phenomenological uncertainty must be acknowledged and explored during this step. Generating analysis models, model uncertainty, and phenomenological uncertainty are discussed in Chapter 5.

3.2.3 Classifying and Addressing Uncertainties

Once models have been created for all desired tradable parameters, the variables required by the models are classified. Some input variables, such as the mass of a component, may be fixed (certain) while others, such as the quantity of that component, may be uncertain. A complex multidisciplinary system may have dozens, even hundreds, of these input variables of which the majority may be uncertain. Classifying the variables into their uncertainty types is useful in understanding their respective impact on the overall design and addressing each of them. Definitions of the different uncertainties encountered by complex multidisciplinary systems were discussed in Chapter 2. With the variables classified, each is probabilistically modeled. Classifying and addressing uncertainties is discussed in Chapter 6.

3.2.4 Quantifying Interaction Uncertainty

The next step in the method quantifies interaction uncertainty. As was discussed in Chapter 2, interaction uncertainty could be either the result of disagreement in opinion between informed experts for a given uncertainty (variable) or the interaction of all the different uncertainties (variables). Quantifying interaction uncertainty is required to ultimately estimate the uncertainty in the tradable parameters. Typically, Monte Carlo simulation (MCS) has been used to address interaction uncertainty. However, MCS is not computationally efficient [Hammersley & Handscomb, 1964] and alternate techniques including Latin hypercube sampling (LHS), descriptive sampling (DS), a modified mean value method (MMVM), and subset simulation (SS) via Markov chain Monte Carlo (MCMC) sampling are possible. The simulation method selected depends on the individual analysis and the computational resources and time available by the decision maker. The MMVM and SS methods are shown in the examples presented in this thesis to offer the potential of significant computational savings over traditional MCS. Quantifying interaction uncertainty and simulation techniques are discussed in Chapter 7.

3.2.5 Determining Margins, Analyzing the Design, and Trading Parameters

With distributions of each tradable parameter provided by simulation, the margins can be determined. Each tradable parameter distribution yields a mean and percentile values. Percentiles provide a confidence indication in the value of a tradable parameter. For example, the 90, 99, and 99.9 percentiles of a tradable parameter might provide a decision maker with low-, medium-, and high-confidence estimates in the probability that a tradable parameter will not be exceeded. These three percentiles may correspond to a risk-seeking, risk-neutral, or risk-averse decision maker, respectively. The difference between the percentile (chosen based on their risk tolerance) and the deterministic result provides the decision maker with the margin value to maintain at the current stage of the design. Hence, the proposed (percent) margin that the method in this thesis presents is this margin divided by the deterministic result (and multiplied by 100):

$$\%\,\text{margin}\Big|_{\text{proposed}} = \left[\left(P_x - R_{\text{det}}\right)/R_{\text{det}}\right]\cdot 100 \tag{3.1}$$

Once the distributions, means, and percentiles are determined, the decision maker may wish to investigate other simulation techniques. The decision maker may also wish to further investigate which variables (uncertainties) are influencing the tradable parameters the most by performing a sensitivity analysis or investigate a completely different design. If uncertainty in the values of variables decreases with time, the probability density distributions for these variables can be updated. Repeating the process as the design progresses yields updated margins estimates. In summary, this method redefines the concept of design margin that was introduced in Chapter 1. Here, margins are a function of risk tolerance and are measured relative to mean expected system performance, not variations in design parameters measured relative to worst-case expected values. Determining margins, analyzing the design, and trading parameters are discussed in Chapter 8.

3.3 Qualitative Benefits of Method

The method proposed in this thesis and introduced in the previous section has several important qualitative benefits in determining margins *vis-à-vis* the current heuristic-based method described in Chapter 1. This section describes these qualitative benefits. A discussion of the quantitative results in applying the method is differed to the penultimate section of this chapter.

- *Uncertainty encountered during design is an integral part of the decision making process, not an afterthought.* Uncertainty quantification, propagation, and mitigation in engineering design are not recent phenomena. However, uncertainty has yet to truly make its way in the decision-making process in the design of space systems. Instead, it is an afterthought to the design and is sometimes completely ignored. The results of this behavior were shown in the margin examples provided in Chapter 1. The method proposed makes uncertainty a central concept in the design of space systems. Uncertainty is treated with the same attention as requirements, design, modeling, and performance that are typically the focus of attention of the decision maker, designers, and stake holder.
- *Flexibility*. Various methods have been created that work well for one type of analysis, object, or discipline. However, these methods break down or require significant changes when another analysis, object, or discipline is investigated. The method proposed can be applied without significant changes to a wide variety of distinct applications. The method can be implemented at varying levels (e.g., system, subsystem, assembly,

component) within a space system.[†] The proposed method allows a balance of creativity and formalism which is often critically important in conceptual design [Salter, 2002].

- *Transparent to participants and provides accountability*. The method proposed is transparent from "above" and "below" (i.e., does not require asymmetric information held by only a portion of the participants to be applied). The method does not depend on proprietary practices or base itself on historical or heuristic methods that only a few of the individuals involved with the method know or understand. Propagating and mitigating uncertainty is no longer the exclusive province of "men of experience" [Luce & Raiffa, 1957] but is a procedure that all can understand and implement. When applied to a space system of interest, the proposed method determines margins specifically tailored to the given project, not based on historic or heuristic values that may only be known to a few participants and only partially relevant at that. The proposed method steps are clearly explained and the decision maker and stake holder will understand the method to the same degree as the system and subsystem engineers who are providing and/or completing the analysis. The method presented is open to productive scrutiny and critique. This transparency helps in returning accountability to the participants at all levels of the design. Participants may disagree about the representation of certain uncertainties (variables) involved. However, when the method is applied with uncertainties agreed upon by all, it will yield results that, in turn, should be agreed upon by all. Margins that have been exceeded can no longer be charged to "bad luck" where the decision maker is relieved of responsibility for what has happened. Margin values can now be justified by the decision maker to stake holder in negotiations and discussions as the design progresses.
- *Comprehensive yet practical to implement in industry.* Several methods and techniques proposed have significant merit and promise in the academic setting where they were developed. However, they require a significant departure from the current method of designing and developing space systems in industry. The method is general enough to allow many of the design methods of other researchers discussed previously to be used in conjunction with its application. Other methods proposed use new or unaccepted mathematical techniques that require learning by the individuals involved in the method and may be distrusted. The proposed method is based on well-established and understood mathematical techniques whenever possible and uses new techniques only

[†]"A theory is the more impressive the greater the simplicity of its premises, the more different kinds of things it relates, and the more extended its area of applicability." – Albert Einstein

when needed. The less well known mathematical techniques, such as subset simulation (SS), used in the method are presented as ways to speed up its application in practice. Their use is not required for applying the proposed method. This in turn requires the minimum amount of learning for individuals that would be applying the method.

- *Allows trading of critical parameters based on the risk tolerance of the decision maker.* Engineering design is, in its simplest form, a set of decisions that are made and implemented by one or more individuals. The resulting design has one or more critical parameters that determine its usefulness or success. If more than one of these parameters exists for a space system, the method allows the decision maker to balance the design, and hence these critical parameters, based on their risk tolerance or risk aversion. One of the overall dominant themes echoed at aerospace manufacturers is a desire to understand uncertainty at a level that would be useful as decision criteria and be able to trade parameters early conceptual design [Walton, 2002]. The method proposed illustrates clearly the risk posture of the decision maker to all the individuals involved in applying the method by the choice in percentile value in Equation (3.1) and allows trading parameters via several methods.
- *Takes advantage of people's knowledge.* Many methods minimize the importance of people's knowledge, relying instead on sophisticated algorithms and impressive amounts of computing yet fail to elucidate conclusions.[‡] The proposed method devised empowers individuals involved in the method by taking advantage of their knowledge and experiences whenever possible in quantifying uncertainties. Bayesian techniques are used in achieving this.
- *Repeatable and allows margins to be determined at any point in the design*. The method presented can be repeated subject to the availability of workforce and funds required to apply and implement it. Although focused primarily on the pre-phase A and Phase A/B portion of space systems design (see Chapter 1), the method could be applied during Phase C/D or even Phase E in estimating operational performance. The method focuses on the front end of development because of the high impact per dollar spent of these phases of development and the significance of the decisions made there on the eventual success or failure of the design (recall Fig. 1.2). For example, pre-proposal and proposal (pre-Phase A) efforts at a major aerospace company have "cost the company 10s of millions of dollars if not hundreds and can be as long as a two year effort" [Walton,

[‡]"The purpose of computing is insight, not numbers" – Richard Hamming, mathematician and information scientist

2002]. Another major aerospace company concluded that changes that cost 10,000 times more when made during the manufacturing (Phase C/D) phase than when made early in the development cycle (pre-Phase A/Phase A) [Burghardt, 1999]. Although applying the proposed method would benefit all phases of design, it is not clear whether the updated margin estimates at a later that stage of the development would be worth the effort and expense of applying the method then.

- *Addresses different uncertainty types, stresses model uncertainty, and acknowledges phenomenological uncertainty.* Many existing methods view uncertainty as just "uncertainty" instead of its different types discussed in Chapter 2. This leads to a muddled view on how to address uncertainty and potentially incorrect analysis techniques [Frey, 1992]. Moreover, existing methods to propagate and mitigate uncertainty neglect model uncertainty and ignore phenomenological uncertainty limiting their usefulness in the design of actual complex multidisciplinary systems. The method proposed uses a detailed uncertainty classification; makes model uncertainty the first uncertainty quantified; and provides several options and actions in exploring phenomenological uncertainty.

It should be stressed that the method proposed in this thesis is normative, not descriptive. Normative or prescriptive decision analysis seeks to advise or guide the decision maker. A normative method states neither how people do behave nor how they should behave in an absolute sense, but how they should behave if they wish to achieve certain ends. The proposed method, if followed, should yield (but by no means guarantees) beneficial results. Indeed, the primary reason for the adoption of a normative theory is the observation that when decision making is left solely to unguided judgment, choices are often made in an internally inconsistent fashion, and this indicates that perhaps the decision maker could do better than he or she is doing. This was demonstrated with the diverse set of exceeded margins presented in Chapter 1. If a person always behaved as this normative theory says they ought to, then there would be no reason to concern ourselves about actual normative theory. People could just be told "do what comes naturally" [Raiffa, 1968]. Since this is not the case in reality, normative theories are powerful techniques in assisting the decision maker. Lastly, although several engineering examples are discussed in the following section, the proposed method is not factually grounded to these examples nor was it developed by simply observing the design of space systems.

3.4 Quantitative Results in Applying Method

Quantitative benefits of the proposed method have been demonstrated via several applications. Thunnissen (2004a) is the seminal paper introducing the method with a major spacecraft component (a composite overwrapped pressure vessel) used as the application example. A more evolved version of the method is applied to a spacecraft propulsion system in Thunnissen and Nakazono (2003) and Thunnissen, Engelbrecht, and Weiss (2003). Further revisions of the proposed method with applications to a thermal control system and attitude control system are provided in Thunnissen and Tsuyuki (2004) and Thunnissen and Swenka (2005), respectively. These four examples are all applied *ex post facto*. The benefits are also demonstrated in the application examples provided in Chapter 9 and Appendix B.

It is perhaps the Mars Exploration Rover (MER) propulsion system example provided in Appendix B that best illustrates the potential of the proposed method in determining margins *vis-à-vis* the current method. The key quantitative results of this example application include

- *Margin values based on the risk tolerance of the decision maker.* The margins values for the tradable parameters of propellant mass, dry mass, schedule duration, and total cost determined via the proposed method are based on the 99th percentile values of these parameters. These margin values for propellant mass, dry mass, schedule duration, and total cost are 98.6%, 92.2%, 15.3%, and 16.7%, respectively. This percentile value choice may represent a risk-neutral decision maker. However, the values could have been based on the 90th percentile value (a risk-seeking decision maker) or the 99.9th percentile value (a risk-averse decision maker). This is a significant departure from heuristically determined designed margins with no clear risk tolerance implied. The percentile value used in the proposed method to determine margins is based on the full cumulative distribution function (CDF); not on possibly misleading statistical parameters (e.g., see Fig. A.1 in Appendix A).
- *Allocation values that were different than those assumed during preliminary design.* The allocations (best estimates + margins) assumed by the MER project for propellant mass, dry mass, schedule duration, and total cost at the preliminary design review are 42.8 kg, 18.4 kg, 749 days, and FY2003$9.9M, respectively. The allocations predicted by the proposed method for these same four tradable parameters are 42.9 kg, 17.3 kg, 816.4 days, and FY2003$12.130M. The actual final values turned out to be 47.0 kg, 16.2 kg, 749 days, and FY2003$11.0M for mass, schedule, and cost, respectively. Hence, the proposed method provided margins that encompassed the actual values better than the

current method. The proposed method would not have resulted in margins exceeded in the design of the MER propulsion system.

- *Potential of several sampling techniques in reducing the computational burden of applying the proposed method compared to traditional sampling methods.* The nominal sampling technique in applying the proposed method is Monte Carlo simulation (MCS). MCS tends toward the actual result through the Law of Large Numbers as the number of samples (calls to the response function) approaches infinity. Alternate techniques such as the modified mean value method (MMVM) and subset simulation (SS) provide a significant decrease in the number of calls to the model (computational expense) compared to MCS. MMVM provides a slightly inferior level of accuracy but requires 58 to 308 times less computational effort. SS provided superior accuracy compared to MCS at the extreme tails (i.e., high percentile values such as 99.9 or 99.99) but requires 5 to 10 times less computational effort. The ability to use alternative sampling techniques provides the decision maker with several computationally efficient options compared to MCS, especially when he or she is concerned about mitigating low probability events.

3.5 Summary

This chapter describes previous work by researchers in a variety of fields that have contributed to the proposed method presented in this thesis. The chapter then introduces this proposed method, briefly describing each step. The qualitative benefits and quantitative results in applying the method to determine design margins exemplify the potential benefit the method may have in actual space systems design if implemented compared to the current heuristic-based approach. As the application examples illustrate, the method has developed significantly since its first application to a composite overwrapped pressure vessel [Thunnissen, 2004a] to the method presented in this thesis. It is likely that this proposed method will evolve and develop further if implemented in an actual complex multidisciplinary design. This evolution and development is anticipated and encouraged since an actual design may shed light on new uncertainties, methods, and techniques to propagate and mitigate them. The following chapters describe each step in applying the method, beginning with identifying tradable parameters which is discussed in the following chapter.

Chapter 4 Identifying Tradable Parameters

The first step in the proposed method is identifying tradable parameters. This chapter begins with a definition and explanation of tradable parameters. Common tradable parameters of performance, risk, schedule, and cost are then discussed.

4.1 Tradable Parameters

This section introduces tradable parameters and their relationship to requirements. A description of constraints and limits on tradable parameters follows. A discussion of parameters that are not tradable and a brief review of utility theory complete this section.

4.1.1 Tradable Parameters and Requirements

The design of a complex multidisciplinary system is motivated by requirements. In the case of a spacecraft, the requirement may be high-resolution imaging (reconnaissance), global positioning (navigation), or global mobile telephony (telecommunications). A complex multidisciplinary system may also have more than one requirement. For a missile, target accuracy (guidance and navigation), time to target intercept (speed), and low-radar signature (stealth) all may be requirements that must be satisfied to some level. The design of a missile proceeds through iterations where the target accuracy, time to target intercept, and radar signature are calculated. Dozens, possibly hundreds, of parameters that are used in estimating these requirements are also changing during preliminary design. The decision maker must understand the complex multidisciplinary system being analyzed to determine which parameters are truly important in satisfying the requirements placed on the system. This set of parameters is "tradable" in a sense that one or more of these parameters could be expended in preliminary design in an effort to improve or reduce another. However, not all parameters need be tradable with all others. The resulting list of tradable parameters helps guide the design of the complex multidisciplinary system.

Tradable parameters are often the requirements. The decision maker typically has other tradable parameters available such as cost, schedule, and risk which may be requirements themselves. Both tradable parameters and requirements are characterized by one of three forms: "higher is better," "lower is better," or "closer to a particular value is better." In the first form there may be a cut-off, or "floor," below which a value that results from a design is not useful, practical, or able to be implemented. Likewise, the second and third forms may have analogous "ceilings" above which values that result from a design are not useful, practical, or able to be implemented. In the case of a reconnaissance spacecraft, image resolution, payload mass, and pointing stability may be tradable parameters. Image resolution follows the first form where a high resolution image is desired so smaller objectives can be distinguished. Payload mass follow the second form where a low payload mass is desired to reduce the total spacecraft mass (and hence launch costs). Finally, pointing stability follows the third form where the pointing stability should be as close to 0 degrees/sec. These three parameters are tradable in the sense that a pointing stability close to 0 degrees/sec provides a stable spacecraft that results in a lower image resolution capability. In this example, payload mass could also be traded with both image resolution and pointing stability. More powerful payload optics and processing capability would provide better resolution but at the cost of payload mass (and vice-versa). Likewise, adding reaction wheels would improve pointing stability at the cost of payload mass (and vice-versa).

4.1.2 Constraints and Limits

Some parameters are tradable yet constrained (i.e., tradable to a degree and no more). An interplanetary spacecraft may have a limited launch window (number of days available within which it can launch) dictated by the synodic period of the planets involved and the launch vehicle selected. The trajectories available for an Earth-Mars transfer, for example, are available for only a few weeks every 26 months. The choice in launch vehicle that provides the injected mass capability to achieve the required trajectory is typically specified by the stake holder or decision maker *a priori*. Even if no launch vehicle is specified, there is a limit in the injected capability (mass that can be launched) of launch vehicles: that of the most powerful launch vehicle available. Nonetheless, the decision maker could trade cost with risk to a degree. A cost savings in the mission could be accomplished by reserving the launch range for a shorter period of time which would reduce the launch window (and hence, increase the risk in not being able to launch the mission). On the other hand, the decision maker may wish to expend cost by reserving the launch range for a longer period of time which would increase the launch window or use a more powerful launch vehicle with a higher injected mass capability. Both options would increase the likelihood of successfully launching and hence reduce the risk. However, there is a combination of launch window length and launch vehicle capability beyond and above which, respectively, no more gains are possible and the limit in the tradable parameters have been reached. For an Earth-Mars mission this may be a launch window of 40 days and a Boeing Delta IV-Heavy launch vehicle.

4.1.3 Parameters That Are Not Tradable

Certain parameters may be deemed tradable when they are not. This occurs often when a new design inherits ideas from a previous design yet the new design has moderately or substantially different requirements. Parameters are also not tradable when deemed not important compared to the rest of the complex multidisciplinary system being designed. If no major decisions concerning these parameters are anticipated during design that would significantly impact the other tradable parameters, it is unlikely these parameters are truly tradable. For example, a spacecraft is designed to be a follow on for a highly successful first-of-kind mission that just concluded. Requirements for the follow-on mission include a stipulation to use as much as the previous design and hardware as possible to save cost. The original design included risk as a parameter that was traded with performance and cost in selecting components and materials for the final design. However, the follow on mission is constrained to make no significant changes in the design (i.e., no major changes in components or materials) and therefore no major decisions concerning risk are made in designing the follow-on mission. Hence risk, although a tradable parameter in the original design, is no longer a tradable parameter in the follow-on design.

4.1.4 Utility Theory

Utility was introduced in Chapter 3 along with issues and challenges in using it in practical problems. Utility theory represents player's values as "utilities" (nondimensional units). Utility theory also incorporates risk-tolerances via the shape of the utility function. For example, wealth (cost) is a parameter whose utility is often different for different individuals and illustrates their risk tolerance well. Risk aversion in individuals is often a function of their assets and can change with an increase or decrease in those assets [Raiffa, 1968]. Hence, a risk-seeking utility function may correspond to a decision maker with significant wealth that is able to afford loses if they occur. Tradable parameters follow these two themes of utility theory and risk tolerance but do not explicitly state them. Likewise, tradable parameters share similarities with objectives in multi-objective utility theory [Keeney & Raiffa, 1976]. This makes the current interpretation and use of tradable parameters in the proposed method somewhat incomplete and less rigorous than if utility theory was used. However, a benefit is that all the difficulties and controversies of utility theory are avoided. Tradable parameters, such as mass, schedule, or cost, are simply mass, schedule, and cost, respectively. Their relative importance to a decision maker and to each other are not be explicitly specified nor are these values converted to "utilities." The risk tolerance will be specified by the choice in the percentile, P_x, in Equation (3.1). Trading of parameters (without the explicit use of utility theory) is discussed in Chapter 8.

4.2 Common Tradable Parameters

Although the hierarchical level of complex multidisciplinary system (i.e., system, subsystem, assembly) is important in determining which parameters are tradable, there are several common tradable parameters common to almost all levels of design. These parameters include performance, risk, schedule duration, and total cost. This section briefly discusses each and some of the uncertainties that often exist in making their determination such a challenge.

4.2.1 Performance

Performance is a general term that might include general engineering parameters such as mass and power required. It might include parameters specific to a particular subsystem (e.g., knowledge accuracy for attitude determination and control). Typically performance parameters are requirements if not explicitly, then implicitly and are the parameters most of interest to the engineers and designers. Engineers and designers often come up with creative and innovative ideas to improve these parameters. Performance parameters are influenced by uncertainties. These uncertainties are specific to a particular performance parameter. For example, the mass of system may be a function of choices a designer has to make, component availability, material properties, requirements, and model-fidelity available. Performance parameters in a space system are often a function of dozens to hundreds of uncertainties.

The choice in performance parameters should be complete in that it includes all relevant aspects of the overarching requirement(s). However, the set of tradable parameters should be as small as possible, independent, and decomposable to the lowest practical limit. Typically, a design is viewed successful by a stake holder via a small number of parameters and not the dozens of parameters of concern to the engineers and designers. Certain performance parameters are highly dependent on each other and specifying both performance parameters may be redundant. Lastly, decomposing performance parameters to the lowest practical limit simplifies the generation of models and subsequent analysis which is discussed in the following chapter.

4.2.2 Risk

The relationship between risk and uncertainty was discussed in Chapter 2 with respect to known and unknown probabilities and outcomes. Risk and uncertainty are often confused with each other because the definitions for each vary so extensively across a variety of fields. This thesis defines uncertainty as "the difference between an anticipated or predicted value (behavior) and a future actual value (behavior)" and risk as "the likelihood of failure." The two are related in that there may be uncertainty about a risk and risk about an uncertainty. For example, the risk in a component failing may be a function of (uncertain) conditions while the amount of uncertainty faced by a project may determine whether the project continues to be funded or cancelled (risk in funding). This thesis concentrates on uncertainty, including uncertainty about risks. Risk should always be considered as a potential tradable parameter in the design of complex multidisciplinary systems.

As with risk aversion that was discussed earlier, there exists a distinct concept of uncertainty aversion. Walton (2002) described the differences between the two using the example of flipping a fair coin. Uncertainty-averse individuals concern themselves with not knowing how likely heads or tails may be while the risk-averse individual is more concerned with the implications of the coin landing on heads or tails. Risk has traditionally been a more common concern than uncertainty in complex multidisciplinary design. Perhaps this is because a failure during operations may be more significant, a higher profile, and/or potentially may cause loss of life (in the case of an aircraft, automobile, etc.) than a failure during development that might be remedied. The examples provided in Chapter 1 illustrate however that not accurately propagating and mitigating uncertainty can have as serious an impact to the space systems industry as an operational failure.

4.2.3 Schedule Duration

Schedule duration is defined as the time, starting from some predetermined point such as the authority to proceed by the customer (and allocation of funds), to design, build, test, and deliver the system or systems of interest. Schedules are always important in complex multidisciplinary systems design, especially when there is a demand for that system to quickly be deployed or operational. For example, an interplanetary science mission may require that a spacecraft with appropriate payload be designed and built by the time the next syzygy (appropriate launch opportunity) arrives. A military mission may require that an operating payload be available within a year for national security reasons while a commercial mission will want to launch as soon as possible to take advantage of "first-to-market" revenue generating opportunities.

Schedule comprises a set of tasks that defines how to design and develop the system of interest. Often, estimates of time and relationships between tasks are specified in a schedule. A simple schedule (for the development of a composite overwrapped pressure vessel) is provided in Fig. 4.1.

#	Activity Name	Duration (weeks)	Prereqs
1	Specification review	1	
2	Preliminary design	4	1
3	Preliminary design review		2
4	Qualification test plan	2	3
5	Miscellaneous data items	2	3
6	Acceptance test plan	2	3
7	Final design and analysis	4	3
8	Intermediate design review		4,5,6
9	Liner first lot fabrication	30	8
10	Development unit winding/processing	2	9
11	Development unit testing	3	10
12	Critical design review		11
13	Qualification tank winding/processing	2	12
14	Qualification testing	3	13
15	Flight unit winding/processing	2	14
16	Design/analysis report	4	14
17	Qualification report	4	14
18	Flight unit acceptance test	2	15
19	Flight unit shipment		16,17,18

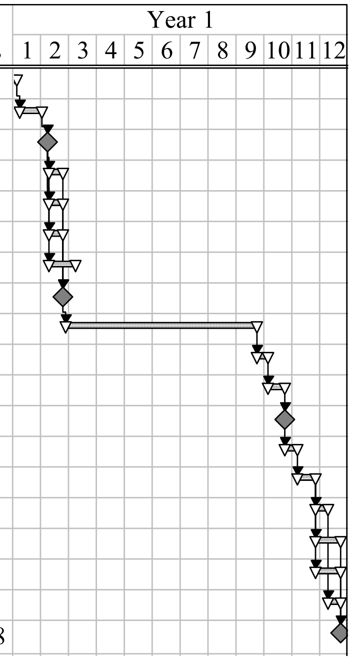

Fig. 4.1 Simple schedule [Thunnissen, 2004a].

Sources of uncertainty in schedules have been studied in large civilian projects [Merrow, 1988]. Uncertainties that are valid for the design of complex multidisciplinary systems include: omission and/or difficulty of tasks; work arising from using advanced technology; design and manufacturing challenges; availability of critically skilled labor; labor relations; regulatory and political factors; contracting issues; and overall project management coordination and strategy.

4.2.4 Total Cost

Total cost is defined as the amount of money required to design, build, test, and deliver the system or systems of interest. As was mentioned in Chapter 1, the design environment for building complex multidisciplinary systems, in particular space systems, has changed. Aerospace design has gone from maximizing performance under technology constraints to minimizing cost under performance constraints. These changes have placed an increased importance on cost to all the participants in a design. Total cost is arguably the most important tradable parameter.

Cost is strongly correlated to schedule due to labor and task duration factors [Merrow, 1988]. The funding profile is often as important if not more important than the total cost to a stake holder due to budgetary constraints. Having a system designed and built within a (possibly uncertain) budgetary profile adds additional complexity to a design. Fig. 4.2 illustrates the project cost and funding profile for an example project.

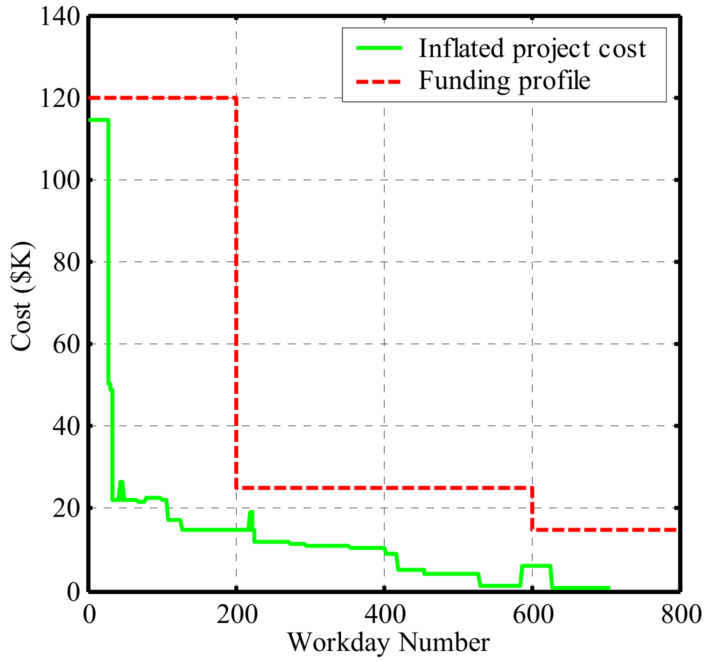

Fig. 4.2 Possible cost and funding profile for a project.

Important uncertainties in cost are similar to those of schedule and include omission and/or difficulty in procuring items; changes in the scope of work; unforeseen technical difficulties; work arising from using advanced technology; schedule delays that require overtime; budgetary constraints; regulatory and political factors; contracting issues; and overall project management coordination and strategy.

4.3 Summary

This chapter defines the concept of a tradable parameter and discusses identifying which parameters are and are not tradable in the design of a complex multidisciplinary system. Common tradable parameters of performance, risk, schedule, and cost are discussed including possible uncertainties which may impact these parameters. With the tradable parameters of a complex multidisciplinary system identified and defined, the next step in the proposed method is generating models to calculate these parameters. This is the topic of the following chapter.

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Chapter 5 Generating Analysis Models

As systems have become increasingly complex and multidisciplinary, the generation and use of models to represent those systems has become more important. Unfortunately, efforts to quantify and test models have not been rigorously pursued. This chapter begins by introducing model formulation. A detailed description of model uncertainty that emphasizes techniques to quantify model uncertainty follows. The chapter concludes with a discussion of phenomenological uncertainty and techniques to address it.

5.1 Model Formulation

Once a list of tradable parameters has been identified, a model must be generated to calculate each of these parameters. The model can be considered a "response function" and may be complicated (e.g., closed-form equations, computational algorithms, "black box" functions) requiring significant expense in time and resources to calculate values. For example, a model that determines engineering parameters often includes dozens or hundreds of physics-based equations and relations. A model that calculates the development schedule of a complex multidisciplinary system might subdivide the tasks required and estimate workforce requirements for each. A cost model might incorporate the schedule and include additional equations relating procurements, inflation, and burden factors. A risk model might estimate whether the complex multidisciplinary system will fail during development or operation. Model generation involves first determining what a requisite model must be and then developing the actual model.

5.1.1 Requisite Model

A model that represents the phenomena of interest over a range of interest is termed a requisite model. A requisite model forms a compact, accurate representation of the functional relationship between typical uncertainties (inputs) and tradable parameters (outputs) of an analysis which models the complex multidisciplinary system. Phillips (1984) proposes that "a model can be considered requisite only when no new intuitions emerge about the problem," or when it contains everything that is essential for solving the problem. A requisite model contains everything that the decision maker considers important in making the decision regarding the tradable parameter of interest. Identifying all of the essential elements may be a matter of working through the problem several times, refining the model on each pass. The only way to get to a requisite decision model is to continue working on the decision until all of the important concerns are fully incorporated. Sensitivity analysis, which is discussed in Chapter 6, is a great help in determining which elements are important [Clemen, 1996].

5.1.2 Model Fidelity

Ideally a model should be as accurate as possible given the resources available. However, the model fidelity required is a function of the need. In the proposed method, the need is the accuracy required in assessing the tradable parameters. A simple qualitative example illustrates this. Consider a model airplane as a toy for a three-year old versus a model airplane as a toy for a ten-year old versus a subscale mock-up for wind-tunnel testing. In the first case the tradable parameter is "fun" (make the toy strong and simple). In the second case the tradable parameter is likely "representative" (make the model airplane detailed and similar to the actual airplane). Finally, the tradable parameter in the third case is "exactitude" (make the model as identical as possible, in the limited size available, to an actual airplane). The same concept arises in generating maps. The level of detail in a map required by hikers, drivers, and the military is likely different. The effort put into generating a detailed map is a function of the end user just as the accuracy in tradable parameters is determined by the stake holder and decision maker. Developing any model entails a trade-off between the level of accuracy and completeness in the model versus the cost of resources in generating and running this model. A model that captures all the relevant features of a phenomenon may be impractical and time-consuming to generate because of insufficient data available and/or costly (i.e., in time and money) to run. On the other hand, a simpler model which represents only a portion of the phenomenon will likely disregard potentially important features but may require minimal computational cost. The ratio of computational cost for a higher-fidelity model to a lower-fidelity model can be high, sometimes exceeding a factor of a 100 [Oberkampf et al., 1999]. In either case, a price is paid.

5.1.3 Models in Complex Multidisciplinary System Design

In the design of complex multidisciplinary systems, a mix of simple and sophisticated models is typically used. Several "submodels" are used to represent portions (e.g., subsystems, assemblies, components) of the system and the inputs and outputs of these distinct models are then linked. Generating such submodels is often easier than larger more encompassing models and allows uncertainties in input variables to be quantified with a higher degree of confidence. Since models are typically computer programs, these programs handle the difficult numerical calculations in modeling the system while allowing the users to assess the uncertainty in the inputs. Data exchange (i.e., linking the inputs and outputs) between submodels has long been the *bête-noire* of preliminary complex multidisciplinary design. However, recent efforts by a variety of individuals and organizations have begun to address this issue (e.g., [Parkin et al., 2003]).

The need for simulation-based analysis tools is particularly important in the design of space systems, as operating environments are often difficult or impossible to reproduce to test prototypes. In space systems design, simple models may be created in Excel spreadsheets or short FORTRAN, C++, or MATLAB® codes by individual engineers or designers that represent their subsystem or component of responsibility. Sophisticated modeling tools in space systems design include both third-party software that is publicly available and proprietary modeling tools that are difficult or impossible to obtain by other individuals and organizations. Several examples of modeling tools used in space systems design are provided in Table 5.1.

Table 5.1 Examples of modeling tools used in space systems design

Modeling Tool (Vendor)	Acronym/ Abbreviation	Associated Discipline	Description
NASA Structural Analysis System (MSC Software Corporation)	NASTRAN	Structural analysis	general purpose finite element analysis program for use in computer-aided engineering; standard in the structural analysis field
Satellite Orbit Analysis Program (JPL/ Aerospace Corporation)	SOAP	Mission design	orbit visualization and analysis
System Improved Numerical Differencing Analyzer (Cullimore & Ring Technologies, Inc.)	SINDA	Thermal control	network-style thermal simulator; standard analyzer for thermal control systems
Satellite Tool Kit (Analytical Graphics Inc.)	STK	Mission design	supports analysis, planning, design, operation, and post-mission analysis for complex and integrated land, sea, air, and space scenarios
Two Dimensional Kinetics (Software and Engineering Associates, Inc.)	TDK	Propulsion	estimates performance parameters such as specific impulse, thrust, mass flow rate, and thrust coefficient using JANNAF[a] liquid rocket thrust chamber performance prediction method
Variable Trajectory Optimization Program (JPL/NASA)	VARITOP	Mission design	two-body, sun-centered, low-thrust trajectory optimization and analysis program

[a]JANNAF = joint army navy NASA air force

5.1.4 Model Validity and Extrapolation

Different models for the same phenomena may have different resolutions and different ranges over which they are valid. For example, a requisite model often used in fluid mechanics to estimate the friction factor in laminar flow through a pipe is

$$f = \frac{64}{Re_D} \qquad Re_D < 2000 \tag{5.1}$$

This model is valid only for laminar flows and models the friction factor poorly when the Reynolds number (based on the pipe diameter) exceeds ~2000. For turbulent flow a different model is used to estimate the friction factor [White, 1991]:

$$f = 0.316 \cdot \left(Re_D\right)^{-1/4} \qquad Re_D > 2000 \tag{5.2}$$

Some models may be amenable to extrapolation beyond specified ranges, others are not. For example, the prediction of aerodynamic heating on a space capsule during reentry into the earth's atmosphere in the 1960s was for velocities well beyond those contained in existing databases of the time. This occurred in the U.S. space program when the manned Apollo spacecraft re-entered the earth's atmosphere after orbiting the moon. A large database existed for reentry at earth orbital speeds (7,600 m/s), but no experimental data existed at entry speeds appropriate for this situation (11,000 m/s). Extrapolating a model depends heavily on the level of understanding of the physical process and the magnitude of the extrapolation [Oberkampf et al., 1999]. When extrapolation extends beyond a certain level, phenomenological uncertainty enters the model. Phenomenological uncertainty is a significant challenge in generating models and is discussed later in this chapter. Lastly, some models may be validated extensively while others may "twist and turn" to accommodate most or all the data points for validation but fail to model the general areas in between. This is often a concern in using curves or response surfaces to model phenomena [Fox, 1994].

5.2 Model Uncertainty

With models formulated, the next step in the proposed method is assessing their uncertainty. Model uncertainty is the accuracy of a mathematical model to describe an actual physical system of interest. Also known as model-form, structural, or prediction-error uncertainty, model uncertainty is a form of epistemic uncertainty (i.e., model uncertainty is often due to a lack of knowledge). The use of one or more simplified relationships between basic variables used in representing the 'real' relationship or phenomenon of interest is a common characteristic of model uncertainty [Melchers, 1999]. Model uncertainty arises from approximation, numerical, and programming errors. This section discusses approximation errors in detail. At the end of this section a brief overview of numerical and programming errors is provided.

5.2.1 Approximation Errors

For physical processes that are relatively well understood, deficiencies in certain models are often called approximation errors rather than model uncertainty. For example, in the modeling of the specific volume of a gas, four models can be ordered in terms of increasing accuracy (decreasing model uncertainty) as follows: ideal-gas law, van der Waals equation, Beattie-Bridgeman equation, and Benedict-Webb-Rubin (BWR) equation. All four models are single equations that determine the specific volume (dependent variable) through two independent variables: temperature and pressure. The ideal gas law neglects intermolecular forces between molecules and uses only one constant:

$$v = \frac{R \cdot T}{p} \tag{5.3}$$

The van der Waals equation uses two constants to allow for interaction and volume effects [van der Waals, 1873]:

$$\left(p + a/v^2\right)\left(v - b\right) = R \cdot T \tag{5.4}$$

The Beattie-Bridgeman equation uses five constants and is accurate over a much larger range [Dodge, 1944]:

$$p = \frac{\Re \cdot T}{\hat{v}^2}\left(1 - \frac{c_0}{\hat{v} \cdot T^3}\right)\left(\hat{v} + B_0 - \frac{B_0 \cdot b}{\hat{v}}\right) - \frac{\hat{v} \cdot A_0 - A_0 \cdot a}{\hat{v}^3} \tag{5.5}$$

Lastly, the BWR equation uses eight constants and is even more versatile [Sonntag & Van Wylen, 1991]:

$$p = \frac{R \cdot T}{v} + \frac{R \cdot T \cdot B_0 - A_0 - C_0/T^2}{v^2} + \frac{R \cdot T \cdot b - \cdot a}{v^3} + \frac{a \cdot \alpha}{v^6} + \frac{c}{v^3 \cdot T^2}\left(1 + \frac{\gamma}{v^2}\right)e^{-\gamma/v^2} \tag{5.6}$$

In general, this ordering is appropriate, but for individual gases at specific conditions one model may be more accurate than another (e.g., the ideal gas law can be the most accurate equation for certain gases at low pressures and high temperatures).

As simulation-based design has become increasingly important and common, the models used to represent complex multidisciplinary systems have become progressively more complicated (see Table 5.1). As the reliance on such models has increased, assessing their uncertainty becomes paramount. Unfortunately, assessing approximation errors in models is often not done. The reasons for this are numerous but include difficultly (or impossibility) in obtaining data (input variables and output parameters) to compare model predictions with; time and cost of performing such an analysis; and unquantified and overconfident belief in models by their creators.

5.2.2 Assessing Approximation Errors

Approximation errors can be assessed and reduced with effort, research, and increased availability of data. Some models have good accuracy relative to test data, for example, mechanical structural analysis. Others may have low accuracy for engineering purposes, for example, fatigue modeling [Du & Chen, 2000]. Consider again the specific volume example introduced in the previous section. Johannes van der Waals determined that the ideal gas law poorly represented actual gas behavior at high pressures and low temperatures and improved upon the ideal gas law in 1873 as part of his doctoral thesis [van der Waals, 1873]. Similarly, Beattie and Bridgeman improved upon the van der Waals equation in 1928 and Benedict, Webb, and Rubin in turn improved upon the Beattie-Bridgeman equation in 1940. All of these researchers were aided with increased and improved data of various gases which allowed them to assess the approximation errors of previous equations and devise increasingly accurate equations. The four equations (models) for the specific volume are simple compared to models for more complicated systems. A complex multidisciplinary system, such as a spacecraft, automobile, or submarine, may use many mathematical submodels, each with possibly dozens of equations. The complexity of the models depends on the physical complexity of each phenomenon being considered, the number of physical phenomena being considered, and the level of coupling of different types of physics [Oberkampf et al., 1999].

Approximation errors can be minimized by calibrating a model if sufficient empirical data are available. Calibration is often feasible in simple models with one or two inputs but difficult or impractical for complicated models. Instead of calibration, the approximation errors in these models can be probabilistically assessed. Approximation errors in a dependent variable can be represented as a random variable and related to the true value [Siddall, 1983]:

$$y^t = y - X \tag{5.7}$$

A probability density function can be determined for X if sufficient true values are available to compare to the values determined by a model. A summary of probability theory including random variables is provided in Appendix A. The advantage of using a probability density function (PDF) to represent approximation errors is that it can be easily convolved with other uncertainties that are represented probabilistically. Representing approximation errors via a PDF can be accomplished via existing data, expert elicitation, or Bayesian techniques.

5.2.2.1 Via Existing Data

Quantifying approximation (model) errors via existing data is rigorous and arguably the least controversial of the three methods available. Provided the procedure for obtaining the data is agreed upon, the empirical (raw) data that results should provide undisputed values to assess approximation errors. Existing data provides values to compare results obtained via the model. The only controversy that arises in using existing data occurs when determining what data are

relevant and what data are not. Data can be manipulated by an assessor with a motivational bias.*
Combating this is possible with careful documentation of what data are used and what data are not, with an explanation for each. With sufficient acceptable data, a PDF representing approximation errors can be generated. Sufficient data depends on the situation but statisticians generally regard ~50 data points as being a minimum number for results to have statistical validity [Devore, 2000].

Returning to the thermodynamic example discussed earlier, the model error of the specific volume can be represented by a PDF. For a range of temperatures and pressures the difference between each of the four equations can be compared with accurate actual measured data [Din, 1961]. These differences can be sorted into bins and transformed to a PDF as shown in Fig 5.1 for nitrogen.

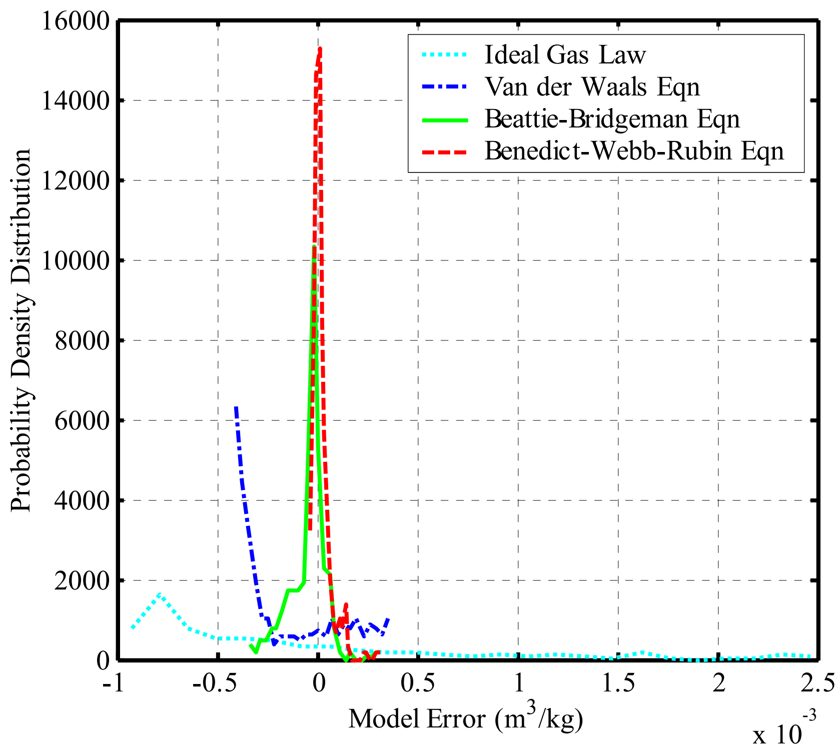

Fig 5.1 Model uncertainty for specific volume.

Fig 5.1 is useful in assessing model uncertainty in the context of all input uncertainties (in this case: temperature and pressure). Almost 400 values of the specific volume were used in creating Fig 5.1 for temperatures ranging from 160 to 650 K (-113 to 377 °C) and pressures ranging from 0.1 to 101.3 MPa (1 to 1000 atm). The more values used, the smoother the resulting PDFs. Fig 5.1 illustrates that the ordering of the four equations is indeed valid. The fact that the

*"There are three kinds of lies: lies, damn lies, and statistics." – Mark Twain

error grows at tails of distributions for the ideal gas law and the van der Waals equation indicate that neither truly represent the thermodynamics of the problem over the given range of the independent variables (temperature and pressure). These two equations would not be deemed requisite models. The ideal gas law, van der Waals equation, and Beattie-Bridgeman equation all underestimate the specific volume. However, the Beattie-Bridgeman equation does represent the thermodynamics of the problem (as does the BWR equation) since the errors drop off nearly symmetrically either side of their peaks.

For simplification, a distribution may be fit to such data instead of using a "custom" PDF that fits the data as shown in Fig 5.1. This procedure uses various statistical tests and is described in Appendix A. Continuing with the thermodynamic example, a normal distribution fits both the Beattie-Bridgeman and BWR PDFs with reasonable accuracy. The Beattie-Bridgeman PDF fit has a mean and standard deviation of approximately $-4.3(10)^{-5}$ and $9.22(10)^{-5}$ m^3/kg, respectively. The BWR PDF fit has a mean and standard deviation of approximately $2.1(10)^{-5}$ and $4.87(10)^{-5}$ m^3/kg, respectively. The much narrower PDF of the BWR fit with its smaller standard deviation implies that the BWR equation is indeed a better model for determining the specific volume of nitrogen than the Beattie-Bridgeman equation over the given range of the independent variables. Another method to obtain a distribution through data is using the maximum entropy method. The maximum entropy method assumes bounds of the unknown function are known or must be assumed. Since bounds of an uncertain variable are often not known, this method is not typically attractive [Siddall, 1983]. It should be noted that the approximation errors for all four models of the specific volume example presented could be addressed via calibration. This would not be the case for complicated models with dozens of uncertainties where calibration would be impractical or impossible.

5.2.2.2 Via Expert Elicitation

Unfortunately it is often impossible to have sufficient data to gauge a model. Little or no data to appropriately gauge a model occurs more frequently in practical engineering analyses than is commonly admitted. The thermodynamic example presented in the previous section had a significant amount of highly accurate test data to compare the various equations of state. With models of new systems there may only be a few actual systems to compare the model with. Furthermore, validating models is expensive and time consuming and few system responses are typically measured in testing or operation as compared to the extraordinary number of system responses that can be predicted by a mathematical model. Lastly, approximation error occurs in the case of poorly characterized model validation (or calibration) experiments for complete engineering systems. System-level experiments are commonly functionality or performance tests with little useful data for computational model validation and uncertainty estimation [Oberkampf, Helton, & Sentz, 2001]. Although a system-level model can often be separated into smaller, more manageable submodels where approximation errors may be addressed with actual data at a lower hierarchical level, this effort is also expensive and time consuming.

In the extreme situation for assessing approximation errors there are no actual data points at all. Assessing the validity of a model in these situations is possible through expert elicitation. The experts for assessing the validity of a model are likely to be the engineers and designers who developed and/or use the model. Elicitation of expert opinion is a well-established procedure that is detailed in Spetzler and von Holstein (1975); Keeney and von Winterfeldt (1991); Cleaves (1994); and Ayyub (2001). Expert opinion results in subjective probabilities and PDFs for model uncertainties that are judgment estimates yet can be mathematically implemented in an analogous manner to those generated by raw or empirical data as described in the previous section. Formal assessments of uncertainty by experts can also be useful when there is disagreement about uncertainties. This aspect of expert elicitation is discussed in Chapter 6 and Chapter 7. This section briefly describes issues and concerns that must be considered in implementing expert elicitation in assessing approximation errors. The actual procedure for implementation is described in the references listed previously.

5.2.2.2.1 Implementation Issues

Assessments of approximation errors are most accurate when rigorous and systematic processes for eliciting judgments are implemented. Such a systematic process controls and compensates for inconsistencies and eccentricities inherent in the human judgment processes. Cleaves (1994) recommends the use of one or more analyst/facilitators (A/Fs) to assist in eliciting expert opinion. A/F responsibilities should include

- Being knowledgeable about the model being assessed and trained in probability encoding techniques. Assessment is difficult without such assistance because experts can become overwhelmed with the task and unaware of biases that creep into their judgments.
- Leading the experts through the process and motivating them to recognize and deliver useful and bias-free judgments.
- Understanding the larger decision context, how the assessment results will be used, and be a liaison between the experts and the decision maker. The A/Fs can match assessment techniques to the personalities of the experts and the characteristics of the uncertain model.

- Challenging the experts to uncover new sources of information concerning the model and confront inconsistencies in expert elicitation when it arises.
- Providing continuity across assessments by different people and disciplines and can assist in mediating disagreements during group assessments.

A critical aspect of eliciting expert opinion is a careful documenting of assumptions. A record of the level of technical experience and personal aversion to risk of the expert being elicited should be kept since these two factors influence their assessments. Unfortunately, due to time and budgetary constraints the documentation of such assumptions and the thought process in the design of complex multidisciplinary systems is done semi-formally, informally, or not at all. The engineers and designers on the project understand the models they use yet may describe modeling aspects in words rather than numbers. This is typical of expert elicitation since words are easier to use than numbers and do not demand data or disciplined precision. This qualitative description of approximation errors is illustrated in Fig. 5.2 which relates verbal expression to probability values which can in turn be transformed to PDFs.

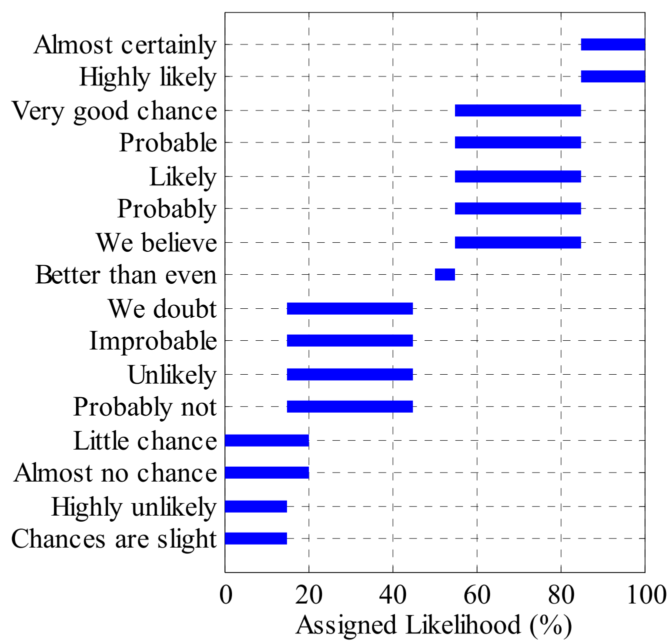

Fig. 5.2 Example relation between verbal expression and assigned likelihood; adapted from Kent (1964).

Lastly, experts are useful in addressing limitations of the model being assessed. This includes both the range of validity, when or when not to use the model, and when the model may fail to perform its function. Thinking of all the possible and potential failure manifestations of the model (i.e., how the model is unsatisfactory) seems perverse, self-depreciating, even sinister, yet is a critical part of how to assess and obviate the limitations of the model in using it to design and develop a complex multidisciplinary system.

5.2.2.2.2 Concerns

There are many concerns in eliciting expert opinion. These concerns fail into two domains: personal and motivation concerns; and probabilistic implementation concerns.

Experts may be predisposed in favor of one decision alternative that they perceive the model they are assessing will be used to support. They in turn may unconsciously or consciously orient their assessments to support it. Although there is no cure for such motivational bias it can be combated in several ways including breaking down the assessment of uncertainty to a level where it would be difficult to be biased; urge A/Fs to document signs of wishful thinking, inappropriate optimism, or pessimism; challenge assessments; assure confidentiality; and use a mixture of A/Fs. Personal feelings about people or organizations may also cloud the judgment of experts. Lastly, experts often overestimate model uncertainty assessments. They would rather be wrong by predicting results that do not happen than by failing to predict events that occur [Cleaves, 1994].

Probabilistic implementation is also a concern in eliciting expert opinion of approximation errors. Experts often will pick a familiar probability distribution (e.g., Normal/Gaussian) to represent their belief in approximation errors. Picking parameters for continuous probability distributions that properly estimate the tails of the distributions is extremely difficult because few people have had any experience with such events or outcomes or distinguishing among small probability values. In situations when no information is available, experts may assume a uniform distribution to assess approximation errors which often underestimates the problem [Oberkampf, Helton, & Sentz, 2001]. Finally, one person's plausible event in assessing model uncertainty is another person's impossibility.

5.2.2.2.3 Disagreements About an Uncertainty

Disagreements can arise between informed experts about the representation of a model uncertainty. Disagreement among informed experts occurs often when there is a lack of empirical basis for estimating uncertainties and/or when only subjective estimates are possible via probability distributions elicited from expert judgments. Weighted averages involve convolving uncertainties based on the importance and/or credibility of the informed experts. The mathematical procedure for convolving uncertainties is described in Appendix A. Bayesian techniques, described in the subsequent section, allow a prior distributions elicited by expert opinion to be updated with actual empirical data. With increased availability of data, Bayesian techniques render the prior distribution increasingly unimportant (see example presented in Appendix A) thereby diminishing differences in opinion that may have arisen between experts.

5.2.2.3 Via Bayesian Techniques

Bayesian techniques are an extension of expert elicitation that can assess uncertainty in a model when some information is available. It is also common in complex multidisciplinary design that no direct experimental data are available for the exact model of interest, but experimental data are available for similar models that have been analyzed in the past. The issue then becomes one of the analysts' judgment concerning the similarities and differences between the previously obtained experimental data and the present system of interest. Another common situation arises where a limited amount of data is available but not a satisfactory amount to construct a PDF as illustrated earlier. Both situations are amenable to Bayesian techniques which are discussed in Appendix A. Appendix A also illustrates how Bayesian techniques can be implemented in an actual example.

Bayesian techniques are not without controversy. Concerns about Bayesian techniques mirror those of expert elicitation. Bayesian techniques are highly influenced by the assumptions that went into the existing belief (the prior distribution), certainly for those cases where little new data are available to update an existing belief. Critics of Bayesian techniques are concerned that this existing belief can spawn less objective evaluations of results than the traditional frequentist approach. Bayesian techniques address this concern, at least somewhat, in that sufficient data renders the prior distribution (existing belief) all but irrelevant. The prior distribution is "washed out" by actual data (the example in Appendix A illustrates this). Despite these concerns, Bayesian techniques take advantage of prior experience in a way that traditional statistical techniques do not. With sufficient scrutiny, Bayesian techniques are a powerful tool at the disposal of analysts with prior information and experience available.

5.2.3 Numerical and Programming Errors

Model uncertainty also arises from numerical and programming error. Numerical error can arise due to finite precision arithmetic and can be reduced by using higher precision computers and software. Examples include spatial discretization error in finite element and finite difference methods; temporal discretization error in time-dependent simulations; and error due to iterative convergence of approximation algorithms. Programming error occurs during development of the model due to blunders or mistakes by the programmer. Although there is no straightforward method for estimating programming errors, they can be detected by the person who committed them, resolved by better communication, or discovered by redundant organizational and operational procedures and protocols [Oberkampf et al., 1999]. Policies and best practices of individual organizations can minimize both numerical and programming errors and are not addressed further in this thesis.

5.3 Phenomenological Uncertainty

Phenomenological uncertainty is a form of epistemic uncertainty that cannot be quantified at present. The concept of phenomenological uncertainty was discussed in Chapter 2 and alluded to under differing names in various fields. This section begins with a detailed definition of phenomenological uncertainty. Examples of phenomenological uncertainty follow. The proposed method is probabilistically based and relies on knowledge of all states concerning the phenomena or systems or interest. Phenomenological uncertainty represents a challenge to the proposed method since all states may not be known. However, techniques to address phenomenological uncertainty are available and conclude the discussion in this section.

5.3.1 Definition

Phenomenological uncertainty arises whenever the design technique or form of development generates uncertainty about any aspect of the possible behavior of the system under development, operation, and extreme conditions. Some relevant information cannot be known *ex ante*, not even in principle, at the time of making decisions during design. This is due to humankind's basic knowledge of the universe at the time decisions must be made. The future cannot be anticipated by a reliable probabilistic representation because the future is yet to be created. The future is to a considerable extent unknowable, because surprises may occur, both as intended and as unintended consequences of human action.

The problem is not merely that there is not enough information to reliably attach probabilities to a given number of events but that an event which cannot yet be imagined may occur in the future. Phenomenological uncertainty is thus particularly important for novel projects or those which attempt to extend the 'state of the art'. Often these projects run into design, development, or operational problems due to an apparently 'unimaginable' phenomenon (so called "unknown unknowns"). As certain phenomena cannot be imagined in the present, it is not possible to attribute probabilities to these phenomena. Associated with this is the fact that in many cases, as something that cannot be imagined may occur, it is not even possible to conceive what complete information would be [Dequech, 2000]. This aspect of phenomenological uncertainty is often characterized by a poorly understood coupling of diverse physical processes or events that may lead to a catastrophic result.

Phenomenological uncertainty should not be confused with mistakes, oversights, or poor effort (e.g., one or more components that an engineer forgets to include in a design). Individuals and organizations should have sufficient self and peer evaluations, procedures, and, if necessary, punishments, to minimize these issues.

5.3.2 Examples

The field of aerospace engineering is only 50 years old yet the history of aerospace projects is replete with examples of how devastating the impact of phenomenological uncertainty can be. In fact the very first spacecraft launched by the United States failed because of phenomenological uncertainty. Explorer 1 was launched on January 31, 1958 and soon after achieving orbit began an uncontrolled spin. The cause was found shortly after to be spacecraft energy dissipation that was not imagined. The failure of the Explorer 1 spacecraft advanced the "state of knowledge" about space systems design, albeit at the price of a successful mission.

Two of the most pernicious failures in the history of the United States space program, Apollo 1 capsule and the Columbia space shuttle, were the result of phenomenological uncertainty. Apollo 1 was destroyed during routine testing at Cape Canaveral on January 27, 1967 when a fire broke out inside the capsule killing the three astronauts onboard. The capsule was pressurized with pure oxygen, the oxygen was at a higher pressure (16.7 psi) than atmospheric pressure (14.7 psi), the inside of the capsule was lined with Velcro, the escape hatch could only open inward, emergency evacuation procedures were complicated, and evacuation procedures had yet to be fully trained for by the astronauts since this period in testing was viewed as routine and not potentially hazardous [NASA, 1967]. On their own each of these characteristics was a potential danger yet the risk of a fire and its impact due to any single one of these characteristics was estimated by engineers and analysts to be manageable. However, no one involved in the Apollo program was able to predict the result of these characteristics coupled together in the event a fire broke out. Indeed, it was Colonel Frank Borman, one of the Apollo 1 accident investigators and future commander of Apollo 8, who described the Apollo 1 tragedy as a "failure of imagination" [NASA, 1967].

The space shuttle Columbia accident is similar. Columbia (Space Transportation System mission #107) launched from Cape Canaveral on January 16, 2003. After a 16 day science mission in orbit, the shuttle orbiter returned to Earth on February 1, 2003 and disintegrated over Texas killing all seven astronauts onboard. The physical cause of the loss of Columbia and its crew was a breach in the Thermal Protection System (TPS) on the leading edge of the left wing, caused by a piece of insulating foam which separated from the external tank 81.7 seconds after launch, and struck the wing. During re-entry this breach in the TPS allowed superheated air to penetrate through the leading edge insulation and progressively melt the aluminum structure of the left wing, resulting in a weakening of the structure until increasing aerodynamic forces caused loss of control, failure of the wing, and breakup of the orbiter [NASA, 2003]. Previous shuttle launches had insulating foam strike the TPS while Shuttle managers were cognizant of potential TPS damage since it occurs on every flight at varying levels of severity [Paté-Cornell & Fischbeck, 1993]. However, insulating foam striking the leading edge was either not imagined or not considered credible by the Space Shuttle community.

Phenomenological uncertainty has certainly impacted a wide variety of other fields as well, recently and perhaps best exemplified by the intelligence community. The *National Commission on Terrorist Attacks upon the United States* (2004) concluded that a "lack of imagination" was the biggest intelligence failing prior to the terrorist attacks of September 11, 2001. Despite a progression of increasingly sophisticated and ruthless attacks by individuals and organized groups (e.g., 1993 World Trade Center bombing; 1995 Oklahoma City bombing; 1995 Manila plot to bomb a dozen airliners over the Pacific; 1995 Tokyo subway attack; 1996 Khobar towers bombing; 1998 Nairobi and Dar es Salaam embassy bombings; 2000 attack on the *USS Cole*), it was not clear if a radically new threat was developing. Indeed, the 9/11 attacks involved two disparate concepts the U.S. intelligence community and government had experience with: suicidal terrorist attacks and using aircraft as weapons. The 1983 Beirut Marine barracks bombing, the October 2000 attack on the *USS Cole*, and the dozens of Palestinian suicide bombings before and during the 2000 *intifada* in Israel and the occupied territory demonstrated the former. *Kamikaze* attacks by the Japanese towards the end of World War II, the 1994 Algerian airline hijacking of a French airliner, North American Aerospace Defense Command (NORAD) simulations, and even a Tom Clancy novel[†] demonstrated the latter. Nonetheless, the coupling of these concepts was not seriously considered by the intelligence community as a serious threat to the United States. Imagining disparate concepts and issues coming together to yield catastrophic results (in the context of vast amounts of information) impact a wide variety of fields beyond aerospace.

5.3.3 Addressing Phenomenological Uncertainty

Since it is not currently possible to quantify phenomenological uncertainty, there are techniques that may mitigate or reduce it, including increasing the "state of knowledge;"

[†] *Debt of Honor*, Putnam Publishing Group, 1994.

increased and expanded systems engineering; and robust design. These techniques have not been rigorously pursued or investigated. Such a task is beyond the scope of this research.

5.3.3.1 Increasing the "State of Knowledge"

As a sub-element of epistemic uncertainty, phenomenological uncertainty fundamentally deals with a lack of knowledge. Any effort that can increase the "state of knowledge" can reduce phenomenological uncertainty. Explorer 1, discussed previously, illustrates this. United States Defense Secretary D. Rumsfeld alluded to addressing phenomenological uncertainty at a press briefing in February 2002:

> Reports that say something hasn't happened are always interesting to me, because as we know, there are known knowns; there are things we know we know. We also know there are known unknowns; that is to say we know there are some things we do not know. But there are also unknown unknowns -- the ones we don't know we don't know. And each year we discover a few more of these unknown unknowns [DoD, 2002].

Increasing the "state of knowledge" can be accomplished in a variety of ways. Fundamental research, experimentation, and testing are perhaps the three most established examples. In particular, in engineering design knowledge is created primarily through analysis and test, which are based on models and experiments that represent reality [DeLaurentis, 1998]. This idea is illustrated by the efforts of researchers to develop increasingly accurate thermodynamic model discussed earlier.

5.3.3.2 Increased and Expanded Systems Engineering

System engineering developed in the decades following the Second World War with the development of the Polaris missile program and then the Mercury/Gemini/Apollo programs. Systems engineering is defined and briefly discussed in Chapter 1. System engineers are responsible for finding out where problems or issues might arise, particularly across interfaces. Too often projects are understaffed with system engineers and development problems occur. Having a sufficient number of system engineers, particularly several who have sufficient free time to stop, take a step back, and look at the entire design instead of continuously going from one task to another, may help uncover phenomenological uncertainty. The role of the systems engineer in eliciting expert opinion was discussed previously in this chapter while the potential of the systems engineering field evolving based on the proposed method is discussed in Chapter 10. Having internal (peer) and external reviews are a proven way to assist system engineers in uncovering phenomenological uncertainty. The type, number, and timing of reviews for maximum benefit to a project have been investigated by others (e.g., [Dillon, 1999]).

Probabilistic risk analysis (PRA), which was discussed in Chapter 1, is the first logical step in assisting engineers, specifically system engineers, in this increased and expanded role. Too often, PRA is viewed, not as part of the design effort, but as something performed by separate engineers and analysts on a project, possibly to confirm pre-conceived notions of risk. However, when applied by the system engineers overseeing the design, PRA can be a powerful tool to uncover potentially serious flaws and risks in a design. One of the potential drawbacks of an extensive PRA effort is too much imagination. It is conceivable that engineers without experimental data or expert opinion available could divert time and resources conjuring up and addressing impossible or highly improbably events.

Although difficult to find documented examples in engineering projects, this issue of too much imagination has been demonstrated in other fields. The intelligence community provides a recent example (again) as they were responsible for too much imagination in the case of weapons of mass destruction (WMD) in Iraq. By imagining what might plausibly be, rather than what it could document to be, the intelligence community, in particular the American, British, and Israeli intelligence communities, adopted a worst-case approach. This extreme imagination in part led the Bush administration to lead an invasion of Iraq in March 2003. The fact that no WMD were discovered in Iraq in the months following the war has been an enormous embarrassment to these organizations [O'Hanlon, 2004]. Nonetheless, participants should be slightly paranoiac during design. Imagination and fear are among the best tools for quantifying uncertainty and preventing tragedy [Zetlin, 1988].

5.3.3.3 Robust Design

Robust design is a procedure by which a designer or engineer determines the set of input variables that both maximizes one or more output values and minimizes the variability in the output values. Robust design is based on Dr. Genichi Taguchi's methods of quality engineering developed in the 1980s. Robust design often separates input variables as either control or noise variables. Control variables are those that a designer is able to select precisely. Noise variables are those that a designer cannot select precisely (i.e., they are uncontrollable). Designs that are robust to noise may also be robust to phenomenological uncertainty. Proven benefits of robust design and its application are discussed in [Phadke, 1989]. Robust design is a mathematical implementation of basic risk management which attempts to maximize the areas where there is control over the outcome while minimizing the areas where there is no control over the outcome and the linkage between effect and cause is not apparent.

Similarly, safety factors discussed in Chapter 1 could be construed as a crude technique to address phenomenological uncertainty when their values are much greater than the union of worst possible conditions. Such safety factors, by performing adequately under highly improbable conditions may be robust to phenomenological uncertainty. However, the issues of safety factors (and the design margins examples) discussed in Chapter 1 illustrate that this possible (not certain) benefit is small compared to all the negative aspects of these methods.

5.4 Summary

This chapter discusses generating models in the proposed method. Model formulation for tradable parameters is first introduced followed by a detailed explanation of model uncertainty. A significant portion of this chapter is dedicated to assessing model uncertainty via existing data, expert elicitation, and Bayesian techniques. A definition of phenomenological uncertainty, examples, and techniques to address this type of uncertainty in the design of complex multidisciplinary systems follows. With the models generated and their uncertainty quantified, the next step in the method involves classifying and addressing other uncertainties. This is the topic of the next chapter.

Chapter 6 Classifying and Addressing Uncertainties

Once models have been created for all tradable parameters, and model uncertainty has been quantified for each tradable parameter, the next step in the proposed method is classifying and quantifying all the uncertainties (input variables) that enter the models. A model for a complex multidisciplinary system may have dozens, even hundreds, of these variables. Classifying the variables into their uncertainty types is useful in understanding their respective impact on the overall design. Some input variables are certain (i.e., fixed quantities), others uncertain. For those input variables that are uncertain, each is probabilistically modeled. This chapter describes the characteristics of each type of uncertainty an input variable may represent as well as techniques to address that type of uncertainty. Ambiguity and aleatory uncertainty are first discussed. The majority of this chapter is dedicated to discussing and addressing behavioral uncertainty. This chapter builds on the previous chapter since many of the techniques used to quantify and address model uncertainty are valid for quantifying and addressing ambiguity, aleatory uncertainty, and behavioral uncertainty. The chapter concludes with a discussion of techniques to ascertain which uncertainties are important.

6.1 Ambiguity and Aleatory Uncertainty

Ambiguity is a linguistic imprecision introduced in Chapter 2. Because little precision is required for general communication, ambiguity remains an unavoidable aspect of human discourse. Although ambiguity can be reduced by linguistic conventions and careful definitions, this is often not done because of the effort required. Fuzzy logic, described in Chapter 3, has been used as a formal method to represent ambiguity. Traditional probabilistic techniques such as generating a probability density function (PDF) described in Chapter 5 are also valid and are assumed in the proposed method to allow combination (convolution) with other probabilistic representations of uncertainties. Probabilistic techniques also appear more amenable than fuzzy logic to successful optimization of designs (a critical aspect of preliminary design) [Maglaras, 1995]. Ambiguity in a quantity or parameter is characterized by an inability to empirically measure it. Ambiguity should not be confused with design uncertainty that is described later in the chapter. Design uncertainty is fuzzy due to unresolved alternatives, not due to linguistic concerns.

Aleatory uncertainty is inherent variation associated with a physical system or environment under consideration. Aleatory uncertainties can typically be singled out from other uncertainties by their representation as distributed quantities that can take on values in an established or known range, but for which the exact value will vary by chance from unit to unit or time to time. Examples include the strength or exact dimension of a component where the manufacturing processes are well understood but variable, and the parts have yet to be produced. Aleatory uncertainty can be represented by a probability density function (PDF) that may be generated via existing data, expert elicitation, or Bayesian techniques. All three procedures are described in Chapter 5. For example, the measured density of a fictitious lot of fifty different (independent) 6061-T6 aluminum samples are provided in Table 6.1.

Table 6.1 Possible measured density data of 6061-T6 aluminum

2709.8	2709.8	2707.3	2709.4	2705.3	2710.9	2711.1	2713.1	2712.1	2706.6
2711.5	2714.6	2710.1	2703.8	2709.8	2708.7	2712.2	2708.8	2715.9	2709.4
2708.2	2708.2	2708.1	2710.4	2708.0	2710.2	2716.3	2705.9	2711.5	2713.6
2709.6	2706.0	2711.6	2714.8	2706.9	2708.9	2705.9	2710.9	2715.6	2706.7
2708.7	2711.4	2711.7	2713.1	2706.3	2708.6	2706.9	2714.7	2709	2711.9

These values can be converted to a PDF as shown by the solid line in Fig. 6.1.

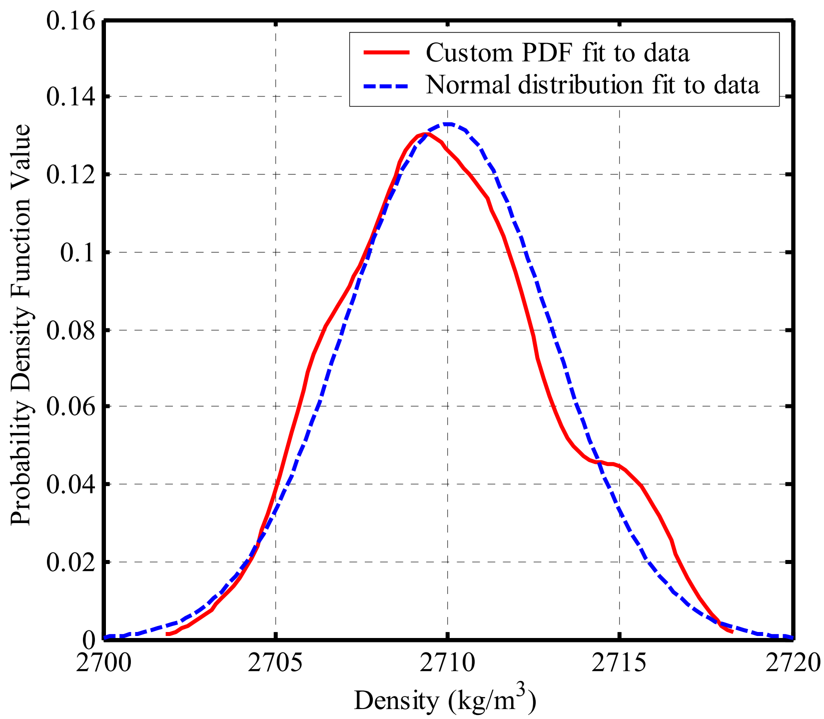

Fig. 6.1 6061-T6 aluminum density uncertainty representation.

As discussed in Chapter 5, the preferred option among existing data, expert elicitation, and Bayesian techniques is obtaining and using existing data since engineers, the analyst/facilitators (A/Fs), the decision maker, and/or the stake holder can make their own interpretations of the data.* These individuals may wish to fit an existing distribution to the data (procedure described in Appendix A) to simplify subsequent analyses instead of using a complicated custom PDF. The trade-off with such a procedure is the introduction of approximation errors. This is shown by the dashed line in Fig. 6.1 as a normal distribution that is fit to the data. In this case the distribution fits the data well by using the mean (2710.0 kg/m^3) and standard deviation of the data (2.959 kg/m^3) as the mean and standard deviation of the fitted distribution: $N(2710,2.959)$. Furthermore, the one-way analysis of variance (ANOVA), Kruskal-Wallis nonparametric one-way ANOVA, and Friedman's nonparametric two-way ANOVA p-values are 0.9947, 0.8903, and 0.8769, respectively (i.e., all significantly greater than 0.05).

However, fitting a distribution to the data can introduce significant errors if the underlying physics are not well understood. In simulation-based design, assuming a normal distribution can cause problems even if such a distribution fits the data well. For example, in quantifying the uncertainty in the emissivity of a material a decision maker may be tempted to use a normal distribution. However, a normal distribution for a low-emissivity material (e.g., a highly polished metal) with high variability would yield probabilities for negative emissivity values. Since emissivities can range only from zero to one, a negative emissivity value could yield catastrophic results when used by a model to calculate, for example, heat transfer. Hence, despite normal (Gaussian) distributions being the most common distributions that occur in nature, *quetelismus*† must be avoided. In the emissivity example, a lognormal distribution would probably be most appropriate since a lognormal distribution is valid only for values greater than zero and allows significant variability. Many other probability distributions are available to represent uncertainties as well. A uniform distribution may be used to model variables whose value is known to be within a range but not about any one particular value. An exponential distribution is often used in lifetime applications. A Weibull distribution is an example of one of the many distributions that can be used in reliability models [Evans, Hastings, & Peacock, 2000]. Several of these distributions are described in Appendix A.

Aleatory uncertainty can also be quantified via expert elicitation or using Bayesian techniques. The latter is appealing for many aleatory uncertainties as expert elicitation can be updated with data as data becomes available (e.g., expert elicitation of uncertainty in a material

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*"Get the data" – Life lesson #6 of Robert McNamara, former U.S. Secretary of Defense (1961-1968) from the *Fog of War* (Sony Pictures Classics)

†Quetelismus is a word coined by the mathematician and economist Francis Ysidro Edgeworth to describe the growing popularity around the turn of the 20th century at discovering normal distributions in places where they did not exist or that failed to meet the conditions that identify genuine normal distributions

density updated with data such as that shown in Table 6.1). It should be noted that a decision maker has little control over aleatory uncertainty in the design of complex systems, far less than other uncertainties. Limited options, such as quality control, exist to reduce (but not eliminate) aleatory uncertainty. As discussed in Chapter 2, aleatory uncertainty is often called irreducible uncertainty. In the extreme, a PDF for a given aleatory uncertainty with sufficient data and quality control likely represents measurement error in the procedure to measure that parameter.

6.2 Behavioral Uncertainty

The uncertainties discussed thus far (model, phenomenological, ambiguity, and aleatory) are addressed via established techniques yet limited options exist to reduce these uncertainties significantly. In terms of the design of complex multidisciplinary systems, these uncertainties might imply a preordained solution. Behavioral uncertainty is uncertainty in how individuals or organizations act and is quite the opposite of the other uncertainties discussed thus far. The techniques to handle behavioral uncertainty are not well established and yet, by definition, individual choices and action may result in significant changes in (and possibly reduction of) uncertainty. Behavioral uncertainty represents at its fundamental level "free will" on the part of the participants in a design. Behavioral uncertainty arises from four sources: design uncertainty, requirement uncertainty, volitional uncertainty, and human errors. Each is described in this section.

6.2.1 Design Uncertainty

Design uncertainty is a choice among alternatives over which an individual or individuals exercises direct control but has not yet decided upon. This choice may be selecting from among a set of discrete alternatives or a single value within a continuous range. Design uncertainty is fuzzy due to unresolved alternatives. Consider an engineer who begins designing a fluid system. The engineer has several discrete choices for the tubing used to route the fluid through the system. These choices along with his or her judgment of that tubing being used in the actual design are shown in Table 6.2.

Table 6.2 Possible component choices for tubing

ID	Name	Class	Diameter, outer (in)	Thickness (in)	Probability of being used
1	SS-T6-S-035-20	3/8" 0.035" wall	0.375	0.035	0.15
2	SS-T8-S-035-20	1/2" 0.035" wall	0.5	0.035	0.25
3	SS-T10-S-065-20	5/8" 0.065" wall	0.625	0.065	0.40
4	SS-T12-S-065-20	3/4" 0.065" wall	0.75	0.065	0.20
5	SS-T16-S-083-20	1" 0.083" wall	1	0.083	0

Within a formal method to determine margins, the design uncertainty listed in Table 6.2 can be represented as a discrete custom probability distribution with two column array of values: $C_d(\underline{\underline{A}})$. The first column of this array is the choice (an integer) while the second column is the probability of that choice being selected (a value between 0 and 1, inclusive):

$$\underline{\underline{A}} = \begin{bmatrix} 1 & 0.15 \\ 2 & 0.25 \\ 3 & 0.4 \\ 4 & 0.20 \end{bmatrix} \tag{6.1}$$

The corresponding discrete probability density function (PDF) for this design uncertainty is shown in Fig. 6.2.

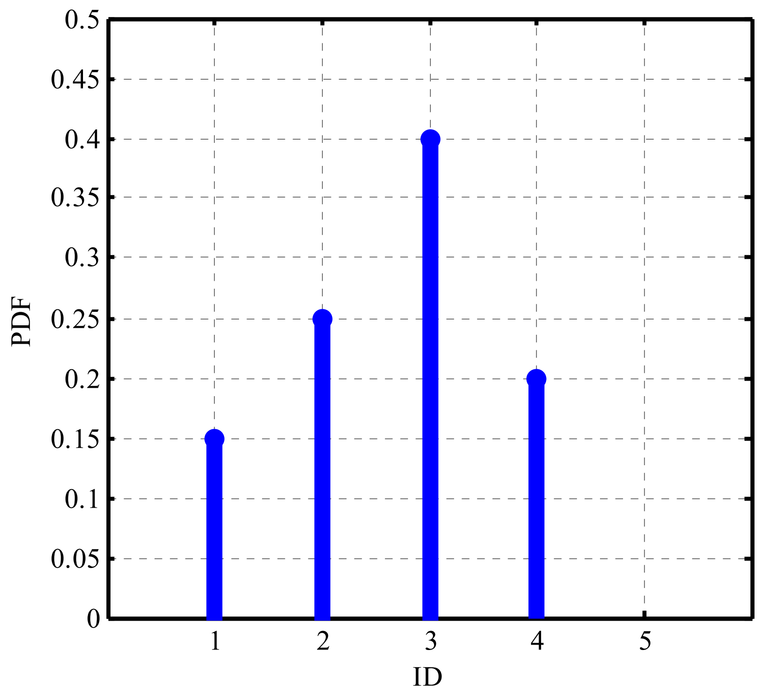

Fig. 6.2 PDF of component choices for tubing.

Hence, the probability values in Table 6.2 and corresponding PDF in Fig. 6.2 represent the subjective estimate of the engineer about what they will ultimately choose. Hence, quantifying design uncertainty is almost exclusively expert elicitation. Bayesian techniques would be the other possibility if expert elicitation could be supplemented with data of past choices the engineer has made in similar designs. The PDF in Fig. 6.2 is a unique PDF for this engineer for this choice. The choice cannot be incrementally improved or worsened. The difference between selections for such a discrete example results in step functions for possible parameters of interest (e.g., tubing diameter, total mass of tubing). A further difficulty in representing design uncertainty via the PDF shown in Fig. 6.2 is the fact that the order of the different tubing types (components) is completely arbitrary, at least from the perspective of a mathematical algorithm, as the ID values represent quantities not represented in the PDF itself. In other words, the order of these components could be switched to any other order, a new component could be added somewhere in the database, and a new and different PDF could be constructed that would be identical to the PDF in Fig. 6.2 provided the probabilities and ID remained matched with their respective choices. More generally, a database for a choice among components may have two, ten, or a hundred options. For a database with ten values in it, two to all ten may have a positive probability of being chosen. These properties on their own are not significant but do become problematic when combining with other uncertainties (a topic that is discussed in Chapter 7).

Design uncertainty is progressively reduced through decisions until, ultimately, all choices have been implemented and the final design is specified precisely. These decisions represent the design process itself and the judgment of engineers and designers represents the most indispensable tool in altering the design. After uncertainties have been propagated and mitigated, optimization is typically the next step an engineer pursues to improve tradable and other parameters in his or her complex multidisciplinary system design. Design uncertainty is thus intertwined with optimization. Optimization techniques that might be combined with the proposed method for propagating and mitigating uncertainty in design of complex multidisciplinary systems are discussed in Chapter 10.

6.2.2 Requirement Uncertainty

Requirement uncertainty includes parameters of interest to and determined by the stake holder, independent of the engineer or designer. An example may be the desired lifetime of a satellite that is explicitly specified by the customer. Although the customer may specify a lifetime value of, for example, 5 years early in the design, the customer is often not sure what value is required at this time. This 5-year requirement may change to 7 years a few months into the design effort. Such an occurrence is referred to as “requirements creep” in many engineering fields. Requirement uncertainty is analogous to design uncertainty in that it is fuzzy due to unresolved alternatives. Ambiguity (linguistic imprecision) in specifying the actual requirement can be mathematically combined with requirement uncertainty (discussed in Chapter 7). Otherwise, ambiguity in the requirements can be reduced by linguistic conventions and careful definitions. Uncertainty in requirements can be the most devastating uncertainty in development because it overrides everything else in the design process. Walton (2002) noted that engineers and decision makers at three of the four major aerospace organizations he interviewed believed that requirements instability and uncertainty are the largest source of uncertainty in the design of space systems. Research by Scott (1998) and McNutt (1999) seem to corroborate the importance and potential impact of requirement uncertainty in a variety of engineering application areas.

Political uncertainties are a form of requirements uncertainty. In reference to the Polaris fleet ballistic missile program of the 1950s, Sapolsky (1972) noted

> The greatest uncertainty in the project becomes the political uncertainty over its own future. To both the observer and participant, the research and development issue looks inefficient; there are likely to be cost overruns because of underbidding, schedule delays because of irregular funding, and inadequate technical performance because of a failure to gain a concentrated effort.

Weigel (2002) dedicated her doctoral research into investigating policy changes and uncertainties in space systems conceptual design and provides qualitative and quantitative methods to address this type of uncertainty. As with design uncertainty, quantifying requirement uncertainty is almost exclusively accomplished via expert elicitation. Expert elicitation may be supplemented with data (if available) of the stake holder's past record in changing requirements for similar designs via Bayesian techniques. Expert elicitation and Bayesian techniques are described in Chapter 5.

It should be noted that the distinction between a design uncertainty and a requirement uncertainty is not universal and not always clear. That is to say, for a given complex multidisciplinary system, a certain variable may be deemed a requirement; for another complex multidisciplinary system that variable may be deemed a design variable. A spacecraft with a particular subsystem illustrates this concept. A spacecraft may have requirements on the orbit to achieve but leave the orbit insertion design to the mission designer making the change in velocity of the spacecraft a design variable. The change in velocity of the spacecraft, however, would likely place a requirement on the propulsion system.

6.2.3 Volitional Uncertainty

Volitional uncertainty is uncertainty about what the subject him/herself will decide. Whereas design and requirement uncertainty can be quantified by participants in the proposed method, volitional uncertainty cannot. Due to human and psychological elements that did not appear amenable to mathematical analysis, volitional uncertainty was not rigorously considered in applications until the mid-twentieth century. von Neumann and Morgenstern (1953) dismiss as "utterly mistaken" the view that the human and psychological elements stand in the way of mathematical analysis. Recalling the lack of mathematical treatment in physics before the sixteenth century or in chemistry or biology before the eighteenth century, they claim that the outlook for mathematical applications in those fields "at these early periods can hardly have been better than that in economics – *mutatis mutandis* – at present." This seminal work in addressing volitional uncertainty by von Neumann and Morgenstern spawned game theory that was discussed in Chapter 3. Elements of game theory, although originally developed for the field of economics, are valid in the design of complex multidisciplinary systems.

Often the participants in a design (e.g., decision maker, stake holder) may have differing goals and objectives. This is especially true in the design of systems built by more than one organization. A complex multidisciplinary system typically has a lead organization (the "prime") that is responsible for integration. This prime may have several "subcontractors" responsible for providing full assemblies, components, analysis, and/or labor. The relationship between the prime and contractors may be similar to that between the stake holder and the prime. The prime has the goal of delivering the complex multidisciplinary system based on the requirements specified by the stake holder at an agreed upon price. The subcontractors have a similar goal of providing their product (i.e., assemblies, components, analysis) based on the requirements of the prime at an agreed upon price. In both cases, the primary goal of the prime or the subcontractors may instead by profit maximization or one or more ulterior (and hidden) motives.

These possible ulterior motives have resulted in inventive and complicated risk and cost sharing agreements between stake holders and primes and primes and subcontractors [Healy et al., 2004]. Fixed-price and profit-sharing contracts represent two ends of the cost sharing agreement spectrum. Under a fixed-price contract, subcontractors often exert a sub-optimal effort level because a lack of incentive exists to increase their effort. Under a profit-sharing contract, subcontractors may misrepresent their ability and exert sub-optimal effort unless they share a certain amount of the profit.

The stake holder and prime (or prime and subcontractors) will thus likely have different utility functions as described in Chapter 4. Such behavior may be what is seen in Fig. 6.3 which plots the final (actual) cost margin value as a function of the original cost margin estimate for ten recent space systems in which the Jet Propulsion Laboratory (JPL) was the prime.

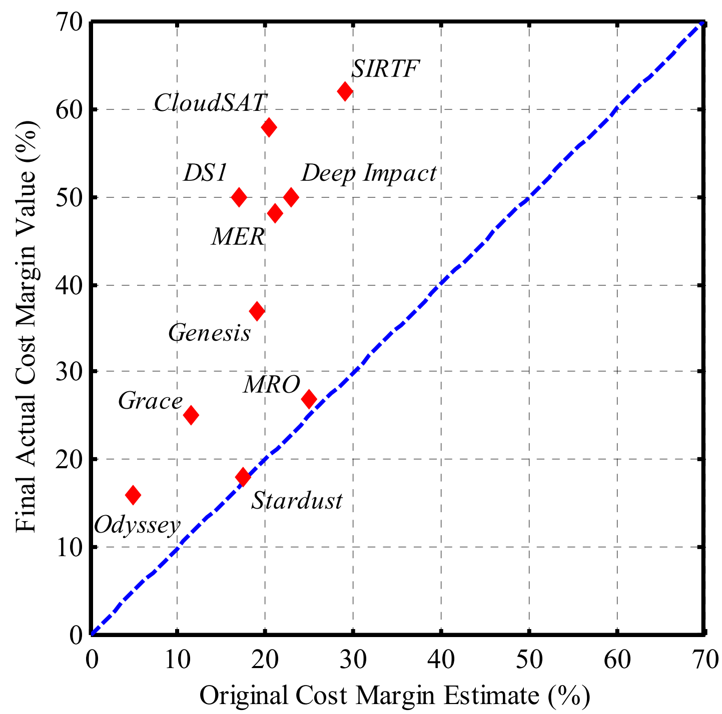

Fig. 6.3 Actual reserves compared to predicted reserves for several spacecraft [Rosenberg, 2004][‡].

Fig. 6.3 indicates that the margins for cost were exceeded for all ten missions (all ten missions are above the dashed line). The lack of a formal method to propagate and mitigate uncertainty (as discussed in Chapter 1) certainly contributed to the poor uncertainty cost estimates. However, the fact that not a single spacecraft is below the dashed line indicates that gaming by the subcontractors may have occurred in the development of the space systems listed. Game theory was developed in part to address this problem of strategic sharing of information to maximize personal gain. The specific portion of game theory which can model this stake holder/prime or prime/subcontractor relationship is *mechanism design*, specifically a *principal agent problem*. This game theory context of mechanism design is different from and should not be confused with the mechanical engineering mechanism design definition (computer aided design and manufacturing of components and assemblies).

Using the prime/subcontractor relationship as the example in the subsequent discussion, the "principal" in the game would be the prime and the "agent" would be the subcontractor. If multiple subcontractors are involved, the game either becomes several independent single-agent models or one multiple-agent model if collusion (coalitions) among subcontractors could occur.

[‡]SIRTF = Space Infrared Telescope Facility; DS1 = Deep Space 1; MER = Mars Exploration Rover; MRO = Mars Reconnaissance Orbiter

This latter case is unlikely in most developed nations where the punishments for such behavior outweighs the possible benefits and is not considered. Utility theory underlies game theory and all of the issues and concerns with utility theory discussed in Chapter 3 apply to mechanism design problems.

Mechanism design transforms a situation where a principal is seemingly at the mercy of a clever agent to one in which the agent has essentially no control over the outcome. In mechanism design problems a principal would like to condition his or her own actions on the private information of agents. For example, the agreement between a prime and a subcontractor on the cost of the services that are being provided by the subcontractor would be a function of private information only the subcontractor has. The principal could simply ask the agent for such information but they will not report it truthfully unless the principal gives them an incentive to do so, either by monetary payments or with some other instrument that the principal controls. Since providing these incentives is costly, the principal faces a tradeoff that often results in an inefficient allocation of his or her resources [Fudenberg & Tirole, 1991]. The distinguishing characteristic of the mechanism-design approach is that the principal is assumed to choose the mechanism that maximizes his or her expected utility, as opposed to using a particular mechanism for historical, heuristic, or institutional reasons.

Mechanism design is typically studied as a three-step game of incomplete information, where the agents' types (e.g., willingness to pay) are private information. The game begins when a principal designs a "mechanism" (contract or incentive scheme). In the second step an agent then either accepts or rejects the mechanism. Finally, agents who accept the mechanism play the game specified by the mechanism. Applications of mechanism design include monopolistic price discrimination, optimal taxation, and the design of auctions [Fudenberg & Tirole, 1991]. Mechanism design was recently applied to address informational and motivational asymmetries in space systems design [Guikema, 2003] that could be incorporated into the proposed method described in this thesis. Guikema (2003) is primarily concerned with informational asymmetries that arise when certain engineers working on a subsystem possess more expertise than other team members and motivational asymmetries that arise if different engineers are seeking different things than the project manager that is supervising them. Guikema (2003) provides a formal method that relies heavily on utility theory and probabilistic risk analysis (PRA) that could be modified to model the relationship between a prime and a subcontractor (or a stake holder and a prime). For example, the method developed by Guikema (2003) could model the situation where a subcontractor provides a design that makes it appear more difficult for the subcontractor to fulfill their agreement with the prime than it truly is. This behavior may persuade the prime to provide the subcontractor a more lucrative agreement to mitigate the perceived risk. The opposite case is also valid and could be modeled: a subcontractor provides a design that makes it seem easier to fulfill their agreement with the prime than it truly is. This behavior may sway the prime to favor this particular subcontractor over others that have bid on the agreement.

Areas of Guikema (2003) may require further extension in applying to a prime/subcontractor situation in the design of a complex multidisciplinary system. For example, Guikema (2003) assumes that all participants in the design process are risk neutral with respect to monetary payoffs. This is a pragmatic assumption since the problem becomes much more complex without risk neutrality. Development of compensation plans for risk averse and risk seeking members is an active area of research; satisfactory approaches applicable to engineering design have yet to be found. Although engineers are likely more risk-averse than the program manager in many practical problems, no research into the risk behavior of primes and subcontractors has been discovered. Lastly, the method outlined in Guikema (2003) does not address phenomenological uncertainty which, as discussed in Chapter 5, remains an enormous challenge in the design of complex multidisciplinary systems.

6.2.4 Human Errors

Similar to the programming errors discussed in Chapter 5, human errors are difficult to estimate. However, facilitative measures and control measures have proved successful in reducing human errors. Facilitative measures might include education, a good work environment, a reduction in task complexity, and improved personnel selection. Control measures might include self-checking, external checking, inspections, and legal sanctions [Melchers, 1999]. Human errors are not discussed further in this thesis.

6.3 Importance of Uncertainty

This chapter and the previous chapter indicate that quantifying model uncertainty, ambiguity, aleatory uncertainty, and behavioral uncertainty can be a time consuming and expensive process. If a probability density function (PDF), or data that can readily create a PDF, is available or easy to create for a given uncertainty, then it should be used. Organizations that keep a detailed database of uncertainties they have quantified in the past for previous projects could assist with this. If uncertainties encountered by the current project are similar or identical to those encountered by previous projects, detailed databases of uncertainties could help speed up this quantification process or allow participants to expend more effort on investigating and quantifying new and specific uncertainties to the current project. The effort expended in quantifying uncertainties should in theory be matched to the impact these uncertainties have on the tradable parameters. Unfortunately, it is not apparent *a priori* which uncertainties have a significant influence on the tradable parameters and which do not. Identifying the significant uncertainties is part art and part science, much like other aspects of preliminary design. The part-science aspect is a sensitivity analysis. Identifying which uncertainties are significant is a more important charge than identifying all uncertainties involved as the proposed method might become intractable to implement in practice when dozens or hundreds of uncertainties are involved. Conversely, a sensitivity analysis also helps in finding which uncertainties have little or no impact thereby reducing disagreements among participants that fixate on a particular uncertainty that turns out to have a minimal impact on the design.

6.3.1 Quantitative Sensitivity Analysis

A quantitative sensitivity analysis is a process by which one or more input variables are varied and the effect on the output is observed. These input variable uncertainties are typically set to a "low" and then a "high" value in two subsequent analyses. Meanwhile, all other input variables are held at their "nominal" values. Hence, with the exception of the one or more input variables being varied, a sensitivity analysis is a deterministic analysis represented by:

$$\underline{y} = \underline{G}(\underline{\theta}) \qquad (6.2)$$

A sensitivity analysis requires "calls" to the transformation (response) function, $\underline{G}$, which may require significant expense in time and resources. In complex multidisciplinary systems with dozens or hundreds of uncertainties, the combinatorial explosion of possible sensitivity scenarios (e.g., one variable "high," another "low," and so on) becomes unmanageable. Nonetheless, a first-order or second-order sensitivity analysis where one or two input variables are varied, respectively, is often valuable information in preliminary design even if higher-order sensitivity analyses are not feasible due to time or budgetary constraints. Furthermore, a sensitivity analysis is especially important in nonlinear models where the results may be sensitive to a given input variable only when other input variables take on certain values and complex interactions arise [Frey, 1992].

6.3.2 Qualitative Sensitivity Analysis

A qualitative sensitivity analysis can be performed via expert elicitation if the response function is not available. This can be accomplished in two steps. In the first step, experts qualitatively estimate the likelihood (e.g., "very high," "high," "moderate," "low," "very low") that an input variable will deviate significantly from its nominal deterministic value. The second step involves estimating the consequence of such a deviation to the tradable parameter(s) of interest (e.g., "negligible," "minor," "moderate," "substantial," "severe"). With likelihoods and consequences estimated, a grid such as that shown in Table 6.3 could be used as a guide in assessing uncertainty importance. Table 6.3 is adapted from the risk analysis field and is similar to the uncertainty classification for systems engineering (INCOSE) described in Chapter 2.

Table 6.3 Consequence vs. likelihood table; adapted from Conrow (2000)

	Consequence				
Likelihood of Significant Deviation	Negligible	Minor	Moderate	Substantial	Severe
Very high	Low-Medium	Medium	Medium-High	High	High
High	Low	Low-Medium	Medium	Medium-High	High
Moderate	Low	Low-Medium	Medium	Medium	Medium-High
Low	Low	Low	Low-Medium	Low-Medium	Medium
Very low	Low	Low	Low	Low	Low-Medium

An uncertainty with a "very high" likelihood of deviating significantly from its deterministic value might be represented by a distribution with significant tails, a high standard deviation, or an unusual shape, one that is perhaps significantly skewed. Often, such qualitative descriptions of uncertainties are known by engineers and managers early in the design. Unfortunately, many are not which, along with difficulty and unreliability in assessing the consequence of these uncertainties on tradable parameter(s), limits the usefulness of this approach in designing and developing a complex multidisciplinary system. At best, a qualitative sensitivity analysis could prioritize uncertainties to investigate further or indicate which uncertainties should be reduced outright with effort. It should be noted that a quantitative and qualitative sensitivity analysis provide no insight into the likelihood of obtaining the tradable parameter or consequence, respectively. Hence, although a sensitivity analysis is useful in determining what possibilities may arise, it is difficult for a decision maker to judge whether such a result truly matters.

6.4 Summary

This chapter discusses ambiguity, aleatory uncertainty, and behavioral uncertainty. Behavioral uncertainty is subdivided into design uncertainty, requirement uncertainty, volitional uncertainty, and human errors. Quantitative and qualitative methods to address these various uncertainty types are provided. Much of this chapter discusses volitional uncertainty and how game theory, in particular a principal agent mechanism design formulation, can assess uncertainty in how individuals act. The work done by Guikema (2003) addresses this type of uncertainty and is amenable to being integrated into the proposed method for propagating and mitigating uncertainty in the design of complex multidisciplinary systems. This chapter also discusses methods to assess the importance of uncertainties. Quantifying the final remaining uncertainty, interaction, is the topic of the next chapter.

Chapter 7 Interaction Uncertainty and Simulation

With all uncertainties in the models and input variables characterized, the next step in the proposed method is propagating these uncertainties through the models to estimate the uncertainty in the tradable parameters. Since a model may have uncertainties that interact and these uncertainties may be represented by discrete or continuous distributions, analytic techniques to propagate these uncertainties are not possible except in trivial models. Simulation techniques offer a feasible alternative regardless of model complexity. A variety of simulation techniques to propagate uncertainties through a model are available. This chapter begins by discussing three well-established simulation techniques: Monte Carlo simulation, Latin hypercube sampling, and descriptive sampling. These techniques estimate uncertainty in the tradable parameters by addressing interaction among input variable uncertainties. Two additional techniques, the mean value method and subset simulation, are modified to handle unique characteristics involved in the design of complex multidisciplinary systems. The chapter continues with an overview of simulation techniques that were considered but eventually ruled out for use in the proposed method. The chapter concludes with a discussion of methods to determine the appropriate number of repetitions required in applying simulation techniques.

7.1 Existing Simulation Techniques

Simulation techniques generate random realizations of the uncertain input variables, $\underline{\theta}$, in the problem according to their specified probability distributions. The set of a random realization of these variables is called a "sample." Consider again the function $\underline{G}$ first introduced in Chapter 1 representing the tradable parameter model of interest. A sample is sent to this function $\underline{G}$ to evaluate a tradable parameter value y (or a set of tradable parameter values $\underline{y}$ if the model generates more than one):

$$\underline{y} = \underline{G}(\underline{\theta}) \tag{7.1}$$

Simulation techniques repeat this basic process many times although each simulation technique's implementation is somewhat different. Regardless of the actual simulation technique used, a probability density function (PDF) of the tradable parameters can be generated if sufficient samples have been generated and subsequently evaluated. With a PDF available, a cumulative distribution function (CDF) is easily generated. This procedure is discussed in the following chapter and Appendix A. Hence, simulation replaces "experiments" as the method of generating data. Simulation techniques are powerful since they allow the individuals involved in the proposed method to concentrate on estimating the uncertainties in $\underline{\theta}$ while allowing computers to perform the tedious and mathematically challenging calculations.

The following section describes three well-established simulation techniques that can be used to evaluate interaction uncertainty and propagate all uncertainties in a model to estimate the uncertainty in the tradable parameters. The most general of these is the computationally intensive Monte Carlo simulation (MCS) method. Latin hypercube sampling (LHS) method is a stratified sampling technique which can often provide comparable accuracy to MCS yet requires significantly less computational expense. Finally, descriptive sampling is a similar, somewhat simpler technique to LHS. All three methods obtain estimates of the uncertainty in tradable parameters in problems which are too complicated to solve analytically.

7.1.1 Monte Carlo

Monte Carlo simulation (MCS) solves a problem by generating suitable random numbers and observing the fraction of the numbers obeying some property or properties. Stanislaw Ulam became the first mathematician to dignify this approach in 1946 with the name in honor of a relative having a propensity to gamble [Hoffman, 1998]. N. Metropolis, E. Fermi, and J. von Neumann also made important contributions to the development of MCS [Hammersley & Handscomb, 1964]. MCS is the most established sampling technique and the benchmark for comparison by other techniques.

MCS involves two steps that were described earlier and are detailed here. First, random realizations of the uncertain input variables, $\underline{\theta}$, are generated according to their specified probability distributions. Assuming there are n input variables, n random variables are thus generated. In the second step the tradable parameters $\underline{y}$ are evaluated for this unique sample (vector of uncertainties) and recorded. This procedure is repeated N times yielding N values of each tradable parameter. These N values for each tradable parameter can be transformed to a PDF or CDF where the mean and other statistical characteristics of interest can be calculated. Hence, for N MCS repetitions, a set of N vectors of input variables (each such sample is n-dimensional) and a set of N vectors of tradable parameters (each such vector is t-dimensional) are formed.

MCS remains the most popular and implemented simulation technique due to its many benefits. Although probabilistic overall, the basic MCS process is deterministic for each repetition evaluation. This allows MCS to easy wrap itself around existing deterministic models and codes. MCS can also represent input variables regardless of whether they are discrete or continuous. In particular, MCS is able to handle discrete choices among alternatives (e.g., design uncertainty) discussed in Chapter 6 which some sampling techniques (e.g., mean value method) have difficulty with. Numerical programs and packages can accomplish the random sample generation step for virtually all probabilistic distributions quickly and efficiently. Furthermore, MCS is independent (essentially) of the quantity and type of $\underline{\theta}$. That is, if dozens, hundreds, or even thousands of input variables are required to determine the tradable parameters the evaluation time is dependent only on the number of MCS repetitions N. Another benefit of MCS occurs if $\underline{G}$ calculates more than one tradable parameter as MCS determines all tradable parameter values concurrently from the same random realizations of $\underline{\theta}$. Arguably the greatest benefit of MCS is that it is the most accurate sampling technique. MCS converges to the actual distribution as the number of repetitions tends to infinity due to the Strong Law of Large numbers.

Unfortunately, MCS is not computationally efficient for estimating low probability events (i.e., the tails of a distribution) since the number of repetitions required to achieve a given accuracy is inversely proportional to the probability when the probability is small. Essentially, estimating the tails of the distribution requires information from rare samples and on average it requires many repetitions (often in the thousands) before the tails are defined. MCS can be computationally prohibitive if $\underline{G}$ is computationally expensive to evaluate which is often the case in complex systems analysis [DeLaurentis & Mavris, 2000]. Using parallel high-performance computer systems is one way to alleviate this issue. However, such systems were not available when MCS was first applied and research into alternate and more efficient sampling methods were undertaken. Virtually all of these alternate sampling techniques introduce error which is the trade-off for reduced computation time.

7.1.2 Latin Hypercube Sampling

Latin hypercube sampling (LHS), also known as stratified sampling, is a technique developed by McKay, Conover, and Beckman (1979) where the random variable distributions are divided into equal probability intervals.* A probability is randomly selected from within each interval for each basic event. Generally, LHS will require fewer samples than MCS for similar accuracy, typically on the order of ten times less [Hammersley & Handscomb, 1964]. However, due to the stratification method LHS may take longer to generate values than MCS. In LHS, the range R of probable values for each uncertain input parameter is divided into s segments of equal probability (R_i, $i = 1, 2, \ldots, s$). That is,

$$R = \cup R_{i=1}^{s},\ R_k \cap R_j = \varnothing,\ k \neq j \tag{7.2}$$

---

*Elements of Latin hypercube sampling have been around since the turn of the 20th century, dating back to its origins in agricultural research

Thus, the whole parameter space, consisting of n input variables, is partitioned into s^n cells, each having equal probability. Consider the case of 3 input variables and 4 segments, the parameter space is divided into 4x4x4 cells. For each variable, one value from each segment is selected at random with respect to that variable's PDF in the interval. These s values are then randomly paired with equivalent values from segments of the other variables. These s n-tuplets are analogous to the N n-dimensional input vectors for MCS. Mathematically, this process is achieved by taking the inverse cumulative distribution function (CDF) value of all n input variables s times [Saliby, 1997]:

$$\theta_j^i = Q_j^{-1}\left(\frac{i-1+U}{s}\right) \quad i=1,\ldots,s;\ j=1,\ldots,n \tag{7.3}$$

LHS concludes when a random set of these θ^i values for each variable (without replacement) is sent to $\underline{G}$ and $\underline{y}$ is recorded. This process is repeated s times until all segments have been accounted for. Hence, $s \cdot n$ inverse CDF calculations, s permutation steps, and s calls to $\underline{G}$ are required by LHS to yield s values of $\underline{y}$. The advantage of this approach is that samples (random realizations of input variables) are generated from the entire range of possible values, thus giving insight into the tails of the probability distributions. LHS is generally more precise for producing random samples than conventional MCS, because the full range of the distribution is sampled more evenly and consistently. Thus, with LHS, a smaller number of trials achieves the same accuracy as a larger number of MCS repetitions would. As with MCS, once $\underline{\theta}$ is set, each of the s LHS calls to $\underline{G}$ is "deterministic" allowing LHS to easily wrap around existing models and codes. The drawback of this method is the extra effort required to generate the samples and the additional memory required to hold the full sample for each assumption while the simulation runs. For distributions with tails that tend to infinity, the inverse CDF sample generation step can be computationally expensive itself.

7.1.3 Descriptive Sampling

Descriptive sampling (DS) is a simpler version of LHS which determines input variable values at the midpoints of the segments instead of at random locations within a segment:

$$\theta_j^i = Q_j^{-1}\left(\frac{i-0.5}{s}\right) \quad i=1,\ldots,s;\ j=1,\ldots,n \tag{7.4}$$

The remainder of DS is identical to LHS. The benefits, drawbacks, and accuracy of DS are comparable to those of LHS. DS may be slightly quicker in the inverse CDF sample generation step depending on the computational implementation [Saliby, 1997].

7.2 Modified Simulation Techniques

The modified mean value method is a simple analytical-based method that can provide satisfactory results with only a limited number of simulations. Subset simulation via Markov chain Monte Carlo is a complicated but computationally efficient method of accurately determining values at the tails of a distribution. Both methods were modified from their original implementation primarily to account for the possibility of discrete choices among alternatives that was discussed in Chapter 6. Since such a choice cannot be incrementally improved it is a challenge coming up with methods to perturb such an input uncertainty that could then be used in determining the uncertainty in the tradable parameters. Both modified simulation techniques are discussed in this section.

7.2.1 Mean Value Method

The mean value method (MVM) is an approximate analytical technique that can often provide a good estimate of the response function $\underline{y}$ (tradable parameter) with relatively few samples compared to MCS. MVM uses the first order terms from a Taylor series expansion of a given $\underline{y}$ at the mean values. For n random variables, MVM is defined by:

$$y_{\mathrm{MV}}^{k} = y^{k}(\mu_{\theta}) + \sum_{j=1}^{n} \left(\left. \frac{\partial y^{k}}{\partial \theta_{j}} \right|_{\mu_{\theta}} \right) \left(\theta_{j} - \mu_{\theta_{j}} \right) \tag{7.5}$$

As discussed in Chapter 1, $\underline{y}$, y^k in Eq. (7.5), is often calculated via a nonlinear, highly complicated set of equations whose evaluation is a computationally expensive. It is unlikely that the partial derivates in Eq. (7.5) can be calculated analytically. However, these derivatives can be calculated numerically by performing perturbations about the mean values. A forward, backward, or centered-finite difference can be used to calculate these partial derivatives. A forward or backward-finite difference method requires one function evaluation per random variable:

$$\left. \frac{\partial y^{k}}{\partial \theta_{j}} \right|_{\theta_{\mathrm{det}}} = \frac{y^{k}(\underline{\theta};\theta_{j}+h) - y^{k}(\mu_{\theta})}{h} \quad [forward] \tag{7.6}$$

$$\left. \frac{\partial y^{k}}{\partial \theta_{j}} \right|_{\theta_{\mathrm{det}}} = \frac{y^{k}(\mu_{\theta}) - y^{k}(\underline{\theta};\theta_{j}-h)}{h} \quad [backward] \tag{7.7}$$

A centered-finite difference method requires two function evaluations per random variable:

$$\left. \frac{\partial y^{k}}{\partial \theta_{j}} \right|_{\theta_{\mathrm{det}}} = \frac{y^{k}(\underline{\theta};\theta_{j}+h) - y^{k}(\underline{\theta};\theta_{j}-h)}{2h} \quad [centered] \tag{7.8}$$

Hence, MVM using a forward, backward, and centered-finite difference method to calculate the partial derivatives in Eq. (7.5) require a total of n+1, n+1, and 2n+1 function evaluations, respectively. The additional function evaluation beyond the n or 2n is from determining the mean value, the first term on the right hand side of Eq. (7.5).

MVM as implemented with the method outlined in this thesis is adapted slightly from MVM described by Eq. (7.5). Equation (7.5) is re-cast in its vector form:

$$\underline{y_{\mathrm{MV}}} = \underline{y^k_{\mathrm{det}}} + \left(\underline{\underline{\theta_{\mathrm{prob}}}} - \underline{\underline{\theta_{\mathrm{det}}}}\right) \cdot \underline{\left.\frac{\partial y^k}{\partial \theta_j}\right|_{\theta_{\mathrm{det}}}} \tag{7.9}$$

The given tradable parameter y^k is first evaluated deterministically via a single function evaluation. This result is a scalar (y_{det}) which is replicated N times to create an N by 1 column vector, the first vector term on the right-hand side of Eq. (7.9). The next two terms within the parentheses are related to the original vector of random variables. The first term within the parentheses is an N by n matrix created by generating N random samples for each of the n random variables. Hence, each column of this matrix is a set of random samples for a given variable. The second term is also an N by n matrix created by replicating the deterministic values of each random variables N times. Hence, each column of this matrix is the deterministic value for a given variable. Finally, the term on the far right-hand side of Eq. (7.9) is an n by 1 column vector representing the partial derivatives.

The result of the matrix subtraction, vector dot product, and vector addition is a vector of values of the given tradable parameter. This vector result is analogous to the vector of results from MCS or LHS. From it probability density functions (PDFs) and cumulative distribution functions (CDFs) are easily generated as detailed in the following chapter. Since the generation of N random samples is computationally inexpensive, N can be in the hundreds, thousands, or even tens of thousands without significantly impacting the total computation time of this method. The choice in the number of samples depends on how smooth the output is desired. The output accuracy of MVM depends primarily on the accuracy of the partial derivatives. Ill-behaved or discontinuous response functions yield poor estimates of the partial derivatives which in turn yield poor estimates using MVM. Unfortunately, models representing complex systems are often ill-behaved and/or discontinuous [Mosher, 2000] making MVM an option that should be used with caution.

MVM used in this thesis may also differ somewhat from the typical MVM applied in other studies (e.g., [Mavris & Bandte, 1997; Kloess, Mourelatos, & Meernik, 2002]) in how the partial derivatives (perturbations) are computed. For most continuous and discrete random variables these perturbations are likely calculated in the same manner. For continuous random variables a step size (*h*) of $1(10)^{-8}$ is chosen in evaluating Eqs. (7.6), (7.7), or (7.8). For discrete random variables, *h* is set to 1 in evaluating these three finite differences. For discrete custom random variables, which could represent choices in components or materials as described in Chapter 1 and Chapter 6, *h* is also set to 1. However, the modified MVM (MMVM) handles the finite differences differently for these special random variables. The deterministic value for these variables is assumed to be the most probable value while the perturbed value is assumed to be the next most probable value. If two values are equally probable, either as the most probable or the next most probable value, decision logic must be employed to select among the choices. In the proposed method, the decision logic favors the lower numbered choice. If three options are roughly equally likely, this implementation will only consider two of the three options. The partial derivative will not represent the true nature of this random variable and MVM that uses this partial derivative may yield erroneous results. These uncertainties, which are typically design choices, are often retired early in design making MVM an attractive option for implementation later in the development.

7.2.2 Subset Simulation

The extreme tails of a tradable parameter distribution are important in the design of many complex multidisciplinary systems. A spacecraft needs an accurate estimate of the 99, 99.9, 99.99 percentile values of its reliability to see if it will survive long enough to complete its mission while an aircraft would like accurate estimates of the extreme tail values of its range to be certain a target or destination can be reached. As was discussed earlier, MCS requires a large number of samples to accurately determine these extreme tail values which may require a prohibitive amount of time and resources to complete. A method that accurately determines the extreme tails of distributions is subset simulation (SS) via Markov chain Monte Carlo (MCMC) [Au, 2001; Au & Beck, 2001a]. Originally developed and applied in estimating small failure probabilities in high dimension structural engineering applications, subset simulation can be modified to handle more general situations.

7.2.2.1 Overview

Subset simulation gains its efficiency by expressing a small failure probability as a product of larger conditional failure probabilities, thereby turning the problem of simulating a rare failure event into several problems that involve the conditional simulation of more frequent events. Subset simulation for determining margins converts the percentile of the tradable parameter of interest to a "failure region." For example, if the P_x in Eq. (1.4) (see Chapter 1) that is based on the 99.99th percentile value is of interest to the decision maker, this P_x would correspond to a P_f = 0.0001. A failure event is then considered when a function evaluation yields a value for a tradable parameter which exceeds the percentile value of interest. Generally, given a "failure event" F, let $F_1 \supset F_2 \supset \ldots \supset F_m = F$ be a decreasing sequence of failure events so that:

$$F_k = \cap_{i=1}^{k} F_i \quad k = 1, \ldots, m \tag{7.10}$$

Thus the actual failure probability can be expressed as a product of a sequence of conditional probabilities $\{P(F_{i+1}|F_i)$: $i = 1, \ldots, m-1\}$ and $P(F_1)$ [Au, 2001]:

$$P_F = P(F_1)\prod_{i=1}^{m-1} P(F_{i+1} \mid F_i) \tag{7.11}$$

The idea of subset simulation is to estimate the failure probability P_F by estimating these quantities. Hence, a decision maker who wants a margin value based on the 99.99th percentile and assumes a conditional probability (p_0) of say 0.1 can determine this extreme percentile value via subset simulation which would determine intermediate percentile values (90th, 99th, and 99.9th) in order to calculate the 99.99th percentile value. Hence, these intermediate percentiles are found for "free" in subset simulation. The corresponding cumulative distribution function (CDF) is thus also generated for "free" via these intermediate simulation runs. By choosing intermediate percentiles (failure events), the conditional probabilities involved in (7.11) can be made sufficiently large such that they can be evaluated efficiently by established simulation techniques. The problem of simulating rare events in the original probability space is thus replaced by a sequence of simulations of more frequent events in the conditional probability space.

Subset simulation uses MCMC to efficiently search each of these subset failure regions. MCMC is a class of powerful algorithms for generating samples according to any given probability distribution. It originates from the Metropolis algorithm developed by Metropolis and his co-workers for applications in statistical physics [Metropolis et al., 1953].[†] A major generalization of the Metropolis algorithm was due to Hastings for applications in Bayesian statistics [Hastings, 1970]. MCMC has been used in a wide variety of applications including image analysis, genetics, archeology, and medicine [Gilks, Richardson, & Spiegelhalter, 1996].

In MCMC, successive samples are generated from a specially designed Markov chain whose limiting stationary distribution tends to the target probability density function (PDF) as the length of the Markov chain increases. Markov chain samples explore and gain information about the failure region as the Markov chain develops. Proper utilization of these samples leads to better

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[†]The Metropolis algorithm was named among the top 10 algorithms having the "greatest influence on the development and practice of science and engineering in the 20th century" [Beichl & Sullivan, 2000]

estimates for the failure probability [Au, 2001]. Subset simulation with a modified Metropolis-Hastings MCMC algorithm developed by Au and Beck (2001a) and described therein and in Au (2001) is assumed in the proposed method for estimating margins. The original Metropolis algorithm is not applicable to simulating random vectors with a high number of independent components. The original Metropolis algorithm differs from the modified algorithm in the way the candidate state is generated. There is a nonzero probability that the next state in a Markov chain will be equal to the current state. It has been found that when the uncertain input variables ($\underline{\theta}$) are independent and the dimension n is large, the probability of the Metropolis algorithm accepting the candidate state is close to zero. Paradoxically, yet common in mathematics, by complicating the problem MCMC has rendered it more amenable to analysis and practical to implement computationally.

7.2.2.2 Algorithm

A description of the subset simulation algorithm is provided in this section. This method is best applied to situations where only tradable (output) parameter generated by the response function is of interest. If multiple tradable parameters generated by the response function are of interest, subset simulation via MCMC would require application to each tradable parameter separately. In these situations, the computational benefit of subset simulation decreases compared to MCS, LHS, or DS. The algorithm and associated nomenclature follows the description in Au and Beck (2001a) insofar as possible. Recall that all nomenclature used in this thesis is provided in the Glossary. A detailed description of subset simulation is provided in Au (2001). The modifications to subset simulation via MCMC that have been implemented are discussed in detail in the following section.

Step 0: For each input variable, determine its standard deviation σ_j (note this is only meaningful for discrete and continuous random variables, not constants, nor choices among components); specify the constants N, P_f, p_0, and χ. Set $P_1 = p_0$. Determine the number of simulation levels required via:

$$m = \left\lceil \log_{10} \frac{p_0}{P_f} \right\rceil + 1 \tag{7.12}$$

Step 1: Run a small MCS (e.g., $N = 500$ calls to the "computationally expensive function" $\underline{G}$ that determines the tradable parameter of interest). This initial MCS is considered the first subset simulation level.

Step 2: Take the $(1- p_0)\cdot N^{th}$ largest value of this $\underline{y}$ (i.e., an order statistic) (e.g., for $p_0 = 0.1$ and $N = 500$, this would be the 451st value). Call this C_1. It corresponds to $P_1 = P(F_1)$. Also calculate the coefficient of variation (c.o.v.) of P_1^*:

$$\delta_1 = \sqrt{\frac{1-P_1}{P_1 \cdot N}} \tag{7.13}$$

Step 3: Assuming $m > 1$, use the initial MCS results $\underline{y}$ (otherwise algorithm over). If $m > 2$, this step uses the results $\underline{y}$ of the previous subset simulation run (result from Step 5). Simulation level indexed by i ($i = 2$ is second subset simulation level since initial MCS with $i = 1$ assumed to be first "subset" simulation level).

a. Take the $(1- p_0)\cdot N^{th}$ through N^{th} largest values (the $N_c = p_0\cdot N$) largest values (e.g., for $P_1 = 0.1$, this would be the 50 largest values). All results are probabilistically equivalent.

b. Use these N_c samples (e.g., $\underline{\theta}_1, \ldots, \underline{\theta}_{50}$) as seeds for N_c Markov chains. Use the results (e.g., $y_1, \ldots, y_{50}$) of these N_c samples in the next step for the first Markov chain sample (see Step 5).

Step 4: For each Markov chain, starting with the relevant seed, determine a proposal PDF p^* for each uncertain input variable θ (i.e., do this n times for each variable, $j = 1, \ldots, n$) using the suggestions listed in Table 7.1.

Table 7.1 Proposal PDFs for different uncertain input variables

Input Variable	Proposal PDF p_j^*	Description
Continuous	$U(\theta_k(j)-\chi\cdot\sigma_j,\ \theta_k(j)+\chi\cdot\sigma_j)$	a continuous uniform distribution centered at the current input variable value with a width equal to $2\cdot\chi\cdot\sigma_j$
Discrete	$U_d(\lfloor\theta_k(j)-\chi\cdot\sigma_j\rfloor,\ \lceil\theta_k(j)+\chi\cdot\sigma_j\rceil)$	a discrete uniform distribution centered at the current input variable value with a width equal to $2\cdot\chi\cdot\sigma_j$ rounded to the nearest integers
Discrete choice among options	$C_d(\underline{A})$	a discrete custom distribution that is identical to the actual variable PDF q_j when the most probable value is the current sample; otherwise the current sample and the most probable value probabilities are swapped (other PDF values and probabilities are unchanged)
Constant	n/a	unchanged for all samples in a given Markov chain so no p_j^* is needed

Step 5: Metropolis-Hastings like algorithm; apply to each Markov chain seed (do N_c times, index here is jj where $jj = 1, \ldots, N_c$):

a. Generate a 'candidate' state $\underline{\theta}^*$: For each input variable $j = 1, \ldots, n$, simulate ξ_j from $p_j^*(\cdot|\theta_k(j))$. Compute the ratio

$$r_j = q_j(\xi_j)/q_j(\theta_k(j)) \tag{7.14}$$

Set $\theta_k^*(j) = \xi_j$ with probability min{1,r_j} and set $\theta_k^*(j) = \theta_k(j)$ with the remaining probability 1 – min{1,r_j}.

b. Accept/reject $\underline{\theta}^*$: Check the location of $\underline{\theta}^*$. If $\underline{y}^* = \underline{G}(\underline{\theta}^*) \geq C_{i-1}$ accept it as the next sample, i.e. $\underline{\theta}_{k+1} = \underline{\theta}^*$; otherwise reject it and take the current sample as the next sample, i.e. $\underline{\theta}_{k+1} = \underline{\theta}_k$. Set $\underline{G}(\underline{\theta}_{k+1})$ to the relevant value. If sample accepted then $I_F(jj,k) = 1$; $I_F(jj,k) = 0$ otherwise. Algorithm pauses when N/N_c Markov chain samples have been run and moves on to next Markov chain (increment jj). Hence, there is one function call for each Markov chain (N/N_c function calls) times N_c chains which yields N total function calls per subset simulation level. These N results for y can be re-ordered as an N-dimensional vector ($\underline{y}$) since all samples are probabilistically equivalent.

Step 6: Calculate a variety of parameters that monitor the success of the algorithm at each simulation level:

a. Take the $(1\text{-}p_0)\cdot N^{th}$ largest value of $\underline{y}$; i.e., an order statistic (e.g., for $p_0 = 0.1$ and $N = 500$, this would be the 451st value). Call this C_i.

b. Estimate of the probability of failure for this simulation level:

$$P_i = p_0 \cdot P_{i-1} \tag{7.15}$$

c. Covariance between indicator function values within a chain where $I_F(jj,k)$ is re-ordered as a row vector (order should not matter since samples are probabilistically equivalent):

$$R_i(k) \approx R_i^*(k) = \left(\frac{1}{N - k \cdot N_c} \sum_{jj=1}^{N_c} \sum_{l=1}^{N/N_c - k} I_{jj,l}^{(i)} I_{jj,l+k}^{(i)} \right) - \left(P_i^*\right)^2 \tag{7.16}$$

d. Correlation coefficient at lag k of the stationary sequence { $I_{jk}(i)$: $k = 1,\ldots, N/N_c$}:

$$\rho_i(k) = R_i(k)/R_i(0) \tag{7.17}$$

e. Correlation factor:

$$\gamma_i = 2 \sum_{k=1}^{N/N_c - 1} \left(1 - \frac{k \cdot N_c}{N}\right) \rho_i(k) \tag{7.18}$$

f. Standard deviation of P_i^*:

$$\sigma_i = \sqrt{\frac{P_i(1 - P_i)}{N}[1 + \gamma_i]} \tag{7.19}$$

g. Coefficient of variation (c.o.v.) of P_i^*:

$$\delta_i = \sqrt{\frac{1 - P_i}{P_i \cdot N}[1 + \gamma_i]} \tag{7.20}$$

h. Total c.o.v. up to and including simulation level i:

$$\delta_i^* = \sqrt{\sum_{ii=1}^{i} \delta_{ii}^2} \tag{7.21}$$

Step 7: Return to Step 3 until all simulation levels complete. Note that the results of Step 5 are used in the subsequent iteration Step 3. Total number of function calls to $\underline{G}$ is $m \cdot N$.

7.2.2.3 Modification to Algorithm

The major modification made to the algorithm developed by Au and Beck (2001a) is in the type of input variables and their corresponding proposal PDFs. In Au and Beck (2001a) only continuous input variables were considered and the first p_j^* in Table 7.1 was always used. The variables in the design of a complex multidisciplinary system may be continuous, discrete, and discrete choices among alternatives so additional and mathematically valid p_j^* are proposed and implemented (see Table 7.1).

Although the algorithm presented here appears to have a different formulation to Au and Beck (2001a), it is in fact unchanged. In Au and Beck (2001a), failure probabilities are specified (e.g., 0.01, 0.001, etc.) whereas the proposed method percentile values are specified (e.g., 99, 99.9, etc.). Both formulations do not explicitly have fixed failure regions but create intermediate failure regions that have relatively large conditional failure probabilities. The SS formulation is thus appealing in determining margins as they do not have fixed failure regions *per se*. Instead, margin values for a subsystem in a complex multidisciplinary system are needed by other subsystems for the design to progress.

Finally, the aforementioned algorithm description assumes that the tail of the distribution of interest to a decision maker is the high percentile end (i.e., 99, 99.9, etc.). The algorithm could easily be modified to search the low percentile end (i.e., 1, 0.1, etc.) of a distribution. In either case, subset simulation via MCMC can efficiently search either end of a distribution of interest.

7.3 Simulation Techniques Ruled Out

The following section briefly describes various simulation techniques that were considered but eventually ruled out for implementation in the proposed method: reliability-based methods, metamodels/response surface methods, and importance sampling using elementary events.

7.3.1 Reliability-Based Methods

A variety of reliability-based methods have been devised to alleviate the computational burden of MCS and other sampling methods. First- and second-order reliability methods (FORM and SORM, respectively) are approximation methods that estimate the probability of an event under consideration (typically termed "failure"). Some of the better known methods include the advanced mean value (AMV), advanced mean value plus (AMV+), adaptive importance sampling (AIS). All these methods share a characteristic that a failure region must exist. These approaches are based on the concept of a "most probable point" (MPP). The MPP is the most likely combination of random variable values for a specific performance or limit state value. In many ways the MPP is analogous to the deterministic result for a simulation or analysis. Most determine the estimated probability of failure through additional sampling near the MPP. In contrast to MCS where sampling is done in the total space defined by the random variables, reliability methods avoid over sampling in the safe region. Unfortunately, locating the MPP may be difficult or impossible with a highly nonlinear or discontinuous response function $\underline{G}$, multiple MPPs, or problems containing random variables where bounded distributions (e.g., uniform) are present. Furthermore, the computational effort in finding the MPP or MPPs is significant, often relying on sequential quadratic programming (SQP). Locating the MPPs can even be a greater computational expense than a detailed MCS. Reliability methods are discussed in a variety of references (e.g., [Wirsching & Wu, 1987; Wu, 1994; Kloess, Mourelatos, & Meernik, 2002]).

Reliability-based methods were investigated but not used in the proposed method since margin determination does not involve a failure region. Although an artificial failure region can be generated by assuming a certain value and reversing the problem to find the probability of that margin value being exceeded, it is not possible to know *a priori* what an appropriate margin value is. For certain tradable parameters, a margin value of 5% may be significant (e.g., a temperature margin), for others tradable parameters a margin of 150% could be insignificant (e.g., propellant mass). The application of reliability methods would have to be combined with an iterative algorithm and repeated to arrive at the correct margin value. Such an implementation is complicated and unlikely to be a computational benefit compared to MCS; it was not investigated in detail.

7.3.2 Metamodels and Response Surface Methods

Metamodels form a compact, accurate representation of the functional relationship between the typical inputs and outputs of an analysis which models phenomena. Hence, metamodels are in effect a model of a model. Metamodels are simpler that the original model and their use can yield potential computational savings. Response surface methods (RSMs) are well-established statistical approaches to forming metamodels. Their use has been documented extensively in a variety of fields the last half century (e.g., [Khuri & Cornell, 1987; Box & Draper, 1987]). RSMs combine experimental and numerical analysis techniques for the purpose of creating a functional relationship between key design variables and system responses that are otherwise too expensive to create. These relationships are manifested as regression equations based on a set of acquired data [DeLaurentis, 1998].

As with other simulation techniques, a trade-off for decreased computational effort is increased error. The error can be significant in complex multidisciplinary design as RSMs typically use a polynomial regression model obtained via a truncated Taylor series expansion. Such a representation is not appropriate in modeling many complex multidisciplinary systems which often have an ill-behaved design space. Evaluating the error in an RSM can be difficult since an RSM may "twist and turn" to accommodate every point in the available data but fail to model the general trend in the data [Fox, 1994]. Furthermore, RSMs may model the general trend in the data but could perform poorly when extrapolated beyond the data range [Thacker et al., 2001]. Nonetheless, metamodels and RSMs have been successfully used in the design of complex multidisciplinary systems, notably in aircraft design [DeLaurentis, 1998]. Metamodels and RSMs could be used within the proposed method (instead of calling $\underline{G}$ directly) but were not pursued since they have already been researched and implemented in details by others (e.g., [DeLaurentis, 1998]). If the error in RSMs can be quantified accurately, metamodels and RSMs would be useful in further reducing computation expense in the proposed method. Fox (1994) provides twelve criteria for evaluating the goodness of a response surface that could be a first step in assessing their benefit in the proposed method.

7.3.3 Importance Sampling Using Elementary Events

Au (2001) and Au and Beck (2001b) developed a highly efficient importance sampling method using elementary events (ISEE) for determining low probability failure events in structural engineering. ISEE provides truly remarkable results *vis-à-vis* MCS: orders of magnitude less computation time for low probability events assuming a comparable coefficient of variation (δ). Unfortunately, ISEE is developed specifically for linear dynamical systems subjected to Gaussian white-noise excitation and as with reliability-based methods discussed previously, an explicit failure region is required. Generally, this situation is not valid in propagating and mitigating uncertainty for estimating margins in complex multidisciplinary system design. Modifying ISEE for implementation in the proposed method was investigated but not pursued due to the fundamental differences between the problem statements.

7.4 Simulation Technique Repetitions Required

The aforementioned simulation techniques all require multiple calls to the model ($\underline{G}$) to evaluate uncertainty in the tradable parameters. For the modified mean value methods (forward-, backward-, centered-finite difference), the number of these calls to $\underline{G}$ is determined by the number of uncertain input variables. For the other simulation techniques discussed (MCS, LHS, DS, subset simulation), the number of these repetitions is a choice. This section discusses statistical tests to estimate how many repetitions are appropriate for these simulation techniques.

7.4.1 Monte Carlo Simulation, Latin Hypercube Sampling, and Descriptive Sampling

Two statistical techniques can be used to estimate the number of repetitions required by MCS for the results to be statistically valid [Morgan & Henrion, 1990]. The first technique estimates the total number of repetitions required based on a small Monte Carlo run. This technique is based on the confidence in the mean value and requires the user to specify both a confidence and a requisite width (a fraction of the mean within which the results should be):

$$N_{MCS} = \left\lceil \left(\frac{2 \cdot \lambda \cdot \sigma}{x \cdot \mu} \right)^2 \right\rceil \tag{7.22}$$

The second technique does not require a small Monte Carlo run. Instead it estimates the total number of repetitions based on fractile confidence intervals:

$$N_{MCS} = \left\lceil F_x \cdot (1 - F_x) \cdot \left(\frac{\lambda}{\Delta F_x} \right)^2 \right\rceil \tag{7.23}$$

For example, if a decision maker wishes to be 99% confident ($\lambda = 2.32$) that the actual 99th percentile value is between the 98.5 and 99.5 percentile values, Eq. (7.23) would yield an N_{MCS} value of 2144. Both techniques implicitly assume that the Monte Carlo data will tend toward a normal distribution via the specified confidence deviation parameter. If this is not true, as is often the case when one or more of the input variables is a discrete choice among alternatives, Eqs. (7.22) and (7.23) will underestimate the total number of MCS repetitions required. As previously discussed, LHS and DS require approximately a tenth the number of MCS repetitions to achieve comparable accuracy. Hence, Eqs. (7.22) and (7.23) can also be used to estimate the number of LHS or DS repetitions (segments s).

It should be noted that the error in the MCS result can still be substantial when using these techniques. The percent error with confidence level based on λ is given by [Ang & Tang, 1984]:

$$\%\ error = 100 \cdot \lambda \sqrt{\frac{P_x}{N_{MCS}(1 - P_x)}} \tag{7.24}$$

For the previous example, if 2144 MCS repetitions are performed the percent error may be as great as 50%. This error can be reduced to below 20% by increasing the number of MCS repetitions to 13,500. Clearly a substantial number of MCS repetitions are required to accurately determine the tails of a distribution which motivates using subset simulation in these situations.

7.4.2 Subset Simulation

Determining the appropriate number of repetitions for the modified subset simulation technique is a function of the p_j^* selected (recall Table 7.1). The scaling parameter χ specifies the spread of p_j^*. The spread governs the maximum allowable distance that the next sample in a Markov chain can depart from the current one, and hence affects the size of the region that can be covered by the algorithm within a given number of steps. In general, the larger the spread, the larger the region covered by the Markov chain samples. Smaller spreads tend to increase the correlation among Markov chain samples, slowing down the convergence of the MCMC estimator. Conversely, a large spread will increase the number of repeated samples and thus slow down the convergence of the MCMC estimator. The reason for this latter situation is that when the spread is large, a candidate state will often be generated far away from the current sample, and so that candidate state may not have a high probability of lying in the "failure" region, and hence be rejected frequently. Thus, the choice of the spread of p_j^* is a trade off between correlation effects arising from proximity and repeated samples from rejection. The choice in N must thus be combined with an appropriate choice of χ [Au, 2001]. Unfortunately, finding this optimal combination of χ for a given N using a statistical test has been elusive. The combination of N and χ selected appears problem specific, depending on the behavior of the model ($\underline{G}$).

7.5 Summary

A variety of simulation techniques are presented that can evaluate interaction uncertainty in the design of a complex multidisciplinary system. Existing simulation techniques such as MCS, LHS, and DS are well-established and relatively easy to implement. Unfortunately, these simulation techniques are often computationally intensive. This issue motivates investigation of other simulation techniques that might be modified to use within the proposed method. Two methods, MVM and SS, are modified and found to be a significant computational benefit under different circumstances. MMVM is beneficial when the underlying model is well-behaved while SS provides a significant computational benefit when extreme values of a tradable parameter (i.e., tails of a distribution) are of interest to a decision maker. Simulation techniques that were not pursued for use in the proposed method are presented. Finally, a discussion of methods to determine the appropriate number of repetitions required for the various simulation techniques are summarized. With uncertainty in the tradable parameters quantified by one of the aforementioned simulation techniques, actual margins can be determined and the design analyzed. These topics are presented in the next chapter.

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Chapter 8 Determining Margins, Analyzing the Design, and Trading Parameters

This chapter begins by discussing the final step in the proposed method: the determination of margins. This step is based on the risk tolerance of the decision maker. Once margins have been established for a given design, the details of that design can be investigated further via three techniques: performing a sensitivity analysis, calculating the correlation coefficients, and data mining the samples/results. An overview of each technique is presented. The chapter concludes with a discussion of two methods to trade parameters: iteration and optimization.

8.1 Determining Margins

The simulation methods described in Chapter 7 generate an *N*-dimensional vector of results for each tradable parameter. This vector can be converted to a histogram by sorting the results into bins of a designated size. This bin size is typically the minimum amount of that tradable parameter that is of significance (e.g., for mass it may be 0.1 kg where a decision maker wants to be confident of the results to within a tenth of a kilogram). This histogram in turn can be converted to probability density function (PDF). If this conversion results in a choppy PDF, it is likely an inappropriate bin size was assumed or an insufficient number of simulation repetitions were performed. The tests discussed at the end of Chapter 7 can provide an indication whether more samples need to be generated and repetitions performed. Otherwise an alternate simulation technique may be required.

The PDF of results for a tradable parameter should be convolved with its corresponding model uncertainty PDF. This process of convolving two distributions is described in Appendix A. With a convolved PDF of each tradable parameter available, a PDF can be integrated to generate a final cumulative distribution function (CDF). Certain formal methods to quantify uncertainty use the mean and the standard deviation as the two key decision functions in design. This technique is simple since it allows a result to be expressed by two values instead of a (potentially complicated) curve. Unfortunately, reducing a CDF to the combination of two statistical parameters loses a tremendous amount of information that the proposed method generates. Solely using the mean and standard deviation in making decisions in design can be misleading (see the example in Appendix A).

A CDF (and the corresponding PDF) is a visualization of uncertainty that is consistent with human intuition. The general shape (skewness) of the convolved PDF for a tradable parameter indicates whether all the uncertainties in the analysis are more likely beneficial or detrimental.

The unique CDF generated by the proposed method for a given tradable parameter is the key decision function in design. A CDF delivers the uncertainty about a tradable parameter in a way that is consistent with the type of decisions upon which the data will be based since a CDF value, selected based on the risk tolerance of the decision maker, is used along with the deterministic result in calculating margins in the proposed definition:

$$\%\ \text{margin}\Big|_{\text{proposed}} = \left[\left(P_x - R_{\text{det}}\right)/R_{\text{det}}\right]\cdot 100 \tag{8.1}$$

The choice in the percentile x that the value P_x will be based on is a function of the risk tolerance of the decision maker. It is often difficult quantifying the risk tolerance of an individual. As with utility functions discussed in Chapter 3, generating a comprehensive equation to represent risk tolerance is difficult since values and knowledge may be changing. In utility theory, the risk tolerance of a decision maker can be accomplished via decision theory lottery techniques or indifference curves [Raiffa, 1968]. These techniques can be used in the proposed method if the tradable parameter value is treated as a utility. Regardless of the method used to determine the percentile (probability) value, whether by lottery techniques, indifference curves, or by fiat from the decision maker or stake holder, the significance of the percentile chosen is easily understood by all participants and easily conveyed to others. A very high percentile may imply the decision maker is risk-averse; lower percentile values may imply a risk-seeking decision maker. For different tradable parameters, difference percentile values might be used. For example, a decision maker may select the 99.99th percentile for the lifetime of a complex multidisciplinary system but only the 90th percentile value on its mass. In this case the decision maker may be viewed as risk-averse with respect to the lifetime tradable parameter but risk-seeking with respect to the tradable parameter mass. The corresponding P_x for such percentiles is now provided by a rigorous quantitative method, not a heuristic approach based on previous mission that may or may not be similar to the system being designed and developed.

8.2 Analyzing the Results

In addition to generating quantitative values for margins, the proposed method generates a significant amount of probabilistic data that can be analyzed. Three techniques are recommended for understanding the uncertainty in the tradable parameters in more detail than solely using the calculated margin value: performing a sensitivity analysis, calculating the correlation coefficients, and data mining the samples/results.

8.2.1 Sensitivity Analysis

A sensitivity analysis was introduced in Chapter 6 as a technique to determine which uncertainties may be significant and which are likely not. Performing a sensitivity analysis after results are obtained can also be beneficial as it will indicate which uncertainties might be investigated in more detail prior to the next margin determination iteration (if planned). Certain design decisions may be delayed as a result of a sensitivity analysis during which time a concentrated effort can be undertaken to refine and (hopefully) reduce such uncertainties. The traceability that a sensitivity analysis provides may, for example, indicate the need for a higher-fidelity model (if model uncertainty is driving the margins) or a renegotiation with the stake holder and/or decision maker of the requirements (if one or requirement uncertainties are driving margins). A sensitivity analysis performed after each iteration of the proposed method provides quantitative guidance for the successive iteration. The ultimate objective of these iterations is to arrive at a requisite model for each tradable parameter and to analyze that model just enough to understand clearly what an appropriate and feasible margin on all tradable parameters in the design should be. A requisite model is a model that represents the phenomena of interest over a range of interest and is described in detail in Chapter 5. By the time the decision maker reaches this point, all important issues will be included in the tradable parameter models and the choice for margins should be clear.

8.2.2 Correlation Coefficient

The correlation coefficient between samples (θ) and the resulting values for a tradable parameter y provides a statistical technique to determine which uncertainties may be driving the uncertainty in the tradable parameters (and hence margins). An N by n+1 array where the first column is the vector of N results for a given tradable parameter of a simulation and the remaining n columns are the N random samples generated for all n input variable uncertainties can be analyzed to yield a correlation coefficient and p-value for each input variable uncertainty. Both the correlation coefficient and p-value are described in Appendix A. For a given tradable parameter, an input variable with a p-value less than 0.05 indicates that the uncertainty may be significant. A positive correlation coefficient implies that positive changes in that variable likely result in positive changes in that tradable parameter whereas a negative correlation coefficient implies that positive changes in the variable likely result in negative changes in that tradable parameter. Combined with a sensitivity analysis, a correlation coefficient can indicate which uncertainties (input variables) warrant further investigation.

8.2.3 Data Mining

Although the decision maker likely is concerned with tradable parameter values and the corresponding margins, the engineers and designers involved in applying the proposed method are likely interested in why certain samples yielded a significantly higher (or lower) tradable parameter result. Investigating the values of the different uncertainties that were sent to the model $\underline{G}$ (along with a sensitivity analysis or calculation of correlation coefficients) should indicate which input variable or combination of input variables caused these high or low results. Due to the nature of complex multidisciplinary design and risk-aversion, engineers and designers are likely concerned primarily with the high tradable parameter repetition results when a low tradable parameter result is desired (or vice-versa: a low tradable parameter result when a high value is desired). An example of the former case could be mass, cost, or schedule where lower is "better" and high results from the probabilistic analysis are a source of consternation. The sample that corresponds to such a high result can be investigated by the engineers and designers in more detail. This data mining procedure may discover a combination of uncertainties that yields an undesirable result but might be readily mitigated in practice. The engineer and designer may also wish to investigate those samples which yielded low tradable parameter values to better understand which uncertainty or combination of uncertainties yields a beneficial scenario of a low tradable parameter value. The sample that corresponds to such low results may, for example, provide clues as to a combination of design choices (sets of designs) the engineer or designer did not explicitly consider. Data mining could thus influence the final choice the engineer or designer then makes.

8.3 Trading Parameters

The final step in the proposed method is trading parameters. The objective in trading parameters is to reach some final system-level balance in the margins of the tradable parameters that is both feasible and acceptable to the stake holder, decision maker, and participants in the method. The assumption implicit in this step is that the proposed method participants are rational. Although there is no universally accepted definition of rationality the one used here is behavior which is consistent with the pursuit of the stated objectives [Tribus, 1969]. That is to say, the balance in tradable parameters sought by the participants follows one or more consistent objectives. Two methods of trading parameters are possible: iteration and optimization. The two methods can be combined.

8.3.1 Iteration

Iteration involves reapplying the method when uncertainties have changed or alternate designs are to be investigated. Iteration is an inherent procedure in engineering design (recall Fig. 1.1) and specifically in complex multidisciplinary design to refine results. The proposed method is no different. Certain uncertainties may decrease as the design progresses since decisions are made, quality control is enacted, and modeling improved. Other uncertainties may increase as knowledge, data, and expert elicitation is acquired and updates a previous uncertainty estimate. The decision maker may also wish to investigate other designs. Indeed, design uncertainty may provide the single biggest opportunity to alter seemingly irreducible uncertainty in certain tradable parameters. By reapplying the method to an alternate design, the margins and CDFs of each tradable parameter for the designs can be compared. The proposed method can thus quantitatively compare uncertainty in different designs. One design may stochastically dominate the other providing quantitative evidence that the dominated design should not be pursued further. Stochastic dominance occurs when one CDF lies completely to one side of another CDF. An example of stochastic dominance is provided in Appendix A.

Beyond trivial examples there will always be uncertainty in designs and iteration provides a way to track how these uncertainties change over time. Iteration in applying the proposed method should go hand in hand with organizational best practices. Best practices for effectively managing complex projects are well documented both internally within an organization and through publicly available references (e.g., [Morris, 1986]). With documentation that carefully records uncertainties and efforts to address them, subsequent iterations of the proposed method will require substantially less time than the original application. Best practices and documentation may also help uncover phenomenological uncertainty that was discussed in Chapter 5.

8.3.2 Optimization

Optimization is defined as an act, process, or method of making something (as a design, system, or decision) as fully perfect, functional, or effective as possible [*Webster's Ninth New Collegiate Dictionary*, 1990]. In a pure mathematical definition, optimization refers to finding the absolute best solution to a problem. Every design problem is thus a "maximization" problem in the sense that the problem is to uncover the best design.* However, a more useful definition, provided by Jilla, Miller, and Sedwick (2000), is the engineering interpretation of optimization

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*a minimization problem can always be mathematically reformulated as a maximization problem (e.g., $\min(f(x)) = \max(-f(x))$)

which is "the process of finding good solutions to the design problem." Whereas an engineer or designer has various variables under his control that he can select to optimize a design (design uncertainty), enumeration of all design possibilities for any practical design is either enormously expensive in resources or impossible. Optimization is a necessary step to assist the engineer or designer in discovering "good" solutions. During preliminary design of complex multidisciplinary systems, optimization, if it is performed at all, is almost always done at the subsystem level and not at the system level. Optimization at the subsystem level rarely achieves optimization at the system level, resulting instead in a design that is feasible but not optimal. However, engineers and designers are often satisfied with nonoptimal yet feasible solutions due to the overall difficulty of designing and developing such systems.

The last decade has witnessed an explosion of research into multidisciplinary design optimization (MDO) techniques (e.g., [Braun, Moore, and Kroo, 1997; Mosher, 2000; Jilla, Miller, & Sedwick, 2000]). The goal of MDO is to discover optimal design via Pareto optimal points (the so-called efficient frontier) [Keeney & Raiffa, 1976]. A design θ is Pareto optimal if:

$$\begin{aligned} f_i(\underline{\phi}) &\leq f_i(\underline{\theta}) \qquad \text{for all } i = 1,2,\ldots,k \\ f_j(\underline{\phi}) &\leq f_j(\underline{\theta}) \qquad \text{for some } j \end{aligned} \tag{8.2}$$

where ϕ is some alternate design. Hence, a problem may have dozens, hundreds, or possibly an infinite number of Pareto optimal points. MDO research efforts proved that the design space for complex multidisciplinary systems is neither smooth nor unimodal but instead has multiple peaks and discontinuities requiring sophisticated analytic and computational implementation techniques to determine the efficient frontier. MDO researchers have investigated a wide variety of applications with multiple objectives yet only a limited amount of research has investigated MDO under uncertainty (e.g., [DeLaurentis, 1998; Walton, 2002]). MDO without considering uncertainty is an important pedagogical benefit in understanding the MDO design space but of limited design value as the optimal solution found will almost certainly not be the actual final optimal solution once the system is built. MDO techniques that consider uncertainty transform a problem from a deterministic optimization problem track a "point" in a multidimensional design space to a probabilistic optimization problem that tracks a "distribution" and their parameters. Unfortunately, this transformation complicates the problem significantly. Since deterministic MDO techniques are intricate and often computationally intensive on their own, probabilistic MDO techniques would likely be even more so.

Integrating MDO into the proposed method without sacrificing design feasibility is a logical choice for assisting in the balance of tradable parameters and their margins. This balancing process would entail viewing each tradable parameter as an objective function and proceeding with multi-objective (multi-criteria) optimization. This possibility is discussed in Chapter 10 as an avenue of future research. However, it is unlikely that turning over the entire process to an automated algorithm will yield the optimal balance in the tradable parameter margins. Instead, MDO techniques in combination with engineering judgment (the most indispensable engineering design tool) may yield promising ("good") designs.

8.4 Summary

The final step in the proposed method is determining margins for each tradable parameter of a given design. This step is based explicitly on the risk tolerance of the decision maker via the choice in a percentile from the probabilistic results. Three techniques to further analyze and understand a given design are possible and discussed: a sensitivity analysis; calculating the correlation coefficient; and data mining the samples/results. If the decision maker is not satisfied with the balance of margins in a design, these parameters can be traded with each other through iteration and/or optimization. With a satisfactory balance of system-level tradable parameter margins, application of the proposed method is complete. The various steps of the proposed method that are described in detail in Chapter 4 through this present chapter can now be demonstrated by an example. This is the topic of the next chapter.

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Chapter 9 Application Example – Attitude Determination and Control System

This chapter provides an example of applying the proposed method. Although the proposed method could be applied to an entire spacecraft, this is unlikely to be a realistic scenario as only trivial modeling tools exist at a spacecraft-system level and participants at a system-level lack sufficient expertise concerning uncertainties encountered. Instead, the proposed method would be applied concurrently to whatever hierarchical level of the spacecraft design (e.g., subsystem, assembly, component) is practical in terms of modeling and personnel. A subsystem, attitude determination and control system (ADCS), is chosen for the example application as it provides a representative spacecraft discipline in terms of complexity, number of uncertainties, and uncertainty types. The specific application is the ADCS on the cruise stage of the Mars Exploration Rover (MER) project. The purpose of this example application is not to describe the individual subsystem or project in detail. A brief summary of both begins the chapter; associated references are noted that describe these topics in detail. The focus of this chapter is to demonstrate the step-by-step application of the proposed method and its benefits in determining margins *vis-à-vis* the current heuristic method. Each step is detailed. The ADCS example and others found in Appendix B demonstrate the applicability of the proposed method to a broad class of subsystems encountered in complex multidisciplinary design.

9.1 Mars Exploration Rover (MER) Project

The MER project had the primary objective of placing two mobile science laboratories, MER-A (Spirit) and MER-B (Opportunity), on the surface of Mars in order to remotely conduct geologic investigations, including characterization of a diversity of rocks and soils that may hold clues to past water activity. The MER project used the 2003 launch opportunity to deliver two identical rovers to different sites in the equatorial region of Mars: MER-A launched June 10, 2003 on a Boeing Delta II 7925; MER-B launched July 8, 2003 on a Boeing Delta II 7925H. The Delta II 7925H, with larger "strap-on" thrust augmentation solid rocket motors, is a slightly more powerful variant of the Delta II 7925.

The MER project was managed by the Jet Propulsion Laboratory (JPL), a division of the National Aeronautics & Space Administration (NASA) administered by the California Institute of Technology. MER design officially began in April 2000. The design of the MER flight system was an adaptation of the JPL/NASA Mars Pathfinder (MPF) spacecraft design which was launched in 1996 and landed on Mars on July 4, 1997. The MER flight system consists of four major components: an Earth-Mars cruise stage; an atmospheric entry, descent, and landing system or aeroshell (consisting of a heatshield and backshell); a lander; and a mobile science rover with an integrated instrument package. Fig. 9.1 illustrates the MER flight system in its Earth-Mars cruise configuration.

Fig. 9.1 MER spacecraft during cruise to Mars.

During this interplanetary transfer from Earth to Mars, MER is a spin-stabilized spacecraft with a nominal spin rate of 2 rpm and the cruise stage provides most of the traditional spacecraft subsystem functionality (such as propulsion, power, communications, thermal, and attitude control). Roncoli and Ludwinski (2002) discuss the MER mission in detail. Uncertainty mitigation in the design of MER was accomplished via system-level margins. These flight system margins and a description of MER margin management are found in Chapter 1.

9.2 Attitude Determination and Control System Overview

The attitude determination and control system (ADCS) orients and stabilizes the spacecraft countering external and internal disturbances that act upon it. ADCS comprises sensors (that determine the attitude of the spacecraft) and effectors (that control the attitude of the spacecraft). Larson and Wertz (1999) and Griffin and French (2004) provide an overview of ADCS while other references comprehensively detail ADCS (e.g., [Kaplan, 1976; Wertz, 1978; Chobotov, 1991; Sidi, 1997; Wie, 1998]). ADCS on MER resides completely on the cruise stage. The MER ADCS was designed and developed by JPL/NASA with several contractors providing components and expertise. The ADCS on MER is controlled by the command and data handling system that resides on the rover within the lander. This is possible via a connection between the rover support board and the remote electronic unit on the cruise stage. The MER cruise stage uses two clusters of four 4.5 N Aerojet MR-111C engines (thrusters), one on each side as shown in Fig. 9.2.

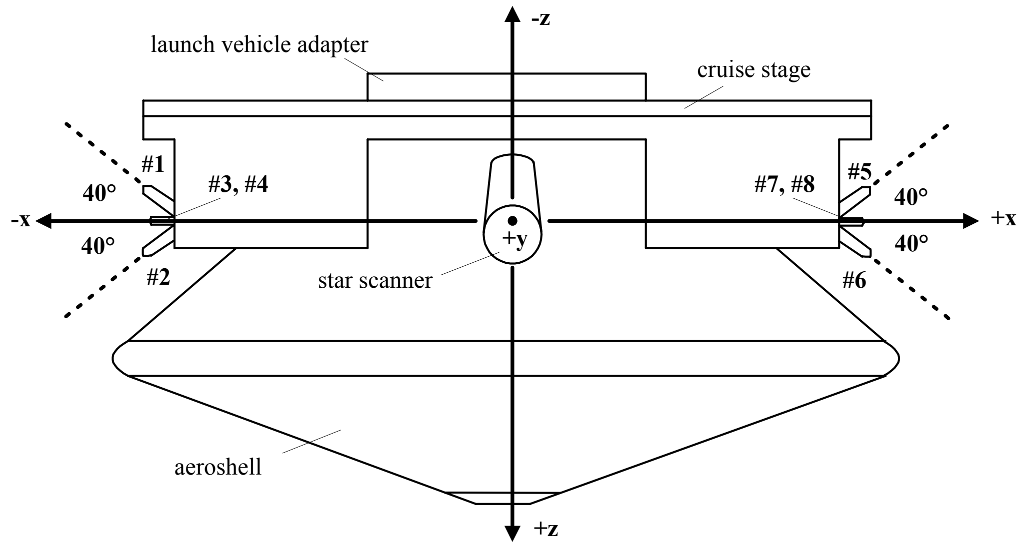

Fig. 9.2 MER engine cluster configuration; adapted from D'Amario (2002).

The z-axis is the spin axis. The spin axis moment of inertia is the spacecraft's maximum moment of inertia. The two engine clusters are on the $+x$ and $-x$ axes. The $+y$ axis is out of the page in Fig. 9.2 and points through the star scanner. Engines 1, 2, 5, and 6 are in the x-z plane whereas engines 3, 4, 7, and 8 are in the x-y plane. All engines are canted at an angle of 40° from the x-axis. The effective moment arm of all engines is therefore:

$$r = R \cdot \sin 40° \approx 0.643R \tag{9.1}$$

Two engines, one on each side of the spacecraft, with equal and opposite thrust vectors are fired for maneuvers. Ideally, a torque is imparted only about the spacecraft's center of mass and no change in the spacecraft trajectory results. For example, firing engines 3 and 8 would spin the spacecraft (counter clockwise) about the $+z$ axis.

9.3 Uncertainties Involved

The preliminary design of a spacecraft ADCS involves all the uncertainties introduced in Chapter 2. Table 9.1 provides examples for each of these uncertainty types in the field of spacecraft attitude determination and control.

Table 9.1 ADCS examples of different uncertainty types

Uncertainty type	Attitude determination & control example	Included in this analysis?
Ambiguity	The pointing control must be 1° [everywhere? continuously?]	No
Epistemic		
Model	The difference between the propellant mass predicted by an analytic model and the actual flight measured total	Yes
Phenomenological	The density profile of Neptune's atmosphere	No
Behavioral		

Uncertainty type	Attitude determination & control example	Included in this analysis?
Design	The choice between two different star scanners for attitude determination	Yes
Requirement	The spacecraft shall be able to de-spin from 10 rpm [and this requirement later changes to 15 rpm]	Yes
Volitional	An analysis an engineer says he will perform but does not	No
Human errors	A mistake in measuring the mass of a sun sensor	No
Aleatory	The thrust of an engine at a given pressure	Yes
Interaction	The combination of choice between two different engines and the fact that their thrust levels are not certain	Yes

Also listed in Table 9.1 is whether a given uncertainty is included in the MER ADCS example described in this chapter. Ambiguity is not considered in this analysis; linguistic imprecision is assumed to have been reduced to a desired level. Phenomenological uncertainty is not significant in the actual MER ADCS design nor in the MER mission profile and is not addressed. Volitional uncertainty is not considered, although the techniques discussed in Chapter 6 would be valid in representing uncertainty in the behavior of contractors that assisted in MER ADCS development. Human errors are neglected due to assumed facilitative measures.

9.4 Tradable Parameters

The tradable parameters identified for the MER ADCS are the propellant mass, schedule duration, and total cost. The propellant mass is defined as the total amount of propellant required for attitude control maneuvers during interplanetary cruise from Earth to Mars. Propellant mass does not include propellant required for change in velocity (ΔV) maneuvers. The schedule duration and the total cost are defined as the total time and cost, respectively, to design, build, test, and deliver *two* attitude determination and control systems (MER-A & MER-B). During MER design these three parameters were traded with each other. At the preliminary design review (PDR), the MER project best estimates for propellant mass, schedule duration, and total cost were 2.9 kg, 664 days, and FY2003$8.2M, respectively. In turn, the margins placed on these three tradable parameters by the MER project were 51.7% (1.5 kg), 14.3% (95 days), and 30% (FY2003$2.5M) [D'Amario, 2002]. Margin estimates for propellant mass impact the propulsion subsystem which must store this propellant in an appropriately sized tank. Schedule duration and total cost estimates impact MER systems engineering and management. MER systems engineering and management must incorporate the ADCS schedule and cost within the schedule and cost of the entire MER project. The 664 day schedule duration best estimate was generally acknowledged to be very optimistic. However, as MER was schedule constrained due to the limited launch opportunity, the schedule duration allocation of 759 days was deemed appropriate.

The example in this chapter is assumed to be performed around PDR and only one iteration of the proposed method is illustrated.

The quantity and type of all ADCS related hardware (sun sensors, star scanners, and engines) was known with certainty early in design since certain flight spares from previous missions were available and "free" to the MER project to use. For example, a Ball Aerospace CT-632 star scanner remained from Mars Pathfinder (MPF) and was used. Thus, dry mass was not considered a tradable parameter although in most other ADCS designs, dry mass would be an important if not the most important tradable parameter. Dry mass was a tradable parameter for many of the other MER subsystems as mass growth was a constant problem during the design of MER. Cost and schedule were traded to reduce mass [Thunnissen & Nakazono, 2003]. Other parameters, such as risk (the likelihood of catastrophic failure of the subsystem) and power required by ADCS, were considered but not selected since no major design decisions were made concerning these parameters. Hence, risk and power required, two parameters that are often tradable in the design of other attitude control systems, were not tradable parameters in the design of the MER ADCS.

9.5 Models and Model Uncertainty

This section describes the models assumed in the ADCS analysis. The section begins with an overview of model assumptions. A detailed explanation of the propellant mass model follows. Model uncertainty is described in the final portion of this section.

9.5.1 Major Assumptions

The models and analyses presented are based on the MER flight system, specifically the Earth-to-Mars interplanetary-cruise portion of the mission. Application of these models and analyses to other spacecraft would require verification of the assumptions and likely alterations to the models described subsequently. The major assumption in the propellant mass model and analysis is the use of a simple feedback control model. The behavior of an actual ADCS system can be understood only if feedback control is correctly implemented and modeled. Nonetheless, for the conceptual estimation of the tradable parameters proposed, the difference between a sophisticated feedback control model and the feedback model implemented is likely small. Higher-fidelity models implementing feedback control for all maneuvers could readily be substituted for the simple models described. Model uncertainty addresses this difference and is accounted for in the analysis.

9.5.2 Additional Assumptions

Several additional important assumptions were made in the models and analyses described. Some of the justifications for these assumptions are provided here, others are justified *ex-post facto* via the results.

- The mass of the spacecraft is constant. Although the amount of attitude control propellant is insignificant compared to the spacecraft mass, a significant amount of propellant for the trajectory correction maneuvers (TCMs) may be expended during cruise (approximately 4% of the total spacecraft wet mass at launch) [Thunnissen & Nakazono, 2003]. This is arguably the most significant of the assumptions listed.
- The spacecraft is axisymmetric with the spin axis being the axis of symmetry. The center of mass is at the origin of the coordinate system in Fig. 9.2 and does not move during cruise. In reality the center of mass shifts slightly along the $-z$ axis towards the front of the spacecraft as propellant is expended.
- The moment of inertia of the spacecraft is constant (a result of the two previous assumptions of constant spacecraft mass and spacecraft center of mass location).
- The inlet pressure to the engines, which has a significant effect on the thrust and a moderate effect on the specific impulse of the engines, is constant throughout the interplanetary cruise. In reality the inlet pressure decreases after each maneuver due to propellant being expelled. The major maneuvers that impact this inlet pressure are the TCMs required during cruise. The modeling of such a pressure decrease on the performance of a propulsion system is described in Thunnissen, Engelbrecht, and Weiss (2003). In this analysis the pressure was kept at its lowest-anticipated level, which corresponds to the pressure when most of the propellant for TCMs has been expended. This assumption of using the lowest inlet pressure allows for a lower impulse bit and (in terms of propellant mass required) is a conservative assumption.
- The inlet fuel temperature, which has only a minor influence on the thrust and specific impulse, is constant for the duration of the interplanetary cruise.
- Internal disturbances are neglected.

Three models, one for each tradable parameter, were created for this analysis based around the assumptions: a propellant mass model, a schedule model, and a cost model. The propellant mass model determines the total propellant required for attitude control during the cruise stage portion of the MER mission. The schedule model determines the total time to design, develop, test, and deliver the ADCS. The results of the schedule model are used in the cost model to determine the total cost to design, develop, test, and deliver the ADCS. The propellant mass model is described in detail in the following section. The schedule and cost model are described in Thunnissen and Nakazono (2003) and Thunnissen (2004a). As existing models were not available, each was created. All three models were created in MATLAB® (m-files), a common engineering software platform. Although the models could have been implemented in another software platform or programming language (e.g., Excel, FORTRAN, C++), the matrix nature, integrated probabilistic features, and visualization options of MATLAB® simplify implementation of the proposed method. Furthermore, MATLAB® is now common enough that most engineers have at least a basic familiarity with it and thus provides an established and accepted reference.

9.5.3 Propellant Mass Model

One of the most important parameters that ADCS estimates during conceptual design is the total propellant mass required to maintain attitude control. For spacecraft with engines as the only effectors available, the propellant available for attitude control may determine the lifetime of the spacecraft. Furthermore, improper modeling and estimation of attitude control propellant may lead to mission failure. Estimating the correct propellant required is also important from a multidisciplinary standpoint as another subsystem (propulsion) is required to store and distribute this additional propellant and provide the engines to effect maneuvers. The total propellant required by the spacecraft for attitude control is the sum of the propellant required for overcoming all spin/de-spin maneuvers, required slew maneuvers, and solar torque build-up slew maneuvers. The model calculates these individual propellant mass maneuver values sequentially based on the time they occur from Earth launch.

This section begins with an overview of the capability and performance of engines, in particular the Aerojet MR-111C engine used by MER. The engine performance directly impacts the three types of maneuvers required for spacecraft attitude control maintenance: spinning the spacecraft, slewing the spacecraft, and compensating for external disturbances. A sub-model for these maneuver types was created within the overall propellant mass model and a detailed description of each follows.

9.5.3.1 <u>Engine Capability and Performance</u>

Steady-state engine thrust and exhaust velocity are strong and weak functions of the inlet pressure to the engine, respectively [Thunnissen, Engelbrecht, & Weiss, 2003]:

$$F = k_1 \cdot p_{\text{inlet}} + k_2 \tag{9.2}$$

$$c = k_3 \cdot p_{\text{inlet}}^{\ k_4} \tag{9.3}$$

The constants k_1, k_2, k_3, and k_4 are unique to the individual engine type (manufacturer model). For example, if the thrust, exhaust velocity, and inlet pressure are in N, m/s, and Pa, respectively, the coefficients k_1, k_2, k_3, and k_4 for the Aerojet MR-111C are $3.871(10)^{-7}$, $5.075(10)^{-3}$, 1080.1, and $4.796(10)^{-2}$, respectively [Morgan, 2003]. Equations (9.2) and (9.3) are plotted in Fig. 9.3 for the Aerojet MR-111C.

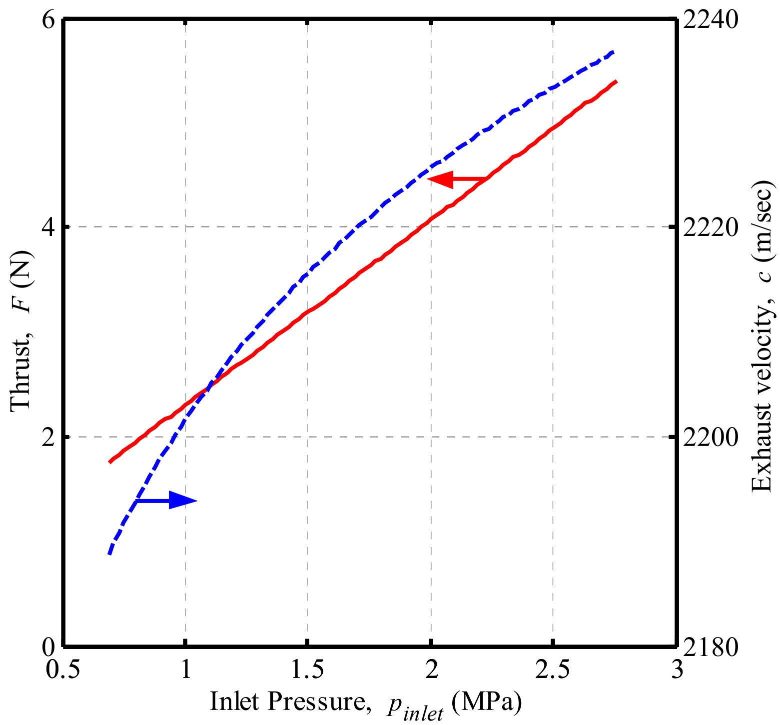

Fig. 9.3 Thrust and exhaust velocity as a function of inlet pressure.

Since a pair of engines is used for maneuvers on MER, the total ideal thrust is

$$F_{\text{ideal\_tot}} = 2 \cdot F \tag{9.4}$$

Unfortunately, the thrust level of a given engine model is variable. Although the thrust variability engine-to-engine is small, it can be significant burn-to-burn, particularly for short burns. Test data indicate burn-to-burn engine variability is normally distributed about the mean thrust level with +/- 3σ value of 7% of the mean-thrust level [Morgan, 2003]:

$$F^{i}_{\text{actual}} = N\left(F, \tfrac{7}{300}F\right) \tag{9.5}$$

Furthermore, engines can be misaligned when installed. The angle between the actual thrust vector and the ideal thrust vector achieved by an engine is the engine misalignment angle. Hence, the misalignment angles of the engines reduce the actual thrust achieved by a pair of engines:

$$F_{\text{act\_tot}} = F^{1}_{\text{actual}} \cdot \cos(\delta_1) + F^{2}_{\text{actual}} \cdot \cos(\delta_2) \tag{9.6}$$

This difference between the total ideal and total actual thrust levels defined by Eqs. (9.4) and (9.6), respectively, impacts the total impulse achieved during maneuvers. One or more additional maneuvers may be required to clean up an original maneuver if the thrust variability and engine misalignment angles are high.

Lastly, pulsing the engines reduces their specific impulse (exhaust velocity) compared to a single steady-state burn and is a function of the engine duty cycle:

$$c_{\mathrm{sd}}^{j} = c \cdot \left(\eta^{j}\right)^{\chi} \tag{9.7}$$

where the duty cycle and length in time it takes the spacecraft to spin half a revolution are

$$\eta^{j} = \frac{t_{\mathrm{min\_on}}^{j}}{t_{\mathrm{half\_rev}}} \tag{9.8}$$

$$t_{\mathrm{half\_rev}} = \frac{\pi}{\omega} \tag{9.9}$$

The specific impulse efficiency parameter is a property of a particular engine. For the Aerojet MR-111C engine this parameter is 0.0375 [Lisman, 1995].

9.5.3.2 Spin

Spinning a spacecraft up or down is done for a variety of reasons including instrument operation, thermal control, and cleaning-up launch vehicle dispersions. Certain components, such as some star scanner models, require a spinning spacecraft to successfully operate. The design of the thermal control subsystem in a spinning spacecraft (so-called "rotisserie mode") is simpler than that of a 3-axis stabilized spacecraft where one or more sides of the spacecraft are constantly facing a temperature extreme. Finally, a launch vehicle upper stage is often spun up for stability prior to its burn and then de-spun once the maneuver is complete. All three examples were the case with the MER flight system. The design used a Ball Aerospace CT-632 star scanner requiring a nominal spin rate of 2 rpm to successfully operate during the Earth-Mars cruise. This decision in turn impacted the thermal design [Ganapathi et al., 2003]. Lastly, the third stage of the Boeing Delta II launch vehicle that was used to inject MER on its interplanetary trajectory was spun up to 12 rpm for gyroscopic stiffness against disturbances during operation of its solid rocket motor. After the solid rocket motor burned out, the spin rate was reduced to the 2 rpm required by the star scanner for the entire cruise to Mars.

The ideal change in spin rate, ideal impulse required, and the time to complete a spin maneuver are

$$\Delta\omega_{\mathrm{ideal}} = \left|\omega_{i} - \omega_{f}\right| \tag{9.10}$$

$$I_{\text{ideal}} = \frac{\Delta\omega_{\text{ideal}} \cdot J_{zz}}{r} \tag{9.11}$$

$$t_{\text{spin}} = \frac{I_{\text{ideal}}}{F_{\text{ideal\_tot}}} \tag{9.12}$$

The actual impulse required, change in spin rate, and propellant required for a spin maneuver are therefore:

$$I_{\text{actual}} = t_{\text{spin}} \cdot F_{\text{act\_tot}} \tag{9.13}$$

$$\Delta\omega_{\text{actual}} = \frac{I_{\text{actual}} \cdot r}{J_{zz}} \tag{9.14}$$

$$m_{\text{p\_spin}} = \frac{I_{\text{actual}}}{c} \tag{9.15}$$

Equation (9.15) assumes a steady-state performance of the engine that follows Eq. (9.3). This assumption may not be justified if the estimated time to complete a spin maneuver is small. As discussed earlier, a simple feedback was implemented in this model to account for uncertainties, particularly in the thrust of the engines used. The aforementioned procedure is repeated until the actual spin rate is within a specified value of the desired spin rate (assumed to be 0.1 rpm in this analysis).

9.5.3.3 Slew

Slew (Re-point) maneuvers are performed by spacecraft for thermal control, power generation, telecommunication, and observation. In the case of MER, the spinning cruise stage slewed periodically from the nominal orientation to one in which the communication antennae could be pointed correctly towards the Earth. MER also slewed from its nominal orientation during cruise to alter the angle of incidence of solar radiation on the spacecraft for thermal control and power generation reasons. The slew algorithm presented is complicated by the fact that only a discrete number of engine pulses is possible and that the thrust of the engines used for pulsing is uncertain.

To reorient the spacecraft a pair of engines is fired for a short interval through an angle $\Delta\phi$. The pulse angle achievable is a function of the engine on time:

$$\Delta\phi = t_{\text{on}} \cdot |\omega| \tag{9.16}$$

The resulting change in torque for such a pulse is

$$\Delta\tau = \frac{2F_{\text{ideal\_tot}} \cdot r}{\Delta\phi} \sin\left(\frac{\Delta\phi}{2}\right) \tag{9.17}$$

The angular momentum of the spacecraft is

$$H = J_{zz} \cdot \omega \tag{9.18}$$

The slew angle achieved is then [Chobotov, 1991]:

$$\Delta\psi = \frac{\Delta\tau \cdot t_{\text{on}}}{H} \tag{9.19}$$

Hence, a typical pulse can range from the minimum on-time the engines can provide to continual thrusting for half a revolution and beyond into additional half revolutions if desired. The magnitude of $\Delta\phi$ is important because the effectiveness of the thrust in producing the desired torque decreases as $\cos(\Delta\phi/2)$ [Kaplan, 1976]. However, pulsing the engines for very short periods of time is inefficient from a propellant standpoint since the exhaust velocity of the engines is poor for low-duty cycles as illustrated by Eqs. (9.7) and (9.8). Therefore, for slew maneuvers that are not strictly time constrained, the minimum propellant required can be optimized through the engine on time (time per pulse). The ideal total propellant required for a slew maneuver is

$$m_{\text{p\_slew}} = n_{\text{pulses\_ideal}} \frac{F_{\text{total\_act}} \cdot t_{\text{on}}}{c_{\text{sd}}} \tag{9.20}$$

where the ideal number of discrete pulses is

$$n_{\text{pulses\_ideal}} = \left\lceil \frac{\psi_{\text{req}}}{\Delta\psi} \right\rceil \tag{9.21}$$

Sequentially substituting in Eqs. (9.7), (9.21), (9.19), (9.17), and (9.16) into Eq. (9.20) and simplifying yields

$$m_{\text{p\_slew}} = \frac{\psi_{\text{req}} \cdot H \cdot \omega \cdot t_{\text{half\_rev}}^{\chi}}{2c \cdot r} \cdot \frac{t_{\text{on}}^{1-\chi}}{\sin\left(\frac{t_{\text{on}} \cdot \omega}{2}\right)} \tag{9.22}$$

Differentiating Eq. (9.22) with respect to the engine on time, setting the resulting expression to zero, and simplifying yields

$$\frac{\omega \cdot t_{on}^{*}}{2} + (\chi - 1)\tan\left(\frac{\omega \cdot t_{on}^{*}}{2}\right) = 0 \tag{9.23}$$

Given the spin rate of the spacecraft and the specific impulse efficiency parameter of the engines used for the slew maneuver, Eq. (9.23) iteratively yields the optimal engine on time per pulse. With the optimal on time known, the pulse angle, change in torque per pulse, and slew angle per pulse can be determined from Eqs. (9.16), (9.17), and (9.19), respectively. The number of pulses required can then be found from Eq. (9.21). The total slew time for the maneuver is then:

$$t_{\text{slew\_tot}} = n_{\text{pulses\_ideal}} \cdot t_{\text{half\_rev}} \tag{9.24}$$

If this total slew time is greater than the time requirement for slewing, the spacecraft must slew faster. Assuming the spacecraft can slew fast enough to satisfy the requirement, the total slew time is set to this requirement and the ideal total number of pulses required becomes

$$n_{\text{pulses\_ideal}} = \left\lceil \frac{t_{\text{slew\_tot}}}{t_{\text{half\_rev}}} \right\rceil \quad \text{if } t_{\text{slew\_tot}} > t_{\text{slew\_req}} \tag{9.25}$$

In either case, the slew angle per pulse must be recalculated using the ideal number of pulses since the value is rounded up to the next integer:

$$\Delta\psi = \frac{\psi}{n_{\text{pulses\_ideal}}} \tag{9.26}$$

The resulting change in impulse torque per pulse and pulse angle are

$$\Delta I_{\text{torque}} = H \cdot \Delta\psi \tag{9.27}$$

$$\Delta\phi = 2 \cdot \sin^{-1}\left(\frac{\left|\Delta I_{\text{torque}}\right| \cdot \left|\omega\right|}{2 \cdot F_{\text{ideal\_tot}} \cdot r} \right) \tag{9.28}$$

With the ideal pulse angle known, the ideal thruster on time is determined via Eq. (9.16). Unfortunately, slewing maneuvers are not ideal due to uncertainties and performance differences between pulses, particularly in the engine thrust level. Once the ideal number of pulses (each of which is the ideal thruster on time in length) has been completed, the actual slew angle performed will likely be different than the requirement. If this difference is greater than the pointing control requirement, additional slew maneuvers will have to be performed. These additional few pulses will either slew the spacecraft back (if the ideal number of pulses slewed the spacecraft too far) or continuing slewing in the original direction (if the ideal number of pulses slewed the spacecraft an insufficient amount). The pointing control requirement is 1° in this analysis. This simple feedback model for slewing could be replaced by a more sophisticated algorithm that determines the angle slewed after each pulse if components onboard are sophisticated enough to measure these small changes.

Finally, the total propellant required for such a slew maneuver is

$$m_{\text{p\_slew}} = \sum_{k=1}^{n_{\text{pulses\_actual}}} \frac{F_{\text{act\_tot}}^{k} \cdot t_{\text{on}}^{k}}{c_{\text{sd}}^{k}} \tag{9.29}$$

where the actual number of pulses is greater than or equal to the ideal number of pulses calculated via Eqs. (9.21) or (9.25).

9.5.3.4 Solar Torque Compensation

The only external torque experienced by MER during its interplanetary cruise is solar torque. The solar flux on a spacecraft decreases according to:

$$f_s = \frac{g_s}{d^2} \tag{9.30}$$

The solar torque due to this solar flux is

$$\tau_s = \frac{f_s}{c_0} A_{\max} \cdot (1+q) \cdot \cos\theta_i \cdot \kappa \tag{9.31}$$

With the angular momentum of the spacecraft known from Eq. (9.18), the nutation frequency and rotational control acceleration are found to be

$$\lambda = \frac{H}{J_{xx}} \tag{9.32}$$

$$\alpha_s = \frac{\tau_s}{J_{xx}} \tag{9.33}$$

If the torque build-up slews the spacecraft with respect to the y-axis, the corresponding torque build-up with respect to the x-axis will be small and periodic:

$$\psi_y = \frac{\alpha_s}{\lambda^2}\left(\lambda \cdot t - \sin(\lambda \cdot t)\right) \tag{9.34}$$

It is apparent from Eq. (9.34) that the slew angle builds as time increases. The analysis herein calculates the solar torque build-up on a daily basis as well as after each other type of maneuver. When the spacecraft slews an amount greater than the pointing control requirement, the spacecraft is re-oriented via a controlled slew maneuver described in the previous section. The amount of propellant required for each of these slew corrections follows Eq. (9.29).

9.5.4 Model Uncertainty

The three models are uncertain. The uncertainties assumed for each model are listed in Table 9.2.

Table 9.2 Model uncertainties assumed

Model	Units	Distribution type and parameters
Propellant mass	kg	$N(0,0.05)$
Schedule duration	days	$T_{NC}(4,1)$
Total cost	FY2003$K	$N(0,50)$

Model uncertainty was assessed by expert opinion (MER engineers and managers). Ideally models would be tested with many actual examples to ascertain these distributions. For example, assuming an actual mission scenario, the propellant mass model could be tested and compared to the actual propellant required for several missions. Unfortunately, there are few examples in the aerospace industry to test models against since organizations rarely keep detailed data in a format that is easily accessible.

9.6 Uncertainty Quantification

The variables discussed in the previous sections are classified as aleatory, design, or requirement uncertainties. This analysis is different than similar analyses (e.g., [Thunnissen & Nakazono, 2003; Thunnissen 2004a; Thunnissen & Tsuyuki, 2004]) in that much of the uncertainty is in the actual operation (mission sequence) of the final subsystem and not in the design. However, these uncertainties in the operation of the final subsystem are significant and do intimately impact the design of the ADCS. Uncertainties in the general variables are first discussed. Uncertainty in the mission sequence is then introduced. A description of uncertainties in component selection concludes this section.

9.6.1 General Input Variables

Variables discussed in the model formulation section, such as the moment of inertias, thruster misalignment angles, and engine moment arm, are assumed to be uncertain quantities. Table 9.3 lists these uncertainties, the relevant model in which they are used, and their assumed probabilistic representation in the analysis.

Table 9.3 General input variables

Variable	Type	Distribution type and parameters	Units
p_{inlet}	Aleatory	$N(100,3.33)$	psi
T_p	Aleatory	$N(25,2.5)$	°C
δ_1	Aleatory	$N(0,0.5)$	deg
δ_2	Aleatory	$N(0,0.5)$	deg
γ_i	Design	$C_d(2,100\%)$	deg
q	Aleatory	$N(0.6,0.06)$	-
J_{xx}	Design	$U(300,450)$	kg-m^2
J_{yy}	Design	$U(300,450)$	kg-m^2
J_{zz}	Design	$U(450,600)$	kg-m^2
$A_{\max}$	Design	$N(5.31,0.053)$	m^2
κ	Design	$U(0.6,0.7)$	m
R	Design	$N(1.3,0.0013)$	m
g_s	Aleatory	$N(1400,14)$	W/m^2
ω_i	Requirement	$N(12,1.33)$	rpm
$\omega_{\text{error\_initial}}$	Requirement	$C_d(0.2,100\%)$	rpm

For each variable, the probability distribution assumed and the corresponding parameters that define that probability distribution are provided. The various distributions listed in Table 9.3

were determined primarily by expert opinion (MER engineers and managers) and, to a lesser degree, statistical analysis.

9.6.2 Mission Sequence

The mission sequence provides a conduit to represent uncertainty in ADCS operation. The nominal mission sequence involves de-spinning the spacecraft from 12 to 2 rpm shortly after separating from the launch vehicle's third stage. After several check out maneuvers, the primary objectives of the ADCS are to perform slew maneuvers for communication and overcome the build-up of solar torque on the spacecraft. ADCS must also be able to provide fault protection (FP) in the event of a major mishap during cruise that might cause the spacecraft to tumble or spin during its journey. Uncertainties in the mission sequence are listed in Table 9.4. Uncertainties also exists in when to perform slew maneuvers (some days are better than others due to visibility of stars for the star scanner) and in the magnitude of the actual slew.

Table 9.4 Mission sequence uncertainties

Mission sequence event	Time[a]	Maneuver type	Maneuver parameter(s)	Distribution type and parameters	Units
De-spin from 3rd stg.	$C_d(1,100\%)$	spin	ω_f	$N(2,0.0667)$	rpm
A-practice	$U_d(6,10)$	slew[b]	ψ	$N(5,0.5)$	deg
ACS-B1	$U_d(15,25)$	slew[b]	ψ	$N(50.45,5)$	deg
ACS-B2	$U_d(40,60)$	slew[b]	ψ	$N(5.13,0.5)$	deg
ACS-B3	$U_d(75,85)$	slew[b]	ψ	$N(6.35,0.6)$	deg
ACS-B4	$U_d(90,100)$	slew[b]	ψ	$N(2.76,0.2)$	deg
ACS-B5	$U_d(110,130)$	slew[b]	ψ	$N(8.51,0.4)$	deg
ACS-B6	$U_d(135,145)$	slew[b]	ψ	$N(9.88,0.5)$	deg
ACS-B7	$U_d(155,165)$	slew[b]	ψ	$N(5.64,0.2)$	deg
ACS-B8	$U_d(166,175)$	slew[b]	ψ	$N(5.04,0.2)$	deg
ACS-B9	$U_d(176,185)$	slew[b]	ψ	$N(5.75,0.2)$	deg
ACS-B10	$U_d(186,195)$	slew[b]	ψ	$N(4.47,0.1)$	deg
ACS-B11	$U_d(196,205)$	slew[b]	ψ	$N(5.53,0.1)$	deg
ACS-B12	$U_d(206,215)$	slew[b]	ψ	$N(5.85,0.1)$	deg
FP: spin event	$C_d(216,100\%)$	spin	ω_i	$\Gamma(11,0.25)$	rpm
FP: spin recovery	$C_d(216,100\%)$	spin	ω_f	$L(2,0.0667)$	rpm
FP: emergency slew 1	$C_d(216,100\%)$	slew[b]	ψ	$\Gamma(1.5,10.5)$	deg
FP: emergency slew 2	$C_d(216,100\%)$	slew[b]	ψ	$\Gamma(1.5,10.5)$	deg
FP: emergency slew 3	$C_d(216,100\%)$	slew[b]	ψ	$\Gamma(1.5,10.5)$	deg
FP: emergency slew 4	$C_d(216,100\%)$	slew[b]	ψ	$\Gamma(1.5,10.5)$	deg
FP: emergency slew 5	$C_d(216,100\%)$	slew[b]	ψ	$\Gamma(1.5,10.5)$	deg
FP: emergency slew 6	$C_d(216,100\%)$	slew[b]	ψ	$\Gamma(1.5,10.5)$	deg

[a]days+launch; [b]no formal time requirement to complete slews within (30 minutes assumed)

9.6.3 Component Selection

The MER project built on the organizational experience gained with the design and development of Mars Pathfinder (MPF). The original design philosophy for ADCS on MER was a replica ("build-to-print") of the MPF design which performed successfully. Unfortunately, due to a fundamentally different configuration of the rover having the "smarts," as opposed to the lander having the smarts which occurred on MPF, the overall MER design changed. This change resulted in the MER ADCS design changing slightly from the original MPF design. The choice in the engine type (Aerojet MR-111C) was assumed early in design based on the MPF experience. This and other early decisions impacted the design of not only ADCS but the entire spacecraft. Hence, dry mass and pointing knowledge were traded for schedule and cost for MER since existing components that were readily available (or easily procured) were assumed instead of casting a wide net of looking at alternate and possibly superior components. However, this trading occurred prior to detailed design and thus not tradable at PDR, the time at which the method is assumed to be applied. It should be noted that in the design of most attitude control systems, dry mass and pointing knowledge are typically traded with propellant mass and each other up to and perhaps beyond PDR.

9.7 Interaction Uncertainty

A mass summary of the deterministic analysis is listed in Table 9.5. Deterministic values of the schedule and cost are 755.3 days and FY2003$13.547M, respectively.

Table 9.5 Deterministic propellant mass results

Propellant required for …	Mass (kg)
Spin	0.301
Slew	0.137
Fighting solar torque	0.200
Fault protection	0.536
TOTAL	1.174

Uncertainty in the tradable parameters is evaluated via four simulation techniques: Monte Carlo simulation (MCS), Latin hypercube sampling (LHS), forward-finite difference modified mean value method (MMVM), and subset simulation (SS). The number of calls to each model was set at $N = 10{,}000$ for MCS, $N = 1{,}000$ for LHS, and $N = 500$ for SS (per SS level). The number of calls to each model for MMVM is one greater than the number of input variable uncertainties which was 48 for propellant mass, 68 for schedule duration, and 92 for total cost (this 92 includes the 68 schedule duration input variable uncertainties that might impact total cost). MMVM does not require a call to a model for input variables that are certain. All subsequent tables and figures reflect the final uncertainty: simulation results convolved with model uncertainty. SS assumed $P_f = 0.0001$, $p_0 = 0.1$, $\chi = 1$ in all three simulations.

9.7.1 Propellant Mass

The propellant mass probability density function (PDF) values for MCS, LHS, and MMVM are provided in Fig. 9.4.

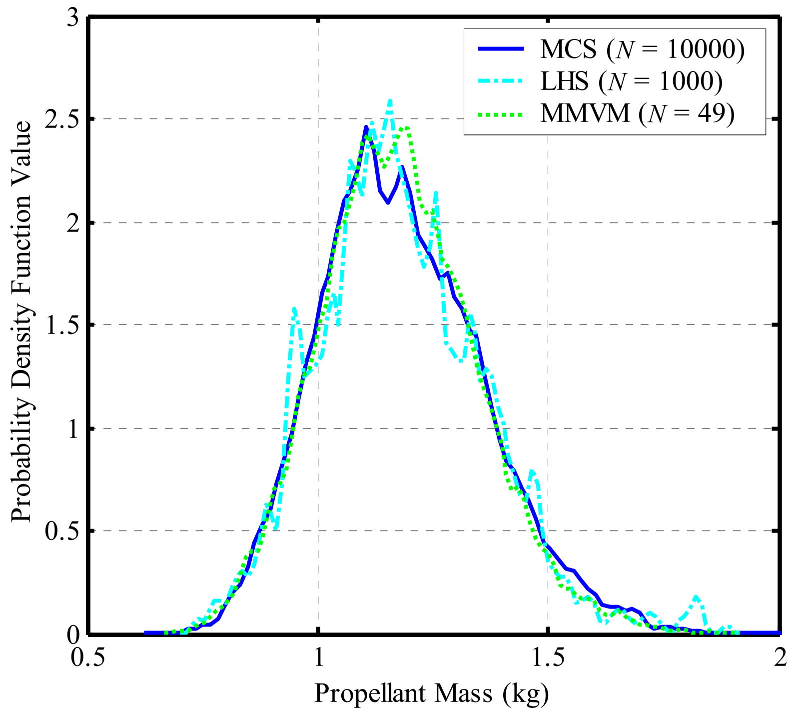

Fig. 9.4 Propellant mass PDFs for MCS, LHS, and MMVM.

The cumulative distribution function (CDF) values for all four simulation techniques are shown in Fig. 9.5 through Fig. 9.8.

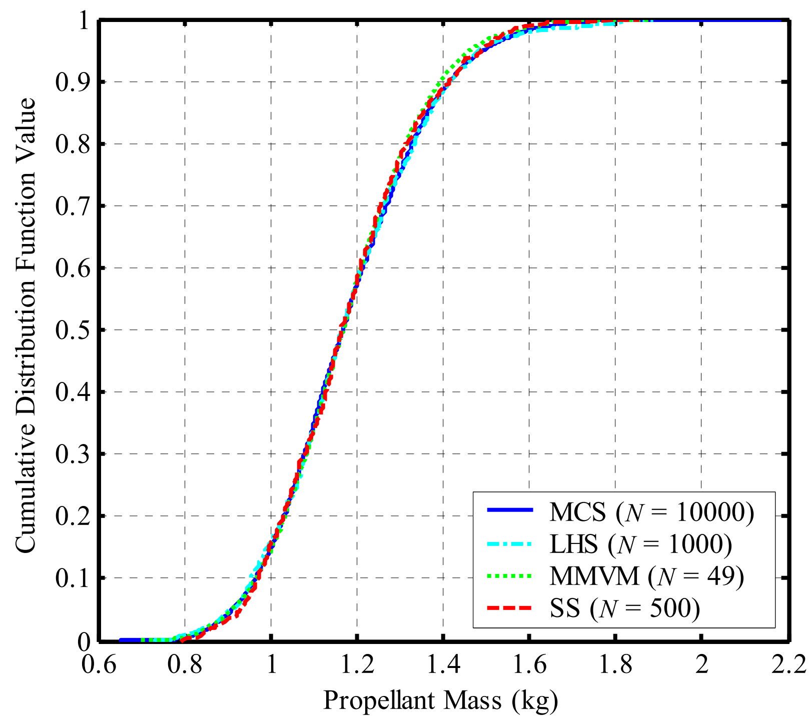

Fig. 9.5 Propellant mass CDFs (simulation level 1).

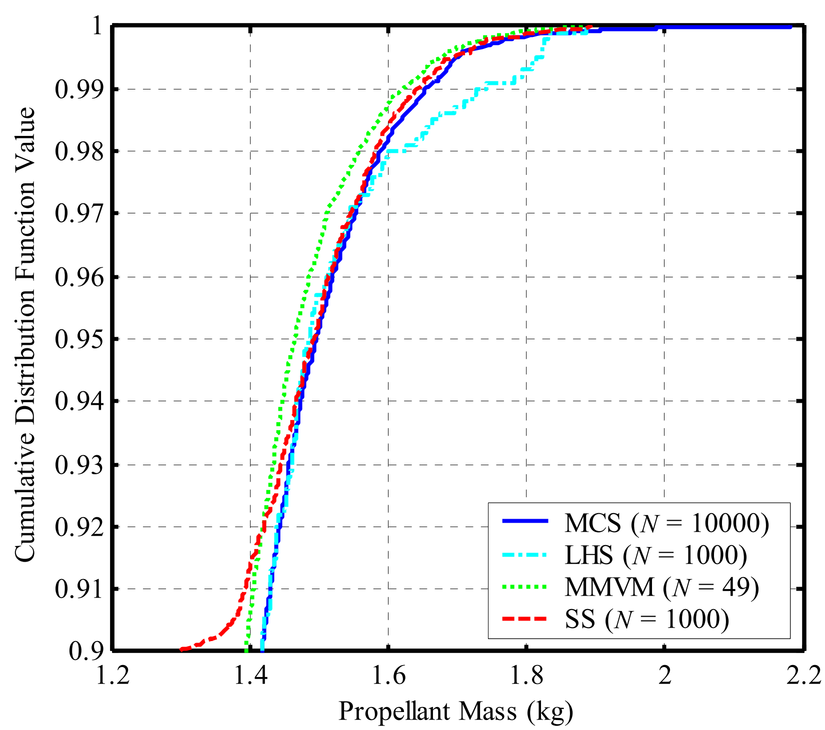

Fig. 9.6 Propellant mass CDFs (simulation level 2).

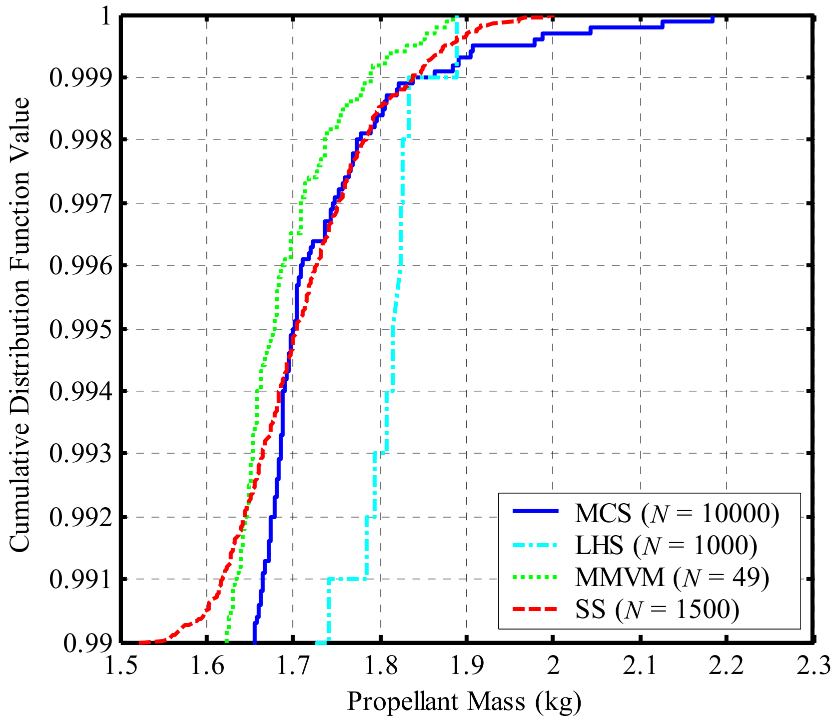

Fig. 9.7 Propellant mass CDFs (simulation level 3).

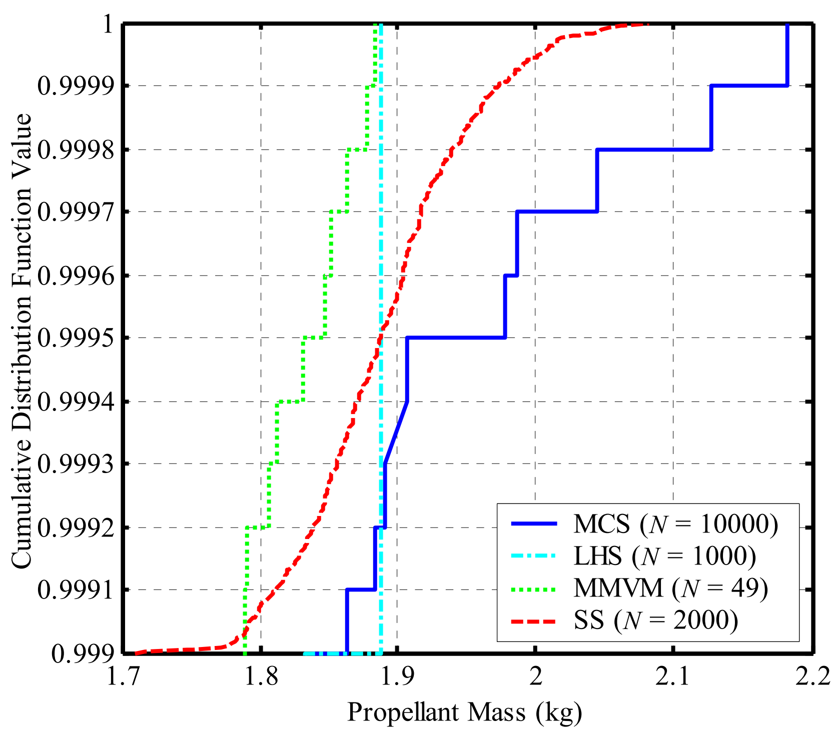

Fig. 9.8 Propellant mass CDFs (simulation level 4).

Fig. 9.6 through Fig. 9.8 demonstrate the performance of the four simulation techniques at the upper tail of the distribution. MCS is the benchmark for comparison but requires a substantial number of calls to the model (N) to obtain values for the entire CDF range. LHS performs well in estimating CDF values less than 0.99 (first and second simulation levels) but poorly for CDF values between 0.99 and 1 (third and fourth simulation levels). With the exception of the extreme tails, MVMM performs well considering the complexity of the underlying model and the fact that only $N = 49$ (corresponding to the number of input variable uncertainties for this tradable parameter plus one) is required, over a magnitude less than LHS and two orders of magnitude less than MCS. As theorized, SS provides a comparable accuracy as MCS at the CDF tail despite requiring only a fifth the calls to the model. The fourth-level SS underestimates the propellant mass but is closer to the MCS result than either LHS or MMVM. Table 9.6 details the statistics of SS by simulation level for propellant mass.

Table 9.6 SS results by level for propellant mass

SS Level	x	P_x (kg)	Error[a] (%)	γ	σ	δ	δ^*	N_{MCS}
1	90	1.416	-0.11	0	0	0.13416	0.13416	500
2	99	1.647	-0.50	1.3123	0.00677	0.20401	0.24418	1661
3	99.9	1.839	-0.66	3.1199	0.00287	0.27232	0.36576	7468
4	99.99	1.974	-8.39	2.2	0.00080	0.24000	0.43747	52247

[a]relative to the 10000 MCS

The low to moderate values of γ in Table 9.6 indicate that the modified Markov chain Monte Carlo (MCMC) algorithm is accepting most samples at each simulation level within a chain. A lower value of χ for this tradable parameter would likely result in more rejections and faster convergence toward the MCS value. The relative error (compared to MCS) is high at the fourth simulation level. However, most of this error is in MCS, not SS as the final column indicates SS achieves a comparable accuracy as 52,247 MCS repetitions (N_{MCS}) whereas only $N = 10{,}000$ were performed for MCS. The error drops to -2.37% when compared to 53,000 MCS repetitions.

Increasing N in SS improves the accuracy of SS *vis-à-vis* actual results (i.e., MCS with N approaching infinity). A modest increase of N to 1,000 (4,000 total repetitions) reduces the relative error in the propellant mass estimate to under 0.5% at the fourth simulation level (holding χ constant). Table 9.7 summarizes the statistics for all four simulation techniques at various percentile values for comparison.

Table 9.7 Propellant mass calculated by each simulation technique

Simulation technique (# of repetitions)	Propellant mass (kg) Mean	Median	90th percentile	99th percentile	99.9th percentile	99.99th percentile
MCS (10000)	1.183	1.169	1.417	1.655	1.851	2.154
LHS (1000)	1.183	1.165	1.416	1.734	1.860	1.888
MMVM (49)	1.176	1.169	1.394	1.623	1.789	1.881
SS[a]	1.180	1.163	1.416	1.647	1.839	1.974

[a]mean, 50th , & 90th percentile; 99th percentile; 99.9th percentile; and 99.99th percentile values taken from first, second, third, and fourth simulation levels, respectively

9.7.2 Schedule Duration

The schedule duration PDF values for MCS, LHS, and MMVM are provided in Fig. 9.9.

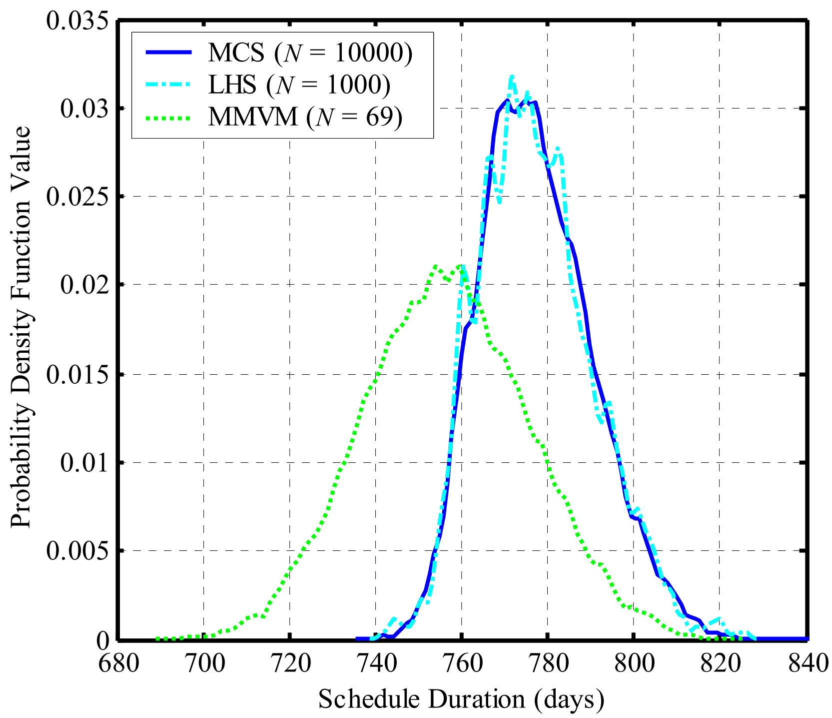

Fig. 9.9 Schedule duration PDFs for MCS, LHS, and MMVM.

The CDF values for all four simulation techniques are shown in Fig. 9.10 through Fig. 9.13.

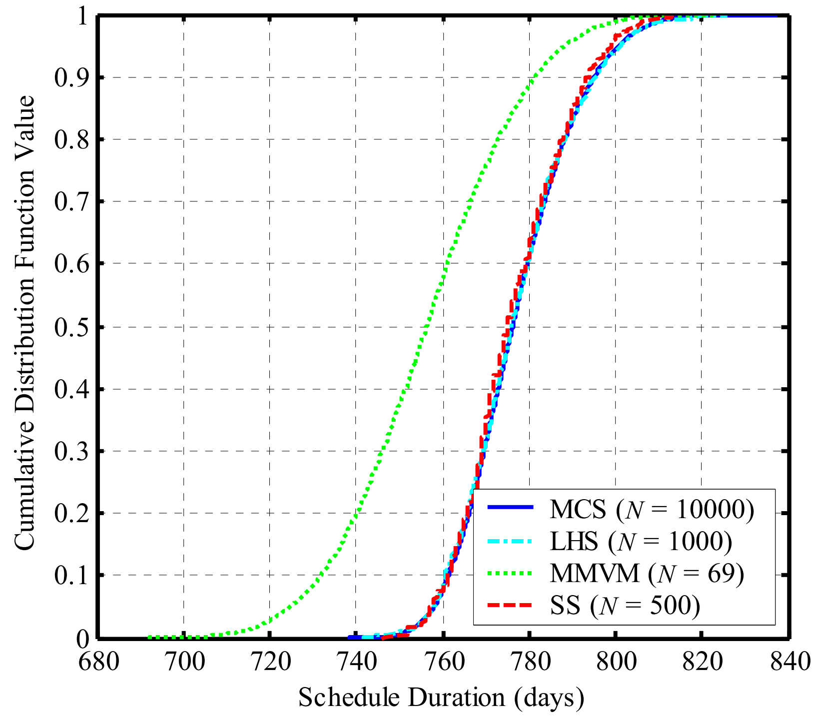

Fig. 9.10 Schedule duration CDFs (simulation level 1).

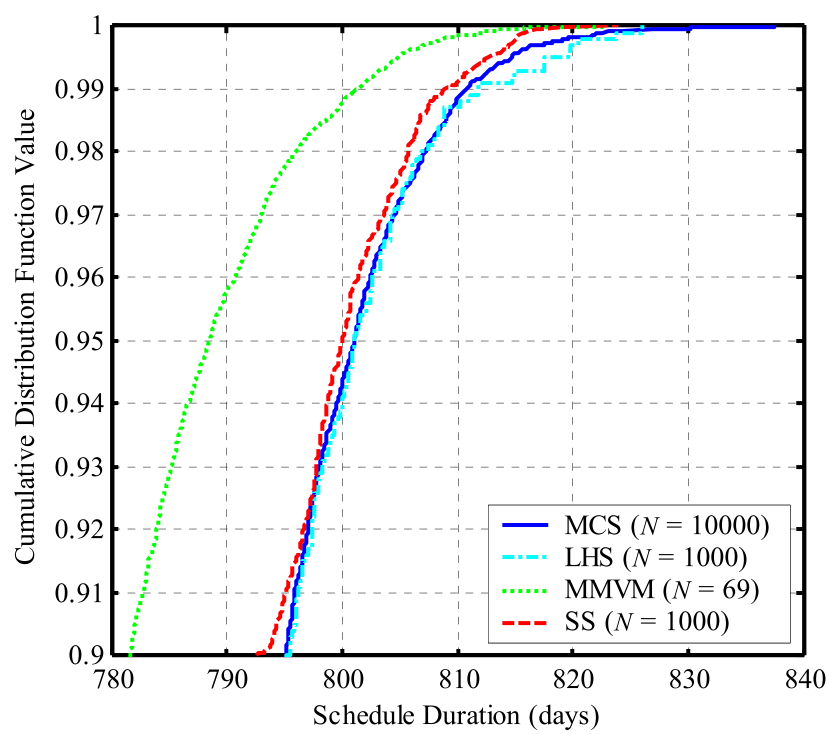

Fig. 9.11 Schedule duration CDFs (simulation level 2).

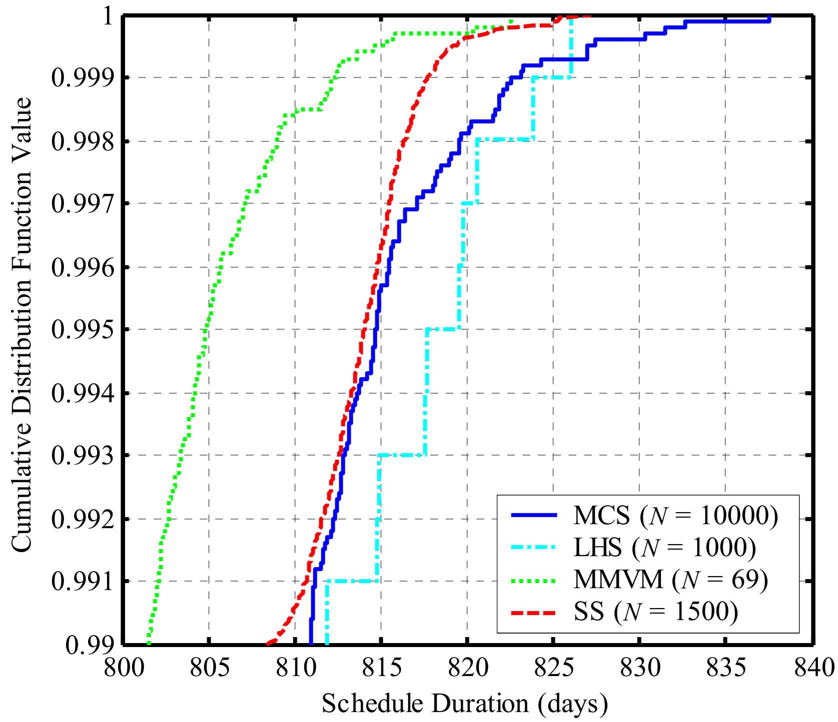

Fig. 9.12 Schedule duration CDFs (simulation level 3).

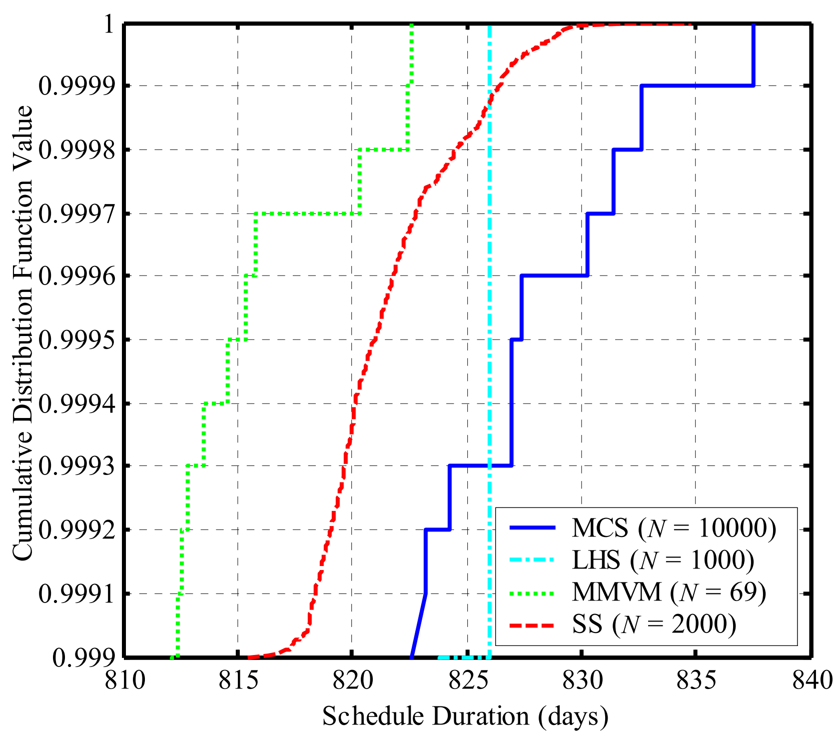

Fig. 9.13 Schedule duration CDFs (simulation level 4).

Fig. 9.11 through Fig. 9.13 demonstrate the performance of the four simulation techniques at the upper tail of the distribution. Again, MCS is the benchmark for comparison but requires a substantial number of calls to the model (*N*) to obtain values for the entire CDF range. LHS performs well in estimating CDF values less than 0.999 (first, second, and third simulation levels) but poorly for CDF values between 0.999 and 1 (fourth simulation level). The PDF for LHS is noticeably "choppier" than its MCS counterpart, likely a facet of having used $N = 1{,}000$ instead of the 10,000 MCS used. MVMM yields a PDF and CDF that is shifted ~15 days to the left and performs poorly for this tradable parameter model. It is possible that using a centered-finite difference (which would require $N = 137$ instead of $N = 69$ that the forward-finite difference uses) would improve the estimate for schedule duration. SS performs adequately and yields a comparable accuracy as MCS at extreme CDF values (fourth simulation level) despite requiring only a fifth the calls to the model. Table 9.8 details the statistics of SS by simulation level for schedule duration.

Table 9.8 SS results by level for schedule duration

SS Level	x	P_x (days)	Error[a] (%)	γ	σ	δ	δ^*	N_{MCS}
1	90	794.0	-0.14	0	0	0.13416	0.13416	500
2	99	809.2	-0.20	3.9149	0.00986	0.29744	0.32630	930
3	99.9	817.8	-0.62	3.1999	0.00290	0.27495	0.42669	5487
4	99.99	826.5	-1.03	3.72	0.00097	0.29148	0.51675	37446

[a]relative to the 10000 MCS

Again, the moderate values of γ in Table 9.8 indicate that the modified MCMC algorithm is accepting and rejecting samples evenly in the chains (i.e., the choice of χ in this example seems appropriate). The final column indicates SS achieves a comparable accuracy as 37,446 MCS repetitions (N_{MCS}) whereas only $N = 10{,}000$ were performed for MCS. The relative error actually increases slightly to -1.37% when compared to 42,000 MCS repetitions (42,000 chosen based on total cost δ^* as discussed subsequently). Increasing *N* in SS would improve the accuracy of SS *vis-à-vis* actual results (i.e., MCS with *N* approaching infinity). Table 9.9 summarizes the statistics for all four simulation techniques at various percentile values for comparison.

Table 9.9 Schedule duration calculated by each simulation technique

Simulation technique (# of repetitions)	Schedule duration (days)					
	Mean	Median	90^{th} percentile	99^{th} percentile	99.9^{th} percentile	99.99^{th} percentile
MCS (10000)	777.4	776.3	795.1	810.9	822.9	835.1
LHS (1000)	777.3	776.1	795.4	811.8	824.9	826.0
MMVM (69)	756.5	756.3	781.6	801.5	812.3	822.5
SS[a]	776.5	775.0	794.0	809.2	817.8	826.5

[a]mean, 50^{th} , & 90^{th} percentile; 99^{th} percentile; 99.9^{th} percentile; and 99.99^{th} percentile values taken from first, second, third, and fourth simulation levels, respectively

9.7.3 Total Cost

The total cost PDF values for MCS, LHS, and MMVM are provided in Fig. 9.14.

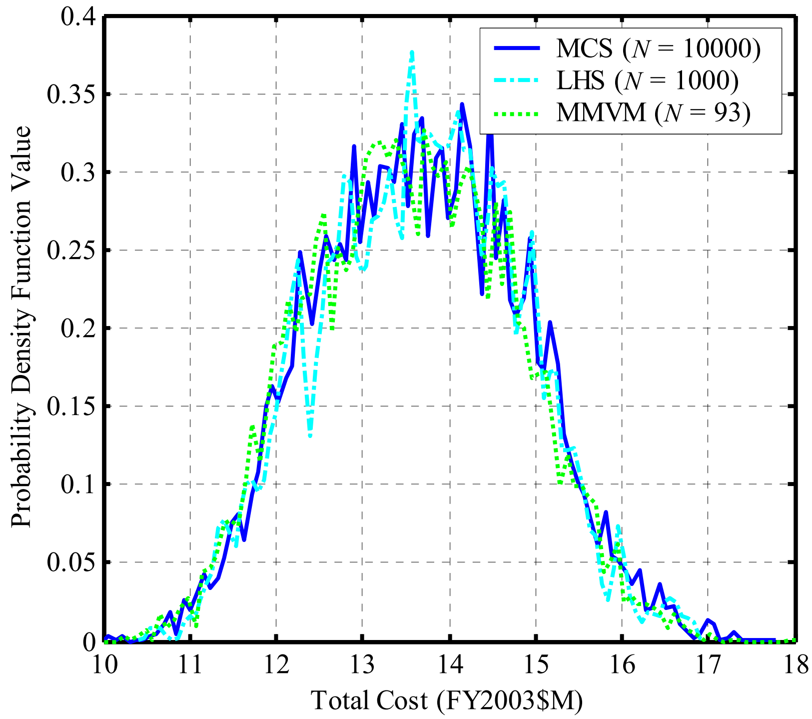

Fig. 9.14 Total cost PDFs for MCS, LHS, and MMVM.

The CDF values for all four simulation techniques are shown in Fig. 9.15 through Fig. 9.18.

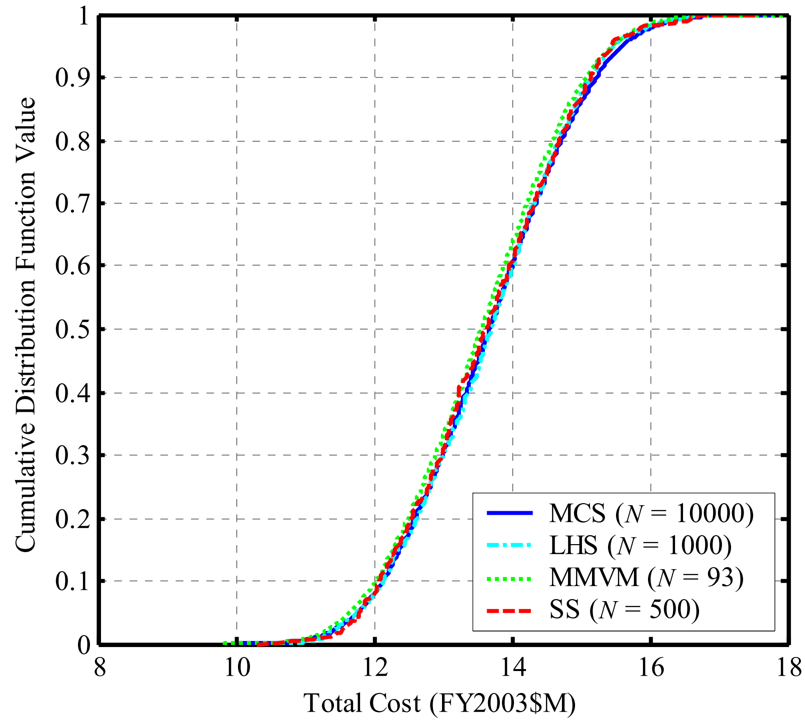

Fig. 9.15 Total cost CDFs (simulation level 1).

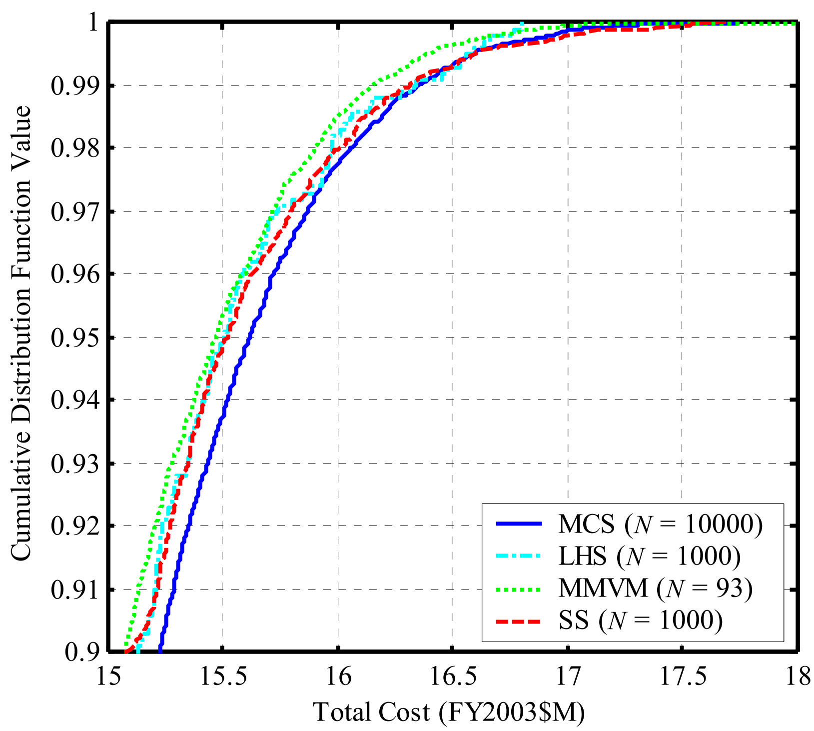

Fig. 9.16 Total cost CDFs (simulation level 2).

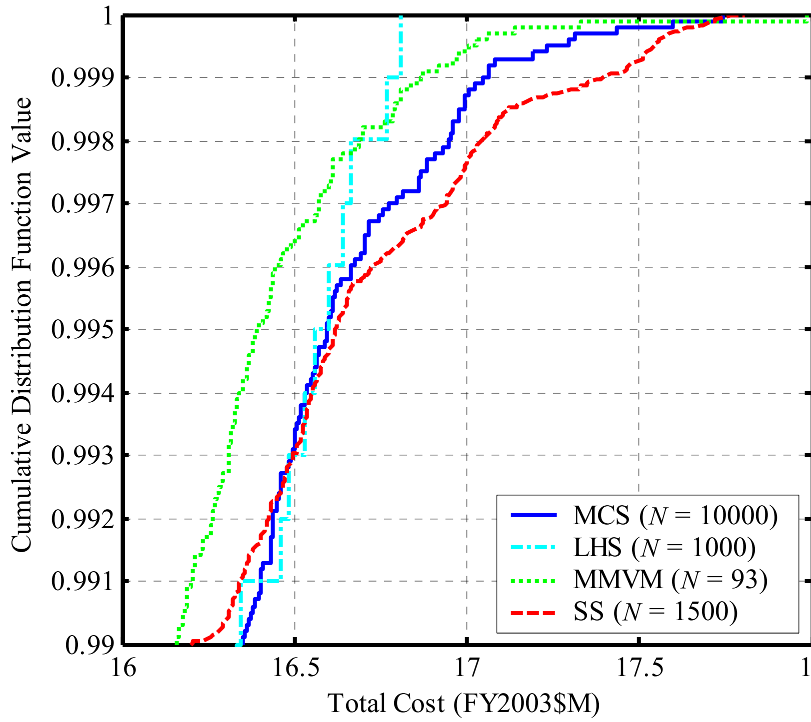

Fig. 9.17 Total cost CDFs (simulation level 3).

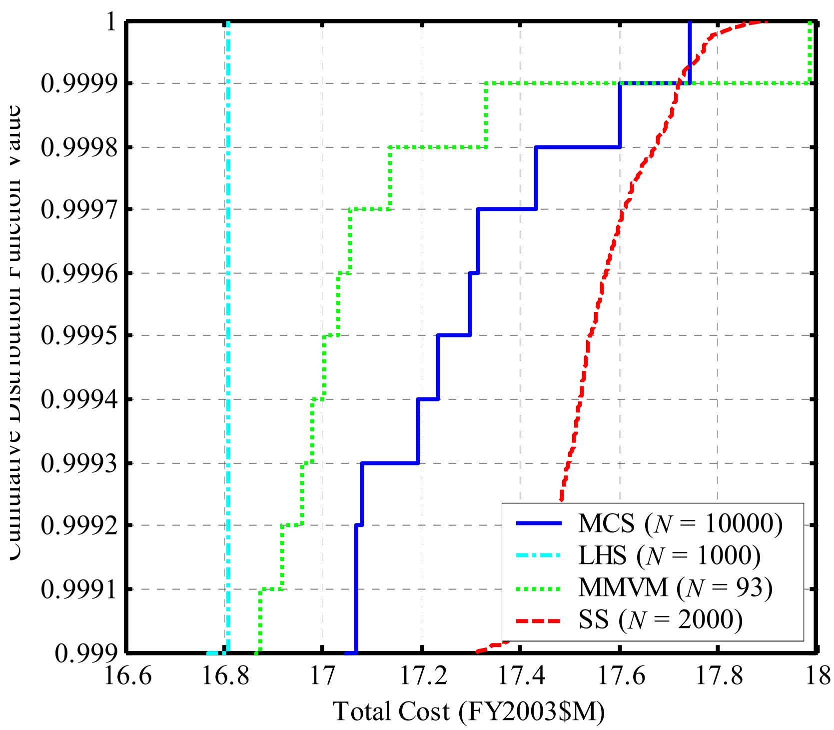

Fig. 9.18 Total cost CDFs (simulation level 4).

Fig. 9.16 through Fig. 9.18 demonstrate the performance of the four simulation techniques at the upper tail of the distribution. Again, MCS is the benchmark for comparison but requires a substantial number of calls to the model (*N*) to obtain values for the entire CDF range. LHS performs well in estimating CDF values less than 0.99 (first and second simulation levels) but poorly for CDF values between 0.99 and 1 (third and fourth simulation levels). For all CDF values MVMM performs surprisingly well (underestimates the cost by only ~FY2003$10K) considering it makes calls to the schedule model which illustrated difficulties (see previous section) and that only $N = 93$ (number of input variable uncertainties for this tradable parameter plus one) are required, over a magnitude less than LHS and two orders of magnitude less than MCS. SS performs extremely well with total cost providing a comparable accuracy as MCS at extreme CDF values (fourth simulation level) despite requiring only a fifth the calls to the model. Table 9.10 details the statistics of SS by simulation level for total cost.

Table 9.10 SS results by level for total cost

SS Level	x	P_x (FY2003 $M)	Error[a] (%)	γ	σ	δ	δ^*	N_{MCS}
1	90	15.147	-0.54	0	0	0.13416	0.13416	500
2	99	16.317	-0.20	1.6727	0.00727	0.21934	0.25711	1498
3	99.9	17.408	2.06	3.5999	0.00303	0.28775	0.38588	6709
4	99.99	17.723	0.30	4.04	0.00100	0.30120	0.48952	41728

[a]relative to the 10000 MCS

At the fourth level, SS achieves a comparable accuracy as 41,728 MCS repetitions (N_{MCS}) whereas only $N = 10{,}000$ were performed for MCS. The relative error drops to 0.05% when compared to 42,000 repetitions. Again, the moderate values of γ indicate the choice in χ is appropriate. Table 9.11 summarizes the statistics for all four simulation techniques at various percentile values for comparison.

Table 9.11 Total cost calculated by each simulation technique

Simulation technique (# of repetitions)	Total cost (FY2003$M) Mean	Median	90th percentile	99th percentile	99.9th percentile	99.99th percentile
MCS (10000)	13.677	13.681	15.229	16.349	17.057	17.671
LHS (1000)	13.670	13.710	15.137	16.339	16.788	16.808
MMVM (93)	13.561	13.560	15.079	16.155	16.869	17.658
SS[a]	13.635	13.631	15.147	16.317	17.408	17.723

[a]mean, 50th , & 90th percentile; 99th percentile; 99.9th percentile; and 99.99th percentile values taken from first, second, third, and fourth simulation levels, respectively

9.8 Margins and Analysis

With the probabilistic data (i.e., CDFs) available and assuming $x = 99$ percentile, Eq. (1.4) is used to determine margin values to hold at this point in the design (i.e., PDR for this example).

This choice of x represents a risk-neutral decision maker. Alternatively, a risk-seeking decision maker might have used the 90th percentile values and a risk-averse decision maker the 99.9th or even the 99.99th percentile values. These margins are listed in Table 9.12 for the three ADCS tradable parameters.

Table 9.12 Calculated (99th percentile) ADCS margin values

	Tradable Parameter Margin (Margin %)		
Simulation technique (# of repetitions)	Propellant mass	Schedule duration	Total cost
MCS (10000)	0.481 kg (41.0%)	55.5 days (7.4%)	2.802[c] (20.7%)
LHS (1000)	0.560 kg (47.7%)	56.5 days (7.5%)	2.793[c] (20.6%)
MMVM[a]	0.449 kg (38.2%)	46.1 days (6.1%)	2.608[c] (19.3%)
SS (1000)[b]	0.473 kg (40.3%)	53.9 days (7.1%)	2.770[c] (20.4%)

[a]90 repetitions for propellant mass; 69 for schedule duration; 93 for total cost; [b]up to and including second SS level for 99th percentile; [c]FY2003$M

The allocation values (best estimate + margins) for each simulation technique are presented in Table 9.13 along with assumed project allocations and final actual values obtained from pre-launch/flight/project data.

Table 9.13 Comparison of assumed and calculated (99th percentile) tradable parameter allocations with actual values

	Tradable Parameter Allocation		
Simulation technique (# of repetitions)	Propellant mass	Schedule duration	Total cost
Project assumptions (n/a)	4.4 kg	759 days	FY2003~$10.7M
MCS (10000)	1.655 kg	810.8 days	FY2003$16.349M
LHS (1000)	1.734 kg	811.8 days	FY2003$16.340M
MMVM[a]	1.623 kg	801.4 days	FY2003$16.155M
SS (1000)[b]	1.647 kg	809.2 days	FY2003$16.317M
Actual mission values (n/a)	0.738 kg[c]	768 days	FY2003~$10.5M

[a]90 repetitions for propellant mass; 69 for schedule duration; 93 for total cost; [b]up to and including second SS level for 99th percentile; [c]value for MER-B, MER-A required 0.646 kg

This comparison indicates that the propellant mass estimates by the MER project were conservative compared to the actual mission values. All four simulation techniques in the proposed method resulted in estimates closer to the actual mission value but still were conservative. It seems the uncertainties assumed in estimating the propellant mass were either overestimated or the propellant mass came in low (~25th percentile value). The schedule duration estimate provided by the proposed method successfully bounded the actual value whereas the project assumptions (current heuristic method) did not. The actual schedule duration of 768 days was 7 days longer than the project assumption and ~30th percentile value. Cost and schedule were traded on the MER ADCS development which may account for this slightly low percentile value.

The proposed method predicted conservative total cost estimates (FY2003~$16.3M) compared to the actual total ADCS cost (FY2003~$10.5M). The actual total cost is ~1st percentile value. This discrepancy may be explained by the difficulty in obtaining an accurate estimate for the ADCS total cost. The ADCS system was intertwined with the command and data handling subsystem that resides on the rover within the lander. The project assumption and actual mission values for total cost represents the best estimate of the total *ADCS* cost related to the *cruise stage* only. The uncertainty in these values is estimated to be on the order of FY2003$0.25M. The total cost predicted by the current heuristic method provided a much more accurate estimate than the proposed method. This example demonstrates that for certain situations and tradable parameters, the current method may indeed provide a superior estimate to the proposed method. Nonetheless, the proposed method does successfully bound the total cost and is calculated via a rigorous, transparent, and tenable method that the current heuristic method fails to provide.

9.9 Summary

This chapter provides an example of applying the proposed method. An ADCS is presented as the application example since it provides a representative spacecraft discipline in terms of complexity, number of uncertainties, and uncertainty types. Each step of the proposed method is detailed. The most significant result of this example is that the margins for these three tradable parameters are now calculated for a specific mission (MER) based on the risk tolerance of the decision maker accounting for specific uncertainties anticipated and not based on heuristics and/or worst-case analysis. Although the propellant mass number is not significant in an absolute sense for the MER example presented, this might not be the case for other missions where propellant mass could be the most important tradable parameter. With an example application of the proposed method provided (and others found in Appendix B), the thesis turns to concluding remarks. This is the topic of the next and final chapter.

Chapter 10 Concluding Remarks

Uncertainty propagation and mitigation techniques were long considered the exclusive province of "men of experience" [Luce & Raiffa, 1957]. Research by a variety of individuals described in Chapter 2 and Chapter 3 and the research presented in this thesis indicate this is not the case. The proposed method provides a rigorous method for propagating and mitigating uncertainty in the design of any complex multidisciplinary design and formalizes this "experience" through a variety of techniques. The proposed method furthers the research of others and provides four original contributions: a classification of uncertainty for use in the design of complex multidisciplinary systems; a formal and comprehensive manner of determining margins that fits within existing engineering practice; a variety of sampling techniques including subset simulation that can reduce the computational burden in applying the proposed method; and several diverse application examples of the proposed method and simulation techniques that demonstrate its generality and benefit. Specific quantitative benefits of the proposed method compared to the current heuristic-based method were illustrated by these diverse application examples in Chapter 9 and Appendix B. These examples, which were applied *ex post facto*, strongly suggest that the use of the proposed method in actual complex multidisciplinary design will lead to better designs and more successful developments.

Uncertainty can be both beneficial and detrimental in design. Ben-Haim (2001) notes that uncertainty may be "pernicious, entailing the threat of failure, or propitious, entailing the possibility of unimagined success" while Walton (2002) also stresses that uncertainty can have both a "downside and upside." This "propitious" aspect or "upside" of uncertainty is in design uncertainty decisions and the process of trading parameters which are both under complete control of the proposed method participants.* The actions of the participants determine the final design. The twenty-first century will likely see increasingly complex multidisciplinary systems with more subsystems and more organizations required to design and develop them. Thus, the knowledge gap among participants will widen. This increase in complexity, subsystems, organizations involved, and the knowledge gap must be balanced by improved analysis methods; efficient computational techniques; detailed documentation; rapid and accurate information exchange; and more educated and experienced participants. The method proposed in this thesis represents a step in achieving this balance.

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*"The future is uncertain ... and in an uncertain environment, having the flexibility to decide what to do after some of that uncertainty is resolved definitely has value." – R. Merton (1997 Nobel laureate)

This chapter begins with a discussion of concerns, both practical and theoretical, in the proposed method. A summary of potential organizational impacts of implementing the proposed method follows. Potential avenues for future research are then discussed.

10.1 Concerns About the Proposed Method

The proposed method has limitations, as any method does. It is arguably as significant to understand and acknowledge these potential issues as is to understand and to acknowledge the method itself.[†] The concerns about the proposed method are practical and theoretical. These concerns are primarily opinions that require further investigation.

10.1.1 Practical Concerns

Practical concerns about the proposed method were primarily discovered during its implementation to various applications (e.g., Chapter 9 and Appendix B). Many of these concerns are related to organizational characteristics that may be tempered in an actual design when applied by professionals from within an organization instead of a university doctoral student working *ex post facto* on analyses.

10.1.1.1 Challenge of Change in the Aerospace Industry

The aerospace industry is in a difficult period in its history. Employment in the aerospace industry in the U.S. recently dropped to its lowest level in 50 years [Aerospace Industries Association, 2003]. Increased foreign competition, outsourcing of aerospace jobs overseas, and a declining interest among students are three of the challenges the aerospace industry faces. For the U.S. to remain the preeminent player in aerospace, industry must adapt by assaying new methods. However, enacting change in the aerospace industry is exceedingly difficult. The aerospace industry is reluctant in general to assist in developing and implementing a method unless its benefit has been demonstrated in a verifiable application. Unfortunately, it is difficult to develop and implement a method without a "real world" example that only the aerospace industry can provide. The examples presented in Chapter 9 and Appendix B were performed *ex post facto* yet due to their generality in theory but specificity in application may provide the most compelling opportunity to break this "catch-22."

Change is also difficult in the aerospace industry due to the procedures by which organizations allocate funds. Funds are assigned to different elements within an organization

[†] "Unfortunately what is little recognized is that the most worthwhile scientific books are those in which the author clearly indicates what he does not know; for an author most hurts his readers by concealing difficulties." – Evariste Galois

(e.g., systems engineering; subsystem engineering; research and development; quality and assurance). These organizational elements allocate a portion of their funds for methods and techniques that, if successful, will benefit that organizational element. Organizational elements will rarely fund new methods or techniques that would be beneficial beyond their purview. Some organizations have developed specific well-funded elements within an organization to assist breaking up this impasse (e.g., the Defense Advanced Research Projects Agency (DARPA) within the Department of Defense). Increased collaboration with and funding of both universities and think tanks may assist the aerospace industry in this area until organizational funding issues can be resolved.

10.1.1.2 Engineering Curricula and Practice

The proposed method requires the stake holder, decision maker, system engineers, and subsystem engineers educated at a minimum in basic probabilistic and statistical techniques for successful implementation. Other mathematical techniques (e.g., simulation) need only be learned by certain individuals in the proposed method. Although most engineers have a basic knowledge of probability and statistics, few engineering curricula have a formal requirement in this area. Engineering curricula are typically loaded with courses that are difficult to compress within a four-year degree as it is. Pressures to reduce overall degree requirements coupled with the desire for more specialized courses in mathematics and engineering analysis are deemed more important than basic and intermediate probability and statistics. Probability and statistics courses are generally viewed as a luxury, perhaps important for some engineering disciplines, but not important enough to require in general curricula. It is interesting to note that it took academia over fifty years to establish applied statistics in mathematics even as its benefit was being demonstrated and funding was available.[‡] Although the tasks are different, the situation for educating employees in industry is similar. A short course on the order of a day in duration sponsored by the employee's organization could provide the necessary education in this area. However, pressures in industry including lack of time, limited funds, and lack of perceived benefit make it difficult for engineers and managers to take such short courses. Attempts at implementing new methods often fail because only one or a handful of individuals truly understand the underlying mathematics of a method.

[‡] In 1860, when Florence Nightingale, after consulting with mathematicians of the time, offered to fund a chair in applied statistics at Oxford, her offer was flatly refused. After thirty years of effort Florence gave up. [Bernstein, 1998]

10.1.1.3 Paranoia in the Aerospace Industry

As discussed in Chapter 5 and Chapter 6, uncertainties can be quantified using existing data, expert elicitation, or Bayesian techniques. All three of these techniques require obtaining and sharing information. Unfortunately, the aerospace industry suffers from paranoia with respect to sharing information. Although not a firm impediment, limited sharing of information will make implementing the proposed method more difficult and require more resources. This paranoia is primarily from two sources: a "competition-sensitive" culture and government regulations.

As discussed earlier, the aerospace industry is facing difficult challenges. The industry has evolved from developing many moderately complex multidisciplinary systems to developing only a handful of very complex systems. Sources of funding available in previous years no longer exists and companies scramble to win the limited contracts that arise. Failing to win these contracts often results in consolidation of these companies within other companies. The U.S. aerospace industry has contracted from ~50 small- to medium-sized companies to five major companies in the past twenty-five years [Velocci, 2000]. Hence, intense pressure exists on companies and their employees to win competitions. Furthermore, systems built typically involve many disciplines and few individuals have the expertise and technical breadth to truly understand the competitive benefit of much of the information involved. Companies and their employees are rarely willing to share information that they perceive might give a competitor any advantage.

Another reason for paranoia in the aerospace industry is government regulations such as the International Traffic in Arms Regulations (ITAR). Originally drafted in the 1970s to monitor sales of military equipment around the world, the laws have grown to cover space-related products such as satellites and rocket parts. Recent high-profile cases against two U.S. companies have brought ITAR forth as a significant impediment in sharing information between U.S. and foreign companies [Select Committee of the U.S. House of Representatives, 1999]. As most complex multidisciplinary systems increasingly involve components, assemblies, and sometimes entire subsystems that are built by foreign companies, information transfer between U.S. companies and international partners is a necessity. ITAR and other government regulations have made this information transfer process much more difficult and are seen as a barrier for future international collaboration. Applying the proposed method, which would entail an increase in this transfer of information between organizations, might be stifled by government regulations such as ITAR.

10.1.1.4 Documentation and Lessons Learned

Practicing designers and engineers are notorious for consciously avoiding any discussion of their own methods and techniques. They rarely document their design assumptions and beliefs. Unfortunately, selective historical amnesia remains a condition many industries, including the aerospace industry, appear to suffer from. Furthermore, openly discussing failures and lessons learned from previous designs is seldom done except in highly-visible public projects or when loss of life was involved. Including failures in the data recorded and opinions elicited is critical in honestly and accurately quantifying uncertainties. The proposed method thus requires rigorous documentation of existing data and expert elicitation of beliefs. The twenty-first century holds the promise of an unprecedented capability of information-exchange, storage and retrieval via the internet; memory; and sophisticated databases and data-mining techniques, respectively. Nonetheless, these capabilities are only beneficial in applying the proposed method if participants take advantage of them. If acquired data and opinions elicited from experts concerning uncertainties are not accurately and honestly documented and stored, subsequent applications of the proposed method will remain a time-consuming and laborious process minimizing the overall benefit.

10.1.2 Theoretical Concerns

Theoretical concerns about the proposed method are due to two categories: volitional and phenomenological uncertainty. Both are discussed in this section.

10.1.2.1 Volitional Uncertainty

The proposed method is vulnerable to being exploited by individuals through expert elicitation of uncertainties. Certain individuals may be familiar enough with the proposed method to specify an uncertainty distribution of a variable in such a way as to achieve a desired outcome when no statistical data or other expert opinion is available. The motivations for such behavior by individuals are numerous: they may want to influence a decision to go a certain way; may believe that they will be evaluated based on the outcome; may want to suppress uncertainty that they actually believe is present in order to appear knowledgeable or authoritative; or perhaps they have taken a strong stand in the past and do not want to appear to contradict themselves by producing an opinion that lends credence to alternative views. Volitional uncertainty concerns were addressed in part in Chapter 6 while these specific motivational concerns have been discussed by others (e.g., [Frey, 1992]). Indeed, this motivational concern would be enhanced if the proposed method uses simulation techniques that are computationally efficient or if the relationships describing the complex multidisciplinary system are relatively simple. One of the strengths of the method, the ability to reapply the method as needed to update margins when uncertainties have changed, could be used to manipulate the process if the proposed method takes on the order of minutes to apply.

Another common situation occurs when only one expert can provide elicitation to an uncertainty. With no hard data to back up this expert, the resulting probability encoding could be characterized as "making up data." Nonetheless, a good faith effort to characterize the uncertainties is more appropriate and defensible than completely side-stepping and ignoring them as is often currently done. If certain uncertainties can only be estimated by one expert, that in and of itself indicates an area in the design of a complex multidisciplinary system where more research effort should be dedicated. This research effort could entail obtaining experimental data or taking time to find other experts or references to supplant the opinion provided by the original expert.

Lastly, critics of the proposed method may point to the fact that the current heuristic method of estimating design margins is replaced by a new and more complicated method that relies heavily upon expert opinion and experience, a form of heuristics: that is, a simple method is being replaced by a much more cumbersome one. This argument has validity except that the proposed method is applied at a lower and less complicated hierarchical level than the level the current method is applied at. At a lower level, difficult problems are simplified and quantifying individual uncertainties is manageable. Bayesian techniques and simulation offer mathematical foundations within the proposed method that results in a much more robust and dynamic method of determining margins than the current method.

10.1.2.2 Phenomenological Uncertainty

Phenomenological uncertainty was introduced in Chapter 2 and discussed in detail in Chapter 5. Techniques were proposed to address phenomenological uncertainty in design as it is not amenable to probabilistic methods. Although few designs spring from up from nothing, "cutting edge" complex multidisciplinary systems that "push the envelope" are those that are most vulnerable to the effects and impacts of phenomenological uncertainty. Mathematically rigorous theories are only as complete as the physical understanding on which they are based and interpreted. The value of the proposed method is thus diminished and limited by phenomenological uncertainty. The next century of engineering design will likely see systems being designed and developed that are more complex than those in use today. Application of the proposed method to these systems will have to be done carefully, at a level in the design (e.g., subsystem, assembly, component) where the physical theories are well understood and the effects of phenomenological uncertainty are diminished. Perhaps a benefit in applying the proposed method and documenting uncertainties will be a pedagogical one where participants make discoveries and gain knowledge thus reducing phenomenological uncertainty for subsequent design iterations and applications of the proposed method. Computationally efficient simulation techniques (discussed in Chapter 7) and continued development of faster computers should facilitate these subsequent applications of the proposed method.

Lastly, the three techniques discussed in Chapter 5 to reduce the effect of phenomenological uncertainty (increasing knowledge, expanded systems engineering, and robust design) are all enhanced if they are supported by legal contracts and enforcement of those contracts. For example, efforts by a contractor to assess phenomenological uncertainty in a system will be spurred by a contract and institution that punishes that contractor if the system fails. Unfortunately, the current process for designing and building space systems undermines such legal contracts since designs and follow-on designs are often given out for political reasons, an insufficient industrial base, or national security reasons. Refining the legal issues in the contracting process for complex multidisciplinary systems may be a fruitful area for addressing phenomenological uncertainty.

10.2 Potential Impact of the Proposed Method

Despite the issues discussed previously, the proposed method has demonstrated qualitative and quantitative benefits over the current heuristic-based method (see Chapter 3). If implemented, the proposed method may alter how complex multidisciplinary system design is undertaken. The engineering impact is the actual method of how margins are calculated. Potential organization impacts are noted in this section. The proposed method will only be useful to an organization if improvements in predicting margins and the benefits that go along with them are greater than the cost of implementing the method. Unfortunately, this will not be known until the method has been applied in practice, preferably several times after the learning curve of the first few implementations is overcome. A proposed step-by-step procedure for implementing the proposed method by an organization is provided in Appendix C.

10.2.1 Probabilistic vs. Deterministic

The proposed method relies on probabilistic techniques that will require more resources to implement than a deterministic/heuristic approach. Unless participants in the method are convinced of the benefit of accurately determining margins early in design, the proposed method will not seem justified. The proposed method will require an up-front investment in effort and personnel to quantify model and input variable uncertainties. Deterministic simulation-based tools would also require front ends to allow them to be called repeatedly with different input variable uncertainties in a probabilistic framework. Lastly, participants will have to adapt from believing in equivocal outcomes in the design to acknowledging stochastic outcomes that rely on probabilistic information. In theory, these initial investments in resources will be recouped during design by identifying and prioritizing uncertainties and later in development when potentially significant unforeseen redesign and integration efforts never materialize.

10.2.2 Systems Engineer Role Expanded

As their name suggests, system engineers are responsible for ensuring success during the development of the entire complex multidisciplinary system. System engineers typically have a broad knowledge base of several subsystems. With this broad knowledge base, detailed subsystem knowledge is sacrificed. Their roles could include working closely with subsystem engineers to working only with other system engineers. System engineers could fill the role of analyst/facilitators that were described in Chapter 5. This would increase their scope and responsibilities on a design as they would work closely with both subsystem engineers and the decision maker. In this role, system engineers would also provide continuity across assessments by different individuals and subsystems and could mediate disagreements among informed experts. The transparency of the proposed method should enhance confidence and trust between these method participants, something often lacking in how such systems are currently designed and developed.

10.2.3 Subsystem Engineers Empowered

In the current method of complex multidisciplinary design, subsystem engineers are often not involved in determining and updating margins on their subsystems. These subsystem engineers might provide feedback but the actual margin levels are set by system engineers and/or the decision maker. The proposed method empowers subsystem engineers via their quantification of uncertainties involved. With the transparency of the proposed method, subsystem engineers will experience an element of ownership in the margins that are established. This is in contrast to the current method where value is often imposed and the only purpose of the subsystem engineer's opinion is a justification exercise to management. With this sense of increased influence and ownership, subsystem engineers may be more responsible in honestly and accurately estimating uncertainties thus increasing involvement and communication among participants in the proposed method. The proposed method may also result in subsystem engineers having a positive attitude about discussing and confronting uncertainty.

10.2.4 Management Held More Accountable

The transparency in the proposed method will also result in increased accountability by management. If a margin is exceeded, a decision maker can no longer, for example, be able claim innocence by pointing to requirements creep. If requirements change or requirement changes are proposed by the stake holder, the method can be reapplied and updated estimates for margins can rapidly be determined and conveyed to the stake holder. Conservatism or risky assumptions are no longer buried within margins. All quantifications for uncertainties will be available for the stake holder to see. Furthermore, these quantifications and comparisons of uncertainties can help guide future information gathering and research. If margins are exceeded, the uncertainty responsible can be traced. Analysis and decision making are clearly separated and a dispassionate representation of these decisions will uncover ulterior motivations if they exist. The increased accountability of management might provide the most significant impetus for successful implementation of the proposed method in an actual design.

10.2.5 Company Best Practices and Personnel

Although implementing the proposed method will likely change aspects of design as discussed, the fundamental design process is not impacted. The proposed method is not application or discipline specific requiring organizations to change how they design and build complex multidisciplinary systems; only in the manner in which they quantify uncertainty and calculate margins. The proposed method should go hand in hand with company best practices, not replace them. The proposed method enhances the design process; it is not a replacement for lessons learned. Like most methods the more experienced the participants involved in the proposed method, the higher the likelihood of successful implementation. Nonetheless, the transparency of the proposed method and the quantification and subsequent documentation of uncertainties allows a mix of experienced and inexperienced participants to be involved. Knowledge, experience, and lessons learned in quantifying uncertainties may be passed on to other employees. Implementation of the proposed method should assist in this transfer of knowledge from one generation of participants to the next which remains a constant challenge in aerospace and other industries as workforce ages and retires.

10.3 Future Directions

The method proposed in this thesis has built upon and extended research by a variety of others. The volitional and phenomenological concerns about the proposed method discussed indicate that a universal method for propagating and mitigating uncertainty in complex multidisciplinary design will probably not occur for years to come, if ever. Appreciating this condition is the first step in investigating avenues for future research that might strengthen, refine, and extend the proposed method. Future modification and refinement of the proposed method is anticipated and encouraged. The following section provides research areas that may be most fruitful for improving the proposed method.

10.3.1 Simulation Techniques

The various simulation techniques discussed in Chapter 7 were implemented to address interaction among uncertainties. Although Monte Carlo simulation (MCS) remains the standard simulation technique, techniques such as the modified mean value method and subset simulation achieve comparable accuracy to MCS in certain situations yet require significantly less computational effort. The challenge in applying simulation techniques in the preliminary design of complex multidisciplinary systems is threefold: the sheer number of uncertainties that are involved (in the dozens to hundreds); the diversity in these uncertainty types (i.e., continuous, discrete, discrete choice among alternatives); and the complexity of the design space and models used to represent that design space. Continued research into simulation techniques that can provide comparable accuracy as MCS but require significantly less computational effort and resources to apply would allow more rapid application of the proposed method.

10.3.2 Uncertainty Types

Certain uncertainty types, such as ambiguity and human errors, were only briefly discussed. Other uncertainties, model and phenomenological uncertainty in particular, were discussed yet remain uncertainties that can dominate the preliminary design of a complex multidisciplinary system. Refining the techniques to handle model uncertainty and investigating the techniques to address phenomenological uncertainty that were suggested in Chapter 5 would quantify the concerns in the proposed method discussed earlier.

10.3.3 Optimization Techniques

The possibility of combining the proposed method with optimization techniques was introduced in Chapter 8. One optimization technique in particular, adapted simulated annealing

(ASA), has been proved to be successful in multidisciplinary design [Jilla, Miller, & Sedwick, 2000]. Simulated annealing is based on the same underlying mathematics (the Metropolis algorithm) that is used so successfully in subset simulation Markov chain Monte Carlo to find high (or low) percentile values. Combing subset simulation with ASA may revolutionize preliminary design by providing a powerful technique to optimize both margins and the overall complex multidisciplinary design concurrently.

10.3.4 Alternate Theories than Probabilistic Methods

The mathematical foundations of the proposed method are probabilistic. The rich history of probability theory and its applications was one of the reasons this probabilistic framework was chosen. However, a variety of other alternate mathematical theories may prove to be successful within the proposed method. These theories are not as well established as probability theory but hold the potential of addressing some of the concerns in the proposed method discussed earlier. The three theories that appear to hold the most promise are: information-gap decision theory; fuzzy logic; and Dempster-Shafer theory.

The central emphasis of information-gap decision theory is that decisions under severe uncertainty must not demand more information, or at least not much more, than the decision maker can reliably supply. An information-gap model of uncertainty is a non-probabilistic quantification of uncertainty that entails no measure functions: neither probability densities nor fuzzy membership functions. Information-gap models concentrate on the disparity between what is known and what could be known, while making very little commitment about the structure of the uncertainty [Ben-Haim, 2001]. Information-gap decision theory may be able address phenomenological uncertainty better than probabilistic methods as it is geared towards severe uncertainty [Ben-Haim, 2004].

Fuzzy logic is a more general case of classical crisp sets that was discussed in Chapter 3. Fuzzy logic is an established alternative to probability theory in representing uncertainty. Dempster-Shafer (evidence) theory is a generalization of classic probability theory. In Dempster-Shafer theory there are two complementary measures to characterize uncertainty: belief and plausibility. Together, these measures can be thought of as representing lower and upper probabilities, or interval-values probabilities [Oberkampf, Helton, & Sentz, 2001]. Although the mathematical foundations of Dempster-Shafer theory are well established and could replace probability theory in the proposed method, it is not clear whether the practical aspects in the proposed method (such as the simulation techniques or sensitivity analysis) would be amenable to this alternate theory. Nonetheless, Dempster-Shafer theory holds promise for dealing with epistemic uncertainty in a more rigorous manner than the probabilistic framework of the proposed method.

10.3.5 Alternate Applications

Applications of the proposed method and their importance in demonstrating its practical viability are presented in Chapter 9 and Appendix B. These examples were all from disciplines in space systems design yet are representative of subsystems that exist in any complex multidisciplinary system and should be of interest to most engineers. The proposed method was specifically developed in a general fashion for application to any complex multidisciplinary system. The issues in applying the proposed method to an aircraft or automobile, for example, would be small in terms of theory, but potentially high in model creation and uncertainty identification. The structure and level of detail in models for aircraft and automobile discipline tradable parameters would be different than those of a space system. Cost per unit (ability to mass produce that complex system) and aesthetics, two parameters of limited or no consequence in space system design, would be of significant importance in aircraft and automobile design. Other complex multidisciplinary systems may also have unique uncertainties that space systems do not encounter. The proposed method would appear to be amenable to these other systems with only minor modifications and limited development yet this hypothesis requires verification with actual alternate complex multidisciplinary systems. Real-world examples provide an opportunity to extend and refine the proposed method and actual implementations may uncover important lessons.

10.4 Final Thoughts

There is a strong desire for a formal method to become a benchmark or standard in propagating and mitigating uncertainty in the design of complex multidisciplinary systems, as no such standard exists. This is certainly the case in the aerospace industry which has and continues to struggle with uncertainty. The theoretical concerns of the proposed method discussed previously indicate that despite its benefits (that are summarized in Chapter 3) it may fail under certain situations in providing statistically rigorous margins. The primary benefit of the proposed method may in fact be in its application and resulting codification of engineering judgment. Having to identify, explain, and quantify different uncertainties as required in the proposed method will help participants steer a rational path between analysis paralysis and impulsive reaction that currently impedes the design of many complex multidisciplinary systems.

The relation between success and failure in uncertainty management constitutes a fundamental paradox in practical engineering design. The accumulation of successful experience tends to embolden managers to hold lower and lower margins for tradable parameters, which seem almost invariably to culminate in a failure that takes all participants by surprise. In the wake of such failures, there is generally a renewed conservatism in margins that leads to successful but uncompetitive designs. As these designs evolve and mature the cautions attendant upon the margins tend to be forgotten and a new period of optimism and hubris ensues. The cycle repeats itself at seemingly regular intervals across a wide range of industries and has stifled innovation in how complex multidisciplinary systems are designed. The proposed method attempts to break this cycle by providing a formal and rigorous method to determine the value of these margins. The proposed method does not explicitly seek to reduce margins. In some cases the proposed method indicates the current heuristic method of margin management is too conservative; in other cases it indicates the current method is too risky. By inculcating in tomorrow's stake holders, decision makers, engineers, and designers an understanding of uncertainty and uncertainty propagation and mitigation techniques provided by the proposed method, future participants will be better prepared, educated, and experienced in determining margins that will ultimately lead to successful complex multidisciplinary system design.

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Appendix A Mathematical Foundations

This appendix provides basic terminology, explicit definitions, and examples of many of the mathematical techniques presented in this thesis.

A.1 Probability and Statistics

Probabilistic methods are the cornerstone of the mathematical rigor presented in this thesis. This section provides basic terminology and mathematical definitions for probability and statistics terms and features used throughout the thesis. Unless stated otherwise, these definitions originate from and follow Devore (2000) and/or Ross (2000).

A.1.1 Random Variables

A discrete random variable is a random variable that can take on only a finite (countable number) of possible values. A continuous random variable can take on a continuum of possible values (i.e., if for some $a < b$, any number x between a and b is possible).

A.1.2 Expected Values

The mean is the expected value of a random variable. Specifically, the mean is the first moment of a random variable:

$$\begin{aligned} \mu &= \int_X x \cdot f(x) \cdot dx, \quad \textit{continuous} \\ \mu &= \sum_{i=1}^{n} x_i \cdot f(x_i), \quad \textit{discrete} \end{aligned} \tag{A.1}$$

The second central moment of a random variable is called the variance:

$$\begin{aligned} \sigma^2 &= \int_X (x-\mu)^2 \cdot f(x) \cdot dx, \quad \textit{continuous} \\ \sigma^2 &= \sum_X (x-\mu)^2 \cdot f(x), \quad \textit{discrete} \end{aligned} \tag{A.2}$$

The square root of the variance is the standard deviation. Decision makers often base decisions involving uncertainty on the means and standard deviations of available data. Unfortunately, looking at purely the means and standard deviations can lead to poor decisions. Consider a problem where two solutions are possible. The costs to a project of implementing these two solutions are shown in Fig. A.1. The two different distributions have the same mean and standard deviation, yet all but risk-seeking decision makers would choose the distribution on the left.

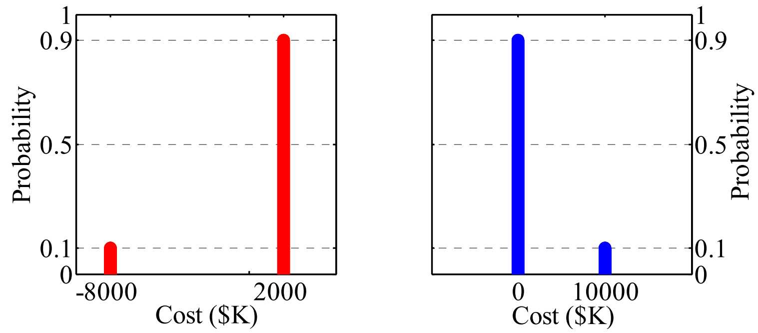

Fig. A.1 Two distributions with identical means and standard deviations.

A.1.3 Probability Density Functions and Cumulative Distribution Functions

A probability density function (PDF) is a mathematical expression that provides the probability of an event for each possible outcome. Specifically, among the various outcomes in S the PDF of a discrete random variable (known as a probability mass function, PMF) is defined for every number x by

$$p(x) = P(X = x) = P(\text{all } s \in S : X(s) = x) \tag{A.3}$$

Two properties must hold for a discrete PMF to be valid:

$$\begin{aligned} &p(x) \geq 0 \\ &\textstyle\sum_{\text{all possible } x} p(x) = 1 \end{aligned} \tag{A.4}$$

For a continuous random variable X, the PDF of X is a function $f(x)$ such that for any two numbers a and b with $a \leq b$:

$$P(a \leq X \leq b) = \int_a^b f(x)dx \tag{A.5}$$

Two properties must hold for a continuous probability density function (PDF) to be valid:

$$\begin{aligned} &f(x) \geq 0 \quad x \in \Re \\ &\int_{\Re} f(x)dx = 1 \end{aligned} \tag{A.6}$$

A PDF is generated via a histogram: all the events (data) are sorted into bins of a specified size. This histogram is normalized (and perhaps smoothed out).

A cumulative distribution function (CDF) is a monotonically increasing mathematical expression that gives the probability that an uncertain quantity is less than or equal to a specific value. Specifically, the CDF $F(x)$ of a discrete random variable X with a PMF $p(x)$ is defined for every number x by

$$F(x) = P(X \leq x) = \sum_{y:y \leq x} p(y) \tag{A.7}$$

For any number x, $F(x)$ is the probability that the observed value of X will be at most x.

The CDF $F(x)$ of a continuous random variable X is defined for every number x by

$$F(x) = P(X \leq x) = \int_{-\infty}^{x} f(y)dy \tag{A.8}$$

The PDF is the derivative of the CDF. The CDF represents the key decision function in design. Little is gained and much is lost when a CDF is reduced to expected values (as discussed in the previous section).

A.1.4 Fractiles and Percentiles

Let f be a number between 0 and 1. The f fractile, X_f, of a distribution is a value such that there is a probability f that the actual value of the random variable will be less than that value:

$$P(X \leq X_f) \equiv f \tag{A.9}$$

The $(100f)^{th}$ percentile of the distribution of a continuous random variable X, denoted by $\eta(p)$, is defined by:

$$p = F(\eta(p)) = \int_{-\infty}^{\eta(p)} f(y)dy \tag{A.10}$$

A.1.5 Major Distribution Types

There are dozens of existing distributions that have been formulated to represent phenomena behavior and uncertainty. This section presents the distributions most commonly used in the examples and discussions in this thesis. The probability density function (PDF) and cumulative distribution function (CDF) equations for these distributions and descriptions of other distributions can be found elsewhere (e.g., [Evans, Hastings, & Peacock, 2000], [Morgan & Henrion, 1990]).

A.1.5.1 Normal (Gaussian)

Arguably the most important distribution in practical applications, the normal distribution is representative of an enormous number of real-world processes, a consequence of the central limit theorem of statistics. The central limit theorem demonstrates that, under certain conditions the sum of a sufficiently large number of individual probability distributions is, in the limit, a normal distribution. This result is true whether or not the underlying distributions are themselves normal. Because most practical systems are susceptible to a large number of underlying noise or error sources that are individually unknown, or unknowable, the central limit theorem implies these noise or errors may be characterized as normally distributed. The normal distribution is also among the more analytically and numerically tractable distributions [Griffin & French, 2004].

However, the normal distribution is a continuous distribution that assumes infinite tails which may cause problems in certain situations as negative values may have a nontrivial probability. A normal distribution is shown in Fig. A.2.

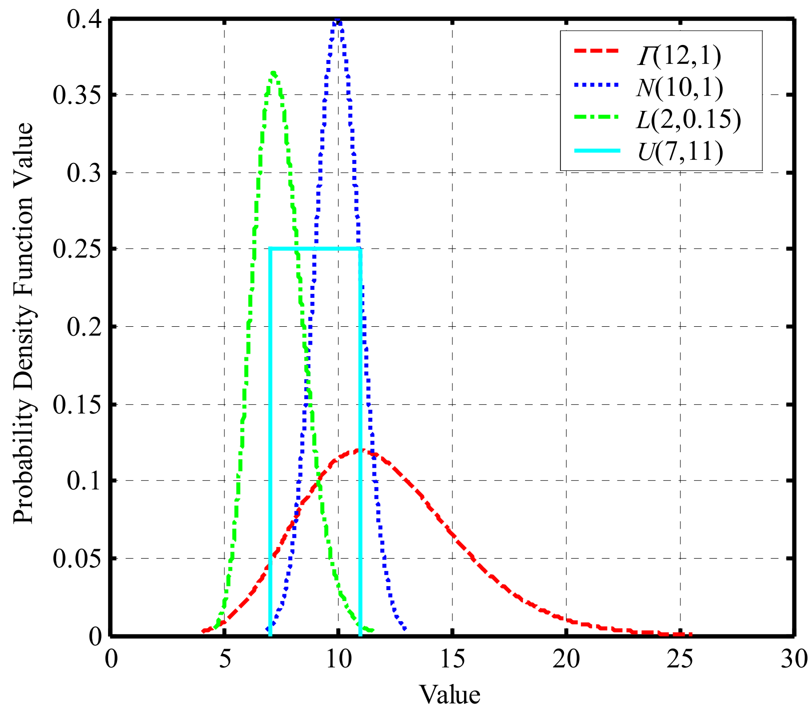

Fig. A.2 PDFs of four continuous distributions (gamma, normal, lognormal, & uniform).

A.1.5.2 Binomial

The binomial distribution is the sampling distribution of a Bernoulli random variable. The binomial distribution uses two parameters: n (number of independent trials) and p (probability of success for each trial). The normal distribution can be used to represent a continuous version of the binomial distribution. That is to say, when the mean $n \cdot p$ is large, the binomial distribution can be approximated by a normal distribution with $\mu = n \cdot p$ and $\sigma^2 = n \cdot p \cdot (1-p)$ and to a degree, vice-versa. Hence, a binomial distribution is useful when a discrete version of a normal distribution is desired. Numerical issues often arise in using the binomial distribution as inverse CDF calculations can be difficult computationally. A binomial distribution is shown in Fig. A.3

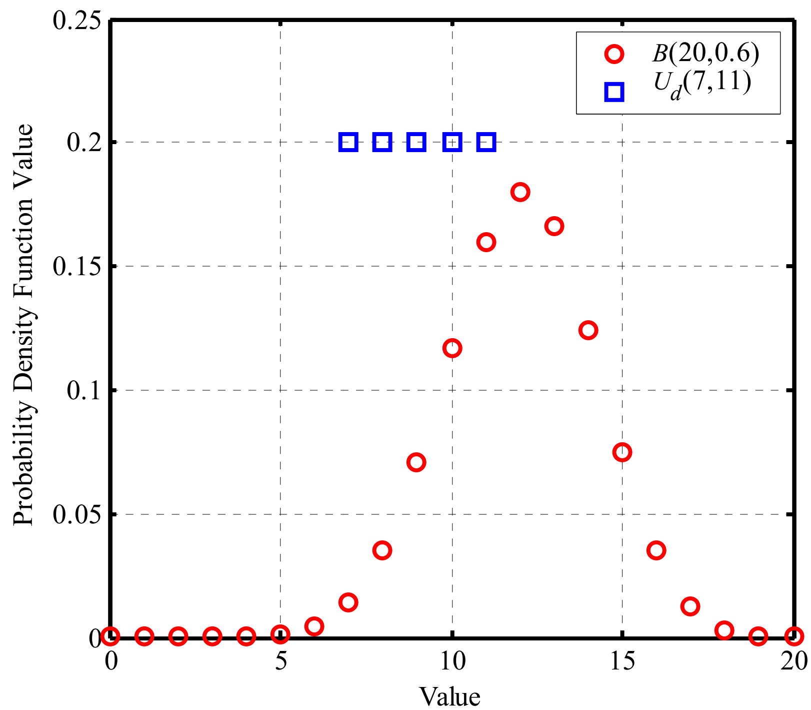

Fig. A.3 PDFs of two discrete distributions (binomial & uniform).

A.1.5.3 Lognormal and Gamma

Two distributions similar to the normal distribution that are often used are the lognormal and gamma distributions. The lognormal distribution is a two-parameter (μ and σ) positively skewed continuous distribution that can be used to represent nonnegative uncertainties (e.g., salaries, masses). The gamma distribution is a two-parameter (A and B) continuous distribution that is widely applicable to many physical quantities. When A is large, the gamma distribution closely approximates a normal distribution with the advantage that the gamma distribution has density only for positive real numbers. A lognormal and gamma distribution are shown in Fig. A.2.

A.1.5.4 Uniform

A uniform distribution provides one of the simplest means of representing uncertainty. It is useful when an expert is willing to identify a range of possible values but unable to decide which values within this range are more likely to occur than others. A uniform distribution can be either discrete or continuous and is specified via two parameters: a minimum and a maximum value. The use of uniform distribution is also a signal that the details about uncertainty in the variable are not known and this uncertainty likely warrants further investigation. A discrete uniform distribution is shown in Fig. A.3 and a continuous uniform distribution is shown in Fig. A.2.

A.1.5.5 Triangle

A triangle distribution provides a convenient way to represent uncertainties where values toward the middle of the range of possible values are considered more likely to occur than values near either extreme. Although not a traditional distribution, the arbitrary shape and "sharp corners" of triangle distribution can be a convenient way to telegraph the message that the details of the shape of the distribution are not precisely known. This may help to prevent over interpretation or false sense of confidence in subtle details of the results [Morgan & Henrion, 1990]. Since the triangle distribution is a distribution not found in nature it is often neglected in many statistical references. A triangle distribution is defined by three parameters: a most likely value (peak), a minus value (minus), and a plus value (plus). The PDF and CDF of both a discrete and continuous triangle distribution with parameters 20, -5, and +5 are shown in Fig. A.4:

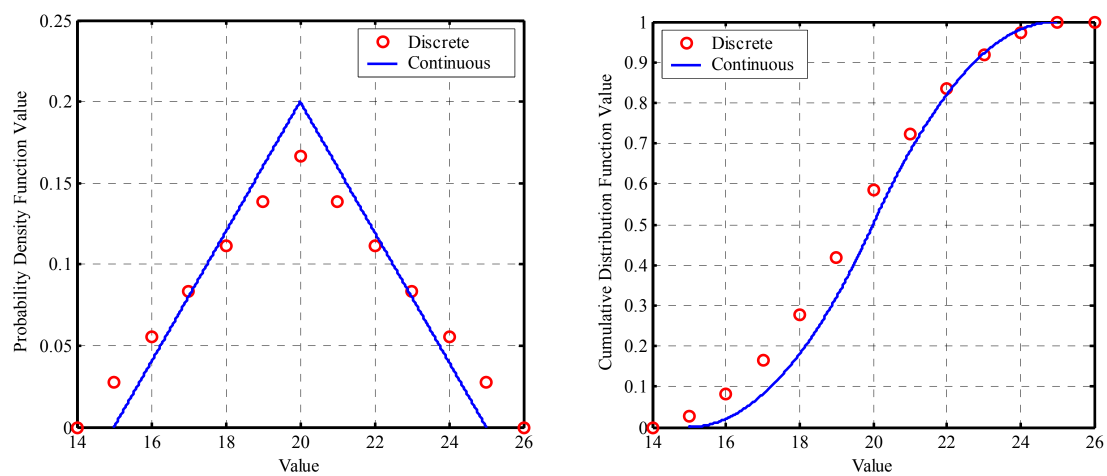

Fig. A.4 PDF (left) and CDF (right) for a discrete and continuous triangle distribution with parameters 20, -5, and +5.

Note the difference in PDF values between the discrete and continuous case in Fig. A.4. The PDF for the discrete case allows values at the low and high range specified thus altering the distribution slightly from the continuous case. This definition may be different than other references but is provided since the intuitive definition of a triangle distribution in the discrete case assumes plus and minus values with respect to the most likely estimate are feasible and should have a positive PDF value. A triangle distribution is a good distribution to use early in expert elicitation since it is easy to obtain judgments for it.

A.1.6 Fitting Distributions to Data

Although a custom distribution can be generated for data, an existing distribution such as those described in the previous section is often fit to the data to simplify subsequent calculations and discussions. In general, a candidate distribution (e.g., normal) is selected and its parameters (e.g., μ and σ) are determined via some statistical techniques such as moment matching or the maximum entropy method. Each candidate distribution can then be compared to the actual data using three statistical methods. The first method is one-way analysis of variance (ANOVA) which involves the analysis of data sampled from two distributions: one based on the existing data and the other the candidate distribution. A second method is the Kruskal-Wallis test which measures the extent to which the average ranks of the samples deviate from their common expected value. A third method is Friedman test which measures the discrepancy between the expected value of each samples rank average with the actual rank average. All three methods are described in Devore (2000) and provide a different statistical take on whether a candidate distribution would be a satisfactory fit to data.

A.1.7 Convolving Distributions

Convolving probability distributions is a technique that allows two random variables to be added to each other to create a joint probability distribution. For example, accounting for model uncertainty once results for a tradable parameter have been generated from a model can be accomplished by convolving the tradable parameter probability density function (PDF) with the model uncertainty PDF for that tradable parameter. Two techniques for convolving distributions are available. The first technique is simpler if existing data are available. Consider a simulation where N samples of a tradable parameter have been generated by a simulation technique (e.g., Monte Carlo simulation) and are available in their raw form. These samples need to be convolved with the model uncertainty which has been assessed via a PDF. N random samples based on that model uncertainty PDF are generated and added to the N tradable parameter samples. This new data can then be normalized to create a formal PDF as described previously. The result is the convolved distribution.

The second and more elegant technique is simpler if distributions (not data) are available for both sets of data. This technique convolves the distributions by taking the Fourier transform of the both PDFs. The transformed PDF of the original data is first multiplied by the absolute value of the model uncertainty transform. An inverse Fourier transform of the result is then performed and the result is normalized to create a formal distribution. This technique is simplified tremendously using fast Fourier transform (FFT) algorithms available in most mathematical computer packages (e.g., MATLAB®). Either technique yields the same joint probability distribution, although the latter method smoothes out much of the fluctuations in the original data PDF.

A.1.8 Probability of Random Variable Greater than Another

The probability one random variable being greater than another random variable can be determined by integrating the intersection of the probability density functions (PDFs) of the two random variables. This technique is especially useful when comparing a tradable parameter PDF with an uncertain requirement for that tradable parameter. Consider the following example taken from Thunnissen (2004b):

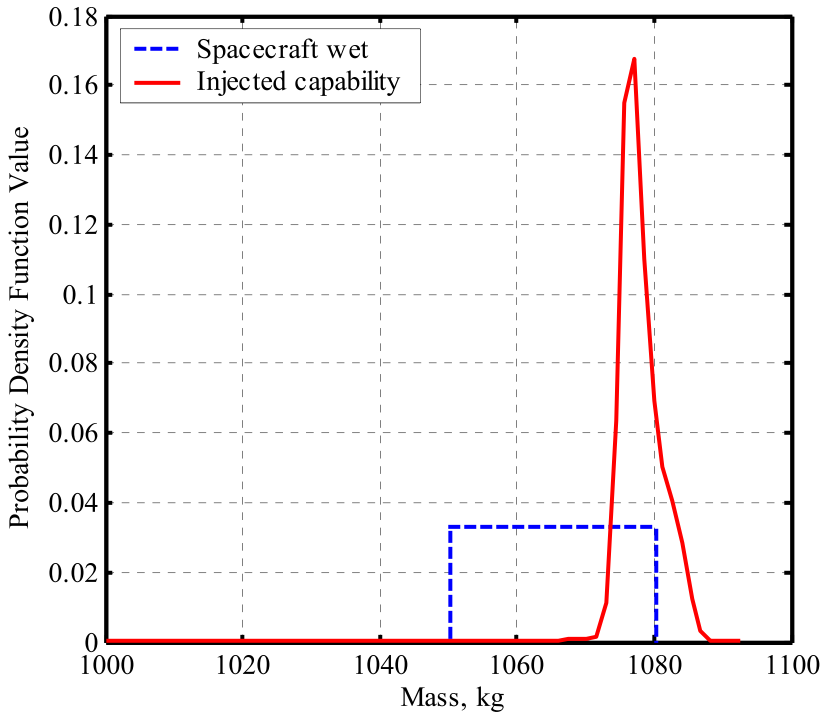

Fig. A.5 Probability of injected capability greater than spacecraft wet mass.

The decision maker in this example is concerned whether the injected mass capability of a launch vehicle (tradable parameter) is greater than the uncertain spacecraft wet mass (requirement) that it must launch. Abbreviating these two distributions as $f(t)$ and $f(r)$, respectively, the probability that the tradable parameter is less than the requirement is

$$P(t < r) = \int_{-\infty}^{\infty} f_r(r) \int_{r}^{\infty} f_t(t)\, dt\, dr \qquad \text{(A.11)}$$

Or equivalently:

$$P(t < r) = \int_{-\infty}^{\infty} f_t(t) \int_{-\infty}^{t} f_r(r)\, dr\, dt \tag{A.12}$$

Such integrals are easily evaluated numerically provided sufficient discretization is used over the integration domain of interest [Siddall, 1983]. The probability the tradable parameter is greater than or equal to requirement is simply:

$$P(t \geq r) = 1 - P(t < r) \tag{A.13}$$

A.1.9 *P*-Value and Correlation Coefficient

A frequentist measure of uncertainty is the "*p*-value" which is designed to tell researchers whether results are statistically "significant" or the product of chance. A *p*-value less than 0.05 is deemed statistically significant. A *p*-value of 0.05 means the odds that the "null hypothesis" would produce the observed effect are just 1 in 20 if the experiment is repeated many times, suggesting that the alternative hypothesis is creating the effect. The correlation coefficient between two sets of random variables *X* and *Y* is defined as:

$$\rho_{X,Y} = \frac{\text{Cov}(X,Y)}{\sigma_x \cdot \sigma_y} \tag{A.14}$$

where Cov(*X*,*Y*) is covariance between the two random variables. *X* and *Y* may represent the sample values for one input variable uncertainty and the output tradable parameter results, respectively. The *p*-value obtained when calculating the correlation coefficient can thus be helpful in assessing whether certain input variable uncertainties may be responsible for high uncertainty in the tradable parameters. Unfortunately, the actual meaning of a *p*-value is difficult to explain to a nonstatistician and *p*-values often tend to overstate the strength of evidence for a difference between two hypotheses. For example, a *p*-value of 0.05 does *not* mean that there is a 95% chance that the null hypothesis is wrong and the alternative hypothesis is correct. Results obtained via Bayesian techniques are often easier to interpret for nonstatisticians and are discussed subsequently.

A.1.10 Stochastic Dominance

One random variable is said to stochastically dominant another random variable when the CDF of that random variable lies completely to the right (or left) of the other [Clemen, 1996]. Consider an example where a larger tradable parameter value is desired. Design B in Fig. A.6 stochastically dominates Design A. Design B is thus the preferred option for all situations with respect to this tradable parameter. Conversely, if a smaller tradable parameter is desired, Design A would stochastically dominate Design B in Fig. A.6.

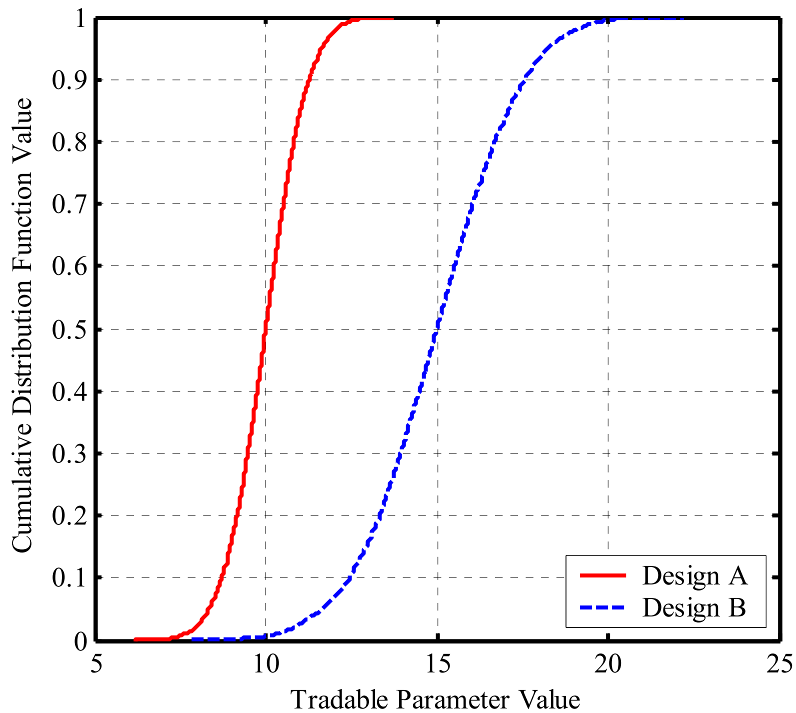

Fig. A.6 Example of stochastic dominance.

A.2 Bayesian Techniques

A brief introduction to Bayesian techniques is provided. An example follows. Bayesian techniques are described in detail in other references (e.g., [Gelman et al., 2004]).

A.2.1 Overview

In analyzing data, traditional statistical methods ignore the past. Bayesian techniques, in contrast, start with an existing belief and update that belief based on new data. The application of Bayesian techniques has recently undergone a renaissance in the fields of engineering and science [Malakoff, 1999]. A prior belief is updated with actual data to form a posterior belief via Bayes theorem:

$$P(H \mid D) = \frac{P(D \mid H) \cdot P(H)}{P(D)} \tag{A.15}$$

Bayes' theorem states that the probability of the hypothesis, given the data, is equal to the probability of the data, given that the hypothesis is correct, multiplied by the probability of the hypothesis before obtaining the data divided by the averaged probability of the data. Application of Bayesian techniques to the field of aerospace engineering is relatively recent. Guikema and Paté-Cornell (2004) used Bayesian techniques to estimate launch vehicle reliability and illustrated that Bayesian techniques offer a different perspective than the frequentist interpretation.

Bayesian techniques quantified the inexperience of a launch vehicle by not only predicting the mean future frequency of launch success but also the uncertainty about the mean since the entire probability density function (PDF) is known. In general, Bayesian techniques offer a significant benefit in assessing approximation errors for models with little data available for model verification. Although Bayesian techniques typically require numerical integration or simulation, in certain cases they can be applied analytically. When certain likelihood distributions are paired with certain prior distributions (known as conjugate priors) the calculation is simplified as both the posterior distribution and the prior distribution are the same family of density functions.

A.2.2 Example

An example of applying Bayesian techniques to estimate the future frequency of launch success for a launch vehicle given actual launch results is presented. This example follows the three-level Bayesian analysis of launch vehicle reliability described in detail in Guikema and Paté-Cornell (2004). The example uses the 115 flights of the Boeing Delta II (6x, 7x) launch vehicle. The Delta launch data used consists of Delta flights #183 to #307 (February 14, 1989 to August 3, 2004) excluding flights #184, #187, #189, #196, #259, #269, #293, #296, and #301. These nine flights were Delta II (3x, 4x, 5x), Delta III, or Delta IV launches. Of the 115 flights, 113 were successful (payload was placed in desired orbit) and two were failures. The two Delta II (6x, 7x) failures were the 42nd flight (#228) and the 55th (#241) Delta flights. Delta launch data are provided by Yearsley (2004).

Four different prior distributions are investigated. The first-level prior assumed a uniform distribution $U(0,1)$ which is equivalent to a $\beta(1,1)$ distribution. A $\beta(1,1)$ distribution implies the expected future fraction of successful launches is equally likely to lie anywhere between 0 and 1. The second-level prior builds upon the first-level Bayesian analysis by using the means of the first-level posterior distributions for all available launch vehicles. Two different prior distributions are assumed in this second-level analysis. The first fits a beta distribution to the means of the first-level posteriors by the method of moments. The second fits a curve to the histogram of the first-order posterior means by interpolation. Finally, the third-level prior also builds upon the first-level Bayesian analysis. However, in this third-level analysis, the first-level posterior distributions for all of the launch vehicles (except the launch vehicle of interest) is used. These first-level posteriors are combined into a new nonbeta distribution by summing all the first-level posteriors and renormalizing the resulting function into a proper density function. Fig. A.7 illustrates these four significantly different prior distributions:

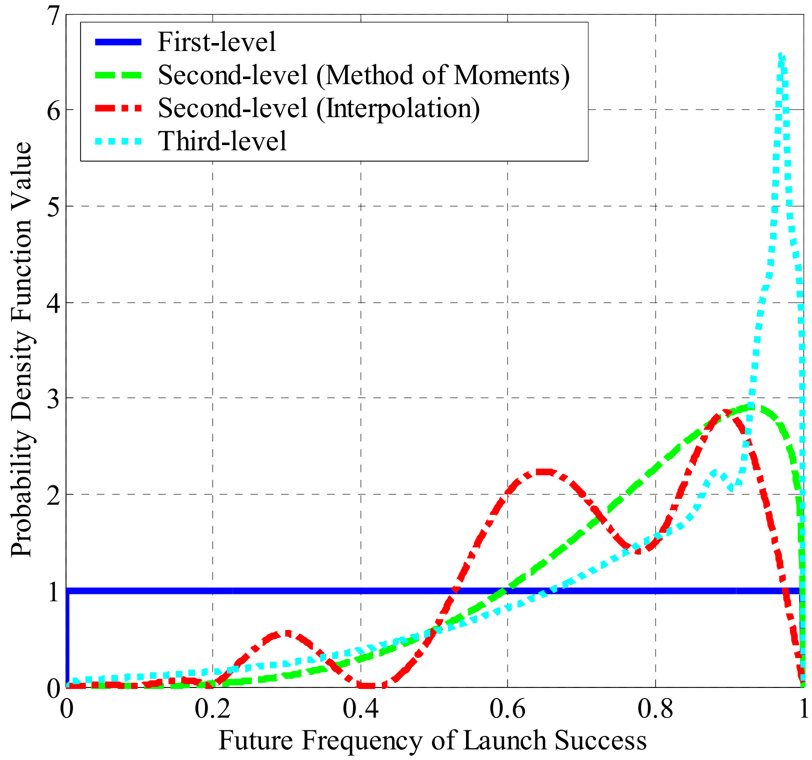

Fig. A.7 Four possible prior distributions in launch vehicle example.

In this example, the first-level prior was an "uninformed" prior. The second- and third-level priors were the results of analysis. The assumptions and analysis that went into estimating (choosing) the prior is a critical (and controversial) aspect of Bayesian analysis. Which prior is best is a subjective belief on the part of the analyst or decision maker.

The next step in a Bayesian analysis consists of updating the prior distribution with observations (actual data). This can be done analytically for the first-level prior and second-level (generated via the method of moments) prior since they are beta distributions (conjugate priors to the binomial distribution that updates them). For the second-level prior (generated via interpolation) and the third-level prior, this updating process must be done numerically. Observations for this latter case are represented by multiplicative transformations as shown in Fig. A.8.

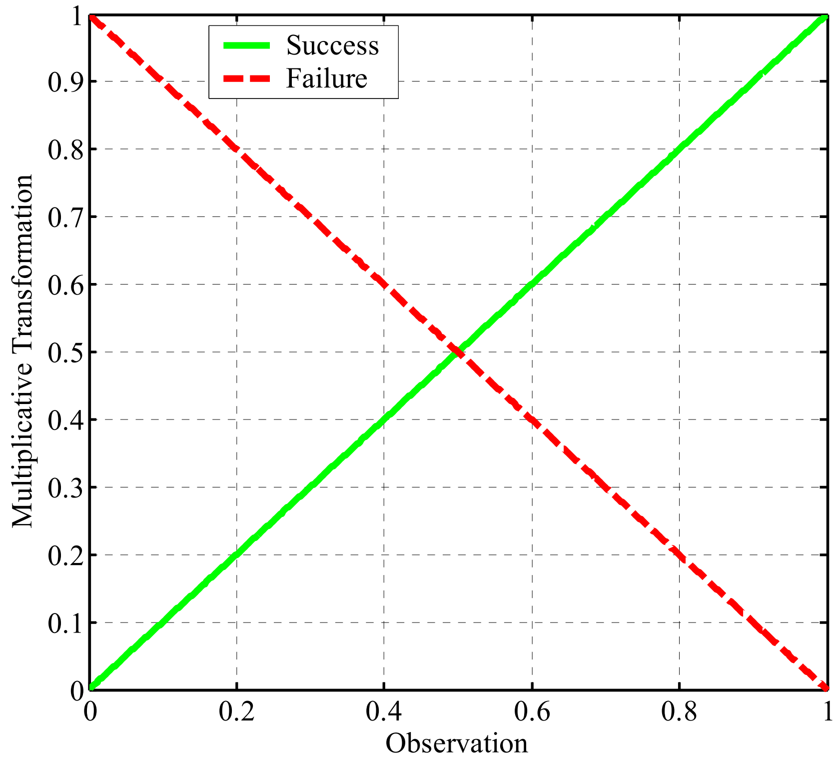

Fig. A.8 The effect of observations in launch vehicle example.

The updating procedure of the four different prior distributions is provided sequentially in Fig. A.9 through Fig. A.12 in fifteen launch increments.

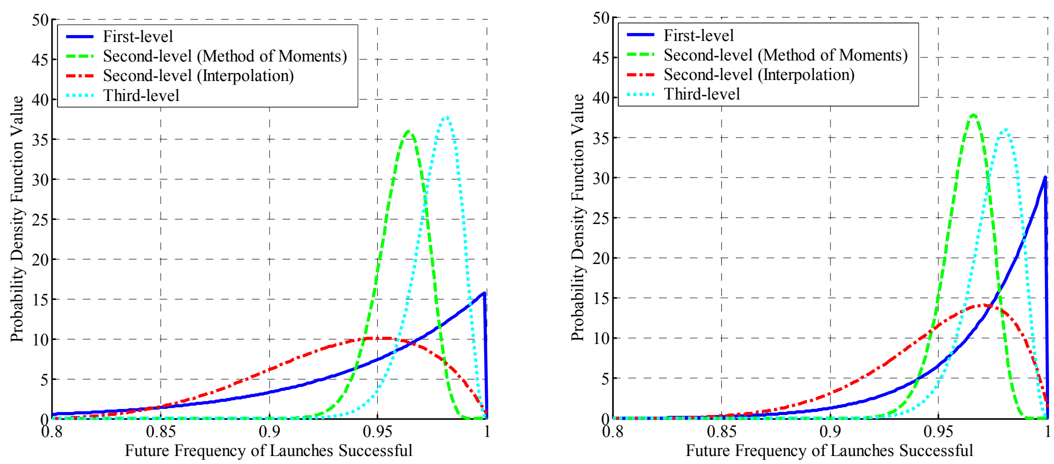

Fig. A.9 Posterior based on first 15 (left) and 30 (right) Delta II launches.

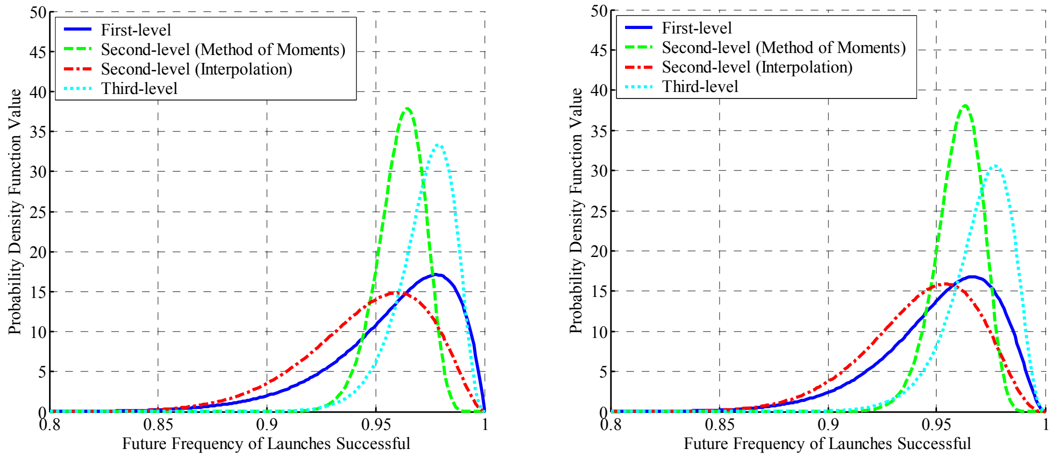

Fig. A.10 Posterior based on first 45 (left) and 60 (right) Delta II launches.

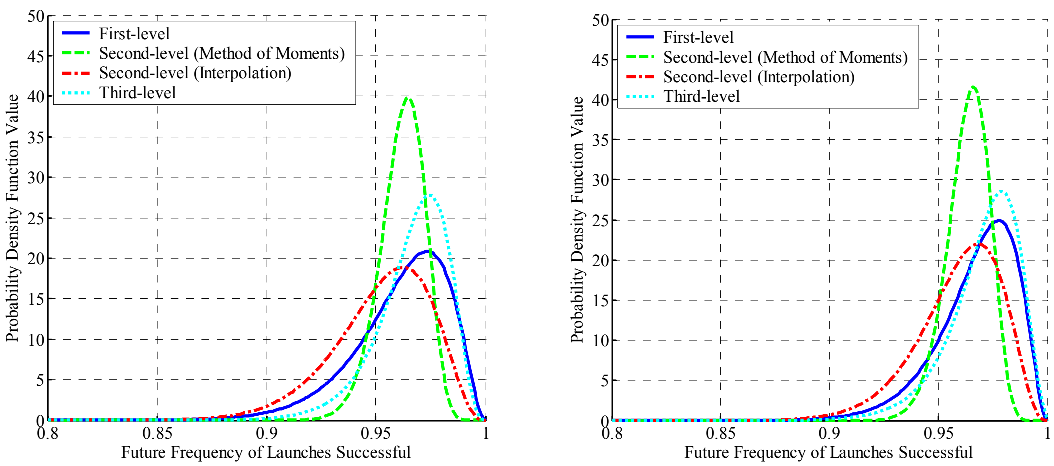

Fig. A.11 Posterior based on first 75 (left) and 90 (right) Delta II launches.

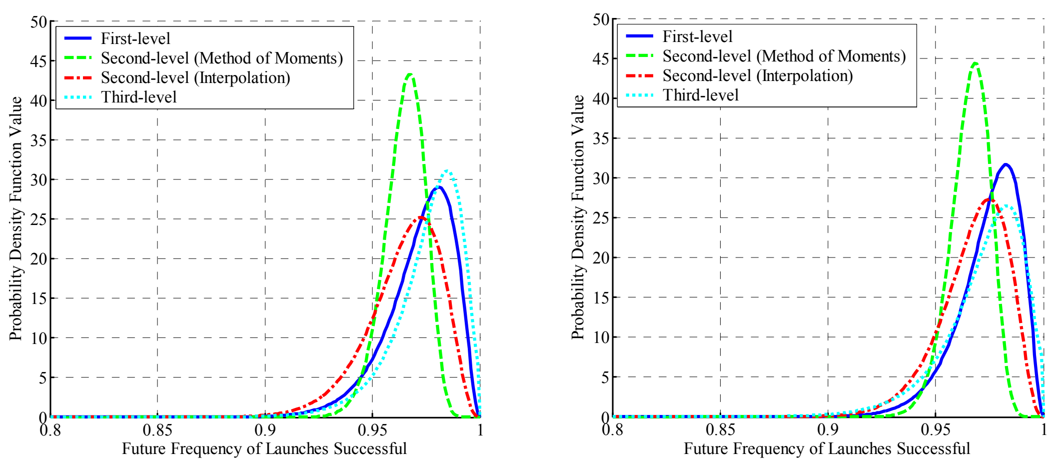

Fig. A.12 Posterior based on first 105 (left) and all 115 (right) Delta II launches.

Fig. A.9 and Fig. A.10 illustrate that the four significantly different prior distributions converge to approximately the same posterior distribution within 45 launches. The four distributions are almost identical by Fig. A.12. The posterior means and standard deviations for each of the four prior distributions after updating with available data are provided in Table A.1 and Table A.2, respectively.

Table A.1 Delta II posterior means for all four prior distributions

	Posterior Mean			
After …	First-level Prior	Second-level (MoM) Prior	Second-level (Interpolation) Prior	Third-level Prior
0 launches (prior)	0.5000	0.9588	0.8918	0.9616
15 launches	0.9332	0.9609	0.9311	0.9718
30 launches	0.9533	0.9629	0.9509	0.9755
45 launches	0.9573	0.9615	0.9457	0.9705
60 launches	0.9516	0.9602	0.9429	0.9665
75 launches	0.9610	0.9619	0.9523	0.9698
90 launches	0.9674	0.9635	0.9592	0.9725
105 launches	0.9720	0.9650	0.9645	0.9748
All 115 launches	0.9744	0.9659	0.9674	0.9760

Table A.2 Delta II posterior standard deviations for all four prior distributions

	Posterior Standard Deviations			
After …	First-level Prior	Second-level (MoM) Prior	Second-level (Interpolation) Prior	Third-level Prior
0 launches (prior)	0.2878	0.0121	0.0636	0.0311
15 launches	0.1003	0.0393	0.0115	0.0190
30 launches	0.1231	0.0310	0.0109	0.0162
45 launches	0.0317	0.0283	0.0108	0.0166
60 launches	0.0270	0.0261	0.0108	0.0166
75 launches	0.0219	0.0224	0.0103	0.0149
90 launches	0.0184	0.0195	0.0099	0.0135
105 launches	0.0159	0.0172	0.0095	0.0123
All 115 launches	0.0146	0.0159	0.0092	0.0117

Since the launch vehicle either places the spacecraft in its desired orbit or it does not, the best value to use for such a single-period decision problem when the entire probability density function (PDF) is available is the mean [Howard, 1970]. Although the mean values for launch vehicle reliability determined by Bayesian techniques often are close or identical to the means determined by traditional statistical methods, especially for those launch vehicles with a significant number of launches, the real value of Bayesian techniques is for those launch vehicles with few or no launches. The means and standard deviations provided in Table A.1 and Table A.2 illustrate that the four different posterior distributions converge to similar values. This example vividly illustrates that as more data are accumulated, the prior distributions matter increasingly less. That is to say, the prior distributions are "washed out" by actual data. Hence, selecting the “correct” prior distribution, which may be a contentious issue among participants in the proposed method, matters increasingly less as more data are accumulated and applied. Details on the assumptions and analysis procedure for this example are provided in Guikema and Paté-Cornell (2004).

Appendix B Application Examples

In addition to the attitude determination and control system (ADCS) example presented in Chapter 9, the proposed method was applied to two other spacecraft subsystems: propulsion and thermal control. Elements of the proposed method were also applied to the discipline of mission design. This appendix summarizes results of the two subsystem application examples and concludes with a discussion of the mission design application. All three applications used the Mars Exploration Rover (MER) as the example mission.

B.1 Propulsion

The propulsion subsystem provides the changes in velocity needed to translate the center of mass of a spacecraft and/or to provide a torque to rotate a vehicle about its center of mass. An early variant of the proposed method was applied to the propulsion system located on the cruise stage of MER in Thunnissen and Nakazono (2003). Thunnissen and Nakazono (2003) describe all the basic steps in the proposed method and assume four tradable parameters: propellant mass, dry mass, schedule duration, and total cost. Model uncertainty is not assessed in Thunnissen and Nakazono (2003) and Monte Carlo Simulation (MCS) is used as the only simulation technique to address interaction uncertainty. In addition to Thunnissen and Nakazono (2003); Thunnissen, Engelbrecht, and Weiss (2003) and Thunnissen (2004a) describe the models used in this propulsion application. This appendix assesses the uncertainty in the models used in the analysis, notes differences in uncertainties assumed, and compares the calculated margins via three simulation techniques: MCS, centered-finite difference modified mean value method (MMVM), and subset simulation (SS). This analysis represents the critical design review (CDR) iteration as described in Thunnissen and Nakazono (2003).

B.1.1 Model Uncertainty

Model uncertainty assessments of the four tradable parameters are provided in Table B.1.

Table B.1 Model uncertainties assumed

Model	Units	Distribution type and parameters
Propellant mass	kg	$N(0,0.25)$
Dry mass	kg	$N(0,0.15)$
Schedule duration	days	$T_{NC}(4,1)$
Total cost	FY2003$K	$N(0,50)$

Model uncertainty was assessed by expert opinion (MER engineers and managers).

B.1.2 Uncertainty Quantification Differences

SS had difficulties with the custom distributions for the five trajectory correction maneuvers (TCMs). Due to the long stretches of TCM *ΔV* values, the probability distribution function (PDF) values are zero and the SS algorithm cannot easily progress. In order to alleviate this numerical issue, χ and *N* were increased to allow more efficient and accurate Markov chain generation for the propellant and dry mass SS analyses.

Additionally, four input variable uncertainties were changed from Thunnissen and Nakazono (2003) for all three simulation techniques. These changes were due to omissions in the original paper and data mining of the output that uncovered errors in sample generation for these uncertainties. The new distribution parameters for these four input variables uncertainties are listed in Table B.2.

Table B.2 Updated input variable uncertainties from Thunnissen and Nakazono (2003)

Input variable uncertainty	Distribution type and parameters	Units
m_{fittings}	*L*(-2.2,0.1)	kg
α	*N*(0.0524,0.00175)	rad
t_{adh}	*N*(0.0127,0.00127)	mm
t_{lin}	*N*(0.152,0.0152)	mm

Finally, the schedule model used in Thunnissen and Nakazono (2003) had a minor bug in it that is fixed in the subsequent propulsion schedule and cost analyses (as it is in the ADCS example in Chapter 9 and the thermal control example presented later). Also, cost variables are represented by lognormal distributions in this updated analysis instead of normal distributions. The parameters for the lognormal distribution are the converted normal distribution parameters (e.g., *N*(80,8) becomes *L*(log(80),0.1)). Hence, the corrected results herein differ slightly from comparable values that appear in Thunnissen and Nakazono (2003).

B.1.3 Interaction Uncertainty

The deterministic results for the propulsion analysis are listed in Table B.3.

Table B.3 Deterministic results for thermal control analysis

Tradable Parameter	Deterministic Result
Propellant mass	21.6 kg
Dry mass	9.0 kg
Schedule duration	708 days
Total cost	FY2003$10.392M

Uncertainty in the four tradable parameters is evaluated via MCS, centered-finite difference MMVM, and SS. The MCS results use more repetitions than the 5,000 used in Thunnissen and

Nakazono (2003); the MMVM and SS results are entirely new. The number of calls to each model was set at $N = 20{,}000$ for MCS and $N = 1{,}000$ for SS (per SS level). The number of repetitions in this example is greater than that in the ADCS example of Chapter 9 due to a greater interest in the extreme tail of these distributions. The number of calls to each model for MMVM using a centered-finite difference is twice the number of input variable uncertainties plus one additional call. For both propellant and dry mass, $N = 65$ as there are 32 input variable uncertainties (an additional 29 input variables for these two models are certain). For schedule duration, $N = 289$ as there are 144 input variable uncertainties (another 96 input variables were certain). For total cost, $N = 344$ of which 289 calls are to the schedule model and the remaining 55 calls are to the cost model as there are 171 input variable uncertainties (144 schedule input variable uncertainties that might impact cost plus 27 cost input variable uncertainties). Note that if the schedule duration and cost duration are calculated via MMVM simultaneously (as is done in the subsequent analysis), a total of 344 calls are required to calculate both parameters (*not* 289+344 = 633). All subsequent tables and figures reflect the final uncertainty: simulation results convolved with model uncertainty. SS assumed $P_f = 0.0001$ and $p_0 = 0.1$ in all simulations; χ and N however are different for the four SS analyses.

B.1.3.1 Propellant Mass

The propellant mass probability density function (PDF) values for MCS and MMVM are provided in Fig. B.1.

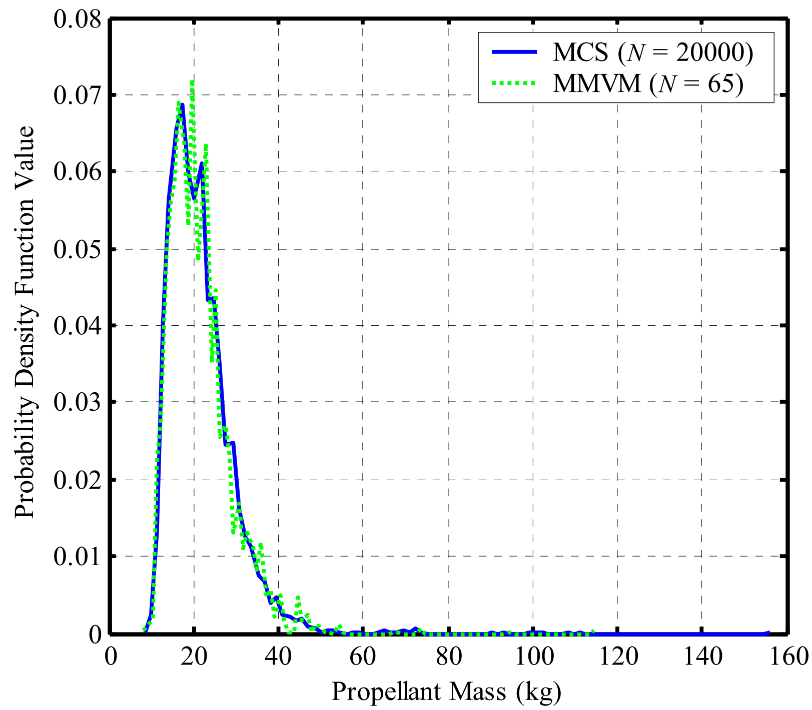

Fig. B.1 Propellant mass PDFs for MCS and MMVM.

The cumulative distribution function (CDF) values for all three simulation techniques are shown in Fig. B.2 through Fig. B.5. SS used $N = 2000$ (per SS level) and $\chi = 10$.

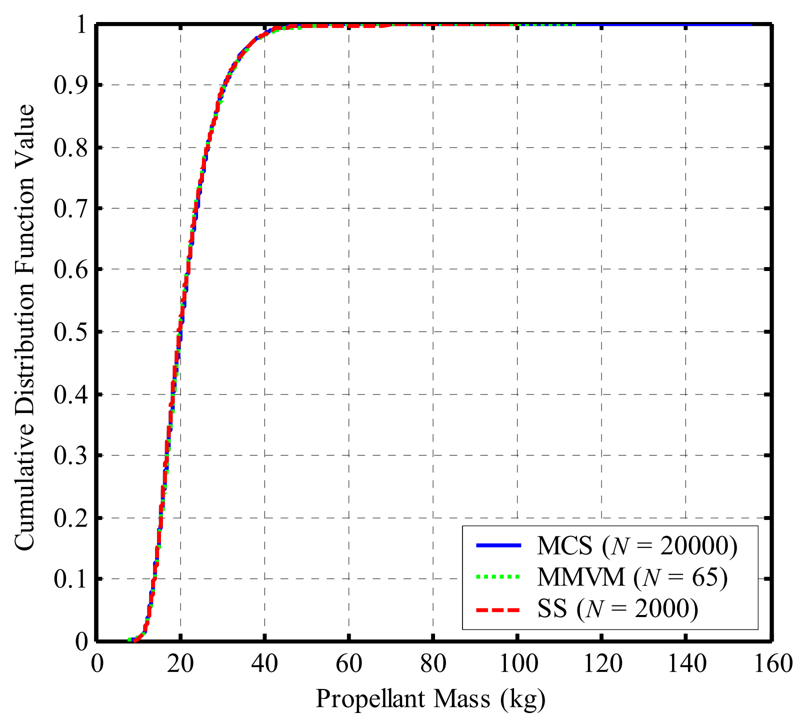

Fig. B.2 Propellant mass CDFs (simulation level 1).

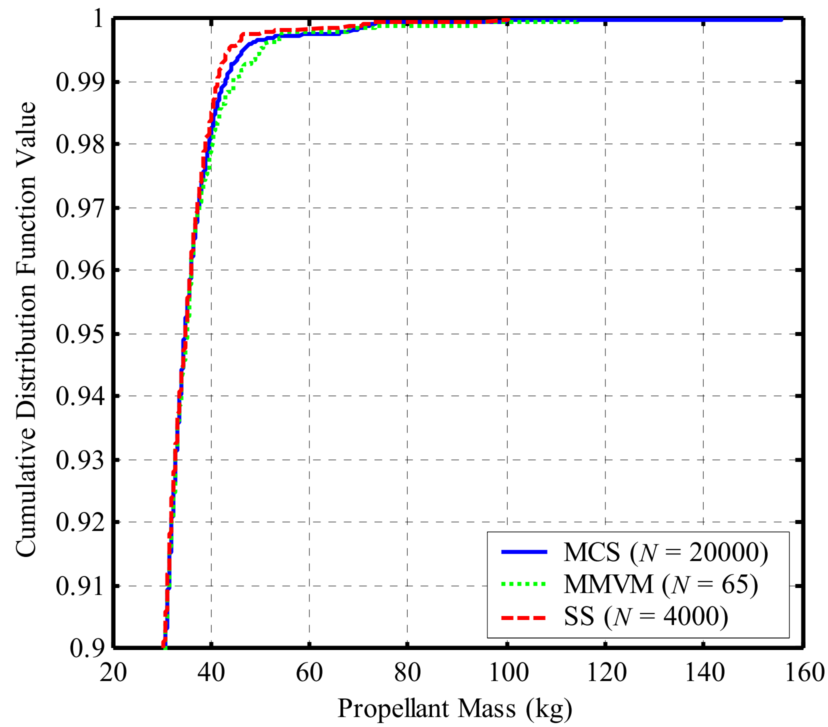

Fig. B.3 Propellant mass CDFs (simulation level 2).

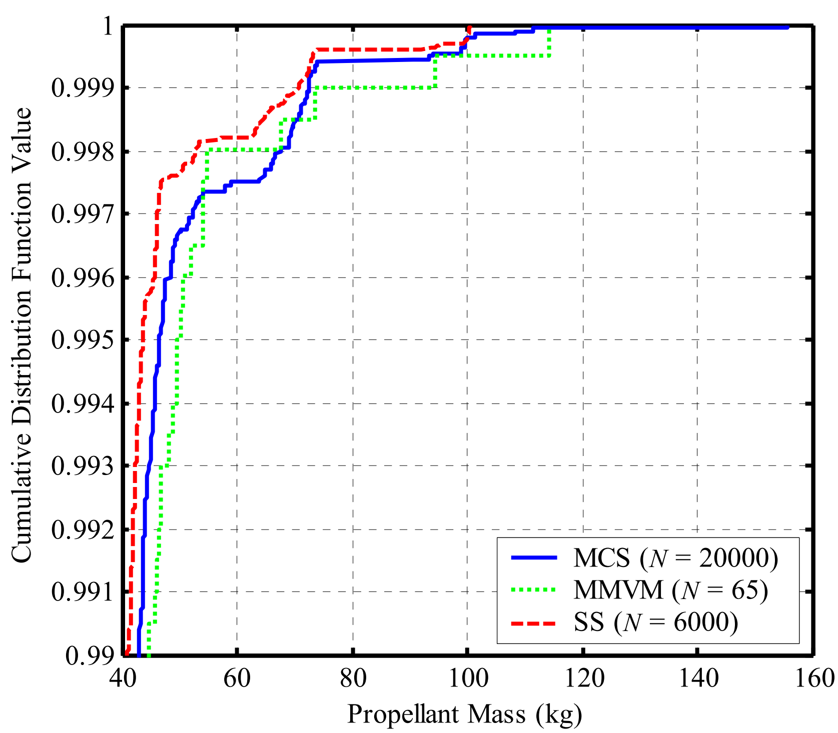

Fig. B.4 Propellant mass CDFs (simulation level 3).

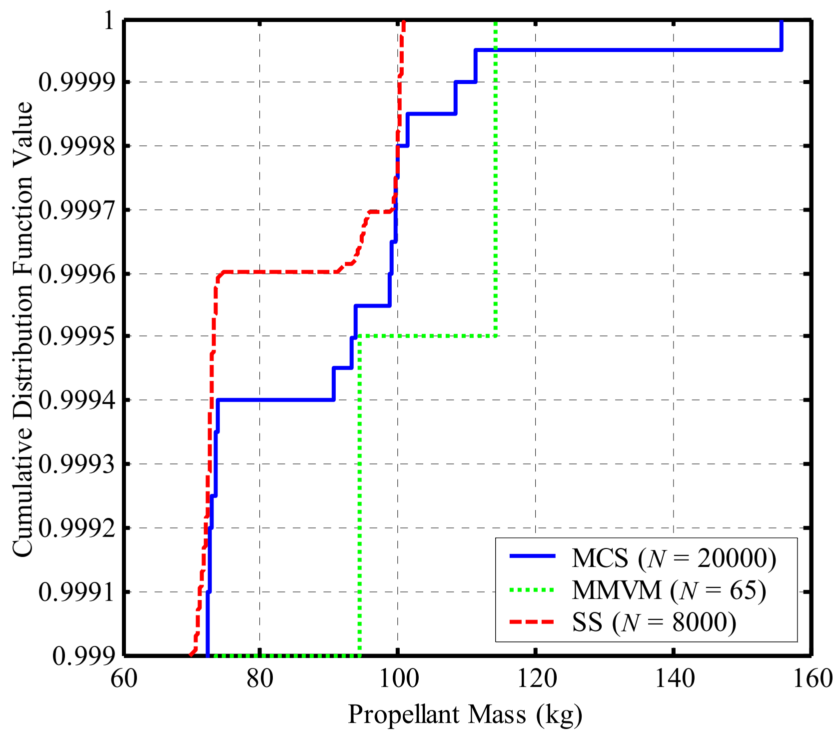

Fig. B.5 Propellant mass CDFs (simulation level 4).

Fig. B.3 through Fig. B.5 demonstrate the performance of the three simulation techniques at the upper tail of the distribution. MCS is the benchmark for comparison but requires a substantial number of calls to the model (N) to obtain values for the entire CDF range. MVMM performs very well considering the complexity of the underlying model and the fact that only $N = 65$ are required. MMVM follows the general MCS trend and requires well over two orders of magnitude less repetitions than MCS. SS follows the general MCS trend for all SS levels although deviating slightly at extreme CDF values (fourth simulation level). Table B.4 details the statistics of SS by simulation level for propellant mass.

Table B.4 SS results by level for propellant mass

SS Level	x	P_x (kg)	Error[a] (%)	γ	σ	δ	δ^*	N_{MCS}
1	90	30.5	-0.85	0	0	0.06708	0.06708	2000
2	99	41.3	-3.56	4.8158	0.00537	0.16178	0.17513	3228
3	99.9	70.6	-2.50	7.33	0.00204	0.19361	0.26107	14658
4	99.99	100.4	-8.60	5.03	0.00055	0.16473	0.30869	104932

[a]relative to the 20000 MCS

The relative error (compared to MCS) in Table B.4 is high at the fourth simulation level. This may be error in MCS, not SS as the final column indicates SS achieves a comparable accuracy as 104,932 MCS repetitions (N_{MCS}) whereas only $N = 20{,}000$ were performed for MCS.

The relatively high choice of N and χ for SS is required for this tradable parameter as the difficulties in Markov chain generation are significant due to the TCM custom distribution representations. Table B.5 summarizes the statistics for all four simulation techniques at various percentile values for comparison.

Table B.5 Propellant mass calculated by each simulation technique

Simulation technique (# of repetitions)	Propellant mass (kg) Mean	Median	90th percentile	99th percentile	99.9th percentile	99.99th percentile
MCS (20000)	21.6	20.2	30.8	42.9	72.4	109.8
MMVM (65)	21.6	20.0	30.8	44.6	84.0	114.2
SS[a] (2000 to 8000)	21.5	19.9	30.5	41.3	70.6	100.4

[a]mean, 50th , & 90th percentile; 99th percentile; 99.9th percentile; and 99.99th percentile values taken from first, second, third, and fourth simulation levels, respectively

B.1.3.2 Dry Mass

The dry mass PDF values for MCS and MMVM are provided in Fig. B.6.

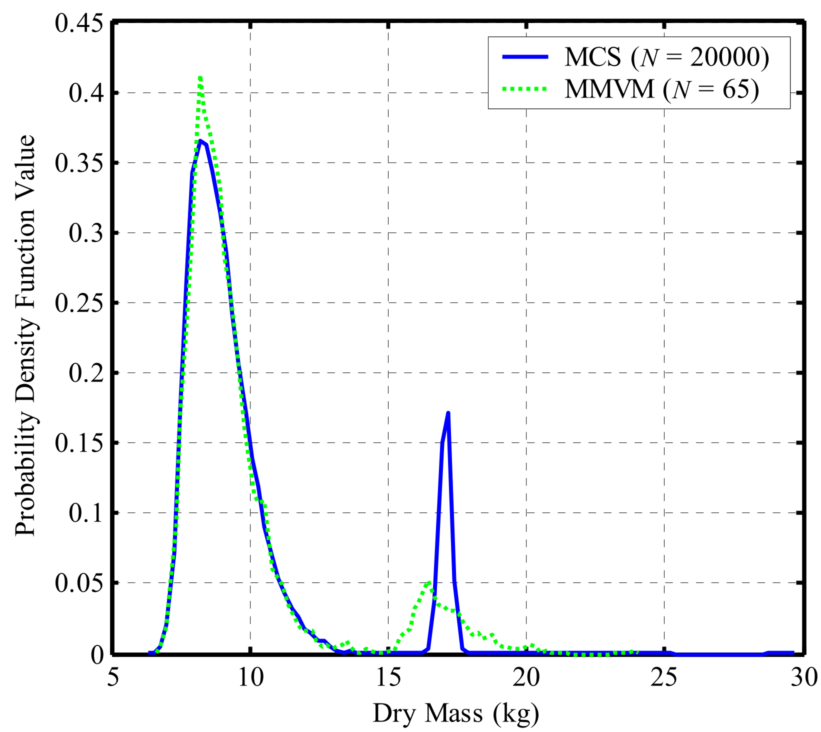

Fig. B.6 Dry mass PDFs for MCS and MMVM.

The CDF values for all three simulation techniques are shown in Fig. B.7 through Fig. B.10. SS used $N = 2000$ (per SS level) and $\chi = 7$.

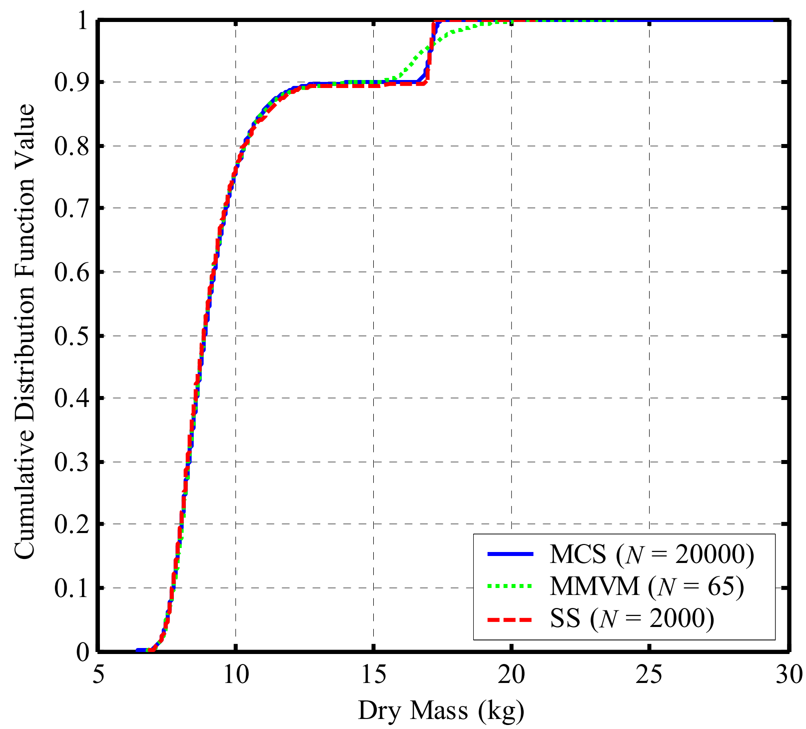

Fig. B.7 Dry mass CDFs (simulation level 1).

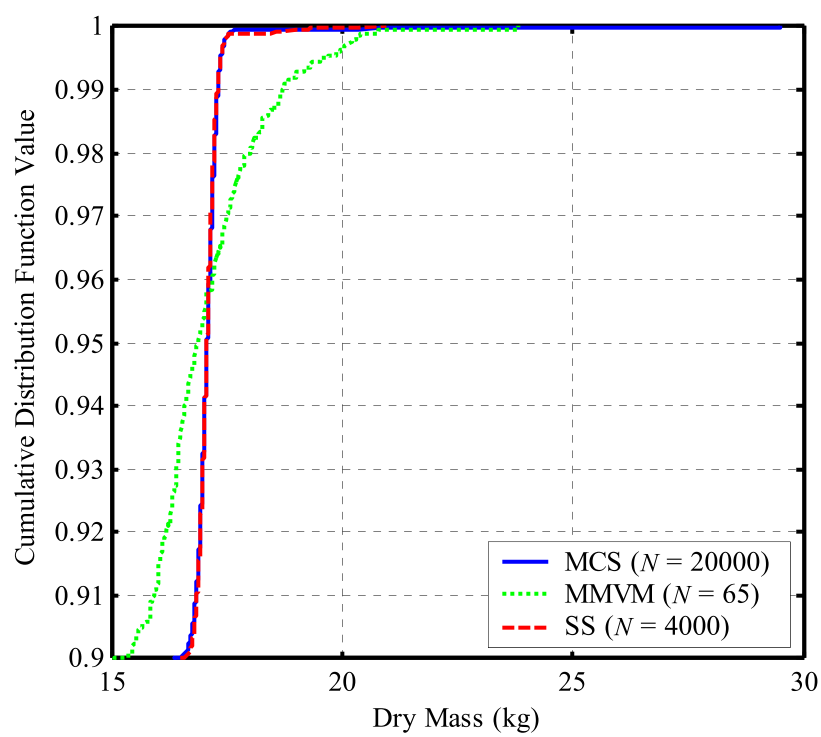

Fig. B.8 Dry mass CDFs (simulation level 2).

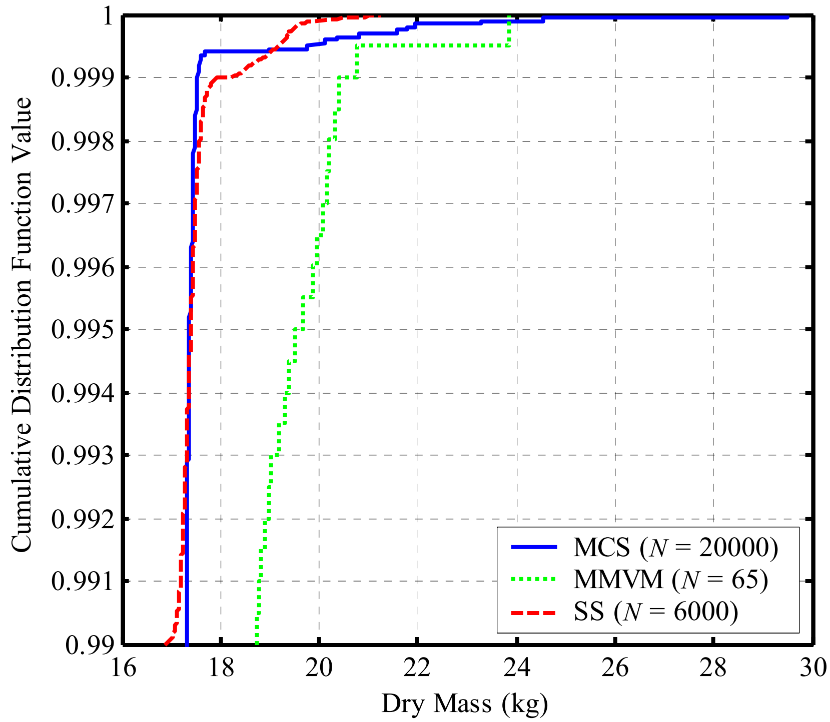

Fig. B.9 Dry mass CDFs (simulation level 3).

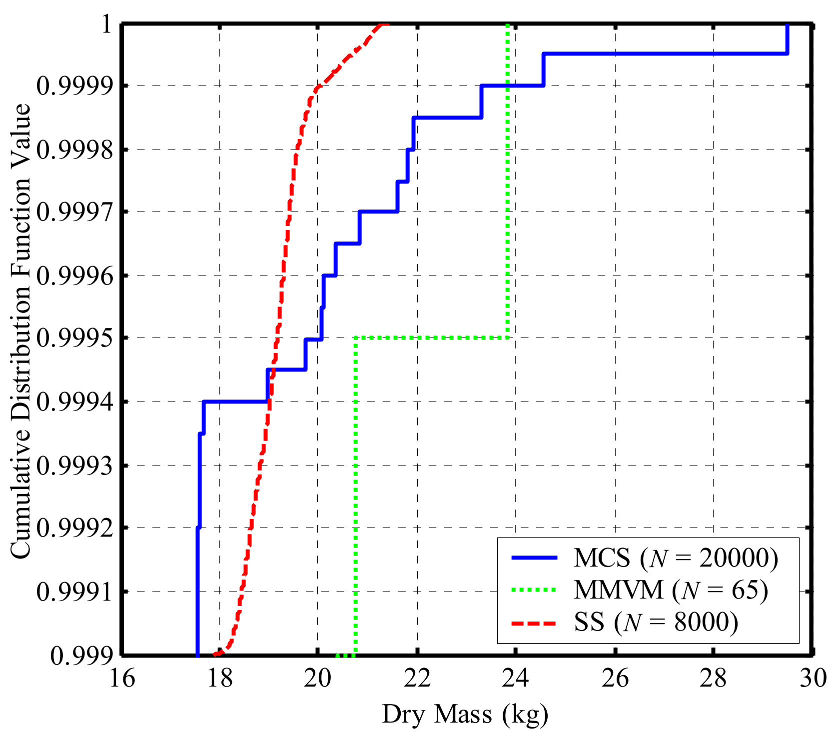

Fig. B.10 Dry mass CDFs (simulation level 4).

Fig. B.8 through Fig. B.10 demonstrate the performance of the three simulation techniques at the upper tail of the distribution. MCS is the benchmark for comparison but requires a large *N* to obtain values for the entire CDF range. MVMM performs adequately at the first SS level but poorly at the second, third, and fourth. The dry mass model is too complicated for the MMVM to accurately determine values. SS requires less than half the number of calls to the model as MCS yet follows the general MCS trend for all SS levels although it deviates at extreme CDF values (fourth simulation level). Table B.6 details the statistics of SS by simulation level for dry mass.

Table B.6 SS results by level for dry mass

SS Level	x	P_x (kg)	Error[a] (%)	γ	σ	δ	δ^*	N_{MCS}
1	90	16.9	3.46	0	0	0.06708	0.06708	2000
2	99	17.3	-0.04	1.4424	0.00348	0.10484	0.12446	6391
3	99.9	18.0	2.77	9	0.00223	0.21213	0.24595	16515
4	99.99	20.1	-16.18	8.73	0.00070	0.20925	0.32292	95890

[a]relative to the 20000 MCS

The increasing value of γ with simulation level in Table B.6 indicates that the modified Markov chain Monte Carlo (MCMC) algorithm is increasingly rejecting samples and remaining stationary for long periods in the chains. Furthermore, the relative error (compared to MCS) is high at the fourth simulation level. This may be error in MCS (in addition to error in SS) as the final column indicates SS achieves a comparable accuracy as 95,890 MCS repetitions (N_{MCS}) whereas only N = 20,000 were performed for MCS. Increasing N and decreasing χ in SS might improve the accuracy of SS *vis-à-vis* actual results (i.e., MCS with N approaching infinity). Table B.7 summarizes the statistics for all four simulation techniques at various percentile values for comparison.

Table B.7 Dry mass calculated by each simulation technique

Simulation technique (# of repetitions)	Dry mass (kg) Mean	Median	90th percentile	99th percentile	99.9th percentile	99.99th percentile
MCS (20000)	9.8	8.9	16.3	17.3	17.6	23.9
MMVM (65)	9.8	8.9	15.2	18.7	20.6	23.8
SS[a] (2000 to 8000)	9.8	8.9	16.9	17.3	18.0	20.1

[a]mean, 50th , & 90th percentile; 99th percentile; 99.9th percentile; and 99.99th percentile values taken from first, second, third, and fourth simulation levels, respectively

B.1.3.3 Schedule Duration

The schedule duration PDF values for MCS and MMVM are provided in Fig. B.11.

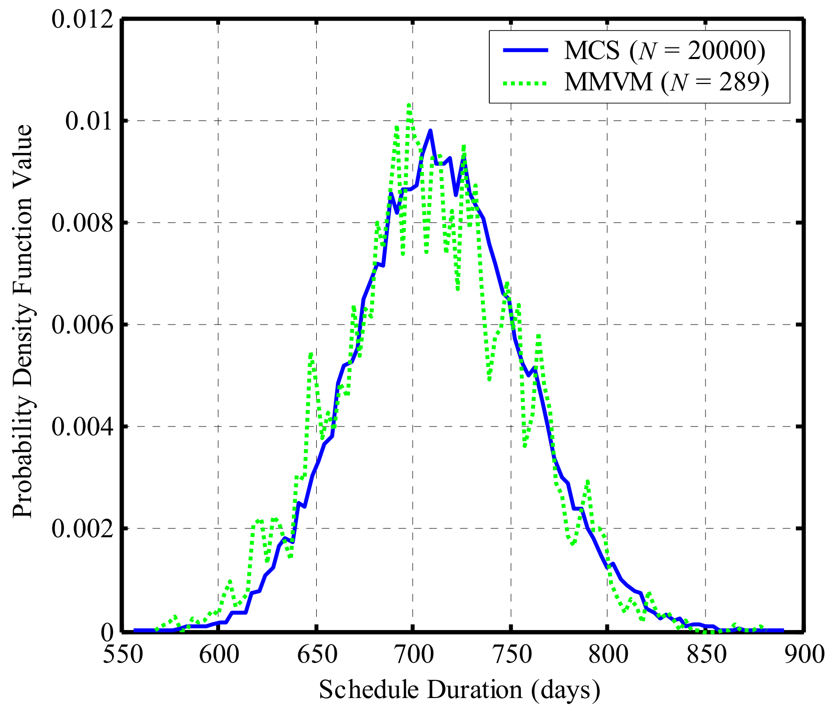

Fig. B.11 Schedule duration PDFs for MCS and MMVM.

The CDF values for all three simulation techniques are shown in Fig. B.12 through Fig. B.15. SS used $N = 1000$ (per SS level) and $\chi = 1$.

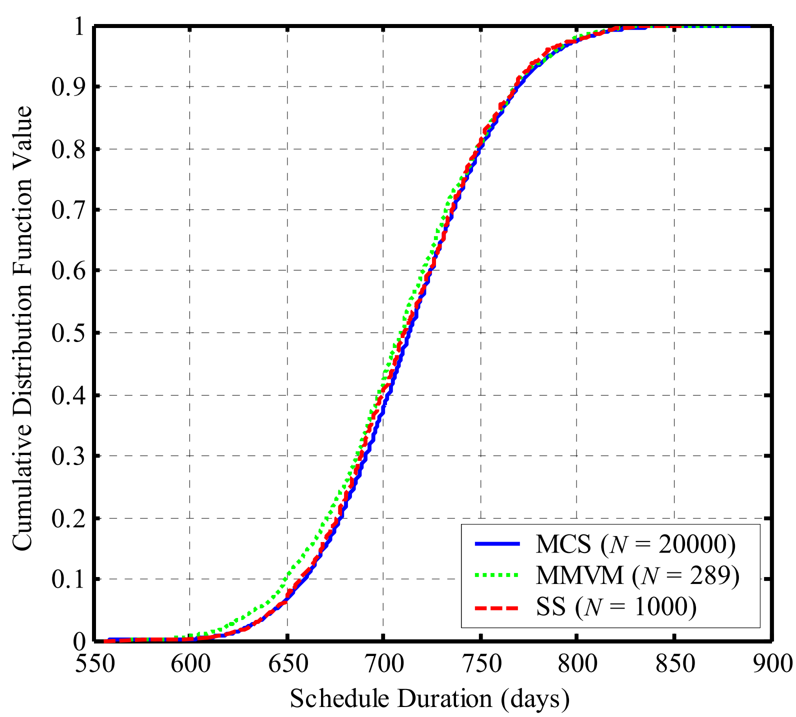

Fig. B.12 Schedule duration CDFs (simulation level 1).

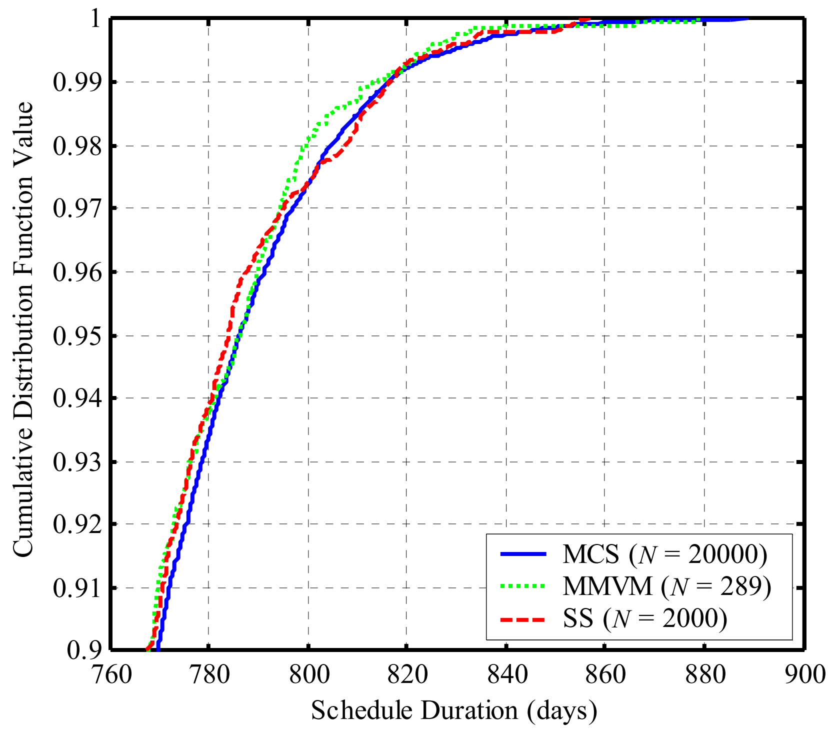

Fig. B.13 Schedule duration CDFs (simulation level 2).

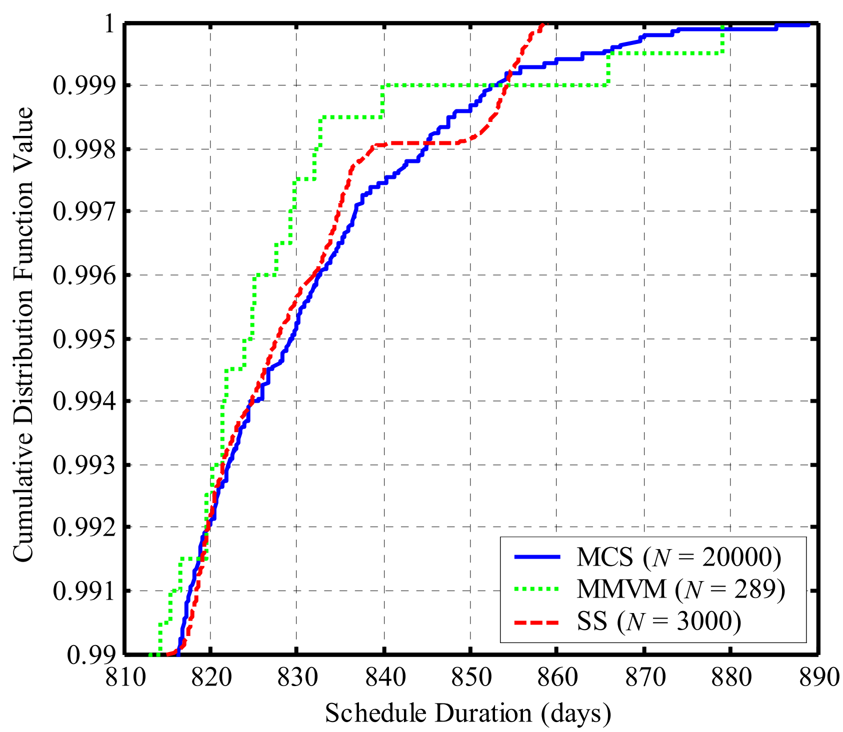

Fig. B.14 Schedule duration CDFs (simulation level 3).

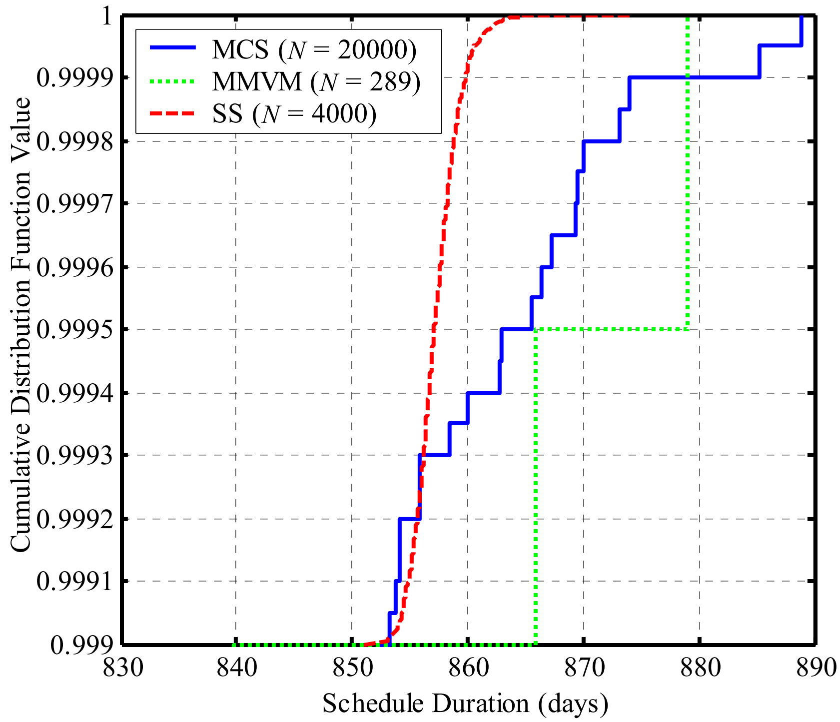

Fig. B.15 Schedule duration CDFs (simulation level 4).

Fig. B.13 through Fig. B.15 demonstrate the performance of the four simulation techniques at the upper tail of the distribution. Again, MCS is the benchmark for comparison but requires a large N to obtain values for the entire CDF range. MVMM yields a PDF and CDF that follows the MCS results closely and does not suffer from a shifting as the schedule distribution for ADCS did in Chapter 9. It is possible that using a centered-finite difference, instead of the forward-finite difference that the ADCS schedule example uses, improves the estimate for schedule duration. SS performs very well, except at extreme CDF values (fourth simulation level), despite requiring only a fifth the calls to the model. Table B.8 details the statistics of SS by simulation level for schedule duration.

Table B.8 SS results by level for schedule duration

SS Level	x	P_x (days)	Error[a] (%)	γ	σ	δ	δ^*	N_{MCS}
1	90	768.5	-0.16	0	0	0.09487	0.09487	1000
2	99	816.8	0.05	8.1191	0.00950	0.28648	0.30178	1088
3	99.9	854.2	0.16	5.88	0.00262	0.24884	0.39114	6530
4	99.99	859.8	-2.25	1.98	0.00055	0.16377	0.42404	55609

[a]relative to the 20000 MCS

Table B.9 summarizes the statistics for all four simulation techniques at various percentile values for comparison.

Table B.9 Schedule duration calculated by each simulation technique

Simulation technique (# of repetitions)	Schedule duration (days)					
	Mean	Median	90th percentile	99th percentile	99.9th percentile	99.99th percentile
MCS (20000)	714.1	713.3	769.8	816.4	852.9	879.6
MMVM (289)	709.4	708.7	770.0	813.8	852.9	879.0
SS[a] (1000 to 4000)	712.4	710.6	768.5	816.8	854.2	859.8

[a]mean, 50th , & 90th percentile; 99th percentile; 99.9th percentile; and 99.99th percentile values taken from first, second, third, and fourth simulation levels, respectively

B.1.3.4 Total Cost

The total cost PDF values for MCS and MMVM are provided in Fig. B.16.

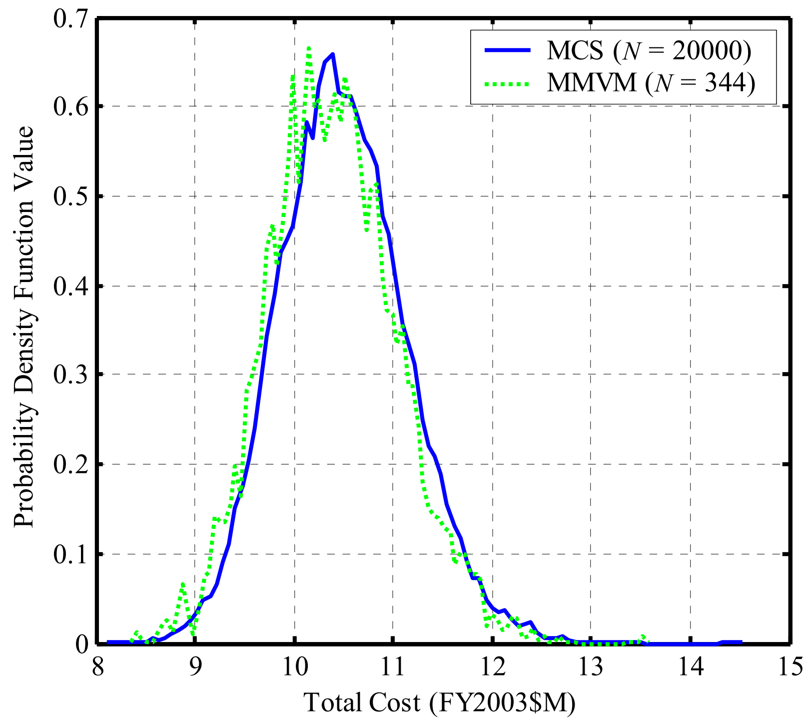

Fig. B.16 Total cost PDFs for MCS and MMVM.

The CDF values for all three simulation techniques are shown in Fig. B.17 through Fig. B.20. SS used $N = 1000$ (per SS level) and $\chi = 1$.

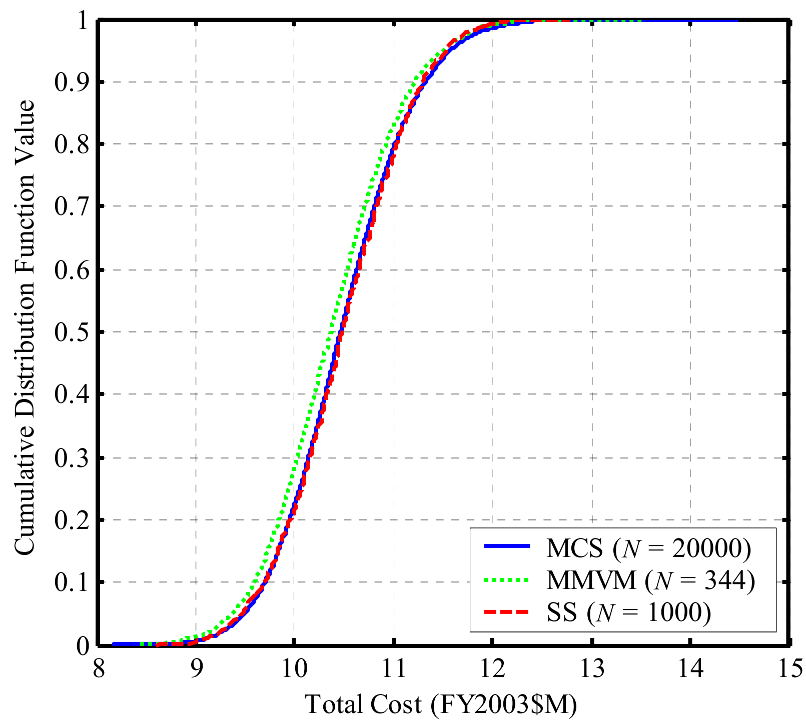

Fig. B.17 Total cost CDFs (simulation level 1).

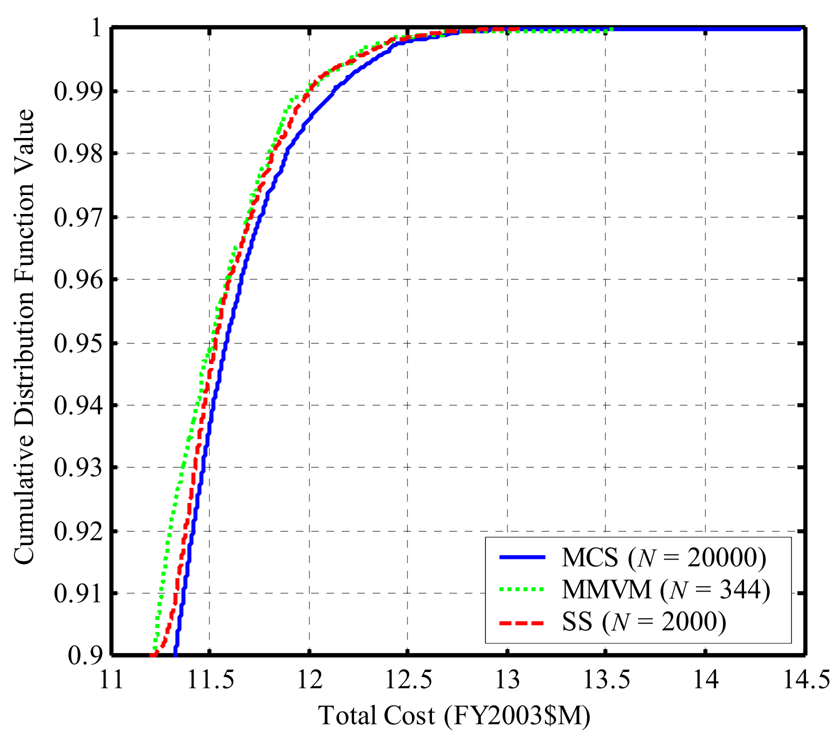

Fig. B.18 Total cost CDFs (simulation level 2).

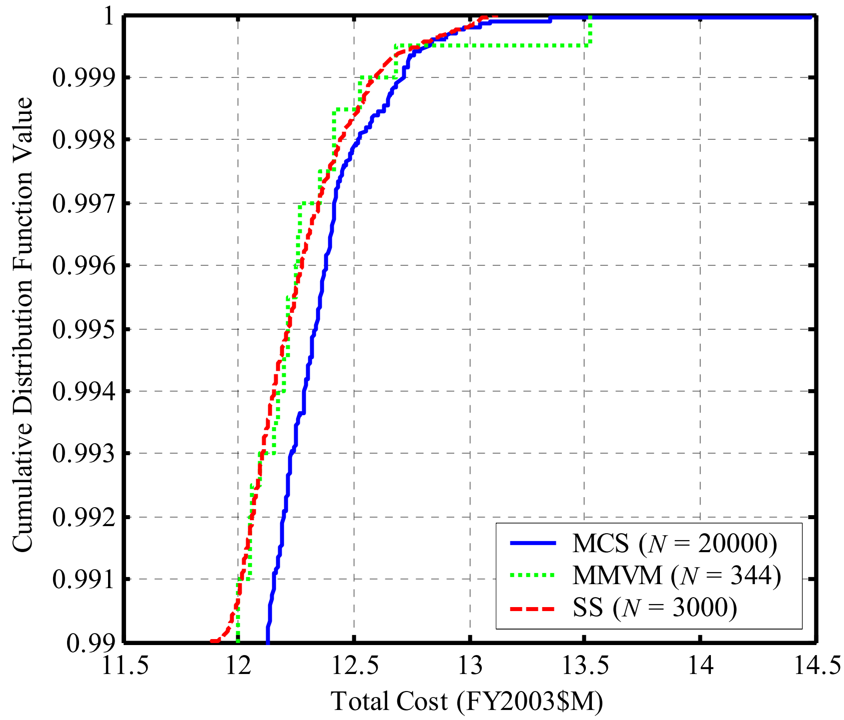

Fig. B.19 Total cost CDFs (simulation level 3).

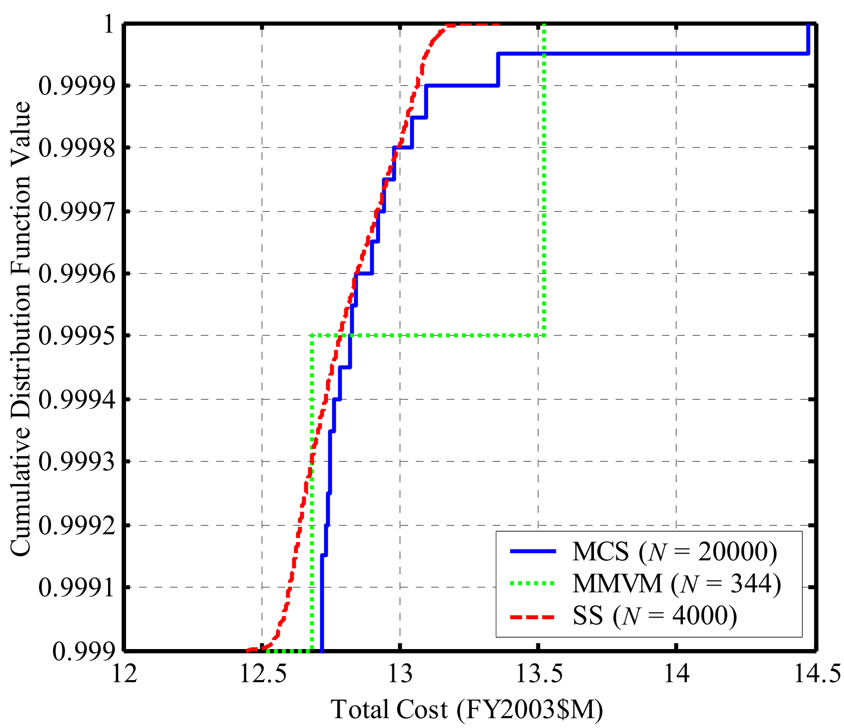

Fig. B.20 Total cost CDFs (simulation level 4).

Fig. B.18 through Fig. B.20 demonstrate the performance of the four simulation techniques at the upper tail of the distribution. Again, MCS is the benchmark for comparison but requires a large *N* to obtain values for the entire CDF range. For all CDF values MVMM performs surprisingly well (underestimates the cost only slightly) considering only *N* = 344 are required, almost two orders of magnitude less than MCS. SS performs extremely well with total cost at all SS levels providing a comparable accuracy as MCS despite requiring only a fifth the calls (or less) to the model. Table B.10 details the statistics of SS by simulation level for total cost.

Table B.10 SS results by level for total cost

SS Level	x	P_x (FY2003 $M)	Error[a] (%)	γ	σ	δ	δ^*	N_{MCS}
1	90	11.299	-0.23	0	0	0.09487	0.09487	1000
2	99	12.013	-0.97	1.5526	0.00503	0.15157	0.17881	3097
3	99.9	12.594	-0.97	7.34	0.00289	0.27397	0.32716	9334
4	99.99	13.062	-1.22	4.54	0.00074	0.22329	0.39610	63732

[a]relative to the 20000 MCS

SS achieves a comparable accuracy as 63,732 MCS repetitions (N_{MCS}) whereas only *N* = 20,000 were performed for MCS. Table B.11 summarizes the statistics for all four simulation techniques at various percentile values for comparison.

Table B.11 Total cost calculated by each simulation technique

Simulation technique (# of repetitions)	Total cost (FY2003$M)					
	Mean	Median	90th percentile	99th percentile	99.9th percentile	99.99th percentile
MCS (20000)	10.495	10.466	11.325	12.130	12.718	13.223
MMVM (344)	10.390	10.372	11.220	11.994	12.605	13.524
SS[a] (1000 to 4000)	10.494	10.479	11.299	12.013	12.594	13.062

[a]mean, 50th , & 90th percentile; 99th percentile; 99.9th percentile; and 99.99th percentile values taken from first, second, third, and fourth simulation levels, respectively

B.1.4 Margins & Analysis

With the probabilistic data (i.e., CDFs) available and assuming *x* = 99 percentile, Eq. (1.4) is used to determine margin values to hold at this point in the design (i.e., around CDR in this example). This choice of *x* represents a risk-neutral decision maker. These margins are listed in Table B.12 for the four propulsion tradable parameters.

Table B.12 Calculated (99th percentile) margin values for propulsion tradable parameters

Simulation technique (# of repetitions)	Tradable Parameter Margin (Margin %)			
	Prop. Mass	Dry Mass	Sch. Duration	Total Cost
MCS (20000)	21.3[a] (98.6%)	8.3[a] (92.2%)	108.4[b] (15.3%)	1.738[c] (16.7%)
MMVM[d]	23.0[a] (106.5%)	9.7[a] (107.8%)	105.8[b] (14.9%)	1.602[c] (15.4%)
SS[e]	19.7[a] (91.2%)	8.3[a] (92.2%)	108.8[b] (15.4%)	1.621[c] (15.6%)

[a]kg; [b]days; [c]FY2003$M; [d]different *N* for each model; [e]SS level 2, different *N* for each model

The allocation values (best estimate + margins) for both simulation techniques are presented in Table B.13 for the four propulsion tradable parameters along with assumed project allocations and final actual values obtained from pre-launch/flight/project data.

Table B.13 Comparison of assumed and calculated (99th percentile) propulsion tradable parameter allocations with actual values

Simulation technique (# of repetitions)	Tradable Parameter Allocation			
	Prop. Mass	Dry Mass	Sch. Duration	Total Cost
Project assumptions (n/a)	42.8 kg	18.4 kg	749 days	9.9[a]
MCS (20000)	42.9 kg	17.3 kg	816.4 days	12.130[a]
MMVM[b]	44.6 kg	18.7 kg	813.8 days	11.994[a]
SS[c]	41.3 kg	17.3 kg	816.8 days	12.013[a]
Mission actuals (n/a)	47.0 kg	16.2 kg	749 days	11.0[a]

[a]FY2003$M; [b]different *N* for each model; [c]SS level 2, different *N* for each model

Table B.13 illustrates that the current method (project assumptions) and proposed method (using all three simulation techniques) failed in accurately predicting the propellant mass. However, this 47.0 kg actual mission number is propellant loaded into MER prior to launch. The MER project filled the propellant tanks to capacity as unforeseen excess injected mass was available prior to launch. Hence, all three simulation techniques predict the 42.8 kg assumption (requirement) well which is the more appropriate value to compare to. Both the current and proposed method succeeded in predicting the dry mass, all were slightly conservative. The current method predicted the schedule duration exactly as it became a fixed requirement as the MER propulsion design progressed. Cost was traded on MER propulsion development to meet this 749 day schedule duration requirement. This trading of cost for schedule is illustrated by the exceeded cost margin calculated by the current method. The proposed method accurately covers cost margin, even being somewhat conservative as FY2003~$1M in cost is calculated but never materialized. This conservatism is likely the result of the conservative schedule results which feed into the cost calculation. A risk-seeking position on cost (90th percentile values), would predict the actual cost more accurately.

B.2 Thermal Control

The thermal control subsystem maintains all components of a spacecraft within their allowable temperature limits for all operating modes of the spacecraft and in all of the expected thermal environments. The proposed method was applied to the thermal control system located on MER in Thunnissen and Tsuyuki (2004). Thunnissen and Tsuyuki (2004) assume eight tradable parameters: four representative maximum component temperatures, total thermal mass, power required, schedule duration, and total cost. The four representative components are the rover electronics module (REM), battery, small deep space transponder (SDST), and solid state power amplifier (SSPA). Thunnissen and Tsuyuki (2004) uses Monte Carlo simulation (MCS) as the only simulation technique to address interaction uncertainty. This appendix compares the MCS results in Thunnissen and Tsuyuki (2004) with descriptive sampling (DS) which has yet to be demonstrated in an example application. Details on all steps of the proposed method applied to this example are provided in Thunnissen and Tsuyuki (2004) including tradable parameter definitions and model descriptions.

B.2.1 Model Uncertainty

Model uncertainty in the component temperatures was assumed to be normally distributed about zero °C with a standard deviation of 2.5 °C [Thunnissen & Tsuyuki, 2004]. Model uncertainties of the other four tradable parameters are provided in Table B.14.

Table B.14 Model uncertainties assumed

Model	Units	Distribution type and parameters
Total thermal mass	kg	$N(0,0.05)$
Power required	W	$U(-5,5)$
Schedule duration	days	$T_{NC}(4,1)$
Total cost	FY2003$K	$N(0,50)$

Model uncertainty was assessed by expert opinion (MER engineers and managers).

B.2.2 Interaction Uncertainty

The deterministic results from Thunnissen and Tsuyuki (2004) are repeated in Table B.15 for reference.

Table B.15 Deterministic results for thermal control analysis

Tradable Parameter	Deterministic Result
REM maximum temperature	17.0 °C
Battery maximum temperature	16.7 °C
SDST maximum temperature	16.7 °C
SSPA maximum temperature	27.8 °C
Total thermal mass	29.3 kg
Power required	97.5 W
Schedule duration	710.4 days
Total cost	FY2003$11.2M

Uncertainty in the eight tradable parameters is evaluated via MCS and DS. The MCS results are unchanged from Thunnissen and Tsuyuki (2004) and are repeated here; the DS results are new. MCS results are based on 3,782 repetitions (samples); DS uses 380 (~1/10th this number). All subsequent tables and figures reflect the final uncertainty: simulation results convolved with model uncertainty.

B.2.2.1 Maximum Component Temperatures

The probability density function (PDF) and cumulative distribution function (CDF) of all four maximum component temperatures are provided in Fig. B.21 and Fig. B.22, respectively.

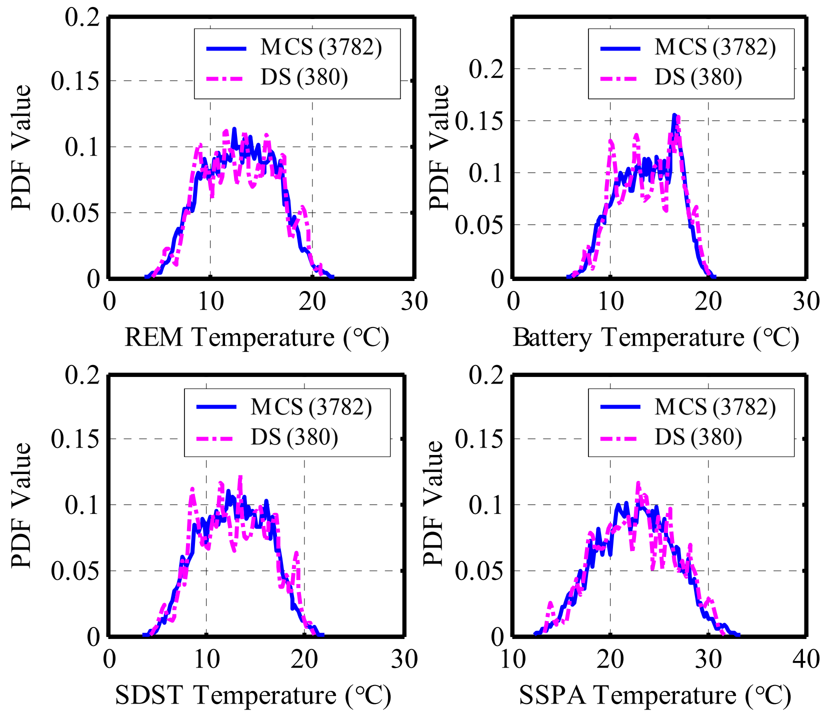

Fig. B.21 Maximum component temperature PDFs for MCS and DS.

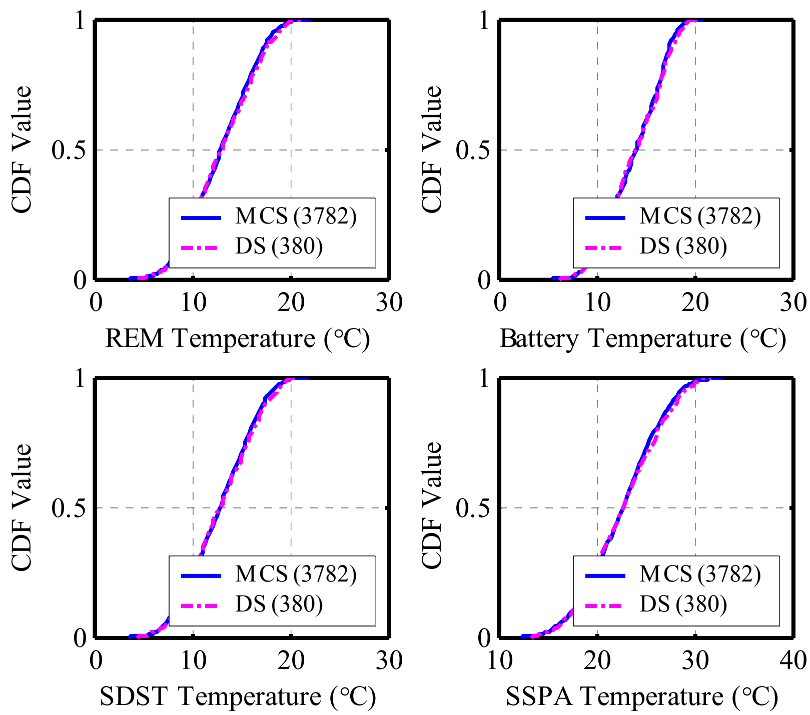

Fig. B.22 Maximum component temperature CDFs for MCS and DS.

Fig. B.21 and Fig. B.22 illustrate the comparable accuracy of the two simulation techniques. As expected, the tails of DS are not as well defined or smooth as MCS. Table B.16 summarizes the statistics for both simulation techniques at various percentile values for comparison. In comparison to MCS, DS results are "choppier" and DS performs poorly at high percentile values, likely a facet of having only performed 380 repetitions.

Table B.16 Maximum component temperature calculated by MCS and DS

Simulation technique (# of repetitions)	Maximum Component Temperature (°C)					
	Mean	Median	90th percentile	99th percentile	99.9th percentile	99.99th percentile
REM						
MCS (3782)	13.0	13.0	18.5	22.5	25.5	26.9
DS (380)	12.9	12.9	18.7	22.8	23.4	23.4
Battery						
MCS (3782)	14.0	14.0	18.9	22.4	24.2	26.0
DS (380)	12.8	12.7	18.3	21.2	24.8	24.8
SDST						
MCS (3782)	12.9	12.9	18.3	22.2	24.6	26.0
DS (380)	12.8	12.8	18.3	22.7	23.9	23.9
SSPA						
MCS (3782)	22.7	22.7	28.6	32.9	35.4	36.6
DS (380)	22.8	22.8	28.8	33.6	35.0	35.0

B.2.2.2 Mass

The PDF and CDF of the total thermal mass are provided in Fig. B.23 and Fig. B.24, respectively.

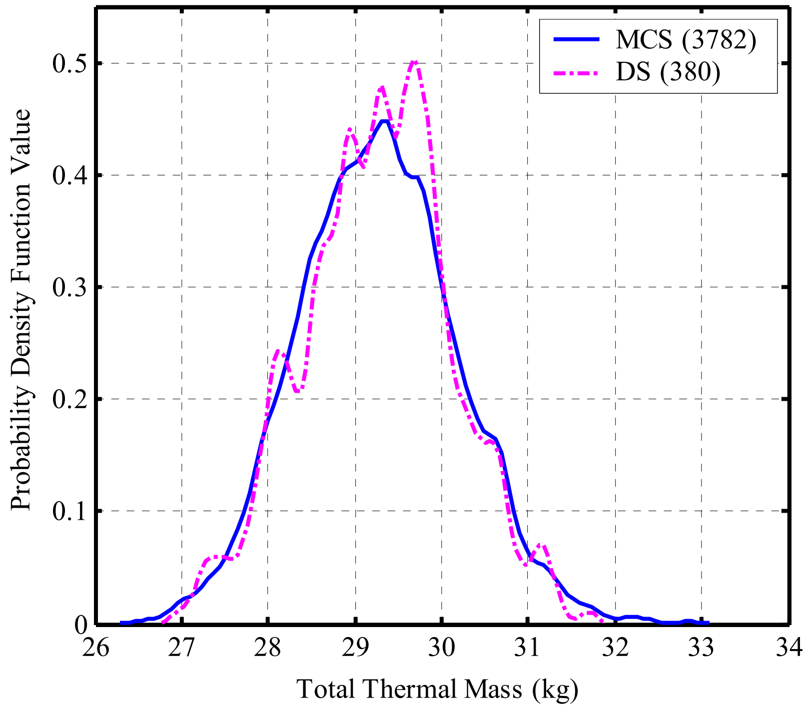

Fig. B.23 Total thermal mass PDFs for MCS and DS.

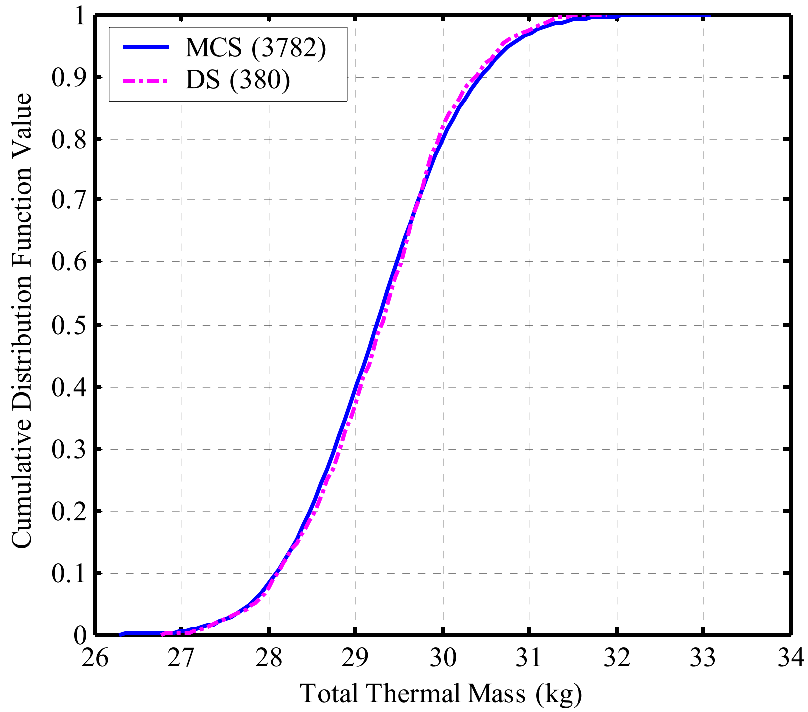

Fig. B.24 Total thermal mass CDFs for MCS and DS.

Table B.17 summarizes the statistics for both simulation techniques at various percentile values for comparison.

Table B.17 Total thermal mass calculated by MCS and DS

Simulation technique (# of repetitions)	Total Thermal Mass (kg)					
	Mean	Median	90th percentile	99th percentile	99.9th percentile	99.99th percentile
MCS (3782)	29.3	29.3	30.5	31.4	32.4	32.8
DS (380)	29.3	29.3	30.4	31.2	31.7	31.7

B.2.2.3 Power Required

The PDF and CDF of the power required are provided in Fig. B.25 and Fig. B.26, respectively.

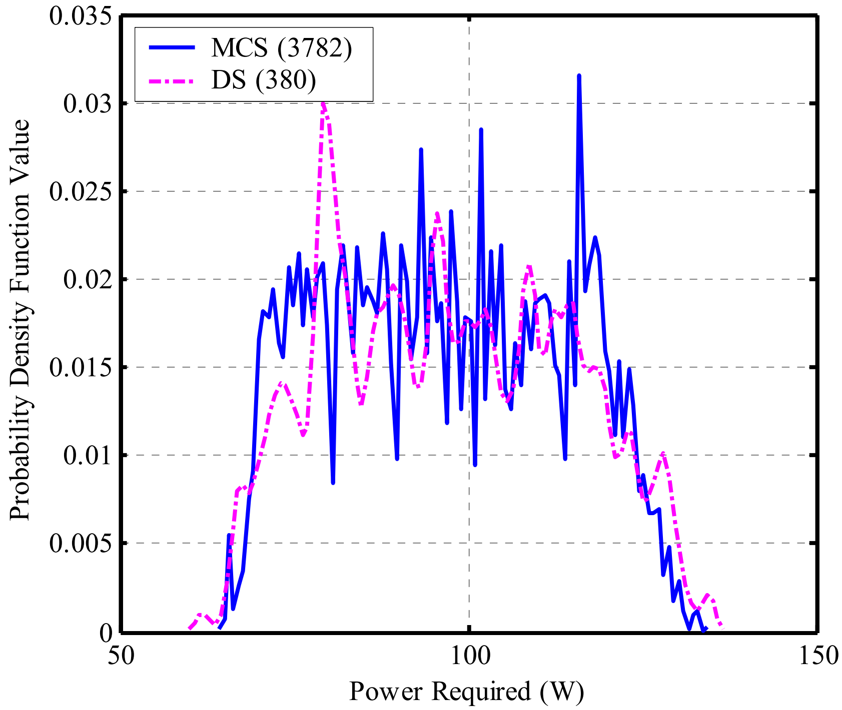

Fig. B.25 Power required PDFs for MCS and DS.

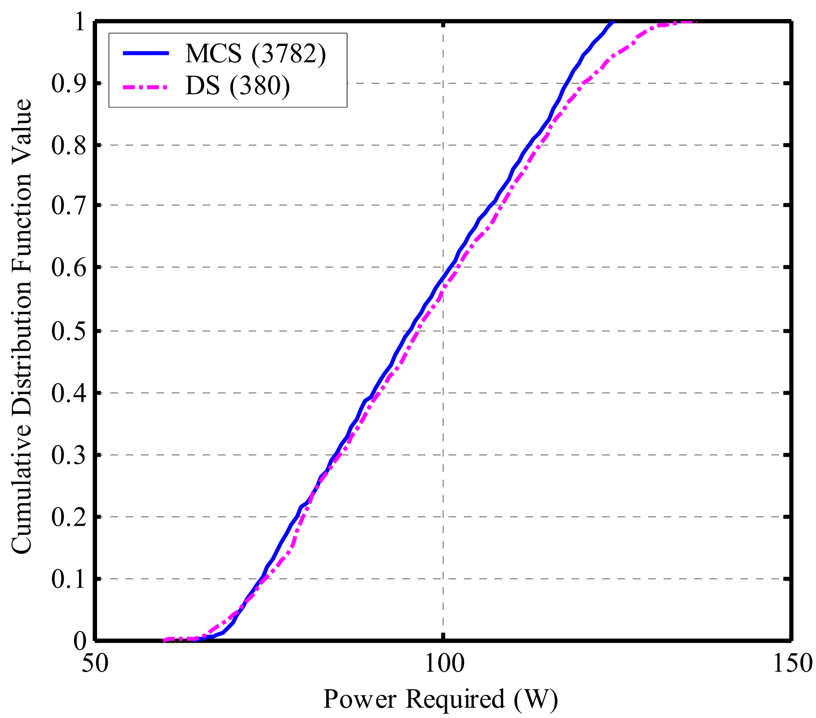

Fig. B.26 Power required CDFs for MCS and DS.

Table B.18 summarizes the statistics for both simulation techniques at various percentile values for comparison.

Table B.18 Power required calculated by MCS and DS

Simulation technique (# of repetitions)	Power Required (W)					
	Mean	Median	90th percentile	99th percentile	99.9th percentile	99.99th percentile
MCS (3782)	97.3	96.9	120.1	130.3	134.7	138.0
DS (380)	97.2	96.2	120.4	130.4	134.7	134.7

B.2.2.4 Schedule Duration

The PDF and CDF of the schedule duration are provided in Fig. B.27 and Fig. B.28, respectively.

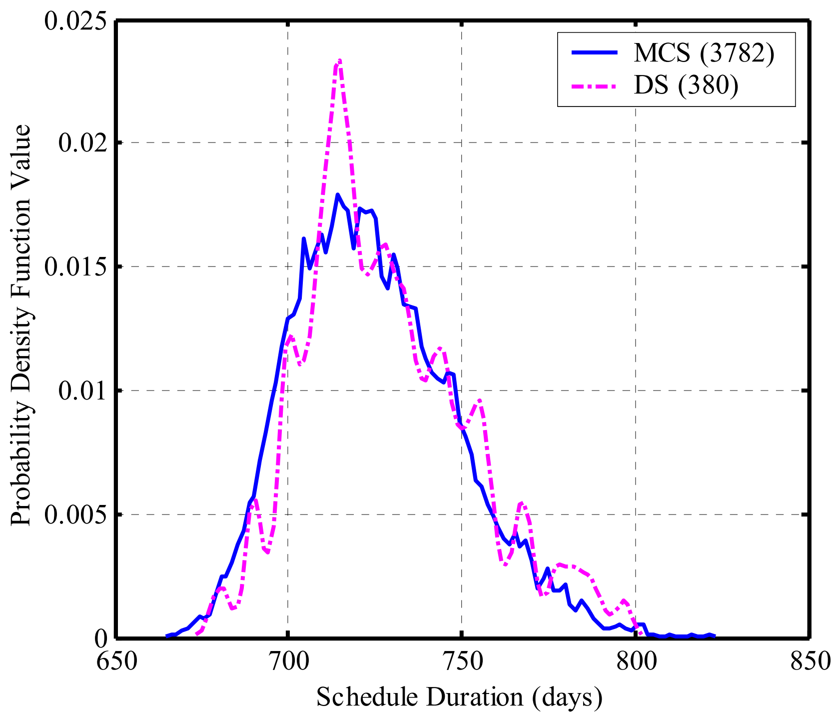

Fig. B.27 Schedule duration PDFs for MCS and DS.

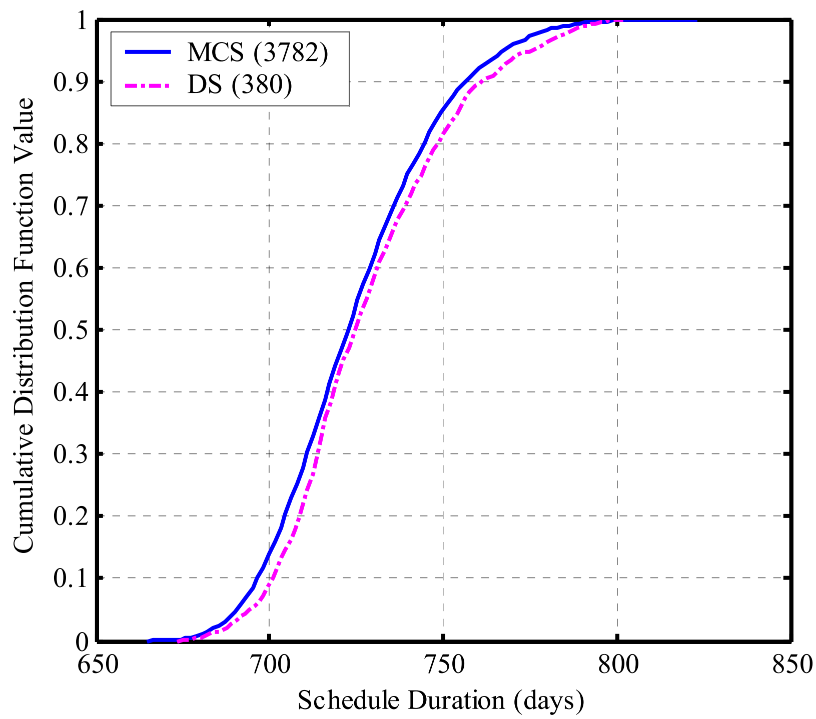

Fig. B.28 Schedule duration CDFs for MCS and DS.

Table B.19 summarizes the statistics for both simulation techniques at various percentile values for comparison.

Table B.19 Schedule duration calculated by MCS and DS

Simulation technique (# of repetitions)	Schedule Duration (days)					
	Mean	Median	90^{th} percentile	99^{th} percentile	99.9^{th} percentile	99.99^{th} percentile
MCS (3782)	726.1	723.8	757.3	786.9	804.5	821.2
DS (380)	728.4	724.4	761.0	791.4	797.8	797.8

B.2.2.5 Total Cost

The PDF and CDF of the total cost are provided in Fig. B.29 and Fig. B.30, respectively.

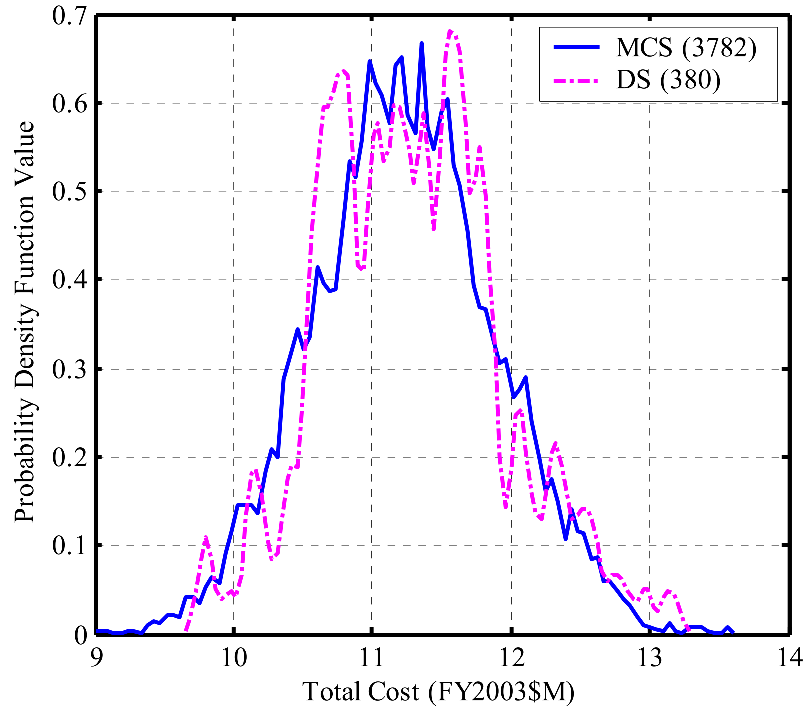

Fig. B.29 Total cost PDFs for MCS and DS.

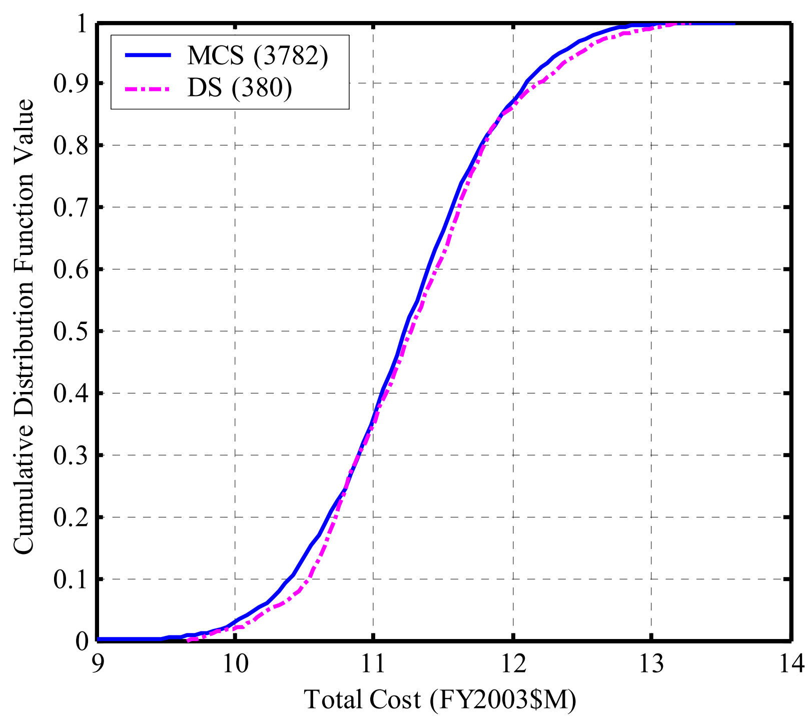

Fig. B.30 Total cost CDFs for MCS and DS.

Table B.20 summarizes the statistics for both simulation techniques at various percentile values for comparison.

Table B.20 Total cost calculated by MCS and DS

Simulation technique (# of repetitions)	Total Cost (FY2003$M)					
	Mean	Median	90th percentile	99th percentile	99.9th percentile	99.99th percentile
MCS (3782)	11.234	11.226	12.100	12.751	13.367	13.719
DS (380)	11.292	11.255	12.175	12.978	13.200	13.200

B.2.3 Margins and Analysis

With the probabilistic data (i.e., CDFs) available and assuming x = 99 percentile, Eq. (1.4) is used to determine margin values to hold at this point in the design (i.e., just before the preliminary design review in this example). This choice of x represents a risk-neutral decision maker. These margins are listed in Table B.21 for the maximum component temperatures and Table B.22 for the remaining tradable parameters.

Table B.21 Calculated (99th percentile) margin values for maximum component temperatures

Simulation technique (# of repetitions)	Maximum Component Temperature Margin in °C (Margin %[a])			
	REM	Battery	SDST	SSPA
MCS (3782)	5.6 (1.9%)	5.6 (1.9%)	5.4 (1.9%)	5.1 (1.7%)
DS (380)	5.8 (2.0%)	4.5 (1.6%)	5.9 (2.0%)	5.8 (1.9%)

[a]based on absolute temperatures in K

Table B.22 Calculated (99th percentile) margin values for mass, power required, schedule duration, and total cost

Simulation technique (# of repetitions)	Tradable Parameter Margin (Margin %)			
	Mass	Power Req.	Sch. Duration	Total Cost
MCS (3782)	2.2[a] (7.4%)	32.8[b] (33.6%)	76.5[c] (10.8%)	1.5[d] (13.7%)
DS (380)	1.9[a] (6.7%)	32.9[b] (33.8%)	77.9[c] (10.9%)	1.7[d] (15.0%)

[a]kg; [b]W; [c]days; [d]FY2003$M

The allocation values (best estimate + margins) for both simulation techniques are presented in Table B.23 for the four maximum component temperatures along with assumed project allocations and final actual values obtained from flight data.

Table B.23 Comparison of assumed and calculated (99th percentile) maximum temperature allocations with actual values

Simulation technique (# of repetitions)	Maximum Component Temperature Allocation in °C			
	REM	Battery	SDST	SSPA
Project assumptions (n/a)	50	10	50	50
MCS (3782)	22.5	22.4	22.2	32.9
DS (380)	22.8	21.2	22.7	33.6
Mission actuals (n/a)	19.6	22.5	19.6	32.5

Table B.23 illustrates that the current method (project assumptions) were conservative for the REM, SDST, and SSPA maximum temperatures compared to actual mission values. This conservatism was likely the result of a worst-case on top of worst-case on top of worst-case type analyses that resulted in additional resources being expended to over design and develop a more thermally robust system than required. The current method failed in predicting the battery temperature which may have increased the possibility of battery failure. The proposed method (both MCS and DS) predicted all four temperatures to within a few degrees.

The allocation values (best estimate + margins) for both simulation techniques are presented in Table B.24 for the four remaining tradable parameters along with assumed project allocations and final actual values obtained from pre-launch/flight/project data.

Table B.24 Comparison of assumed and calculated (99th percentile) mass, power required, schedule duration, and total cost allocations with actual values

Simulation technique (# of repetitions)	Tradable Parameter Allocation			
	Mass	Power Req.	Sch. Duration	Total Cost
Project assumptions (n/a)	36.2 kg	104.0 W	770 days	12.5[a]
MCS (3782)	31.4 kg	130.3 W	787 days	12.8[a]
DS (380)	31.2 kg	130.4 W	791 days	13.0[a]
Mission actuals (n/a)	29.1 kg	93.1 W	749 days	12.8[a]

[a]FY2003$M

Table B.24 illustrates that the current method (project assumptions) was conservative with mass compared to the final measured subsystem mass, allocating 7 kg that never materialized. The proposed method (MCS and DS) was more accurate with respect to this tradable parameter. On the other hand, the proposed method was more conservative with respect to power and schedule duration. The overshoot by the proposed method for power required can be explained by the uniform distributions assumed for the number of heaters on. If a more operationally realistic distribution was used, the proposed method would likely result in closer prediction to actual mission values. The proposed method overestimated schedule durations where the actual final schedule duration was an ~85th percentile value indicating the decision maker could have been more risk-seeking with respect to this tradable parameter. The current method slightly underestimated the total cost whereas the proposed method (both MCS and DS) accurately predicted it. Cost was traded for schedule during the actual MER thermal design which accounts for the current method predicting the schedule more accurately and the cost less accurately than the proposed method.

Lastly, a sensitivity analysis and calculation of correlation coefficients can be performed to investigate which uncertainties are driving the total uncertainty. This is illustrated in Table B.25 and Fig. B.31 for the total cost.

Table B.25 Most statistically significant correlation coefficients (*p*-values < 0.0001) for total cost

Input Variable Uncertainty	Correlation Coefficient	*p*-Value
Burden factor	+0.8166	0.0000
Integrated pump assembly (IPA) cost	+0.3501	0.0000
Design engineer salary	+0.2800	0.0000
Cruise-stage HRS[a] technician salary	+0.1419	0.0000
Cognizant engineer salary	+0.1186	0.0000
GSE[b] engineer salary	+0.1147	0.0000
IVSR[c] engineer salary	+0.0995	0.0000
Inflation rate	+0.0890	0.0000
Thermal systems engineer salary	+0.0742	0.0000
GSE[b]/ATLO[d] technician salary	+0.0721	0.0000

[a]HRS = heat rejection system; [b]GSE = ground support engineering; [c]IVSR = IPA, vent, shunt limiter, & radiator; [d]ATLO = assembly, test, & launch operations

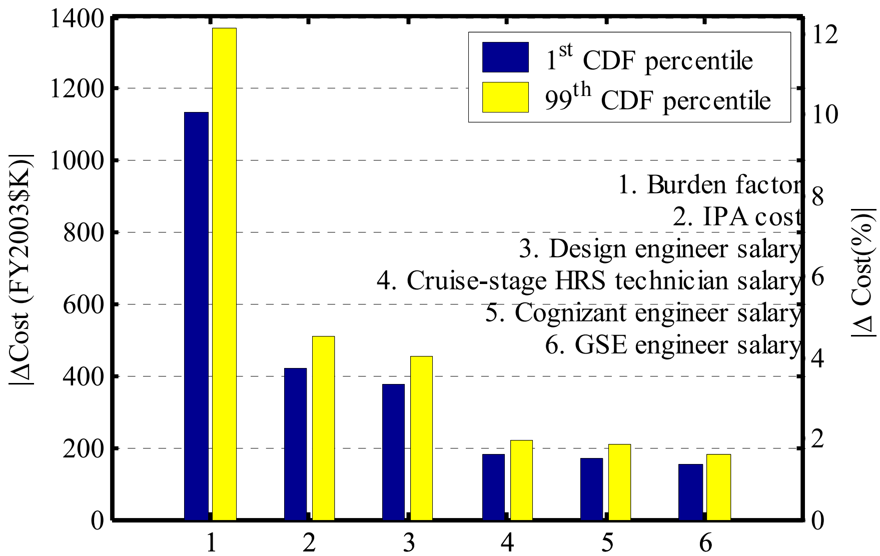

Fig. B.31 Top six uncertainties driving total cost.

Table B.25 and Fig. B.31 are remarkably similar: the top six uncertainties calculated via a sensitivity analysis are the top six most statistically significant uncertainties. Although there are usually similarities between a sensitivity analysis and correlation coefficient calculations, it is rare that the order of uncertainties is identical. This identical ordering likely confirms that the uncertainties listed are clearly the most significant. Incidentally, 27 schedule and cost input variable uncertainties were found to have a *p*-value less than or equal to 0.05 indicating many input variable uncertainties drive the total cost.

B.3 Mission Design

Elements of the proposed method were applied to space system mission design [Thunnissen, 2004b]. Mission design is not a traditional space system discipline since it is not a physical subsystem with explicit margins. Instead mission design is analysis and agreements with disciplines and other organizations. Nonetheless, uncertainty is a big driver in decisions made in mission design and many of the themes and techniques in the proposed method would be applicable and useful to use for this discipline. Application to other subsystems such as power, telecommunications, and structures was considered but not investigated in any significant detail. The three subsystems investigated along with mission design are representative in complexity, the number of uncertainties, and the types of uncertainties of all subsystems. Hence, it is likely the proposed method would perform satisfactorily when applied to these other spacecraft subsystems but this remains a topic for further research.

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Appendix C Implementation

This appendix provides a short step-by-step list an organization could follow if there is interest in implementing the proposed method for a complex multidisciplinary system that organization designs and/or develops. An overview of a general three-step plan for implementation is first discussed. A description of detailed steps for implementation follows.

C.1 General Implementation

A three-step plan for implementation is recommended to reduce the amount of resources initially required by the organization implementing the proposed method, boost the confidence participants have in the proposed method, and reduce the possibility of unsuccessful implementation.

1. Apply the proposed method to one subsystem or major assembly (application) in conjunction with the current historical/heuristic margin determination methods the organization assumes. Based on the results, hold the maximum of the two margins for each tradable parameter during the duration of design. If unsuccessful, revise those elements of the proposed method that were unsuccessful. At this early stage the application serves to corroborate the proposed method.
2. If Step 1 was successful, apply the proposed method to multiple subsystems or an entire complex multidisciplinary system in conjunction with current historical/heuristic margin determination methods the organization assumes. This step may lead to margins and results beyond the obvious and the familiar. Based on the results, decide on which of the two margins for each tradable parameter to use for the duration of design. If unsuccessful, revise those elements of the proposed method that were unsuccessful. Here the theory and the application of the proposed method corroborate each other mutually.
3. Beyond the first two steps lies the possibility of real success: genuine prediction of margins via the proposed method. If applications of the proposed method have been successful thus far, apply it to an entire complex multidisciplinary system in lieu of current historical/heuristic margin determination methods. Re-apply the proposed method as the design progresses to update margin values. Other methods that have been successfully developed and implemented in design have gone through similar successive phases of evolution.

C.2 Specific Implementation

The following section provides the specifics to implementing the proposed method. Each step should require management approval before the next step commences. The purpose of this management approval is twofold. First, it illustrates management interest and support of participants in the proposed method. Second, since program management and system engineering are intertwined with the proposed method, it provides management accountability for implementation to the stake holder. This section expands upon a similar step-by-step description provided in Chapter 3.

C.2.1 Motivation for Participants

The first step involves motivating the participants as to the benefit of the proposed method over the current heuristic method of determining margins. Motivation is described and examples are provided in Chapter 1. Organizations will probably have additional internal motivating examples from their design history. These internal examples will likely be of more interest to the participants than the examples in Chapter 1. During this phase the organization should also devise and institute reward schemes for employees based on successful learning and application of method. In addition, with respect to addressing uncertainties, Fischhoff (1990) urges organizations to "create (and demonstrate) an incentive structure that rewards experts for saying what they really believe, rather than for exuding confidence, avoiding responsibility, generating alarm, or allaying fears." Reward systems in organizations encourage confidence and boost morale.

C.2.2 Training System and Subsystem Engineers

With the participants properly motivated, system and subsystem engineers must be trained in uncertainty types, mathematical techniques, and expert elicitation techniques used in the proposed method. Uncertainty classifications and definitions are provided in Chapter 2. Probabilistic methods and other mathematical techniques used in this thesis are summarized in Appendix A. Mathematical and other references are found at the end of this thesis. Expert elicitation and other techniques to address uncertainty are described in Chapter 5 and Chapter 6. Participants should also understand the examples provided (Chapter 9 and Appendix B) at this stage.

C.2.3 Allocation of Workforce

The decision maker must allocate workforce to implement the proposed method. One or more analyst/facilitators (A/Fs) are required in addition to subsystem (discipline-specific) experts. A documentarian is recommended the first few times the method is applied to record success and issues in implementing the proposed method. Secondary analysts to assist subsystem engineers in developing front-end to models, assessing model uncertainty, and so forth may also be required. A clear organizational structure illustrating each participant (including the decision maker and stake holder) should be made available to all participants. Workforce allocated should be chosen from the pool of trained employees (see previous step).

C.2.4 Apply Method

With motivation, organization, training, and the allocation of workforce for applying the proposed method complete, the actual method can be applied.

C.2.4.1 Identify Tradable Parameters

Identify the number and characteristics of the tradable parameters for the complex multidisciplinary system. This step determines to a significant degree the amount of effort that will be required in subsequent steps. Hence, the tradable parameters selected should be peer reviewed before progressing to the next step. Identification of tradable parameters is described in Chapter 4.

C.2.4.2 Generation and Use of Analysis Models

For each tradable parameter, one or more models must be selected. Models may either exist from previous projects or require development and/or modification specifically for the complex multidisciplinary system being designed. In either case, model uncertainty for each of these models must assessed via existing data, expert elicitation, and/or Bayesian techniques. This step is described in Chapter 5. If preliminary design effort reveals that model uncertainty is significant, it is possible that phenomenological uncertainty is the culprit. Ways to reduce phenomenological uncertainty are also described in Chapter 5. If appropriate models must be generated or require significant modification, this step may well be the most resource consuming.

C.2.4.3 Investigate Other Uncertainties

Uncertainties in the input variables to each tradable parameter model are then addressed. As with model uncertainty, these uncertainties can be assessed via existing data, expert elicitation, and/or Bayesian techniques. Identification and addressing of these uncertainties is described in Chapter 6.

C.2.4.4 Decide on One or More Simulation Techniques

The decision maker, possibly in conjunction with the A/Fs, must decide on one or more simulation techniques to use in addressing uncertainty interaction. Certain simulation techniques may be appropriate early in design, others late in design. The choice and number of simulation techniques investigated will likely be a function of resources available. This step also requires determining how many repetitions are required to assess accuracy in tradable parameter uncertainties. Simulation techniques are described in Chapter 7.

C.2.4.5 Determine Margins, Analyze Results, and Iterate

With the probabilistic results available from one or more simulation techniques, the margin values can be determined. The proposed method may want to be re-applied as design progresses and uncertainties in models and/or input variables to those models have changed. The first application of the proposed method will be the major up-front time commitment. Subsequent iterations in applying the method will require substantially less time. If an analysis into which sampling technique worked best for the application of interest (see previous step), that simulation technique could be used in future iterations to save resources. Determining margins, analyzing results, and iteration is described in Chapter 8.

C.2.5 Revise Method and Reward Participants

Based on individual organizational preferences, issues, and comparison with other applications, the method may want to be revised by the participants. With the design complete, the final step in implementing the proposed method should be rewarding participants based on the reward schemes devised (described earlier).

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