Optimization of complex multidisciplinary designs under uncertainty via simulated annealing

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OPTIMIZATION OF COMPLEX MULTIDISCIPLINARY DESIGNS UNDER UNCERTAINTY VIA SIMULATED ANNEALING

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Abstract

The objective of this research is to develop a method that combines a multi-objective multidisciplinary design optimization algorithm with a method for propagating and mitigating uncertainties. Simulated annealing is chosen as the multidisciplinary design optimization algorithm and a probabilistic method is implemented to handle uncertainties via Monte Carlo simulation.

A multi-objective simulated annealing algorithm is implemented and evaluated on a representative test problem. Separately, a probabilistic uncertainty method is implemented and applied to the Ship Tracking and Environmental Protection Satellite conceptual-design problem. The next step applies a deterministic simulated annealing algorithm to the design problem. Finally, the simulated annealing algorithm is combined with the probabilistic uncertainty method and is applied to the design problem.

In addition to developing a novel simulated annealing under uncertainty method, this thesis provides three additional principal contributions. The first is an implementation of multi-objective optimization under uncertainty. This research also represents the first application of a method for quantifying and mitigating uncertainties to a system-level satellite model. Finally, a novel method for deriving a composite solution from a subset of leading solutions provided by the algorithm is also introduced.

The composite solution is then compared to solutions obtained from a baseline study performed using concurrent engineering methods, a deterministic multi-objective simulated annealing algorithm, and the single best solution of the investigated method. The investigated method provides a better solution than the

baseline at median confidence levels; however, at higher confidence levels the baseline solution is superior. The composite solution of the investigated method is superior to the single best solution at all confidence levels. Similarly the composite solution yields a superior result compared to the deterministic simulated annealing solution.

1. Introduction

The purpose of this research is to integrate a method for determining and mitigating uncertainties with a multidisciplinary design optimization (MDO) algorithm to create an improved method for determining optimal designs for complex multidisciplinary systems. The complex multidisciplinary system application presented in this thesis is a satellite. Early-stage design concepts are often plagued with uncertainties that can at best be dealt with in an inconsistent manner if dealt with at all. Although MDO algorithms for satellite design are currently in use [Jilla & Miller, 2004], they fail to incorporate methods of quantifying uncertainties. The end result is a design which may be theoretically optimal, but will almost certainly not correlate to the final system once it has been built. By incorporating a method quantifying and propagating uncertainties with an MDO algorithm, it is hoped that a method can be developed which will not only determine a theoretical “optimal” design for a complex multidisciplinary system but also do so in a way that will account for uncertainties in a quantifiable and repeatable manner and provide solutions that are robust to uncertain conditions.

1.1. Background

Engineering design is the process followed to develop and build systems that satisfy customer needs and requirements. This process comprises a sequence of steps, the first of which is a statement of requirements that the system must fulfill. Subsequently, engineers explore possible options in effectuating a system that meets these requirements, culminating in a conceptual design. A detailed design follows where engineering drawings or schematics and other documentation outlining the technical specifications of the design are produced. This then leads to the building and testing of the system and finally providing the system to customers [Pahl & Bientz, 1996]. In

this research, the focus is on the conceptual design phase of this process since mitigating problems that could arise from uncertainties at an early stage tends to be of greater benefit.

In complex multidisciplinary system design, such as in the design of a satellite, numerous engineers must work individually on separate subsystems, which are often themselves complex, and further collaborate on the integration of those subsystems to develop a complete satellite system. However, due to the complicated nature of the design process, developing efficient designs can be difficult as the resources at the disposal of engineers are often insufficient for exploring the large number of possible designs. As such, designs that are implemented frequently can at best be described as feasible, but rarely is “optimality” achieved. In engineering, an optimum design can be defined as the point at which any stated objectives (quantified by a variable value) can no longer be improved without reducing any competing objectives [Jilla, Miller, & Sedwick, 2000]. Consider as an example a satellite design which seeks to maximize payload capability (e.g., resolution for an imaging satellite) and simultaneously minimize cost. An optimum design is achieved when cost can no longer be reduced without reducing payload capability or vice versa. This example is an oversimplification of the problem as generally complex designs seek to optimize a large number of objectives. As a consequence, rarely is there a single optimal solution but rather a set of optimal solutions which include tradeoffs in the various parameters sought to be optimized. These sets of solutions are more commonly known as Pareto sets named after the economist Vilfredo Pareto who formalized the concept [Pareto, 1906]. Thus, the challenge for engineers is to arrive at designs that can achieve such optima and subsequently select the design which is deemed to best suit their purposes.

Multidisciplinary design optimization algorithms provide a solution to this problem. Simply put, these algorithms provide a formal method, conveyed in a series of steps, which can more fully investigate the nature of the entire solution space and determine those design architectures belonging in the Pareto set. Multidisciplinary design optimization algorithms have been successfully employed since their inception in a variety of fields [Geman & Geman, 1984; Haneishi et al., 1990; Brooks, Iyenger, & Rai, 1998; Schoonover, Crossley, & Heister, 2000; Hassan, Cohanin, & de Weck, 2005]. Application of such algorithms to satellite design problems is challenging due to the complex nature of these systems coupled with the large number of parameters that are required for even a simple satellite model. Recent work has nonetheless demonstrated the viability of such algorithms in determining good solutions to such problems [Jilla, Miller, & Sedwick, 2000; Mosher, 1999].

Simulated annealing is a specific MDO algorithm that will be focused on in this thesis. Developed by Kirkpatrick, Gelatt, and Vecchi in 1983, it was initially conceived to solve a circuit layout design problem. Since then it has been used on satellite design problems initially as a single-objective optimization algorithm [Jilla, Miller, & Sedwick, 2000] and later as a multi-objective optimization algorithm [Jilla & Miller, 2004].

Uncertainty analysis in satellite design has a relatively short history as an area of research. Interest in the topic has been born out of a history of projects that run behind schedule or are over budget, indicating that the current methods for handling uncertainties in the design process are inadequate [Thunnissen, 2005]. A proper treatment of uncertainties is thus seen as a critical component in improving the design process. Current treatment of uncertainties in satellite design centers heavily around the application of margins. Margins can be defined as the variation in parameters

measured relative to current “best-estimate” values [Thunnissen, 2005]. Typically these margins are determined heuristically or based on historical data. The application of margins possesses a number of drawbacks, among which is the fact that they are applied to deterministic designs *ex-post facto* and they incur a bias in their determination. In particular the application of historical data requires the determination of *representative* systems [Thunnissen, 2005] where the definition of *representative* is wholly subjective. As an example, consider mass margins which are often applied based on a mass category of a satellite. A satellite may be placed in a specific class based on it fitting within a certain range of masses. However one might classify a satellite by a number of other criteria (e.g., earth-orbiting, interplanetary, communications, scientific, constellation) where data based on historically *representative* satellite could differ enormously. Consequently, a formal method for propagating and mitigating uncertainties is desirable.

Optimization under uncertainty (OUU) seeks to unify MDO methods such as simulated annealing with methods for quantifying and propagating uncertainties. A number of different approaches exist to achieve this goal. The most common approach involves performing a single run of an MDO and performing uncertainty analysis for each point the MDO evaluates. An alternate approach to this method involves generating samples of Pareto fronts. This alternate approach involves optimizing with respect to a sampled set of uncertainties and repeating the process a fixed number of times, thus generating a number of Pareto fronts corresponding to varying uncertainties. With an increasing number of iterations one would expect that the better solutions would be more robust to uncertain conditions.

The Ship Tracking and Environmental Protection Satellite (STEPS) project serves as the application for the method developed in this thesis. The STEPS system is a

maritime-reconnaissance satellite with requirements provided by the Defense Science Organization National Laboratories of Singapore. The purpose of STEPS is to provide the ability to track and identify ships passing through the Strait of Malacca and to monitor for possible environmental problems such as oil spills. Due to the wide range of objectives and the complexity of satellite in general, numerous uncertainties are associated with such a design problem making it a very suitable candidate for research of this nature.

1.2. Objective

The objective of this research is to develop a method that combines a multi-objective MDO algorithm with a method for propagating and mitigating uncertainties. This new method is then to be applied to a conceptual-satellite design problem. Although methods for performing OUU exist [Giunta et al., 2004], application to the field of satellite design has only begun in the last few years by a handful of researchers [Hassan & Crossley, 2004; Martin & Simpson, 2006]. The desire is therefore to demonstrate a novel method for performing OUU on a satellite model, representative down to the component level, via multi-objective simulated annealing.

1.3. Motivation

The primary reason for pursuing this research is to improve theoretical designs that will more closely correlate to the final real-world product. Since many MDO algorithms currently do not include uncertainties in the variable space, these algorithms fail to consider a critically important aspect of the design process. It is comparable to attempting to create an optimal design of a system at an early stage while completely neglecting an entire subsystem of the design. The method outlined in Thunnissen (2005) provides a technique that allows an accurate determination of

uncertainties that has been shown to correlate well with final real-world designs. Additionally, this method has the potential to be successfully integrated with current MDO algorithms. In doing so it is hoped that this improved optimization algorithm will more fully represent the design variable space and as a consequence yield optimized conceptual designs that more readily translate from paper to a tangible product.

Beyond the obvious reason of improving real-world correlation with theoretical design, developing such a method would yield numerous other advantages. Incorporating the method in Thunnissen (2005) may prove to help reduce the risk in the final design. The statistical analysis incorporated by the method in Thunnissen (2005) helps determine the most likely range of values a variable can take and assigns it a probability density function (PDF). Subsequent determination of the corresponding cumulative distribution function (CDF) of the outputs of interest allow designers to control more precisely how much risk is associated with a design by setting a bound on the confidence level of the CDF. Furthermore, by including the method in Thunnissen (2005) with an MDO algorithm it is likely that designs are exposed as being more or less efficient than might otherwise be indicated by current optimization algorithms. In other words, by ignoring uncertainties, certain non-optimal designs will erroneously be identified by an MDO algorithm as belonging to the Pareto set. The method presented in this thesis will not only improve the correlation of optimized designs with the real-world actualization of the design but additionally determine other designs belonging in the Pareto set that may not otherwise appear optimal or exclude designs that a deterministic MDO algorithm might mistakenly include as a result of not accounting for uncertainties.

There is also an intellectual motivation for pursuing this research. This thesis introduces a number of novel contributions: an innovative method for performing optimization under uncertainty, the first implementation of multi-objective OOU, a novel method for determining a proposed solution by compositing a number of top solutions, and the first application of a method for quantifying and propagating uncertainties to system-level satellite model. Table 1.1 provides a summary of the achievements on which this research is based, and also illustrates the evolutionary advancement of the research presented herein.

Table 1.1 Summary of OOU research

	Thunnissen et al.	Jilla et al.	Mosher	Hassan et al.	Martin et al.*	Magnin et al.
Optimization method						
Simulated annealing		✓			✓	✓
Genetic algorithms			✓	✓		
Multi-objective		✓				✓
Uncertainty analysis	✓			✓	✓	✓
Hierarchical model level						
Component	✓	✓		✓	✓	✓
Subsystem	✓	✓	✓	✓	✓	✓
System		✓	✓	✓		✓

* The work by Martin and Simpson reports a system-level model; however, only meets a subsystem level as defined in this thesis

1.4. Report Outline

This chapter introduced the background concepts for the method presented in this thesis and provided motivation for conducting this research. In Chapter 2 the various MDO algorithms are reviewed and a suitable algorithm (simulated annealing) is selected for implementation. A representative test problem is used to demonstrate the performance of the algorithm. A conceptual-design satellite-level model is developed based on the STEPS mission and is described in Chapter 3. In Chapter 4 uncertainty quantification and uncertainty propagation methods are reviewed and the selected

methods are applied to the satellite model. The application of a deterministic MDO algorithm to the STEPS model is treated in Chapter 5. Chapter 6 reviews various approaches for performing OUU and a novel approach is outlined and implemented. This novel OUU method is then evaluated on the STEPS model application and compares the results to those of Chapter 4 as well as a deterministic SA algorithm. Chapter 7 discusses directions for future work and provides conclusions of this research. Finally, appendices are included at the end of this thesis outlining each satellite discipline and the associated variables.

2. Multi-Objective Optimization

The application of optimization techniques has been well established in the aerospace industry for a variety of problems, particularly at the component level. On a satellite-system level, the applications have been more limited for two main reasons: the complexity of the design problem and the computational demand of the algorithms capable of providing solutions. The nature of the conceptual-satellite design optimization is complex as a result of four main factors: mixed variables (discrete and continuous), a discontinuous solution space, a non-convex solution space, and multiple-optimizing objectives. This chapter discusses various multidisciplinary design optimization (MDO) methods available and provides the rationale for the selected method. Subsequently the selected method is tested to ensure it performs well.

2.1. Multidisciplinary Design Optimization Methods Review

Numerous MDO methods already exist and have been applied in a wide variety of fields. Each possesses particular strengths and weaknesses in achieving different goals. Determining which MDO method is most suitable for this research is of critical importance as an improper choice could result in non-optimal designs, infeasible designs, or prohibitively lengthy computational time requirements. Furthermore, satellite-system design problems tend to be combinatorial, meaning that optimization algorithms meant to handle linear and continuous functions (e.g., gradient-based algorithms) are unable to determine solutions to the problem. The solution space for these complex systems also requires a large number of design to be analyzed. Hence, a computationally efficient algorithm that can fully explore the solution space without enumerating every possible solution is necessary. Additionally, the design space of

such problems is discontinuous with numerous local maxima existing. An algorithm that does not have a tendency to get trapped in a specific region is of utmost importance as the aim is to determine global optimal solutions. In the Ship Tracking and Environmental Protection Satellite (STEPS) application the MDO method must optimize the design with respect to three objectives: total cost, coverage time, and resolution. Having multiple optimization objectives adds another layer of complexity to the problem and requires the MDO method to be able to handle a multi-objective problem. The three MDO methods presented are simulated annealing, genetic algorithms, and particle swarm optimization. All three of these algorithms have a precedent in the literature of successful multi-objective applications. Other optimization approaches such as linear programming, integer programming, and gradient-based methods were not considered due to their inability to handle the diverse challenges posed by this sort of problem.

2.1.1. Simulated Annealing

Introduced by Kirkpatrick, Gelatt, and Vecchi in 1983, simulated annealing (SA) has been demonstrated as an efficient method for solving global optimization problems. The central concept is the analogy between the cooling of a material to minimum energy (annealing) in statistical mechanics with the minimization of an objective function in the optimization process. In the annealing process, molecules in the material have high energies at the initially-high temperature and move quickly through the material. As the material cools and crystallizes the movement subsides until, at a low temperature, the molecules have reached their ground energy and have achieved a minimum-energy configuration. By analogy the input parameters of an objective function behave much like the molecules exploring the solution space at the initial high temperatures. As the temperature decreases they tend to enter the minimum

energy configurations which represent the optimal solutions [Kirkpatrick, Gelatt, & Vecchi, 1983; Spall, 2003].

While initially applied to a circuit board layout problem [Kirkpatrick, Gelatt, & Vecchi, 1983], SA has found some application in the aerospace industry. Applications in aerospace have ranged from problems in aerodynamic shape design [Wang, Damodaran, & Lee, 2002] to interstellar trajectories [Axelrod, Guelman, & Mishne, 2002]. In conceptual-satellite design the SA algorithm has been demonstrated as effective method for determining good solutions [Jilla, Miller, & Sedwick, 2000]. Further research has developed an SA algorithm capable of determining the Pareto front in multi-objective design problems. Most notably, recent work in multi-objective satellite design by Jilla and Miller (2004) has successfully applied such a technique.

2.1.2. Genetic Algorithms

The idea of a genetic algorithm (GA) was introduced by Holland (1975). The principal concept involves simulating the evolutionary process where input parameters represent genes and the objective function represents the organism. Designs are then evaluated on their fitness which is a function of the output of interest. The algorithm is initialized with a randomly generated population of designs. Designs with high fitness levels are then mated to produce a new generation of designs. In theory, weak genes will yield weak designs, consequently removing them from the gene pool (i.e., the solution space) and strong genes will propagate resulting in improved designs. The algorithm terminates after a fixed number of generations or a predetermined fitness level has been achieved [Holland, 1975; Goldberg, 1989].

Application of GAs has, much like SA, covered a wide range of problems. Specific application in the aerospace industry has covered problems including inflatable space structures [Peng, Hu, & Ng, 2006], launch vehicles [Schoonover, Crossley, & Heister,

2000], and space-based life-support systems [Rodríguez, Bell, & Kortenkamp, 2006]. With regards to conceptual-satellite design, GAs have been successfully implemented, most notably by Mosher (1999). More recent work has successfully applied a multi-objective GA to the problem of conceptual-satellite design [Ferringer & Spencer, 2006].

2.1.3. Particle Swarm Optimization

Developed by Kennedy and Eberhart (1995), particle swarm optimization (PSO) attempts to simulate the behavior of groups of living organisms such as bees, birds, or schools of fish based on the precept of a collective intelligence. In nature swarms are observed to move in a particular direction when one part of the swarm determines a desirable path to follow. While the swarm as a whole explores in a general direction, individuals within the swarm may deviate slightly from that direction. In its implementation, design solutions are represented by individuals in the swarm and possess two attributes: position and velocity. The position represents the current design and the velocity represents the inclined motion of the design (i.e., the direction of exploration) [Kennedy & Eberhart, 1995].

Particle swarm optimization has been applied to a variety of problems and has found success in particular with problems containing a large number of continuous variables [Fourie & Groenwald, 2002]. Aerospace applications for this algorithm are fewer in number than either SA or GAs in part due to the recent development of this algorithm. Nonetheless, several examples of its successful application do exist in the literature including airfoil design [Ray & Tsai, 2004] and formation flying of satellite constellations [Hoskins & Atkins, 2005]. Specific application to conceptual-satellite design has been less successful. Direct comparison to GAs found that PSO performed less efficiently [Hassan, Cohanin, & de Weck, 2005]. This is possibly due to the fact

that the algorithm performs better on problems with continuous variables whereas satellite design problems tend to have large numbers of discrete variables. Multi-objective applications of PSO do exist, however the application to aerospace problems is limited in scope. The most relevant application has been to satellite formation design [Hoskins & Atkins, 2006] although no applications could be found in the literature specifically involving conceptual-satellite design.

2.1.4. Selected Multidisciplinary Design Optimization Method

Review of the various MDO methods seems to suggest that SA would be promising as it has been developed for multi-objective problems and successfully applied to a satellite design problem. Although, GAs also appear to be an effective method for solving this type of problem, this approach is left as an area of future work. Particle swarm optimization appears to be inappropriate for this application as it does not handle mixed-variable problems very well.

2.2. Multi-Objective Simulated Annealing Algorithm Description

Any optimization problem can be formulated as

$$\min y = G(\theta) \quad (2.1)$$

where y is the output parameter of interest, G is the objective function, and θ is the vector of input variables. In the case of multi-objective optimization this is simply reformulated as

$$\min \mathbf{y} = \mathbf{G}(\theta) \quad (2.2)$$

where in this case $\mathbf{y}$ is now a vector of output parameters of interest, and $\mathbf{G}$ is a set of objective functions. It should be noted that any maximization problem can be recast as a minimization problem simply by multiplying the right-hand side of Eq. (2.2) by -1.

As such, an optimization problem always refers to the minimization of the outputs without any loss of generality. Additionally, a multi-objective optimization algorithm cannot seek a single optimal solution like a single-objective optimization algorithm since different solutions may possess an advantage in only some of the outputs of interest. When comparing two solutions, if one solution is found to be better for every output of interest it is said to dominate the other solution. Otherwise the solutions are said to be Pareto-equivalent or optimal. As a result several solutions can simultaneously be considered optimal. This set of solutions is referred to as a Pareto set [Pareto, 1906]. The full algorithm is outlined in the following steps [Jilla & Miller, 2004]:

1. Choose an initial input vector θ_i and set an initial system temperature, T_i
2. Evaluate $G(\theta_i)$
3. Perturb θ_i to produce an input vector θ_{i+1}
4. Evaluate $G(\theta_{i+1})$
5. If $G(\theta_{i+1})$ is not dominated by any member of the Pareto set than it becomes the new input vector
6. If $G(\theta_{i+1})$ is dominated by a member of the Pareto set it is compared to the acceptance criterion and accepted with probability dependant on the system temperature, otherwise θ_i remains the input vector
7. Reduce system temperature according to a predefined cooling schedule
8. Increment i and repeat steps 3 through 7 until the predefined final system temperature has been reached

The subsequent sections discuss the cooling schedule of the algorithm, a detailed description of the perturbing function, and the acceptance criterion.

2.2.1. Cooling Schedule

A key aspect of the simulated annealing algorithm is the cooling schedule. As in the real-world annealing process, cooling too quickly can lead to sub-optimal results (i.e., a metal with inferior properties). On the other hand cooling too slowly unnecessarily increases the computational demand of the problem. A linear cooling schedule is used and given by

$$T_{i+1} = \lambda T_i \quad (2.3)$$

where T_{i+1} is the system temperature, λ is the cooling rate, and T_i is the current system temperature. The system is set at an initial temperature, T_0 . When T_{i+1} reaches the final system temperature, T_f , the algorithm halts. A cooling rate of 0.858 was used in this research which is very close to the value of 0.85 used by Jilla and Miller (2004) for two reasons: it allows for a sufficient number of function evaluations and has been shown to be effective with an optimization problem of this nature. The reason for the discrepancy between the number used by Jilla and Miller (2004) and in this thesis is that a value of 0.858 allows for a optimization run with exactly 150 function evaluations without compromising the efficacy of the algorithm. It should be noted that the term temperature is used as an analogy to the physical temperature in the annealing process. In simulated annealing, it is not a real temperature and does not have actual units as such.

2.2.2. Perturbation Function

Another crucial component of the simulated annealing algorithm is the perturbing function. The fundamental concept is that with every iteration, each parameter in the input vector is perturbed according to

$$\theta_{i+1} = \theta_i + H(a, b) \quad (2.4)$$

where a and b are the lower- and upper-bound constraints on the input parameter, θ , respectively, and H represents a perturbing function acting over the range of a and b . The perturbing function can significantly influence the performance of the algorithm and consequently is an area where further research could yield improvements in computation time. The binomial function was selected as the perturbing function in this implementation for the sake of simplicity as it is a discrete distribution. However, other functions could be substituted such as a uniform or normal distribution.

2.2.3. Acceptance Criterion

Another important aspect of the algorithm is the acceptance criterion. This is the step in the algorithm that determines whether a dominated solution is accepted and is given by

$$\chi \leq e^{-\Delta/\tau_i} \quad (2.5)$$

where χ is a random number generated from a uniform distribution over the range of 0 and 1. A non-optimal solution is accepted when the criterion of Eq. (2.5) evaluates as true. In traditional single-objective simulated annealing, Δ is simply the difference in the output values,

$$\Delta = G(\theta_{i+1}) - G(\theta_i) \quad (2.6)$$

In a multi-objective optimization, output values of interest such as cost and mass can differ by orders of magnitude (e.g., mass on the order of hundreds of kilograms and costs on the order of hundreds of millions of dollars). Consequently such direct comparisons do not yield meaningful results. An alternate method for computing Δ for multi-objective optimization problems proposed by Jilla and Miller (2004) is given by

$$\Delta = \frac{\sum_{j=1}^J \frac{G_j(\theta_{i+1}) - G_j(\theta_i)}{\delta_j}}{J} \quad (2.7)$$

In this approach δ_j represents the range of values $G_j(\theta_i)$ can assume and acts as a normalizing factor. The value, J , represents the number of outputs which are being optimized. Consequently a value for Δ can be taken by averaging the difference of the normalized outputs [Jilla & Miller, 2004].

Also of importance in the acceptance criterion is the initial temperature. Since the value in the exponent is inversely proportional to the temperature, the initial temperature level can significantly affect how the algorithm behaves both in its early and later stages. High values of T lead to higher acceptance rates for non-Pareto solutions rendering the algorithm more erratic (i.e., it behaves more randomly). Setting this value too high results in excessive computational time spent randomly searching the solution space. Conversely, setting this value too low makes the acceptance criterion too rigid. This prevents the solution space from being properly explored before the optimal areas are explored in greater depth, which can lead to certain Pareto-optimal designs being missed entirely. In this research initial temperatures ranging from 10000 to 0.0001 were explored.

2.3. Random Search Algorithm

In order to test the performance of the SA algorithm, a random search algorithm was used as a baseline measure. It can be safely assumed that if the SA algorithm is performing properly it should outperform a random search of the solution space. The random search algorithm is given in the following steps [Spall, 2003].

1. Choose an initial input vector θ_i where each variable within the vector is randomly selected subject to the boundary constraints

2. Evaluate $G(\theta_i)$
3. Choose a new input vector θ_{i+1} where each variable within the vector is subject to uniform distribution $U(a,b)$ where a is the lower bound on a given input parameter and b is the upper bound on a given input parameter
4. Evaluate $G(\theta_{i+1})$
5. Increment i and repeat steps 3 through 4 for a fixed number of iterations (e.g., 100 or 1000)

2.4. Test Function

The test function selected was originally proposed by Viennet, Fonteix, and Marc (1996). It was selected since it possesses a number of properties which are representative of conceptual-satellite design: it is a multi-objective problem and the solution space is both non-convex and discontinuous. Additionally, the problem has been used extensively as a test problem and is considered fairly challenging for an optimization algorithm to fully characterize the entire Pareto front. The function is given as follows:

$$\begin{aligned}
 G_1(\theta_1, \theta_2) &= 0.5(\theta_1^2 + \theta_2^2) + \sin(\theta_1^2 + \theta_2^2) \\
 G_2(\theta_1, \theta_2) &= \frac{(3\theta_1 - 2\theta_2 + 4)^2}{8} + \frac{(\theta_1 - \theta_2 + 1)^2}{27} + 15 \\
 G_3(\theta_1, \theta_2) &= \frac{1}{(\theta_1^2 + \theta_2^2 + 1)} - 1.1e^{(-\theta_1^2 - \theta_2^2)}
 \end{aligned} \tag{2.8}$$

subject to the constraints,

$$\theta_i : -3 \leq \theta_i \leq 3, \quad i = 1, 2 \tag{2.9}$$

For the purposes of testing the algorithm, the test function is discretized and the solution space subsequently fully enumerated. The step size was set at 0.05 yielding a solution space with 14641 possible solutions of which 254 are Pareto optimal. Figures 2.1 and 2.2 illustrate the Pareto solution space of the input vector and Pareto solution space of the output vector, respectively.

Fig. 2.1 Test problem - true Pareto solution space (inputs)

Fig. 2.2 Test problem - true Pareto solution space (outputs)

2.5. Performance Analysis

In analyzing the performance of the SA algorithm various initial temperature values were tested. In order to ensure the algorithm consistently performs well it was run 50 times for each initial temperature. Similarly, the random search algorithm was also run 50 times to ascertain average performance. The final temperature for each set of solutions corresponds to $1/10000^{\text{th}}$ the initial temperature. This was done to keep the total number of function evaluations equal for each set of conditions. The total number of function evaluations for each run was 1440 which represents $\sim 10\%$ of total number of possible solutions. Table 2.1 provides the key results of the analysis.

Table 2.1 Performance analysis results for 1000 simulations

	Average Pareto-optimal solutions found	Standard deviation
Random Search	25	4
Simulated Annealing, $T_i = 10000$	25	5
Simulated Annealing, $T_i = 1000$	28	7
Simulated Annealing, $T_i = 100$	33	13
Simulated Annealing, $T_i = 10$	45	16
Simulated Annealing, $T_i = 1.0$	59	24
Simulated Annealing, $T_i = 0.1$	69	16
Simulated Annealing, $T_i = 0.01$	76	12
Simulated Annealing, $T_i = 0.001$	77	13
Simulated Annealing, $T_i = 0.0001$	74	14

As can be seen in Table 2.1, at high temperatures the simulated annealing algorithm performs on par with the random search and improves as the initial temperature is reduced. However, reducing temperature ceases to provide significant benefits beyond $T = 0.01$. These results are consistent with the theory that the algorithm is more erratic at higher temperatures and hence more random in its search. The random search provides ~10% of the Pareto solutions after searching ~10% of the solution space. In comparison, the simulated annealing algorithm at $T_i = 0.01$ provides approximately 30% of the Pareto solutions by searching only 10% of the solution space. This represents a threefold improvement over the random search algorithm. The results from a representative run (i.e., average number of Pareto solutions found) are shown in Figs. 2.3 and 2.4 for the Pareto solution space of the inputs and those of the outputs, respectively.

Fig. 2.3 Estimated Pareto solution space (inputs) for $T_i = 0.01$ using SA (Run 7 of 50 where 76 true Pareto solutions were found)

Fig. 2.4 Estimated Pareto solution space (outputs) for $T_i = 0.01$ using SA (Run 7 of 50 where 76 true Pareto solutions were found)

Run number 7 of 50 is used for Figs. 2.3 and 2.4 since the number of Pareto solutions found corresponds to the average number of solutions found over all 50 runs. It should be noted that the number of data points in Figs. 2.3 and 2.4 do not correspond to the number of points found listed in Table 2.1. The reason for this is that the algorithm provides an estimate of the location of the Pareto front. Consequently, some of the points the algorithm estimates as Pareto-optimal points are in fact sub-optimal. The discrepancy lies in the sub-optimal points included in the estimated Pareto front in Figs. 2.3 and 2.4 whereas the points in Table 2.1 are limited to the true Pareto values. Comparing Figs. 2.1 and 2.2 with Figs. 2.3 and 2.4 it is clear that the Pareto front is not as fully formed; however, the SA algorithm was able to find points on all regions of the solution space and shows the general trend of the Pareto front.

3. Satellite & Mission Overview

The Ship Tracking and Environmental Protection Satellite (STEPS) is a conceptual design of a maritime-reconnaissance satellite performed over 10 weeks (May to July 2006) by ten primarily undergraduate students in the School of Mechanical and Aerospace Engineering at Nanyang Technological University, Singapore. The Defense Science Organization National Laboratories served as the “customer” for this project by providing requirements and direction [Loh et al., 2007]. This mission serves as the application for the algorithm presented in this thesis.

3.1. Satellite Overview

The general objectives of the mission include ship tracking, piracy detection, and environmental monitoring. The specific requirements include a design capable of observational windows on the Straits of Malacca at a minimum of 10 times a day. Other requirements driving the design include a mission duration of 3 years, an orbital altitude of less than 1000km, inclination in the vicinity of 0° , pointing accuracy of 0.5° , and a satellite position knowledge to within 20m [Loh et al., 2007].

3.2. Baseline Model Description

The STEPS design process was conducted using the integrated concurrent engineering (ICE) process. Physics-based models were developed for each subsystem in the STEPS design. Over 100 core equations, hundreds of sub-core equations, and ~500 parameters are used in total to represent the satellite. The full satellite system is subdivided into 11 different disciplines including mission design, systems engineering, cost analysis, and eight satellite-engineering subsystems. Table 3.1 lists these disciplines and provides an explanation of their function.

Table 3.1 Satellite disciplines; adapted from Thunnissen (2006)

Discipline	Description
Payload	Instruments and devices used to achieve the mission goals
Mission Design	Defines operating modes and mission phases; characterizes all aspects of launch and orbit; determines velocity changes necessary to achieve and maintain orbit
Propulsion	Provides forces and torques necessary to translate and/or rotate the satellite
Attitude Determination & Control System	Orients and stabilizes the satellite for specific events countering external and internal disturbances that act upon it
Telecommunications	Receives and transmits signals between the satellite and ground stations on Earth or other satellite
Command & Data Handling	Stores and processes commands and data
Power	Generates, conditions, regulates, stores, and distributes power throughout the satellite
Structures & Mechanisms	Supports and protects all other subsystems for all operating modes of the satellite in all of the expected mission phases; deploys components and/or separates from other elements during the mission
Thermal Control	Maintains all components of a satellite within their allowable temperature limits for all operating modes of the satellite and in all of the expected thermal environments
Systems Engineering	Computes margins and contingencies applicable to all subsystems; ensures mission objectives are achieved; liaison with customer
Cost	Estimates total cost of the satellite, launch, and all other costs associated with achieving and operating the mission

The disciplines listed in Table 3.1 are all strongly coupled to each other in typical conceptual-satellite design. This coupling complicates the interaction during the design process and creates competing demands to optimize individual subsystems at the expense of the total satellite [Loh et al., 2007].

3.3. Model Description

The model used in this analysis is based on the STEPS models created in Microsoft® Excel by the original STEPS team. Modifications are made to adapt the model for MATLAB® primarily because the statistical tools required for the analysis

are not available or readily implementable in Excel. The MATLAB® environment allows the development of smaller models of subsystems and even components which are developed in m-files (files containing sub-functions that can be called in the main model). Since the model is a recursive function it must be solved iteratively. Figure 3.1 illustrates the iteration loop of the model and the 11 satellite disciplines.

Fig. 3.1 Iteration loop for the STEPS model

The satellite discipline order in the iteration loop is based on how the disciplines interact. The iteration loop is said to converge when the difference in satellite dry mass from the previous iteration and the current iteration is less than a predefined quantity, termed the mass criterion. In this thesis, a function evaluation is defined as the evaluation of the model until convergence to within the mass criterion is achieved. In this research the mass criterion is set at 0.5kg. For any unforeseen cases where the model cannot converge to within the mass criterion, an artificial limit has been set of

15 iteration loops. This value was deemed sufficient for convergence for any of the payloads after some analysis was performed.

In the traditional ICE process, engineers monitor and adjust their subsystem models each iteration in order to ensure that their design decisions are, at a minimum, feasible. Due to the large number of iterations involved in the probabilistic and optimization analysis (due to the large number of samples and inherent iterative aspect of optimization), this sort of human interaction is impossible. Hence, an input vector is defined for each of the 11 disciplines where some of the inputs are fixed (known) values, some are uncertain, some are from other disciplines, and the remainder are optimizable. Additionally, many of the subsystems can select components from a database which returns values representing the selected components. Most of the simplifying assumptions made in the development of this model are justifiable since the application is for early-stage conceptual design at which point a rigorous analysis with detailed models is not performed. The primary goal of a conceptual design is to ascertain the feasibility of the mission within the constraints defined by the requirements and possibly to suggest promising design configurations worthy of further investigation. If successful, a conceptual design results in additional funding to produce a more detailed (preliminary) design where more resources (e.g., people, more sophisticated models, etc.) are made available. The procedure outlined in this research achieves both these goals. The following sections will describe the characteristics of the baseline STEPS design which was used as the application for the optimization under uncertainty algorithm.

3.3.1. Payload

The STEPS payload consists of a primary payload (i.e., multispectral imager, multispectral thermal imager, or synthetic aperture radar) and an automatic

identification system (AIS). The multispectral imager (MSI) mass is estimated based on scaling equations given in Wertz & Larson (1999) relating the assumed aperture diameter to an actual aperture diameter on a similar instrument used in the TOPSAT mission [Surrey Satellite Technology Ltd., 2001]. The multispectral thermal imager (MTI) mass is estimated in the same way, but is based on a characteristic payload provided in Wertz & Larson (1999). The resolution of the MSI and MTI are determined based on equations given in Wertz & Larson (1999). The synthetic aperture radar (SAR) resolution and power are calculated according to equations given in Curlander (1991), DiFranco & Rubin (1980), and Elachi (1987). The mass is calculated according to scaling equations given in Wertz & Larson (1999) and uses the RADARSAT-2 mission [Riendeau & Grenier, 2007] as a reference payload. In order to meet the revisits requirement an AIS is assumed to accompany the primary payload to permit ship verification. No scaling has been performed on the AIS which is assumed to perform according to the baseline specifications determined for the NCUBE mission [Otterstad, 2003].

3.3.2. Mission Design

The mission design discipline calculates the phase durations, velocity changes, and orbit characteristics. This discipline also selects the appropriate launch vehicle based on a programmed selection criteria. Simplifying assumptions include limiting the orbit to one that is circular with 0° inclination and representing the Earth as a perfect sphere. All orbit perturbations have been assumed constant over the lifetime of the mission and calculated under worst-case conditions. All calculations are based on equations in Wertz & Larson (1999). Eight mission phases are assumed and defined in Table 3.2 according to phase number.

Table 3.2 Phase descriptions

Phase number	Phase description
1	Launch
2	Orbit Insertion
3	Daytime Data Collection/Transmission
4	Daytime Silent Mode
5	Night-time Data Collection/Transmission
6	Night-time Silent Mode
7	De-orbit
8	Emergency Mode

During the different phases the satellite requires different levels of power, is subjected to changing thermal loads, and varying communication requirements.

3.3.3. Propulsion

The propulsion subsystem model determines propulsion specific component (e.g., filters, latch valves, thrusters, propellant/pressurant tanks, etc.) masses, propellant mass for orbital maneuvers, power requirements by phase, temperature tolerances, and required burn times for orbital maneuvers. The available types of propulsion systems have been restricted to a monopropellant-blowdown system, a monopropellant-regulated system, and bi-propellant regulated system. Simplifying assumptions made, involve fixing the propulsion system schematics (i.e., the quantity of each component used in a given propulsion system schematic is fixed). The calculations are based on Humble, Henry & Larson (1995) and Thunnisen, Engelbrecht, & Weiss (2003).

3.3.4. Attitude Determination & Control

This subsystem model determines attitude determination and control specific component (e.g., horizon sensors, sun sensors, star trackers, etc.) masses, propellant mass required for attitude control maneuvers, power requirements by phase, and

satellite pointing capabilities. Sun sensors are assumed due to the inclusion of a sun-tracking solar array (discussed in a subsequent section). An additional position sensor is assumed in the form of either a horizon sensor or a star tracker. To meet the satellite position knowledge requirement, a global position system (GPS) receiver is defined as a fixed component. A significant assumption with this subsystem is to model disturbance torques as time-independent. More thorough time-dependent dynamics equations are deemed too computationally expensive to solve for an early stage conceptual design problem. Calculations for this discipline are based on equations provided in Wertz (1978) and Wertz & Larson (1999).

3.3.5. Telecommunications

The telecommunications subsystem model determines telecommunications specific component (e.g., antennas, filters, duplexers, transmitters, etc.) masses, power requirements by phase, temperature tolerances, and pointing requirements based on equations given in Wertz & Larson (1999). Simplifying assumptions include the use of both a high-gain and a low-gain antenna. The high-gain antenna is assumed to be a dedicated antenna for data transmission, whereas the low-gain antenna provides the ability to communicate engineering telemetry with ground stations.

3.3.6. Command & Data Handling

The command and data handling (C&DH) subsystem model determines masses of the processor and solid-state recorder, power requirements by phase, temperature tolerances, and onboard data-storage capacity. A significant assumption affecting this discipline is that component selection is dependent on the required data rate and data-storage capacity. Below a threshold data rate, the processor is classified as simple requiring less mass and power. Above this threshold it is classified as complex, thus

requiring greater power and mass. Similarly, a solid-state recorder is classified as small or large depending on the data-storage requirement and a data-storage threshold. All calculations for this discipline are based on Wertz & Larson (1999).

3.3.7. Power & Pyrotechnic Devices

The power subsystem model determines power specific component (e.g., batteries, solar array, distributor, pyrotechnic charges, etc.) masses, battery capacities, solar-array area, and component temperature tolerances. It is assumed that a primary battery provides power during the phases 1, 2, and 7 whereas a secondary battery provides power during phases 5, 6, and 8. The solar arrays are assumed to be deployed with two degrees of freedom to allow for effective tracking of the sun with the aid of sun sensors. Mass of the pyrotechnic charges and the power distributor are modeled as uncertainties. All calculations performed are based on Wertz & Larson (1999) and Griffin & French (2004).

3.3.8. Structures & Mechanisms

The structures and mechanisms subsystem model determines structure masses, mechanism masses, power requirements by phase, and satellite-bus dimensions. A rectangular-box shape is assumed for the satellite bus. Structure masses are computed based on rules of thumb derived from previous satellite designs [Sercel, 2000]. Load calculations for the satellite bus are not performed as an adequate calculation would require a detailed analysis which is beyond the scope of conceptual design. Moment-of-inertia calculations are performed under the assumption that the bus mass is uniformly distributed, primarily because there was insufficient time to automate component configuration, which is a substantially complex problem.

3.3.9. Thermal Control

The thermal control subsystem model determines thermal specific component (e.g., radiator, louver, heaters, etc.) masses, radiator area, and power requirements by phase. View factors [Wertz & Larson, 1999] are assumed for each of the six satellite faces and energy balance computations are then performed. The model computes a worst-case maximum-satellite temperature and sizes a radiator to ensure that an energy balance is achieved. A similar calculation sizes the heaters for the worst-case-minimum temperature. Hence, a significant assumption in the thermal analysis is that the temperature of the satellite is analyzed only at specific extreme-case intervals of the orbit. A more rigorous analysis would require the development of a detailed heat transfer design model in a thermal-analysis software package which exceeds the scope of conceptual design. Additionally the inclusion of multi-layer insulation (MLI) is assumed.

3.3.10. Systems Engineering

The systems engineering model provides all the general purpose functions required in the iteration process. Before the iteration process is initiated all input values are converted to SI units (International System of Units), ensuring dimensional fidelity of all calculations. Additionally, the initialization process provides the model with a starting guess of the output values before iteration begins. The total dry, wet, and injected masses of the satellite are recomputed after every subsystem calculation and passed to the subsequent subsystem.

3.3.11. Cost

The cost model determines the final cost of the satellite. Cost estimating relationships (CER) are used to determine the cost based on the small-satellite cost

model [Wertz & Larson, 1996; Wertz & Larson, 1999]. In cases where more than one CER is provided to determine the cost of a subsystem, a weighted average is taken of all available CERs for the given subsystem where the weights are inversely proportional to the square of the standard error of the CER. The total deployment cost of the satellite includes the satellite cost, the cost of the launch vehicle, as well as supplementary costs such as contractor fees, ground station operations, integration, assembly, and testing. All cost calculations are made in US\$ for fiscal year 2007.

3.4. Subsystem Model Example

An in depth description of each discipline is prohibitive in this thesis. However, the power subsystem is presented as an example subsystem in the satellite model. The power subsystem represents a model of average complexity. The power model calls 14 MATLAB[®] sub-routines (m-files) and comprises approximately 500 lines of code, not including calls made to general systems-level functions. Its operation is separated into three main areas: solar-array sizing, primary-battery sizing, and secondary-battery sizing as shown in Fig. 3.1. A description of the primary-battery sizing will be detailed.

Fig. 3.2 Power subsystem model flowchart

The primary-battery sizing is performed by first determining the phase which drives the power requirements. It is the primary battery that provides power during phases 1, 2 and 7. The primary-battery model exemplifies multidisciplinary design well as this model requires various parameters from other disciplines (e.g., payload, mission, propulsion, structures and mechanisms) and, in turn, provides various parameters to other disciplines (e.g., cost, structures and mechanisms, thermal control). The energy requirements, E_{req} , of these three phases are determined from the combination of the total power required by all satellite disciplines during those phases and the actual duration of the phases:

$$E_{\text{req}} = P_1 t_1 + P_2 t_2 + P_7 t_7 \quad (3.1)$$

In this equation, P_i is the power requirement of the i^{th} phase and t_i is the duration of the i^{th} phase. The battery capacity, Q_b , can then be calculated from these two parameters taking loss factors into account:

$$Q_b = \frac{E_{\text{req}}}{\eta V_{\text{bus}}} \quad (3.3)$$

where the bus voltage, V_{bus} , is computed by the secondary-battery model and η is defined as

$$\eta = k_{\text{batt_to_dist}} k_{\text{dist_to_load}} \quad (3.4)$$

and includes various conversion inefficiencies between the battery and the loads such as; the loss from the battery to the distributor, $k_{\text{batt_to_dist}}$; and the loss from the distributor to the load, $k_{\text{dist_to_load}}$.

The final steps for the primary-battery model involve computing the total mass and dimensions of the primary battery. The mass and height are computed according to

$$m_b = \frac{E_{\text{req}}}{\eta e_b} \quad (3.5)$$

and

$$h_b = \left(\frac{E_{\text{req}}}{2\eta \varepsilon_b} \right)^{1/3} \quad (3.6)$$

respectively, where the specific energy e_b and energy density ε_b of the primary battery are extracted from the product database based on the type of primary battery selected. The ratio of the battery dimensions is assumed to be 1:1:2 for the height (h_b): length (l_b): width (w_b). The type of battery also determines the temperature requirements which are needed by the thermal control discipline. The primary-battery sizing process is presented graphically in Fig. 3.2. The physics-based equations that govern these calculations, as well as the calculations for the solar array and secondary battery, are provided in Wertz & Larson (1999) and Griffin & French (2004). Similar procedures are followed for the solar array and the secondary battery.

Fig. 3.3 Primary-battery model flowchart

4. Uncertainty Method Application

Uncertainty can be defined as the difference or variation between an expected value and the true value. While significant work has been done in the estimation and propagation of uncertainties in satellite design, no work has yet been performed on a complete satellite model comprising all major disciplines at a consistent fidelity (component level). This chapter addresses this new area and begins by discussing the uncertainties considered in this study and the approaches for quantifying and propagating uncertainties. With methods selected for performing the necessary uncertainty analysis, a detailed examination of the uncertainties handled in the Ship Tracking and Environmental Protection Satellite (STEPS) power-subsystem model (continuing with an in-depth example subsystem) follows. Finally, the results of the uncertainty analysis of the conceptual-satellite design are presented, analyzed, and compared to the STEPS baseline case described in Loh et al. (2007).

4.1. Uncertainty Quantification Methods Review

The first step in performing any type of uncertainty analysis is to quantify the uncertainties. The methods examined for quantifying uncertainties are heuristic methods, probability theory, fuzzy sets, and evidence theory.

4.1.1. Heuristic Methods

Current methods for handling uncertainties in conceptual design involve applying design margins to a deterministic estimate, usually determined via physics-based models. Mathematically such a model can be represented by the equation,

$$y = G(\theta) \tag{4.1}$$

where θ represents the input vector and y represents the output vector which is determined by the set of objective functions G , which represent the physical relations between the inputs and the outputs (i.e., the physics-based model or models). The input variables in this approach are considered to be deterministic with margins applied *ex-post facto*. Standards such as the American Institute of Aeronautics and Astronautics (AIAA)/American National Standards Institute (ANSI) apply margins to output parameters such as total system mass or power requirements in satellite design [ANSI/AIAA, 2006; ANSI/AIAA, 2007]. These margins account for the likely changes in satellite parameters due to uncertainty as the design progresses. Application of margins occurs in a variety of other areas in conceptual-satellite design including power, cost, link budgets (signal-to-noise ratio of a telecommunications link), and source lines of code. These margins are often chosen based on historical data and may be conservative which can result in conceptual designs that are exceedingly massive and/or prohibitively expensive or conversely, overly optimistic in both mass and cost projections. Ideally, a method for handling uncertainties in a quantifiable and repeatable manner specific to a design is desirable.

4.1.2. Probabilistic Methods

By applying a probabilistic approach to determine uncertainties in the outputs of interest a general model can be described by the equation

$$Y = G(\Theta) \quad (4.2)$$

where Θ represents the input vector of possibly uncertain parameters which can be discrete, continuous, or constant values and Y is the vector representing the uncertain distributions of the outputs of interest. Assuming that the objective function G incurs

errors in the determination of Y from the true value of Y , the approximation error in a given value of Y can be defined by:

$$Y' = Y + X \quad (4.3)$$

where Y' is the true value of Y and X is the approximation error (model uncertainty) for a given parameter. The cumulative distribution function (CDF) of the output values can be obtained as a convolution of the CDF of Y and the CDF of X . The confidence in an estimate for an output parameter depends on the percentile value, p , associated with the CDF. An engineer can define confidence levels associated with various values of p . As an example, a decision maker can set low-, medium-, and high-confidence levels corresponding to 90%, 99%, and 99.9% percentiles. These may represent risk-tolerant, risk-neutral, and risk-averse positions, respectively [Thunnissen, Au, & Tsuyuki, 2006].

4.1.3. Fuzzy Sets

Fuzzy sets were developed by Zadeh (1965) and represent a generalization of classical crisp sets. The corresponding fuzzy logic can be used to represent uncertainties and has been successfully demonstrated in a number of applications. While benefits with respect to probability theory exist, probability theory remains better understood and more thoroughly developed [Maglaras, 1995].

4.1.4. Evidence Theory

Another compelling theory that addresses uncertainty is evidence theory (also known as Dempster-Schafer theory). Rather than assign a probability distribution, evidence theory assigns two measures of uncertainty to a given parameter: belief and plausibility [Oberkampf, Helton, & Sentz, 2001]. These measures correspond to a set of possible values a parameter can take. The advantage of evidence theory is its ability

to handle cases where the type of probability distribution associated with a parameter is unknown. Applying the incorrect distribution can result in significant errors, particularly in the tails of distributions. By relying on the measures of belief and plausibility, evidence theory avoids this problem by providing a range of likelihoods. When correct distributions are known, evidence theory then reduces to probability theory, giving it an added flexibility. However, questions remain as to the applicability of evidence theory in situations where “black-box” models are being used and its ability to propagate uncertainties through such models via sampling methods. Additional questions surround the conversion rate of evidence theory when sampling methods are used [Oberkampf, Helton, & Sentz, 2001]. Application to an airfoil design problem has demonstrated the ability for evidence theory to handle uncertainty in black-box design problems yet the computational time required increased exponentially as a function of the number of uncertain input variables [Bae, Grandhi, & Cranfield, 2002]. This limitation is acute in conceptual-satellite design where dozens or hundreds of uncertainties may exist.

4.1.5. Selected Uncertainty Quantification Method

Heuristic methods represent the current state-of-the-art. In this application a bottoms-up approach such as probability theory or evidence theory is preferable. Probability theory appears to be the most reliable method to quantify uncertainty and is certainly the most universally accepted. Evidence theory appears intriguing, possessing the ability to quantify uncertainties where the distribution is unknown. However, at this stage evidence theory appears computationally infeasible. Hence, probability theory represents the best choice.

4.2. Uncertainty Propagation Methods Review

Propagating uncertainties through the model is the next step that must be examined. Numerous sampling methods exist to perform this task. Discussion here will be limited to two methods: Monte Carlo simulation and Subset Simulation [Au, & Beck, 2001; Au, 2001]. A more comprehensive review of sampling methods is provided in Thunnissen (2005).

4.2.1. Monte Carlo Simulation

Monte Carlo simulation (MCS) has been demonstrated as a useful tool for quantifying uncertainty [Metropolis & Ulam, 1949]. By creating a number of random realizations (samples) of the variable of interest, a probability distribution is formed. Representing the uncertainty in output parameters requires creating an uncertainty distribution for every element of the input vector which is uncertain. This can be problematic as accurate representations of the uncertainties in question can require a large number of samples via MCS at the confidence levels required in satellite design [Thunnissen, Au, & Tsuyuki, 2006]. Furthermore, higher-integrity models possess a vast solution space with a large number of variables resulting in a problem that is computationally demanding. For example, in conceptual-satellite design, dozens to hundreds of physics-based equations using hundreds of variables are required.

4.2.2. Subset Simulation

An alternative approach to MCS is known as Subset Simulation (SS). This technique has the advantage of exploring primarily the tails of distributions. Variables which require a large number of MCS samples can be analyzed more efficiently with SS [Au, & Beck, 2001; Au, 2001]. Although initially developed to assess seismic performance of structures, SS has been successfully demonstrated for uncertainty

analysis in satellite applications on the subsystem and component level [Thunnissen, Au, & Tsuyuki, 2006]. This suggests that SS would be feasible if applied to a complete satellite-system model.

4.2.3. Selected Uncertainty Propagation Method

Monte Carlo simulation is the best understood and most extensively documented simulation method. Subset Simulation presents an advantage with reduced computational demand. In this case the reliability of MCS is preferable, and it will provide a baseline should any future studies with SS be performed.

4.3. Uncertainties Involved

Uncertainty can be classified into four broad groups: aleatory, interaction, ambiguity, and epistemic [Thunnissen, 2005]. This thesis will focus on the treatment of aleatory, interaction, and epistemic uncertainties. Ambiguity is not dealt with in this thesis as all communications are assumed to be clear and correctly understood. Aleatory uncertainties are irreducible uncertainties that result from random variations in nature. Complex interactions between disciplines, often found in multidisciplinary design problems, constitute interaction uncertainties. Epistemic uncertainties arise due to a lack of knowledge or information during the modeling process. Epistemic uncertainty can be further divided into model, phenomenological, and behavioral uncertainty [Thunnissen, Engelbrecht, & Weiss, 2003].

Model uncertainties are the uncertainties associated with a mathematical model meant to describe a real-world system and can be subdivided into approximation, numerical, and programming errors. Approximation errors are characterized by simplifying assumptions that are often made to overcome a lack of knowledge in the relationship between various factors. An example is the use of worst-case scenarios in

thermal analysis as opposed to finite element models. In early-stage conceptual design, thermal analyses generally involve the calculation of worst-case hot and worst-case cold scenarios to determine the thermal demands place on a satellite. The satellite thermal control system is then designed to handle these worst-case scenarios. In reality this results in a thermal control system that is over-designed, but requires a model that is less computationally demanding. Numerical uncertainties are the result of limitations in calculations to express complete values of numbers (i.e., rounding errors). Programming errors are simply errors committed by the programmer of the model such as calculation errors or logic errors. Both numerical uncertainties and programming errors can be effectively mitigated via increased computational precision and institutional training and are not discussed further in this thesis [Thunnissen, Engelbrecht, & Weiss, 2003].

Behavioral uncertainties are uncertainties associated with the actions of people, be they the engineers responsible for designing a system or the customers/outside organizations that ultimately use the system being designed. Often the most important behavioral uncertainties is design uncertainty. An example of a design uncertainty is a discrete choice that an engineer needs to make during the design process. Such decisions include a choice between different available components (e.g., computer A or computer B). Also of concern are requirement uncertainties which are brought about by the customer. Customers may change requirements during the design process for any number of reasons which can significantly impact the design [Thunnissen, 2005].

It should be noted that the distributions attributed to uncertain variables were chosen based on the researchers' best judgment. Expert opinion may reveal that other

distributions may be better suited. However, for the purposes of demonstrating the feasibility of the outlined method, the researchers' judgment was deemed satisfactory.

4.4. Example Input Distribution

Overall, 160 input variables in the satellite model are represented as uncertainties. Table 4.1 lists inputs for the power subsystem (continuing as an example), along with their corresponding uncertainty distributions and the parameters defining those distributions. It should be noted that Table 4.1 includes the primary battery type and the solar cell type as uncertainties, where they are technically optimizable variables. However, for the analysis performed in this chapter they were treated as uncertainties since no optimization was performed.

The solar flux can be classified as a typical aleatory uncertainty. Loss factors can be classified as epistemic uncertainties. The beta function is deemed to best describe the loss factors, since the loss factors generally possess values between 0.9 and 0.99. Uncertain component masses are classified as aleatory uncertainties and are represented by uniform distributions. The model uncertainty of the power subsystem is applied to the total subsystem mass and is represented by a uniform distribution. Custom distributions are applied to battery and solar cell types to represent the uncertainty of the design engineer in making a component selection. For example, a power-system engineer who is given the option between a nickel-hydrogen battery and a lithium-ion battery for a secondary battery may be leaning towards the nickel-hydrogen battery (80% likelihood) but still considers the lithium-ion battery (20% likelihood). Note that these likelihoods are used for illustrative purposes only. Such likelihoods can be defined in a custom distribution where a random variable is generated with 80% likelihood of being A (nickel-hydrogen) and 20% likelihood of

being B (lithium-ion). Higher-performance components are more likely to be selected, thus would likely have a higher probability. However, technologically proven components also represent a higher desirability. Consequently the highest probabilities may be assigned to the component types that represent higher performance at reasonable reliability. High-risk and low-performance components may be assigned lower probabilities.

Table 4.1 Power model uncertainties assumed

Parameter	Distribution type and parameters
$h_{\text{solar_panel}}^c$	Uniform(25,35)
$k_{\text{assembly_mismatch}}$	Beta(1000,20)
$k_{\text{batt_to_conv}}$	Beta(1000,110)
$k_{\text{batt_to_dist}}$	Beta(10000,50)
$k_{\text{conv_eff}}$	Beta(1000,110)
$k_{\text{conv_to_harm}}$	Beta(10000,50)
$k_{\text{coverglass_coating}}$	Beta(1000,20)
$k_{\text{dist_to_load}}$	Beta(1000,11)
$k_{\text{fuse_to_load}}$	Beta(10000,50)
$k_{\text{harm_to_fuse}}$	Beta(10000,50)
$k_{\text{meteoroid_damage}}$	Beta(1000,20)
k_{packing}	Beta(1000,110)
$k_{\text{propellant_contamination}}$	Beta(1000,20)
$k_{\text{shadowing}}$	Beta(1000,250)
k_{uv}	Beta(1000,30)
k_{voltage}	Beta(190,4)
$m_{\text{power_dist}}^a$	Uniform(3,5)
$m_{\text{uncertainty_power_total}}^a$	Uniform(-1,3.5)
$m_{\text{pyro_charge}}^a$	Uniform(0.1,0.2)
Φ_{solar}^b	Normal(1386.5,35)
$\tau_{\text{primary_battery}}$	Custom ^d
$\tau_{\text{solar_cell}}$	Custom ^d

^a units of kg; ^b units of W/m²; ^c units of mm; ^d see description in Section 4.4

In order to graphically present the uncertainty in a parameter MCS was performed for the high-gain antenna (HGA) efficiency. The HGA efficiency represents an aleatory uncertainty which is described by a normal distribution. Figure 4.1 shows a

representative distribution of the HGA for 10000 randomly-generated samples as an example.

Fig. 4.1 Sample distribution for the HGA efficiency (10000 samples; bin size = 0.005)

The HGA efficiency is determined based on a normal distribution with a median value of 0.55 and a standard deviation of 0.02. As can be seen in Fig. 4.1, the majority of samples will produce an efficiency well within a standard deviation; however, unlikely situations where the efficiency varies by as much as three standard deviations can also be accounted for.

4.5. Computational Effort

Performing the analyses for the STEPS application presented in the previous chapter is computationally demanding. All simulations were performed on a 3GHz Pentium D processor, with 2GB of RAM. A single evaluation an iteration loop

requires ~10 seconds. The function ceases iteration when the change in the injected mass is less than 0.5kg, which, on average, requires 6 iterations. Consequently, a single such function evaluation requires approximately 1 minute and generates one sample. For a 99.9% confidence level, a minimum of 10,000 samples are needed which requires ~167 hours (7 days) of computation time. Furthermore, heavier payloads required such as the MTI and SAR (which are implemented in Chapters 5 and 6) require more iterations to converge and subsequently raise that average computation time of a function evaluation to 2 minutes.

4.6. Results & Analysis

The dry mass of the satellite and the total cost are output parameters of interest analyzed from a data set consisting of 10000 fully-iterated satellite designs. A sample size of 10000 was used as it was found to give statistically significant results to the 99.9th percentile. Mass and cost were selected since they are generally the most significant early-stage design performance parameters where decisions are being made regarding continuation of design studies for a particular mission. Quantifying uncertainty in these parameters is crucial in determining both the technological and the economic feasibility of the designs. To simplify the analysis, only the multispectral imager payload was considered for the uncertainty example presented in this chapter. Finally, new values for the dry mass and total cost were calculated for the baseline values to represent changes to the STEPS model from Loh et al. (2007). These new values were found to be 128kg dry mass and a total cost of \$89.2M (FY2007). All costs henceforth are for the fiscal year 2007 US dollars.

4.6.1. Mass Distribution

The distribution of the samples for the satellite dry mass is shown in Fig. 4.2. The result of the MCS yields a median dry mass of 148kg.

Fig. 4.2 Sample distribution of dry mass (10000 samples; bin size = 1kg)

While this demonstrates that the 128kg calculated in the baseline model is comparatively low it does not provide much information in how much confidence a decision maker could place in that value. Additional information about the confidence levels of the dry mass values can be obtained from the corresponding cumulative distribution function (CDF) given in Fig. 4.3.

Fig. 4.3 Confidence in the dry mass of the satellite (10000 samples)

From the CDF shown in Fig. 4.3 it becomes apparent that the median dry mass of 148kg provides a significantly higher confidence level than the 128kg calculated from the baseline STEPS model. Table 4.2 outlines values for the dry mass of the satellite and the corresponding confidence level that the given value will not be exceeded. The first row provides information regarding the STEPS baseline design. The final four rows provide dry masses obtained from the uncertainty analysis for the median, low-confidence, medium- confidence, and high-confidence levels.

Table 4.2 Mass uncertainty results

	Mass, kg	Percentile, %
Baseline (no margin)	128	3.6
Baseline (with margin)	243	99.99
Median	148	50.0
Risk tolerant	165	90.0
Risk neutral	184	99.0
Risk averse	203	99.9

From the results shown in Table 4.2 it becomes clear that the dry mass calculated in the original STEPS model provides an extremely low-confidence level of only 3.6%. To reach a confidence level of 90% an additional 37kg of mass should be budgeted. A risk-neutral designer seeking a 99% confidence level would require a budgeted mass of 184kg which represents an increase of 56kg (~44%) increase from the STEPS baseline mass. On the other hand, when compared with the baseline with margin, even a risk averse position provides a less conservative estimate.

4.6.2. Total Cost Distribution

The distribution of the samples for the total cost of the satellite is shown in Fig. 4.4. The result of the MCS yields a median total cost of \$93.9M. While the median total cost is within 5% of the baseline estimate for the total cost it is worth exploring the additional information about the confidence levels of the total cost values from the corresponding CDF given in Fig. 4.5.

Fig. 4.4 Sample distribution of the total cost (10000 samples; bin size = US\$1M)

Fig. 4.5 Confidence in the total cost of the satellite (10000 samples)

Figure 4.5 clearly shows the baseline STEPS model underestimates the total cost of the satellite. The estimated cost of \$89.2M provides a confidence level below the 20th percentile. Table 4.3 outlines values for the STEPS baseline design, as well as the median, low-, medium-, and high-confidence levels of the uncertainty in the total cost.

Table 4.3 Total cost uncertainty results

	Cost, US\$M	Percentile, %
Baseline (no margin)	89.2	15.3
Baseline (with margin)	120.5	99.99
Median	93.9	50.0
Risk tolerant	99.9	90.0
Risk neutral	105.3	99.0
Risk averse	109.9	99.9

The estimated STEPS total cost of \$89.2M provides a low-confidence level of 15.3%. To obtain a 99% confidence level an additional \$16.1M is necessary which represents a ~18% increase in the STEPS total cost. This represents a very significant amount and indicates the total cost is likely being underestimated in the deterministic STEPS model. Conversely, the baseline with margin provides a much more conservative estimate than even a risk averse position.

4.7. Analysis Conclusions

The primary conclusion drawn from this research is that the application of a rigorous, repeatable method for quantifying and propagating uncertainties at a systems level is feasible. Results from this analysis indicate that the original baseline STEPS design may fail to budget adequate quantities for both the dry mass and the total cost of the system. In both cases the uncertainty analysis indicates that significantly higher

values are must be budgeted for the dry mass and the cost to achieve a risk-neutral design.

5. Deterministic Multidisciplinary Design Optimization

Before performing probabilistic simulated annealing on the multidisciplinary satellite model, a deterministic optimization run can be performed to better understand the solution space. Information obtained from the results of the deterministic multidisciplinary design optimization process can be used to reduce the computational effort through measures such as constricting the bounds on the optimization variables. Additionally, minimizing the number of function evaluations is critically important, when the probabilistic approach is applied, to further reduce the computational effort. Deterministic multidisciplinary design optimization simulations with various numbers of total function evaluations were investigated to determine the satisfactory minimum number of function evaluations.

5.1. Multi-Objective Simulated Annealing

The deterministic multidisciplinary optimization is performed according to the algorithm described in Section 2.2 of this thesis. The outputs are normalized in the multi-objective case as per Eq. (2.7). An engineer/decision maker can apply weightings appropriate to the primary drivers of the design (i.e. cost-constrained designs can apply greater weight to optimizing with respect to cost). However, for the purposes of this thesis the normalized weightings are deemed sufficient. The algorithm makes reference to a cooling schedule which in this work is defined by the following equation:

$$T_{i+1} = \lambda T_i \quad (5.1)$$

where T_{i+1} is the system temperature, λ is the cooling rate, and T_i is the current system temperature. The system is set at an initial temperature, T_0 . When T_{i+1} reaches the final

system temperature, T_f , the algorithm halts. The values for the algorithm parameters are given in Table 5.1.

Table 5.1 Algorithm parameter settings

Parameter	Value
Degrees of freedom	17
Function evaluation limit	1; 2; 4; 8; 16
λ	0.85755
T_0	0.01
T_f	0.0000001

The degrees of freedom represents the number of optimizable inputs perturbed each time. In this case all 17 of the optimizable input variables are perturbed. The function evaluation limit represents the maximum number of function evaluations at a given temperature. Changing the function evaluation limit permits control over the total number of function evaluations since the initial temperature and the cooling rate are kept the same for each run. Function evaluation limit values of 1, 2, 4, 8, and 16 are used to achieve 75, 150, 300, 600, and 1200 total function evaluations, respectively.

5.2. STEPS Model Settings

The satellite model is optimized with respect to 17 input variables from eight different disciplines. A majority of these variables involve discrete choices between components. The remaining variables are continuous in nature but have been discretized in order to reduce the computational effort. Table 5.2 provides a list of all 17 optimizable input variables along with their parent discipline, unit type, step size (discretization), lower bound, and upper bound.

Table 5.2 Satellite optimization parameters

Parameter	Discipline	Units	Step Size	Lower Bound	Upper Bound
τ_{payload}	Payload	n/a	1	1	3
$f_{\text{bandwidth_sar}}$	Payload	MHz	2	4	20
$d_{\text{aperture_msi}}$	Payload	cm	4	4	40
$d_{\text{aperture_mti}}$	Payload	cm	20	20	140
$h_{\text{altitude_orbital}}$	Mission	km	50	400	1000
$\tau_{\text{main_engine}}$	Propulsion	n/a	1	1	5
τ_{thruster}	Propulsion	n/a	1	1	2
$\tau_{\text{position_sensor}}$	ADACS	n/a	1	1	4
$\tau_{\text{sun_sensor}}$	ADACS	n/a	1	1	5
d_{hga}	Telecom	cm	5	30	80
$\tau_{\text{primary_battery}}$	Power	n/a	1	2	6
$\tau_{\text{solar_cell}}$	Power	n/a	1	3	6
$\tau_{\text{structure}}$	Structures	n/a	1	1	2
κ_{louver}	Thermal	n/a	1	0	1
τ_{mli}	Thermal	n/a	1	9	14
$\tau_{\text{surface_finish_louver}}$	Thermal	n/a	1	12	14
$\tau_{\text{surface_finish_radiator}}$	Thermal	n/a	1	1	4

Definition of the parameters and the components that correspond to the component type number can be found in their respective discipline appendix at the end of this thesis. The constraints on the variables are left as broad as possible to allow sufficient freedom in exploring design options but also sufficiently constrained to prevent an excessively large solution space. It should be noted that the parameters in Table 5.1 result in a solution space with over 3.5 trillion possible design configurations.

In the Ship Tracking and Environmental Protection Satellite (STEPS) application the algorithm must optimize the design with respect to multiple objectives: total cost, coverage time, and resolution. The total cost is desired to be minimized and includes not only the system bus cost but also launch costs and supplementary costs such as contractor fees, ground station operations, integration, assembly, and testing. The coverage time should be maximized and is chosen as a performance metric rather than

the revisit frequency since the altitude is limited to 1000km reducing the variability in revisit frequency. Finally, the resolution is sought to be minimized (while low-resolution is generally taken to mean decreased performance, from a numerical perspective a high-resolution system has a measured value, in meters for instance, that is smaller than a low-resolution system, hence improving resolution is a minimization problem), thus providing a high-performance system capable of discovering smaller vessels.

5.3. Results & Analysis

A total of 1200 function evaluations were performed in the run. The number 1200 was selected since it could be computed in a reasonable amount of time. Each payload was given a fixed coverage time, of 800, 1600, and 2600s, for the multispectral imager (MSI), the multispectral thermal imager (MTI), and the synthetic aperture radar (SAR), respectively. While it is understood that the coverage time for a given payload will vary with the altitude of the satellite, those variations are deemed insignificant compared to the change in coverage time from switching payload types. Of primary importance is that the MSI is restricted to cloudless daylight observation, the MTI is restricted to cloudless observation (night and day), and the SAR is not restricted in any manner. It is with respect to these differences that the coverage time of the system is optimized. The results are given in Fig. 5.1. It was also assumed that differences in resolution were negligible at less than 0.1m and differences in cost were considered to within US\$100K. All costs presented are in fiscal year 2007 US dollars.

Fig. 5.1 Total cost - resolution - coverage time solution space (1200 function evaluations)

Pareto optimal solutions are found for each payload type over a wide range of resolutions. Costs do not exceed \$500M for any Pareto optimal solution although some non-optimal solutions reach costs over \$4B. This may seem unusually high, but is not unexpected due to the fact that some options the optimizer is able to select can result in very poor designs. Figures 5.2, 5.3, and 5.4 have been separated by payload to more clearly illustrate the tradeoff between total deployment cost and resolution. These figures have been generated from the same data set that was used to produce Fig. 5.1, and consequently do not represent three distinct Pareto fronts, but rather show the segments of the overall Pareto front for the given payload.

Fig. 5.2 MSI solution space (1200 function evaluations; ~800s coverage time)

Fig. 5.3 MTI solution space (1200 function evaluations; ~1600s coverage time)

Fig. 5.4 SAR solution space (1200 function evaluations; ~2600s coverage time)

The MSI and SAR are the two dominant payloads, with very few of the MTI payloads appearing on the Pareto front. The advantage of the MSI payload over the other options is its low total cost. By contrast the SAR payload, despite its high cost, is selected based on its superior coverage time and good resolution. At good resolutions the cost of the MTI is seen to rise quite dramatically and consequently the MTI is only successful at poorer resolutions (i.e., above 30m) where its cost is significantly lower. It should also be pointed out that at sub-20m resolutions, the MTI has no Pareto optimal solutions. This is because those solutions are dominated by SAR solutions which, at the same resolutions, have lower cost and higher coverage time.

Figure 5.5 shows the Pareto optimal solutions for all the payloads. The results in Fig. 5.5 indicate that in general the MTI is an inappropriate payload for this mission in all but the most cost-constrained of programs. It should be recalled that the coverage

time for each payload type is different, thus while the MSI appears to dominate the other two payloads, it does not in reality, as it has the lowest coverage time. Note that since only the Pareto fronts are given in Fig. 5.5, the costs have been provided in US\$M.

Fig. 5.5 Satellite cost - resolution solution space (1200 function evaluations)

Table 5.3 presents the actual values for each point in the Pareto set. Both the MTI and SAR options only yielded eight Pareto optimal points as opposed to the ten Pareto solutions found for the MSI payload.

Table 5.3 Satellite Pareto set (1200 function evaluations)

MSI ^a (10 solutions)		MTI ^b (8 solutions)		SAR ^c (8 solutions)	
Resolution, m	Total Cost, US\$M	Resolution, m	Total Cost, US\$M	Resolution, m	Total Cost, US\$M
7.0	183.2	20.5	238.4	9.2	303.1
7.2	180.9	27.3	194.3	9.8	279.3
7.8	174.1	27.5	193.9	12.4	268.9
8.8	114.0	27.9	191.5	12.7	255.1
10.1	113.7	41.0	175.0	14.5	241.6
11.7	109.3	41.2	171.8	22.9	219.1
12.3	106.3	82.0	91.3	31.4	211.5
14.0	97.1	83.1	91.0	47.1	206.2
17.5	93.7				
35.4	93.6				

^a 800s coverage time; ^b 1600s coverage time; ^c 2600s coverage time

5.4. Boundary Constraints Analysis

Analysis of the deterministic annealing results yields insight into the behavior of the boundaries of the Pareto-optimal solution space. This can allow the boundary constraints on some optimizable variables to be constrained further, reducing the computational demand during the probabilistic-annealing process. Figure 5.6 shows the selection frequency of antenna diameters for the all options and then is broken down into individual payload options.

While a diameter of 40cm seems to be preferred, it would be premature at this stage to assume the antenna size could be restricted to that diameter. It would be fair to conclude that smaller diameters are preferred with no designs using antennas over 65cm. Subsequent annealing runs could then likely be restricted to 30 to 65cm compared with the currently used 30 to 80cm. It should be noted that although dish diameters over 65cm are infrequently optimal solutions, these larger dish sizes may in fact yield some very satisfactory solutions. Nonetheless, the fact that the majority of

the good solutions appear at lower diameters and to reduce computational demand, subsequent analysis will be restricted to diameters under 65cm.

Fig. 5.6 Antenna diameter selection frequency as a function of payload type

A similar investigative analysis can be performed with the orbital altitude. Altitudes were considered ranging from 400 to 1000km at 50km intervals. Figure 5.7 shows the distribution of the selected altitudes for the overall satellite and then for the individual payloads.

As seen from Fig. 5.7, the overall distribution of altitudes appears to show a preference for an 800km altitude. However, the story is more complicated when one looks deeper at the individual payloads. The MSI primarily selects altitudes above 750km (with the exception of two cases), mainly due to the adverse system impact aerodynamic drag at lower altitudes has on the satellite. The MTI clearly tends towards the higher altitudes for a similar reason. On the other hand the SAR shows a

Fig. 5.7 Orbital altitude selection frequency as a function of payload type

clear preference for the 450 to 650km range. This is due to a system tradeoff between the higher drag at low altitudes (more propellant required) and the higher-power requirements at higher altitudes (larger solar arrays required). Since the SAR power requirements are inversely proportional to the slant range raised to the fourth power ($(h_{\text{slant_max}})^4$), a lower altitude is desirable. However, below 450km the atmospheric drag is too high to warrant the power saving given the three-year lifetime requirement of the satellite (assumed to be fixed and certain in the deterministic case). Note that very little restriction on the orbital altitude is possible based on these results, and the minimum altitude can only be raised from 400 to 450km. The maximum altitude of 1000km remains unchanged.

Not all the optimizable inputs are dependent on the type of payload in this manner. Figure 5.8 shows the frequency with which louvers are included.

Fig. 5.8 Louver selection frequency

In this case it is clearly apparent that irrespective of payload, the inclusion of louvers is beneficial. Consequently, changing the inclusion of louvers from an optimizable variable to one that is fixed (included in all designs) is reasonable based on the results.

5.5. Function Evaluation Analysis

The number of function evaluations performed during an annealing run (an annealing run represents running the algorithm once and generating a single Pareto set) has consequences in terms of the computation and the quality of the solutions. For a larger number of function evaluations, better solutions can be obtained but the computation time can be significantly higher. Keeping the function evaluations at a minimum becomes more important when performing a probabilistic annealing run where dozens to hundreds of SA samples (a single SA run generates one SA sample)

may be required. The cooling schedule was altered to investigate the fidelity of the results. The cooling schedule directly impacts the total number of function evaluations according to Eq. (5.1). Annealing runs were performed for 75, 150, 300, 600, and 1200 function evaluations. Each function evaluation requires approximately two minutes to perform.* Consequently a 75 function evaluation run would require approximately 2.5 hours to complete. By contrast a 1200 function evaluation run would require approximately 40 hours to complete (i.e., almost 2 days). When put in the context of requiring, for example, 100 SA samples, this can mean requiring anywhere from 10 days to 166 days of computation time. Clearly minimizing this value is critical. Figures 5.9, 5.10, and 5.11 provide the results for MSI, MTI, and SAR payloads, respectively.

Fig. 5.9 MSI Pareto fronts for five different function evaluation totals

* Assuming a 3.0 GHz Pentium D Processor with 2.0 GB of RAM

Fig. 5.10 MTI Pareto fronts for five different function evaluation totals

Fig. 5.11 SAR Pareto fronts for five different function evaluation totals

In each case the 1200 function evaluation run yields the best results as the Pareto front is shifted toward the lower-cost and higher-resolution solutions. However, results from the 600, 300, and 150 function evaluation runs provide competitive results. It is especially clear in Figs. 5.9 and 5.11 that the 75 function evaluation run provides sub-par results compared with Pareto solutions for those with 150 or more function evaluations. It is also worth noting that the 150, 300, 600, and 1200 function evaluation runs return a Pareto set with ~ 25 solutions, whereas the 75 function evaluation run yields a Pareto set with only ~ 15 solutions. It should be remembered that the Pareto set returned in each case represents an estimation of the true Pareto set (i.e., this represents the best solutions the algorithm could find on a given run, not the Pareto optimal solutions of the entire solution space). Thus while the 15 solutions returned by the 75 function evaluation run represent a higher proportion of returned solutions to function evaluations, they do not represent higher-quality solutions. The conclusion therefore is that the 150 function evaluations are satisfactory in providing both a larger number of Pareto solutions and a sufficiently high quality of Pareto solutions.

5.6. Analysis Conclusions

After performing the deterministic multidisciplinary optimization, information acquired about the solution space allows changes to be made which can reduce the computational demand of the algorithm. Restriction of the boundary conditions on a number of optimization input variables is one beneficial way to reduce the computational effort by reducing the total size of the solution space. Analysis of the number of function evaluations concluded that optimizing with 150 function evaluations provided solutions of good quality for a relatively low number of function

evaluations. Further reduction in the number of function evaluations resulted in an unsatisfactory degradation of the quality of the solutions.

6. Optimization Under Uncertainty Method Application

The first section of this chapter reviews methods for performing optimization under uncertainty (OUU). This chapter continues by outlining the algorithm used in the selected OUU method. Subsequent sections will discuss the uncertainties involved in the analysis and the variables to be optimized along with their boundary constraints. The results of the analysis will then be presented and analyzed. Finally some concluding remarks will be made. As in previous chapters, the Ship Tracking and Environmental Protection Satellite (STEPS) mission introduced in Chapter 3 is the example application.

6.1. Optimization Under Uncertainty Methods Review

Optimization under uncertainty is a relatively new field that distinguishes itself from traditional multidisciplinary design optimization (MDO) methods by treating inputs as probabilistic rather than deterministic. Three main approaches exist for performing OUU, which will be reviewed in the following sections. A thorough review of OUU methods can be found in Giunta et al. (2004).

6.1.1. Optimization Under Uncertainty with Direct Sampling Methods

Performing OUU in conjunction with a sampling method such as Monte Carlo simulation (MCS) is perhaps one of the simplest approaches. This method generally involves generating samples for every iteration of the optimization algorithm and directly evaluating the model. The most significant problem with this approach is the high computation time required if the model is computationally expensive. The advantage, however, is that this method affords the greatest accuracy. Previous work has demonstrated the success of such an approach via simulated annealing (SA)

applied to an aerospace shaping problem [Odot & Aly, 2004] and via genetic algorithms applied to a satellite design problem [Hassan & Crossley, 2004].

An alternate approach to this method would involve generating samples of Pareto fronts. The first method involves optimizing once and generating samples for every point evaluated by the optimization algorithm. By contrast, generating samples of Pareto fronts (henceforth termed SA samples) involves optimizing with respect to a sampled set of uncertainties and repeating the process N times (where N is an integer), thus optimizing N times and generating N Pareto fronts with varying uncertainties. With increasing N one would expect the better solutions that are more robust to uncertain conditions. Furthermore, with only a single run of an optimization algorithm there exists a risk that the algorithm can get trapped in a local minimum, yielding a relatively poor Pareto front. By performing multiple runs of the optimization algorithm, this ceases to be a concern. No reference to this approach has been found in any of the literature reviewed.

6.1.2. Optimization Under Uncertainty with Surrogate Models and Sampling Methods

One solution to reduce the computational expense of the previous method involves the introduction of a surrogate model which is less computationally expensive to evaluate than the full model. While computationally advantageous, this approach sacrifices accuracy and requires the surrogate model be updated periodically with respect to the main model to ensure it remains representative. It also adds a new uncertainty to the process in the form of the uncertainty associated with the surrogate model which is somewhat counter-productive in the attempt to mitigate uncertainties in the design process. This approach has been demonstrated on a satellite design problem via SA and kriging models [Martin & Simpson, 2006].

6.1.3. Optimization Under Uncertainty with Analytic Reliability Methods

Optimization under uncertainty with analytic reliability models replaces the sampling approach for propagating uncertainties and instead employs an approximation method which estimates the probability of an event, termed a failure. First-order reliability method (FORM) and second-order reliability method (SORM) are two examples of this approximation approach. These reliability methods are more limited in scope since they focus on the failure regions of the design and consequently are less suitable to this application [Giunta et al., 2004].

6.1.4. Selected Optimization Under Uncertainty Method

The most accurate of the outlined methods is the OOU with direct sampling of the model. The novel approach introduced in Section 6.1.1 is believed the more reliable approach as it avoids the problem of a poor result from an optimization run trapped in a local minimum. Consequently this is the method selected for performing OOU in this research.

6.2. Optimization Under Uncertainty Algorithm Description

The algorithm for performing optimization under uncertainty is based on the deterministic optimization algorithm presented in Section 2.2. The key difference lies in the addition of an iterative loop for performing the MCS. The algorithm is as follows:

1. Identify outputs of interest (y)
2. Generate analysis models (G)
3. Classify and set input variables/uncertainties (θ)

- a. set fixed values for input variables that are certain ($\bar{\theta}$) and dummy temporary values for those input variables that are exchanged between disciplines ($\hat{\theta}$)
 - b. probabilistically model uncertain input variables ($\tilde{\theta}$) via a distribution and relevant statistical parameters (e.g., a normal distribution with a mean μ and a standard deviation σ)
 - c. set bounds on optimizable input variables ($\tilde{\theta}$) where bounds on optimizable variables have the form $b_i < \tilde{\theta}_i < a_i$ where b_i and a_i are the lower and upper bounds on $\tilde{\theta}_i$, respectively
4. Generate the values for $\tilde{\theta}$
5. Use multi-objective SA algorithm to efficiently and accurately determine $\hat{\theta}$ and $\tilde{\theta}$ that “minimizes” y given $\bar{\theta}$ and $\tilde{\theta}$
6. Repeat steps 4 and 5 N times for each simulated annealing sample in the case of Monte Carlo simulation
7. Generate distributions for y , $\hat{\theta}$, and $\tilde{\theta}$ (represented by Y , $\hat{\Theta}$, and $\tilde{\Theta}$, respectively)
8. Derive a single value for each element of $\hat{\Theta}$ and $\tilde{\Theta}$ based on a set of best solutions and represent these values by $\hat{\theta}^*$ and $\tilde{\theta}^*$
9. Repeat uncertainty analysis with $\hat{\theta} = \hat{\theta}^*$, $\tilde{\theta} = \tilde{\theta}^*$, and $\bar{\theta}$ as fixed values and $\tilde{\theta}$ uncertain. Uncertainty analysis yields optimal values of y under uncertainty represented by Y^*

A significant assumption in this research is that boundary constraints are certain. This assumption was made to simplify the analysis. However, it is very possible that the boundary constraints are uncertain.

6.3. Algorithm Settings

Increasingly larger SA sample sizes (up to 400 samples) were collected for the STEPS application with 150 function evaluations per SA sample. The number of SA samples was primarily limited by the computation time required. As described earlier a single function evaluation requires on the order of 2 minutes, thus a single SA sample requires approximately 5 hours to compute. The algorithm parameter values are given in Table 6.1.

Table 6.1 Algorithm parameter settings

Parameter	Value
Degrees of freedom	16
Function evaluation limit	2
λ	0.85755
T_0	0.01
T_f	0.0000001
SA sample size	400

6.4. Optimization Inputs

A total of 16 optimizable variables are involved in this analysis. These variables are listed in Table 6.2 along with their corresponding units, step size, and constraints.

Table 6.2 Satellite optimization parameters

Parameter	Discipline	Units	Step Size	Lower Bound	Upper Bound
τ_{payload}	Payload	n/a	1	1	3
$f_{\text{bandwidth_sar}}$	Payload	MHz	2	4	20
$d_{\text{aperture_msi}}$	Payload	cm	4	4	40
$d_{\text{aperture_mti}}$	Payload	cm	20	20	140
$h_{\text{altitude_orbital}}$	Mission	km	50	450	1000
$\tau_{\text{main_engine}}$	Propulsion	n/a	1	1	4
τ_{thruster}	Propulsion	n/a	1	1	2
$\tau_{\text{position_sensor}}$	ADACS	n/a	1	3	4
$\tau_{\text{sun_sensor}}$	ADACS	n/a	1	1	3
d_{hga}	Telecom	cm	5	30	65
$\tau_{\text{primary_battery}}$	Power	n/a	1	4	6
$\tau_{\text{solar_cell}}$	Power	n/a	1	5	6
$\tau_{\text{structure}}$	Structures	n/a	1	1	2
τ_{mli}	Thermal	n/a	1	12	14
$\tau_{\text{surface_finish_louver}}$	Thermal	n/a	1	12	14
$\tau_{\text{surface_finish_radiator}}$	Thermal	n/a	1	2	4

It should be noted that $\tau_{\text{payload}} = 1$ represents an MSI, $\tau_{\text{payload}} = 2$ represents a SAR, and $\tau_{\text{payload}} = 3$ represents an MTI. Definition of the remaining parameters and the components that correspond to the component type number can be found in their respective discipline appendix at the end of this thesis. This set of boundary conditions creates a solution space with ~36 million possible solutions. This is a significant reduction from the number of solutions possible in Chapter 5, but nonetheless represents a fairly large solution space.

6.5. Results & Analysis

The performance of the SA algorithm under uncertainty is evaluated for increasingly larger SA sample sizes (i.e., sample sizes of 100, 200, and 400) and analyzed to determine whether solutions improve with larger SA sample sizes. Subsequently, the results are compared to the results of a deterministic SA run.

Finally, the results of SA under uncertainty are compared to the original baseline design.

6.5.1. SA Sample Size Comparison

In each case a composite best result is obtained by determining a set of the top results according to a weighted score, y^* , based on the three optimization objectives given in the following equation.

$$y^* = \sum_{j=1}^M \frac{\omega_j y_j}{\delta_j} \quad (6.1)$$

where the weightings are given by ω_j of the j^{th} optimization objective, and δ_j represents the magnitude of the range of values y_j can assume. The weightings used for each input are 0.4, -0.4, and -0.2 for the coverage time, resolution, and total cost, respectively. The weightings for the resolution and total cost are negative since those objectives are minimized whereas the coverage time is maximized. These weightings were selected simply to exemplify an approach by which a solution can be selected based on an engineer's/decision maker's priorities and are meant to represent a hypothetical organization which is primarily concerned with performance rather than cost. The solutions with the largest values of y^* are included in the set for determining the composite solutions. The optimization inputs with the highest selection frequency amongst solution set are then selected as the optimization inputs of the composite solution. The size of the set is 25 solutions, which is deemed sufficiently large to give a meaningful result, yet small enough to minimize the computational demand. For example, among the top 25 solutions of the 400 SA sample set, Fig. 6.1 shows the selection frequency of various high-gain antenna (HGA) diameters.

Fig. 6.1 Selection frequency of various diameters for the HGA

Clearly the 35cm diameter antenna is selected with the greatest frequency and thus represents the value used for the composite solution. In cases of ties between two or more values, the value used by the overall top scoring solution is used. While with some inputs there is no clear preferred choice, with others there is little doubt, such as for the preferred payload. In each case, all 25 of the top solutions were synthetic-aperture radar (SAR) based systems. Table 6.3 provides all the input values determined for the composite solution derived for varying SA sample sizes.

Definition of the parameters and the components that correspond to the component type number can be found in their respective discipline appendix at the end of this thesis. The corresponding 100, 200, and 400 SA sample Pareto sets from which each composite solution was derived are respectively provided in Figs. 6.2, 6.3, and 6.4. All cost values are given in fiscal year 2007 US dollars.

Table 6.3 Optimizable input parameters (100, 200, and 400 SA samples)

Parameter	Discipline	OUU (100 SA Samples)	OUU (200 SA Samples)	OUU (400 SA Samples)
τ_{payload}	Payload	SAR	SAR	SAR
$f_{\text{bandwidth_sar}}$	Payload	18 MHz	18 MHz	18 MHz
$h_{\text{altitude_orbital}}$	Mission	500 km	500 km	500 km
$\tau_{\text{main_engine}}$	Propulsion	3	1	2
τ_{thruster}	Propulsion	2	1	1
$\tau_{\text{position_sensor}}$	ADACS	4	3	4
$\tau_{\text{sun_sensor}}$	ADACS	2	3	3
d_{hga}	Telecom	55 cm	35 cm	35 cm
$\tau_{\text{primary_battery}}$	Power	6	6	5
$\tau_{\text{solar_cell}}$	Power	5	5	6
$\tau_{\text{structure}}$	Structures	1	1	1
τ_{mli}	Thermal	14	14	14
$\tau_{\text{surface_finish_louver}}$	Thermal	12	13	14
$\tau_{\text{surface_finish_radiator}}$	Thermal	2	2	2

Fig. 6.2 Comparison of 100 SA sample solution set with 25 best solutions

Fig. 6.3 Comparison of 200 SA sample solution set with 25 best solutions

Fig. 6.4 Comparison of 400 SA sample solution set with 25 best solutions

It can be seen that with a larger number of SA samples the Pareto set becomes an increasingly defined region, particularly at the extremities. On the other hand it is not particularly clear how much benefit can be derived from increasing the SA sample size. Subsequently, both a deterministic evaluation of the model and an MCS of 500 samples were performed on each composite solution to provide the confidence levels of the cost. The number of samples was limited to 500 primarily due to time constraints. Ideally, 10000 samples are needed for 99.9th percentile confidence levels; however, this would require approximately one week of computation time per investigated solution type. With six types of solutions examined, that would require a total of approximately six weeks of uninterrupted computation time, which is simply not feasible for this research.

Table 6.4 provides the outputs corresponding to the composite solution for each SA sample size. The deterministic calculation represents uncertainties by the mean values of their associated distributions. By contrast the median value represents the median value of the outputs of interest resulting from the MCS. While the two may in some cases be the same, generally this is not the case as can be seen in Table 6.4 when comparing the cost from a deterministic calculation with the median cost of the MCS. Note that since all the systems are SAR-based, coverage time is not included as it is essentially equal for all cases. All cost values in this chapter are given in fiscal year 2007 US dollars.

Table 6.4 Comparison of SA sample size results

OUU SA Sample Size	Resolution, m	Total Cost, US\$M			
		Deterministic	Median	90 th Percentile	99 th Percentile
100	9.6	265.3	271.0	290.6	310.0
200	9.6	261.5	268.2	288.8	304.4
400	9.6	259.4	266.4	282.7	299.0

As could be anticipated, with increasing SA sample size, the quality of the solutions improves. The composite solution from 400 SA samples yields a median cost of 1.7% less than the composite solution from the 100 sample population. This translates to a \$4.6M savings. At the 99th percentile the savings for the 400 sample composite solution over the 100 SA sample composite solution increases to 3.5% or \$11M. Thus, not only does the larger SA sample size provide a better solution, it also provides larger improvements in the solutions at increasing confidence levels.

6.5.2. Baseline Comparison

Simulated annealing under uncertainty yields a result which differs greatly from the baseline design described in Loh et al. (2007). Chief among these differences is the selection of a multispectral imager (MSI) as the primary payload in the baseline design whereas only SAR was chosen in OUU. Table 6.5 summarizes the inputs of the two designs.

Table 6.5 Optimizable input parameters (baseline & composite OUU)

Parameter	Discipline	Baseline design	Composite OUU solution
τ_{payload}	Payload	MSI	SAR
$f_{\text{bandwidth_sar}}$	Payload	n/a	18 MHz
$d_{\text{aperture_msi}}$	Payload	14 cm	n/a
$h_{\text{altitude_orbital}}$	Mission	711 km	500 km
$\tau_{\text{main_engine}}$	Propulsion	1	2
τ_{thruster}	Propulsion	2	1
$\tau_{\text{position_sensor}}$	ADACS	1	4
$\tau_{\text{sun_sensor}}$	ADACS	1	3
d_{hga}	Telecom	19 cm	35 cm
$\tau_{\text{primary_battery}}$	Power	4	5
$\tau_{\text{solar_cell}}$	Power	5	6
$\tau_{\text{structure}}$	Structures	2	1
τ_{mli}	Thermal	9	14
$\tau_{\text{surface_finish_louver}}$	Thermal	12	14
$\tau_{\text{surface_finish_radiator}}$	Thermal	2	2

Definition of the parameters and the components that correspond to the component type number can be found in their respective discipline appendix at the end of this thesis. In only 1 case out of 13 was the same option chosen as an input. With the exception of the surface finish of the radiator, all other input variables between the two designs differ. This is primarily due to the differing payloads which places fairly different demands on the each design. Consequently, it may prove valuable to examine a composite MSI solution derived from SA under uncertainty to provide a better comparison with the baseline design. It should be noted that since the baseline design was performed by a design team and was not the product of an algorithm [Loh et al., 2007], values for $h_{\text{altitude_orbital}}$ and d_{hga} were not restricted to the same constraints given in Table 6.2. However, in order to optimize the STEPS model, certain changes needed to be made to the model. Other changes were made in order to improve the fidelity of the original model. Therefore, the outputs provided in this thesis for the baseline design do not correspond with the values provided in Loh et al. (2007). One of the changes from to the original STEPS model outlined in Loh et al. (2007) was the inclusion of a main engine. This was needed as the MTI and SAR payloads resulted in much heavier satellites where a main engine might be justified. Table 6.6 compares the inputs of the baseline design with the composite MSI solution obtained from the 400 SA sample set.

Even with the same type of payload instrument, the payload nonetheless differs significantly with a much larger aperture diameter for the composite MSI solution. This in turn results in two designs that differ quite significantly overall. Fig. 6.5 shows how a deterministic evaluation of the solutions fit on the Pareto curve obtained from the 400 SA sample set.

Table 6.6 Optimization inputs (baseline & composite MSI)

Parameter	Discipline	Baseline design	Composite MSI solution
τ_{payload}	Payload	MSI	MSI
$d_{\text{aperture_msi}}$	Payload	14 cm	32 cm
$h_{\text{altitude_orbital}}$	Mission	711 km	800 km
$\tau_{\text{main_engine}}$	Propulsion	1	3
τ_{thruster}	Propulsion	2	2
$\tau_{\text{position_sensor}}$	ADACS	1	3
$\tau_{\text{sun_sensor}}$	ADACS	1	1
d_{hga}	Telecom	19 cm	35 cm
$\tau_{\text{primary_battery}}$	Power	4	5
$\tau_{\text{solar_cell}}$	Power	5	5
$\tau_{\text{structure}}$	Structures	2	1
τ_{mli}	Thermal	9	12
$\tau_{\text{surface_finish_louver}}$	Thermal	12	14
$\tau_{\text{surface_finish_radiator}}$	Thermal	2	3

Fig. 6.5 Comparison of baseline and composite MSI solutions

Since the points for the baseline and composite solutions are based on a deterministic evaluation, they do not lie at the extreme edge of the Pareto set, but rather towards the center. To provide a better numerical comparison an MCS of each solution was performed for 500 samples. The results of the MCS are given in Table 6.7.

Table 6.7 Comparison with baseline results

Design method	Resolution, m	Total Cost, US\$M			
		Deterministic	Median	90 th Percentile	99 th Percentile
Baseline MSI design	20.6	89.2	92.0	97.4	102.2
Composite MSI solution	8.8	107.9	110.0	120.0	176.0

It is interesting to note that the composite MSI solution sees a large increase in cost when evaluated at the 99th percentile. At the 90th percentile confidence level the difference in cost between the baseline and composite solution is \$22.6M whereas at the 99th percentile it becomes \$73.8M. Upon further investigation, the reason for this change is that the system becomes too massive for the launch vehicle and is pushed onto a larger launch platform resulting in a significantly higher cost. Thus, when uncertainties are propagated through the design, the resulting increase in mass forces an unforeseen change in launch vehicle. This represents a shortcoming in the method in determining the best solution as at higher-confidence levels this solution is no longer competitive with the baseline design, which maintains a low enough mass to remain on the smaller and less expensive launch vehicle.

6.5.3. Single Solution Comparison

The next question to be approached is whether such a composite solution is in fact superior to the single-best solution found from the same data set, according to the

weightings given in Section 6.5.1. The single solution is obtained from the 400 SA sample population and is compared with the composite solution in Table 6.8, with the values of the input parameters for each case.

Table 6.8 Optimizable input parameters (single OUU & composite OUU)

Parameter	Discipline	Single solution	Composite OUU solution
τ_{payload}	Payload	SAR	SAR
$f_{\text{bandwidth_sar}}$	Payload	18 MHz	18 MHz
$h_{\text{altitude_orbital}}$	Mission	450 km	500 km
$\tau_{\text{main_engine}}$	Propulsion	3	2
τ_{thruster}	Propulsion	1	1
$\tau_{\text{position_sensor}}$	ADACS	3	4
$\tau_{\text{sun_sensor}}$	ADACS	1	3
d_{hga}	Telecom	35 cm	35 cm
$\tau_{\text{primary_battery}}$	Power	5	5
$\tau_{\text{solar_cell}}$	Power	6	6
$\tau_{\text{structure}}$	Structures	1	1
τ_{mli}	Thermal	13	14
$\tau_{\text{surface_finish_louver}}$	Thermal	14	14
$\tau_{\text{surface_finish_radiator}}$	Thermal	2	2

Definition of the parameters and the components that correspond to the component type number can be found in their respective discipline appendix at the end of this thesis. At first glance the solutions appear quite similar with 10 of the 14 inputs being the same. Figure 6.6 illustrates the difference in a deterministic evaluation of the two systems.

Fig. 6.6 Comparison of single and composite OUU solutions

It can be seen that the composite solution appears to dominate the single solution providing a better resolution at a lower cost, although the difference in resolution is not large. An MCS of 500 samples was performed to demonstrate how each solution behaves under uncertainty. The results of the MCS are given in Table 6.9.

Table 6.9 Comparison with single solution results

Optimization method	Resolution, m	Total Cost, US\$M			
		Deterministic	Median	90 th Percentile	99 th Percentile
Single solution	9.8	271.0	281.8	308.7	337.2
Composite OUU solution	9.6	259.4	266.4	282.7	299.0

Somewhat surprisingly, the median cost of the composite solution system is significantly lower than the single-solution system. The difference in cost stands at \$15.4M which represents approximately a 5.5% savings. At the 99th percentile confidence level the difference becomes even more pronounced where the composite

solution yields a savings of \$38.2M or an 11.3% reduction. This is possibly a consequence of the fact that the composite solution is a system that has, on average, yielded the best results over a variety of uncertain conditions whereas the single solution is an optimal solution for a specific set of conditions. When evaluated across a sampling of uncertain conditions the composite solution proves that it can be more robust and yields a superior result, even at higher confidence levels.

6.5.4. Deterministic Simulated Annealing Comparison

Comparing the composite solution derived from SA under uncertainty with a solution obtained from a purely deterministic SA algorithm is also of value in examining the performance of SA under uncertainty. The deterministic SA optimization was performed at all the same settings with the exception of the maximum number of function evaluations at a given temperature, which is set to 5. This yields a total number of 375 function evaluations for the deterministic run. This was deemed an appropriate number which could feasibly be computed in a reasonable amount of time. While this does not match the number of function evaluations performed by SA under uncertainty, it is necessary to understand that the deterministic SA algorithm cannot be computed in parallel on several computers. For this reason, performing a deterministic SA run with an equivalent number of function evaluations is not feasible as the computation time would be immense. Table 6.10 compares the difference in input values for the optimizable variables between the deterministic SA run and the SA run under uncertainty.

Table 6.10 Optimizable input parameters (deterministic SA & composite OUU)

Parameter	Discipline	Deterministic SA	Composite OUU solution
τ_{payload}	Payload	SAR	SAR
$f_{\text{bandwidth_sar}}$	Payload	18 MHz	18 MHz
$h_{\text{altitude_orbital}}$	Mission	500 km	500 km
$\tau_{\text{main_engine}}$	Propulsion	4	2
τ_{thruster}	Propulsion	1	1
$\tau_{\text{position_sensor}}$	ADACS	4	4
$\tau_{\text{sun_sensor}}$	ADACS	1	3
d_{hga}	Telecom	45 cm	35 cm
$\tau_{\text{primary_battery}}$	Power	4	5
$\tau_{\text{solar_cell}}$	Power	5	6
$\tau_{\text{structure}}$	Structures	2	1
τ_{mli}	Thermal	12	14
$\tau_{\text{surface_finish_louver}}$	Thermal	14	14
$\tau_{\text{surface_finish_radiator}}$	Thermal	2	2

Definition of the parameters and the components that correspond to the component type number can be found in their respective discipline appendix at the end of this thesis. Both cases result in an identical payload configuration. Beyond this the two systems show little similarity with only 4 of the 12 remaining inputs the same. Figure 6.7 shows a deterministic evaluation of the composite OUU and deterministic SA solutions with respect to the 400 SA sample Pareto set.

Fig. 6.7 Comparison of deterministic SA and composite OUU solutions

Both solutions despite their differences appear to be located in a very similar region of the Pareto set. An MCS of 500 samples was performed on each solution to more thoroughly investigate them. The results are presented in Table 6.11.

Table 6.11 Comparison with deterministic SA results

Optimization method	Resolution, m	Total Cost, US\$M			
		Deterministic	Median	90 th Percentile	99 th Percentile
Deterministic SA	9.6	277.6	278.8	298.4	321.2
Composite OUU solution	9.6	259.4	266.4	282.7	299.0

By contrast with Fig. 6.5, Table 6.11 shows a clear advantage in the cost of the composite OUU solution. The best solution from the deterministic SA run results in a significantly higher-overall median cost, running \$12.4M higher than the composite OUU solution. When evaluated at the 99th percentile the deterministic SA solution is a

full \$22.2M higher in cost. Clearly the composite OUU solution results in a significant improvement over the deterministic SA solution.

6.6. Analysis Conclusions

After performing SA under uncertainty the results indicate that with a larger SA sample size, solution quality increases. Simulated annealing sample sizes of 100, 200, and 400 were compared, with 400 SA samples providing the best results. Furthermore, the differences become more pronounced at higher confidence levels. On the other hand, there is likely a limit to the improvements as solutions approach the true optimum and no further improvement can be obtained.

In the analysis of SA under uncertainty it was found that SAR solutions outperform MSI solutions based on the weightings of the performance metrics of interest. However, in order to provide a means of comparing the two approaches more readily, a composite MSI solution was derived from the OUU data set. In comparing these solutions, initially the composite MSI solution appears favourable. When an MCS is performed on both solutions, a short-coming of the OUU is illustrated which results in the baseline solution being the superior one. It should be noted that this issue does not represent a failure of SA under uncertainty, but rather an area for future work and will be discussed further in Section 7.1.3.

A composite solution was compared to the single-best solution found in the 400 SA sample set. In this case it was found that the composite solution provided an equally capable system for a significantly lower cost. Surprisingly, the difference increases at higher confidence levels, suggesting that despite the shortcoming seen in the comparison with the baseline solution, this method can still yield more robust results in some circumstances. This is likely a result of the fact that the single-best solution is

based on a single set of conditions, whereas the composite solution is based on various uncertain conditions.

Finally, a solution from a deterministic simulated annealing run was compared with the composite solution. Again the composite solution provided better results, with increasing improvements at higher confidence levels.

7. Conclusion & Future Work

This chapter begins with a brief summary of the results and concludes with final remarks. This is followed by summarizing areas of future work seen as important in furthering the advancements presented in this thesis.

7.1. Conclusion

The goals outlined in the initial proposal have successfully been achieved with this research. Firstly, a multi-objective MDO algorithm was fully implemented and tested. A satellite model was developed and rigorously tested to produce consistent deterministic results. Subsequently, Monte Carlo simulation of the model and the resulting uncertainty analysis were performed. The multi-objective MDO algorithm was applied to the deterministic satellite model and the results analyzed. Finally, the simulated annealing algorithm was applied under uncertainty to the satellite model and the results compared with the baseline and deterministic cases.

Simulated annealing was selected as the multi-objective MDO algorithm to be implemented for this research based on the success of prior applications to conceptual-satellite design. The algorithm was then tested and tuned through comparison to a random search algorithm by application to an existing test problem. After tuning, it was found that a threefold increase in performance could be achieved by simulated annealing over the random search algorithm.

Monte Carlo simulation of the satellite model demonstrated that uncertainties could successfully be quantified in conceptual-satellite design. While previous work has demonstrated this approach on satellite subsystems, this constitutes the first time a rigorous, repeatable method for determining uncertainties has been successfully

applied to a complete satellite model which is representative down to a component level. The analysis demonstrated that the baseline design determined values with very-low confidence levels. In the cases of both the dry mass and the cost, substantial increases in budgeted values were required to achieve risk-neutral (i.e., 99th percentile) positions.

The simulated annealing algorithm was applied to the deterministic satellite model as a preliminary step to performing optimization under uncertainty. This was done for two reasons: reducing computational effort by determining reasonable boundary constraints of the optimizable input parameters and identifying the minimum number of function evaluations necessary to obtain good results from the simulated annealing process. The new boundary constraints introduced as a result of this analysis reduced the number of possible solutions in the solution space from ~3.5 trillion to ~36 million. In analyzing the number of function evaluations required to obtain good results from the algorithm, it was found that 150 provided acceptable results from the simulated annealing algorithm.

In applying simulated annealing under uncertainty to the satellite model, the goal was to achieve a design that was robust under uncertainty and performed well in extreme cases. A composite solution was generated based on assumed weightings of the outputs. Composite solutions for increasing SA sample populations were compared and it was found that solution quality improved with larger SA sample populations. A composite solution derived from a 400 SA sample set was then compared with baseline design. It was found that the composite solution, while better in the median case, was inferior at confidence levels above the 99th percentile. By contrast, in comparison with single-best solution of the 400 SA sample set, the composite solution was found to be far more robust under uncertainty and yielded an equally capable

system (i.e., same resolution and coverage time) for a significantly lower cost. Similarly, in comparison with the optimal deterministic simulated annealing solution, the composite solution provided superior results at all confidence levels.

In conclusion, while the proposed optimization under uncertainty method proposed in this research provided robust results under uncertainty, it did not in all cases anticipate the negative impact of more extreme uncertain cases. However, a possible remedy would be to replace MCS with another simulation method such as SS, which is specifically designed to explore the tails of distributions. Consequently, this research constitutes a significant step forward in developing a feasible approach to performing optimization under uncertainty which can yield results that are less costly and/or more capable across a range of confidence levels. This then provides decision-makers with more information about possible design choices early in the process, allowing better decisions to be made. With better decisions early in the design process, less revision is necessary later in the design process, which can help to mitigate unforeseen cost increases.

7.2. Future Work

While significant progress has been made in developing an algorithm to perform optimization under uncertainty (OUU) there remain several areas for future work.

7.2.1. Simulated Annealing Sample Size

Determining an appropriate simulated annealing (SA) sample size is of great importance as this strongly affects both solution quality and computational demand. In this research it was determined that larger SA sample sizes provide better solutions, although this comes at the expense of greater computational effort. However, the question of what is a sufficiently large SA sample size was not adequately resolved,

particularly in consideration of the fact that this is a value that is likely dependant on the application. Determining a method to address this problem would constitute a useful step in improving the OUU method presented in this thesis.

7.2.2. Composite Solution

In this work composite solutions were developed based on the results of the 25 best solutions. This number was selected as it provided a large enough sampling to provide a realistic representation of which optimization values were selected with the greatest frequency. Ideally, one would desire to keep this value at a minimum to ensure that only the very best solutions are being used. On the other hand a larger number of solutions provides greater statistical relevance. As such, there is value in exploring this tradeoff.

7.2.3. Subset Simulation

As discussed in Section 6.5, simulated annealing (SA) under uncertainty performs well in many cases but still possesses some shortcomings in specific situations, specifically seen in the comparison with the baseline design (Section 6.5.2). This is likely a result of the employment of Monte Carlo simulation (MCS). The reason for this belief is that Monte Carlo simulation tends to yield results from the central region of the distribution (i.e., 5th – 95th percentile range) and less frequently yields results from the tails. In actuality a sampling method that samples primarily from the tails of distributions would be of greater benefit in analyzing extreme cases. One solution to this problem would be employing Subset Simulation (SS). Subset Simulation was specifically designed with the intent of exploring the tails of distributions and would likely be beneficial in improving results such as those seen in Section 6.5.2. For this reason, it is also conceivable that SS could require fewer samples than MCS. This is

particularly important for reducing the computation time. As such, finding a way of unifying SS with SA under uncertainty could result in a significant step forward in examining the extreme cases in satellite design and improve the quality and robustness of solutions computed in optimization under uncertainty.

7.2.4. Satellite Model

Another area for further work is developing a higher-fidelity satellite model. Most notably, developing finite-element models for both structural and thermal analysis could provide additional insight into the effectiveness of the proposed method. Additional optimization could also be performed in the power system, by considering the timing of equipment at a higher fidelity than the phase level. The inclusion a configuration discipline would also provide greater model fidelity. Another discipline that was neglected in this research was radiation analysis.

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Appendix

A. Payload Discipline

Michael Magnin (& Leong Yoke Fun Hannah)

The STEPS payload consists of a primary payload (i.e., multispectral imager, multispectral thermal imager, or synthetic aperture radar) and an automatic identification system (AIS).

Major Model Assumptions

- AIS is included in all designs as a secondary payload for the purpose of ship verification
- Assume signal to noise ratio and pulse length for the synthetic aperture radar are constant known values
- Small angle approximation in calculating resolutions of the multispectral imager and the multispectral thermal imager
- One possible AIS

References Used

Payload subsystem based on seven references:

- "Surrey missions: Topsat," Surrey Satellite Technology Ltd., SSTL-5020-02, Guildford, UK, June 2001.
- Curlander, J. *Synthetic Aperture Radar: Systems and Signal Processing*, 1st ed., Wiley-Interscience, New York, NY, USA, 1991.
- DiFranco, J. and Rubin, W., *Radar Detection*, 1st ed., Artech House Inc., Dedham, MA, USA, 1980.
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- Wertz, J. and Larson, W., *Space Mission Analysis and Design*, 3rd ed., Microcosm, Torrance, CA, USA, 1999.

Files Used

Payload specific (8 files):

ais_determination.m, *imager_mass.m*, *msi.m*, *main_payload.m*, *mti.m*, *payload_outputs.m*, *payload_trl.m*, *sar.m*

Systems/Databases (3 files):

ais_data.m, *imager_data.m*, *payload_components.xls*

Payload Model Flow Chart

Fig. A.1 Payload subsystem model flowchart

- Subsystem input variables are listed in sections: Uncontrollable Design Variables, Constant Input Variables, and Controllable Input Variables and Their Constraints
- Multidisciplinary variables are listed in section: Inputs from Other Subsystems
- Payload outputs are listed in section: Outputs to Other Subsystems

Payload Nomenclature

Table A.1 Payload-related variables nomenclature

Symbol	Definition
b	bits per pixel
d	diameter
D	data rate
f	Frequency
h	height
k	factor
l	length
m	mass
n	quantity or number
SNR	signal to noise ratio
t	time or duration
T	temperature
v	velocity
w	width
Γ	technology readiness level
η	efficiency
θ	angle
τ	type

Table A.2 Payload-related subscript nomenclature

Symbol	Definition
max	maximum
min	minimum
msi	multispectral imager
mti	multispectral thermal imager
op	operational
sar	synthetic aperture radar

Inputs from Other Subsystems (2)

- Note that subscript $i = \{1, 2, 3, 4, 5, 6, 7, 8\}$ and represents the phase number

Mission design:

$h_{\text{altitude_orbital}}$, $v_{\text{rel_ground}}$

Uncontrollable Design Variables (10)**Table A.3 Payload model uncertainties assumed**

Parameter	Units	Distribution type and parameters
$\theta_{\text{earth_central_max}}$	degrees	Normal(6.5,0.25)
k_{noise}	n/a	Normal(2,0.1)
$k_{\text{antenna_length}}$	n/a	Normal(1,0.0033)
$k_{\text{antenna_width}}$	n/a	Normal(1,0.0033)
$k_{\text{aperture_msi}}$	n/a	Normal(1,0.0066)
$k_{\text{aperture_mti}}$	n/a	Normal(1,0.0066)
$k_{\text{bandwidth_sar}}$	n/a	Normal(1,0.0066)
$m_{\text{uncertainty_payload_total}}$	kg	Uniform(-1,2.5)
T_{noise}	K	Uniform(280,295)
w_{swath}	km	Normal(300,5)

Constant Input Variables (4)**Table A.4 Payload Constant Inputs**

Parameter	Value	Units
b	8	n/a
SNR_{required}	40	dB
t_{pulse}	0.03	ms
η_{antenna}	1	n/a

Controllable Input Variables (2) and their Constraints

$d_{\text{aperture_msi}}$: $d_{\text{aperture_msi}} \in \{0.04, 0.08, \dots, 0.36, 0.40\}$

$d_{\text{aperture_mti}}$: $d_{\text{aperture_mti}} \in \{0.2, 0.4, \dots, 1.2, 1.4\}$

$f_{\text{bandwidth_sar}}$: $f_{\text{bandwidth_sar}} \in \{4, 6, \dots, 18, 20\}$

τ_{payload} : $\tau_{\text{payload}} \in \{1, 2, 3\}$

Table A.5 Payload types

Payload number	Payload type
1	MSI
2	SAR
3	MTI

Outputs to Other Subsystems [44]

ADACS:

$\theta_{\text{look_max}}$

C&DH:

$D_i, \tau_{\text{payload}}$

Cost:

Γ_{payload}

Mission design:

$\tau_{\text{payload}}, \theta_{\text{longitude_max}}, \theta_{\text{longitude_min}}$

Power:

$P_{\text{avg_payload_phase_i}}, P_{\text{peak_payload_phase_i}}, \theta_{\text{look_max}}$

Structures:

$m_{\text{imager}}, n_{\text{imager}}$

Systems:

$m_{\text{total_payload}}, R, \Gamma_{\text{payload}}$

Telecom:

$D_i, h_{\text{slant_max}}$

Thermal:

$h_{\text{payload_component_1}}, h_{\text{payload_component_2}}, l_{\text{payload_component_1}}, l_{\text{payload_component_2}}, P_{\text{avg_payload_phase_i}},$
 $P_{\text{peak_payload_phase_i}}, T_{\text{op_max_payload_component_1}}, T_{\text{op_max_payload_component_2}},$
 $T_{\text{op_min_payload_component_1}}, T_{\text{op_min_payload_component_2}}, w_{\text{payload_component_1}}, w_{\text{payload_component_2}}$

B. Mission Design Discipline

Michael Magnin (& Teng Lingying)

The mission design discipline calculates the phase durations, velocity changes, and orbit characteristics. This discipline also selects the appropriate launch vehicle based on a programmed selection criteria.

Major Model Assumptions

- Limited to only two launch vehicles that can be launched at a 0° inclination
- Assume perfectly circular earth
- Ignore effects of precession
- Orbit perturbations assumed constant over the lifetime of the mission and calculated under worst-case conditions

References Used

Mission design discipline based on one reference:

- Wertz, J. and Larson, W., *Space Mission Analysis and Design*, 3rd ed., Microcosm, Torrance, CA, USA, 1999.

Files Used

Mission design specific (9 files):

ballistic_coefficient.m, *coverage_time.m*, *delta_v.m*, *lv_selection.m*, ***main_mission.m***, *mission_outputs.m*, *orbital_period_SC.m*, *other_mission_outputs.m*, *phase_duration.m*

Systems/Databases (2 files):

launch_vehicles.xls, *lv_data.m*

Mission Design Model Flow Chart

Fig. B.1 Mission design discipline model flowchart

- Subsystem input variables are listed in sections: Uncontrollable Design Variables, Constant Input Variables, and Controllable Input Variables and Their Constraints
- Multidisciplinary variables are listed in section: Inputs from Other Subsystems
- Mission design outputs are listed in section: Outputs to Other Subsystems

Mission Design Nomenclature

Table B.1 Mission design -related variables nomenclature

Symbol	Definition
A	area
C	coefficient
h	height
k	factor
m	mass
n	quantity or number
t	time or duration
Δv	change in velocity
θ	angle
τ	type
$\$$	cost

Table B.2 Mission design-related subscript nomenclature

Symbol	Definition
2, 3, 7	phase numbers
i	phases 1 to 8
max	maximum
min	minimum
rel	relative to
lv	launch vehicle

Inputs from Other Subsystems (11)

- Note that subscript $i = \{1, 2, 3, 4, 5, 6, 7, 8\}$ and represents the phase number

Payload:

$\tau_{\text{payload}}, \theta_{\text{longitude_max}}, \theta_{\text{longitude_min}}$

Power :

$A_{\text{solar_array}}$

Propulsion:

$t_{2_propulsion}, t_{7_propulsion}$

Structures:

$h_{\text{bus}}, l_{\text{bus}}$

Systems:

$m_{\text{injected}}, m_{\text{total_sc_dry}}, m_{\text{total_sc_wet}}$

Uncontrollable Design Variables (8)**Table B.3 Mission design model uncertainties assumed**

Parameter	Units	Distribution type and parameters
$C_{\text{drag_max}}$	n/a	Normal(4.5,0.15)
$C_{\text{drag_min}}$	n/a	Normal(2.5,0.15)
$h_{\text{perigee_deorbit}}$	km	Lognormal(3.9,0.07)
$k_{\text{cloud_coverage}}$	n/a	Uniform(0.55,0.65)
$k_{\text{reflection}}$	n/a	Uniform(0.55,0.65)
t_1	hours	Uniform(4,6)
t_8	s	Uniform(300,900)
t_{mission}	years	Custom(3 0.5; 4 0.25; 5 0.25)

Constant Input Variables (4)**Table B.4 Mission design constant input variables**

Parameter	Value	Units
$h_{\text{altitude_max_pegasus}}$	1400	km
$h_{\text{altitude_max_zenit}}$	20000	km
n_{phase}	8	n/a
$\theta_{\text{inclination}}$	0	degrees

Controllable Input Variables (1) and their Constraints

$h_{\text{altitude_orbital}}$: $h_{\text{altitude_orbital}} \in \{450, 500, \dots, 950, 1000\}$

Outputs to Other Subsystems [26]

ADACS:

$h_{\text{altitude_orbital}}, C_{\text{drag_max}}, t_{\text{mission}}, t_{\text{orbit}}, t_3, \tau_{\text{lv}}$

C&DH:

t_i

Cost:

$\$_{\text{lv}}$

Payload:

$h_{\text{altitude_orbital}}, v_{\text{rel_ground}}$

Power:

$n_{\text{phase}}, t_{\text{mission}}, t_i$

Propulsion:

Δv_i

Structures:

τ_{lv}

Systems:

Δv_{total} , t_{coverage} , t_{orbit}

Thermal:

$h_{\text{altitude_orbital}}$

C. Propulsion Discipline

Daniel Thunnissen (& Kelvin Loh Kwong Lam)

The propulsion subsystem model determines propulsion specific component masses (e.g., filters, latch valves, thrusters, propellant/pressurant tanks, etc.), propellant mass for orbital maneuvers, power requirements by phase, temperature tolerances, and required burn times for orbital maneuvers.

Major Model Assumptions

- Four possible propulsion system types: cold-gas regulated (no main engine), monopropellant hydrazine blowdown (no main engine), monopropellant hydrazine regulated (with main engine), regulated dual-mode (with main engine)
- Number of components should be optimized factoring in reliability but considering reliability as a system-level tradable parameter is beyond the scope of this research
- Eight possible cold-gases (air, hydrogen, helium, nitrogen, oxygen, argon, carbon dioxide, methane)
- Two possible pressurants (helium and nitrogen) for the two monopropellant (hydrazine) systems
- One possible cold-gas thrusters (Moog 58-118)
- Two possible monopropellant thrusters (Aerojet MR-103G/H & MR-111C/E)
- Three possible monopropellant main engines (Aerojet MR-104A, MR-107B, MR-107J) and one possible dual-mode main engine (Royal Ordnance Leros-1c)
- Single spherical commercial-off-the-shelf composite overwrapped cold-gas tank (for the cold-gas case)
 - No main engine, two pairs of attitude control thrusters (4 total) used for ΔV maneuvers
- Single spherical commercial-off-the-shelf titanium propellant tank (for the monopropellant blowdown case)
 - No main engine, two pairs of attitude control thrusters (4 total) used for ΔV maneuvers
- Single spherical commercial-off-the-shelf composite overwrapped pressurant tank and a single spherical commercial-off-the-shelf titanium propellant tank (for the monopropellant regulated case)
- Single spherical commercial-off-the-shelf composite overwrapped pressurant tank and a three (two fuel, one oxidizer) spherical commercial-off-the-shelf titanium propellant tanks (for the dual-mode case)
- All maneuvers assumed to be isothermal
- Pressure drop through components and tubing neglected (thruster performance is based on decreasing tank pressure for monopropellant blowdown system and regular outlet pressure for cold-gas and monopropellant-regulated systems)

References Used

Propulsion system model based primarily on two references:

- Humble, R., Henry, G., and Larson, W., *Space Propulsion Analysis and Design*, McGraw-Hill Co., New York, New York, 1995.
- Thunnissen, D., Engelbrecht, C., and Weiss, J., "Assessing Model Uncertainty in the Conceptual Design of a Monopropellant Propulsion System," AIAA 2003-4469, July 2003.

Other references used:

- Dodge, B., *Chemical Engineering Thermodynamics*, McGraw-Hill Co., New York, New York, 1944, pp. 680.
- Schmidt, E., *Hydrazine and Its Derivatives*, John Wiley & Co., New York, New York, 1984.
- USAF Propellant Handbook

Files Used

Power specific (9 files):

beattie_bridgeman.m, *cold_gas.m*, *dual_mode.m*, ***main_prop.m***, *mono_blowdown.m*, *mono_regulated.m*, *prop_outputs.m*, *prop_power.m*, *prop_trl.m*, *specific_impulse.m*, *thrust.m*

Systems/Databases (4 files):

engines_new.m, *fuels.m*, *gases_new.m*, *oxidizers.m*, *propulsion_components.xls*, *thrusters.m*

Propulsion Model Flow Chart

Fig. C.1 Propulsion subsystem model flowchart

- Subsystem input variables are listed in sections: Uncontrollable Design Variables, Constant Input Variables, and Controllable Input Variables and Their Constraints
- Multidisciplinary variables are listed in section: Inputs from Other Subsystems
- Propulsion outputs are listed in section: Outputs to Other Subsystems

Propulsion Nomenclature

Table C.1 Propulsion-related variables nomenclature

Symbol	Definition
F	thrust
k	factor
m	mass
n	quantity or number
p	pressure
P	Power
T	temperature
t	time or duration
Δv	change in velocity
Γ	technology readiness level
η	efficiency
Ξ	pressure-volume/weight (PV/W) tank factor
τ	type
ψ	percent value

Table C.2 Propulsion-related subscript nomenclature

Symbol	Definition
adacs	attitude determination & control subsystem
max	maximum
min	minimum
sc	spacecraft

Inputs from Other Subsystems (10)

- Note that subscript $i = \{1, 2, 3, 4, 5, 6, 7, 8\}$ and represents the phase number

ADACS:

$m_{\text{propellant_adacs}}$

Mission design:

Δv_i

Systems:

$m_{\text{sc_total_wet}}$

Uncontrollable Design Variables (24)**Table C.3 Propulsion model uncertainties assumed**

Parameter	Units	Distribution type and parameters
$F_{\text{thrust_max_req}}$	N	Uniform(5,7)
$F_{\text{thrust_min_req}}$	N	Uniform(0.5,1.5)
$m_{\text{check_valve}}$	kg	Uniform(0.25,0.5)
$m_{\text{filter_gas}}$	kg	Uniform(0.15,0.25)
$m_{\text{filter_liquid}}$	kg	Uniform(0.15,0.25)
$m_{\text{latch_valve}}$	kg	Uniform(0.5,1)
$m_{\text{pressure_transducer}}$	kg	Uniform(0.27,0.5)
$m_{\text{uncertainty_propulsion_total}}$	kg	Uniform(-0.5,1)
$m_{\text{pyrotechnic_valve}}$	kg	Uniform(0.3,0.5)
$m_{\text{regulator}}$	kg	Uniform(0.75,1.25)
$m_{\text{service_valve_gas}}$	kg	Uniform(0.15,0.3)
$m_{\text{service_valve_liquid}}$	kg	Uniform(0.15,0.3)
$m_{\text{tubing_and_fittings}}$	kg	Uniform(1,2)
$P_{\text{pres_tank_max_expected_dm}}$	psi	Normal(4200,40)
$P_{\text{pres_tank_max_expected_reg}}$	psi	Normal(300,4)
$P_{\text{pres_tank_max_expected_cg}}$	psi	Normal(300,4)
$P_{\text{prop_tank_max_expected_bd}}$	psi	Normal(427,4)
$P_{\text{prop_tank_max_expected_dm}}$	psi	Normal(300,4)
$P_{\text{prop_tank_max_expected_reg}}$	psi	Normal(300,4)
T_{pres}	°C	Normal(25,2)
T_{prop}	°C	Normal(25,2)
$\bar{E}_{\text{pressurant_tank}}$	in	Normal(850000,85000)
$\bar{E}_{\text{propellant_tank}}$	in	Normal(300000,30000)
$\eta_{\text{expulsion_propellant_tank}}$	n/a	Beta(330,1)

Constant Input Variables (10)**Table C.4 Propulsion constant input variables**

Parameter	Value	Units
$k_{burst_pressurant_tank}$	1.5	n/a
$k_{burst_propellant_tank}$	1.5	n/a
$n_{pressurant_tank}$	1	n/a
$n_{propellant_tank}$	1	n/a
$n_{thruster_pairs}$	6	n/a
$P_{avg_catbed_heater}$	2	W
$P_{peak_catbed_heater}$	2	W
$p_{regulator_out}$	215	psi
τ_{pres}	3	n/a
τ_{cold_gas}	3	n/a

Controllable Input Variables (2) and their Constraints

$\tau_{propulsion_system}$: $\tau_{propulsion_system} \in \{1, 2, 3, 4, 5\}$

$\tau_{thruster}$: $\tau_{thruster} \in \{1, 2, 3\}$

Table C.5 Main engine types

Main engine number	Main engine type
1	No main engine
2	Aerojet MR-104A
3	Aerojet MR-107B
4	Royal Ordnance Leros 1c
5	Aerojet MR-107J

Table C.6 Thruster types

Thruster number	Thruster type
1	Aerojet MR-103G/H
2	Aerojet MR-111C/E
3	Moog 58-118

Outputs to Other Subsystems [31]

ADACS:

$v_{exhaust_thruster}$, $F_{thruster}$

Cost:

$n_{thrusters}$, $\Gamma_{propulsion}$

Mission design: $t_{2_propulsion}, t_{7_propulsion}$ **Power:** $P_{avg_propulsion_phase_i}, P_{peak_propulsion_phase_i}$ **Structures:** $m_{oxidant_tank}, m_{pressurant_tank}, m_{propellant_tank}, m_{thruster}, n_{oxidant_tank}, n_{pressurant_tank}, n_{propellant_tank}, n_{thruster}$ **Systems:** $m_{propulsion_total}, m_{total_propellant}, \Gamma_{propulsion}$ **Thermal:** $P_{avg_propulsion_phase_i}, P_{peak_propulsion_phase_i}$

D. ADACS Discipline

Michael Magnin (& Anbu Sollin Selvan)

This subsystem model determines attitude determination and control specific component masses (e.g., horizon sensors, sun sensors, star trackers, etc.), propellant mass required for attitude control maneuvers, power requirements by phase, and satellite pointing capabilities

Major Model Assumptions

- Use propulsion thrusters for attitude control maneuvers
- Orientation and number of thrusters fixed
- Disturbance torques are time-independent
- Schematics of each propulsion system type fixed (i.e., number of each component type fixed and only difference could be in choice of thruster and pressurant)
- Ideally number of components should be optimized factoring in reliability but considering reliability as a system-level tradable parameter is beyond the scope of this research
- One possible GPS
- Six possible position sensors
- Eight possible sun sensors
- Slew maneuvers assumed for observation to be performed in 200 s

References Used

ADACS system model based primarily on two references:

- Wertz, J., *Spacecraft Attitude Determination and Control*, 1st ed., Microcosm, Torrance, CA, USA, 1978.
- Wertz, J. and Larson, W., *Space Mission Analysis and Design*, 3rd ed., Microcosm, Torrance, CA, USA, 1999.

Files Used

ADACS specific (8 files):

adacs_outputs.m, *adacs_propellant.m*, *adacs_sensors.m*, *adacs_trl.m*, ***main_adacs.m***, *orbit_insertion.m*, *slew.m*, *torque.m*

Systems/Databases (4 files):

adacs_components.xls, *gps_data.m*, *position_sensor_data.m*, *sun_sensor_data.m*, *thrusters.m*

ADACS Model Flow Chart **Fig. D.1 ADACS subsystem model flowchart**

- Subsystem input variables are listed in sections: Uncontrollable Design Variables, Constant Input Variables, and Controllable Input Variables and Their Constraints
- Multidisciplinary variables are listed in section: Inputs from Other Subsystems
- ADACS outputs are listed in section: Outputs to Other Subsystems

ADACS Nomenclature

Table D.1 ADACS-related variables nomenclature

Symbol	Definition
A	area
C	coefficient
F	thrust
h	height
I	moment of inertia
k	factor
l	length
m	mass
n	quantity or number
P	power
t	time or duration
v	velocity
w	width
Γ	technology readiness level
θ	angle
μ	magnetic dipole moment

Table D.2 ADACS-related subscript nomenclature

Symbol	Definition
3	phase number
adacs	attitude determination & control subsystem
cp	center of pressure
lv	launch vehicle
max	maximum
sc	spacecraft
scdsa	spacecraft, deployed solar array
scusa	spacecraft, undeployed solar array

Inputs from Other Subsystems (21)

Mission design:

 $h_{\text{altitude_orbital}}, C_{\text{drag_max}}, t_{\text{mission}}, t_{\text{orbit}}, t_3, \tau_{\text{lv}}$

Payload:

 $\theta_{\text{look_max}}$

Power: $A_{\text{solar_array}}, \Phi_{\text{solar}}, \theta_{\text{sun}}$ **Propulsion:** $v_{\text{exhaust_thruster}}, F_{\text{thruster}}$ **Structures:** $h_{\text{bus}}, I_{xx_scdsa}, I_{xx_scusa}, I_{yy_scusa}, I_{yy_scdsa}, I_{zz_scusa}, I_{zz_scdsa}, l_{\text{bus}}, w_{\text{bus}}$ **Uncontrollable Design Variables (8)****Table D.3 ADACS model uncertainties assumed**

Parameter	Units	Distribution type and parameters
$k_{\text{reflectance}}$	n/a	Beta(1000,250)
$l_{\text{cp_offset_x}}$	cm	Normal(10,0.1)
$l_{\text{cp_offset_y}}$	cm	Normal(10,0.1)
$l_{\text{cp_offset_z}}$	cm	Normal(10,0.1)
$m_{\text{uncertainty_adacs_total}}$	kg	Uniform(-0.5,3)
$t_{\text{corr_slew}}$	s	Uniform(60,120)
$\theta_{\text{pointing_accuracy}}$	degrees	Uniform(1.08,1.11)
μ_{sc}	A/m ²	Normal(1,0.05)

Constant Input Variables (2)**Table D.4 ADACS constant input variables**

Parameter	Value	Units
t_{slew}	200	s
τ_{gps}	1	n/a

Controllable Input Variables (2) and their Constraints $\tau_{\text{position_sensor}}: \tau_{\text{position_sensor}} \in \{1,2,3,4,5,6\}$ $\tau_{\text{sun_sensor}}: \tau_{\text{sun_sensor}} \in \{1,2,3,4,5,6,7,8\}$

Table D.5 Position sensor types

Position sensor number	Position sensor type
1	Valley Forge horizon sensor
2	Valley Forge Earth sensor
3	Servo mini dual Earth sensor
4	Valley Forge star camera
5	Goodrich 13-410 assembly
6	Goodrich 13-470 assembly

Table D.6 Sun sensor types

Sun sensor number	Sun sensor type
1	TNO hybrid sun acquisition/quadrant sun sensor
2	Valley Forge composite sensor
3	TNO quadrant Sun sensor
4	TNO digital Sun sensor
5	Fine solar aspect sensor
6	TNO Sun acquisition sensor
7	Aeroastro coarse Sun sensor
8	Aeroastro medium Sun sensor

Outputs to Other Subsystems [28]

- Note that subscript $i = \{1, 2, 3, 4, 5, 6, 7, 8\}$ and represents the phase number

Cost:

$m_{\text{total_adacs}}, \theta_{\text{pointing_accuracy}}, \theta_{\text{pointing_knowledge}}, \Gamma_{\text{adacs}}$

Power:

$P_{\text{avg_adacs_phase_i}}, P_{\text{peak_adacs_phase_i}}, t_{\text{slew}}$

Propulsion:

$m_{\text{propellant_adacs}}$

Structures:

$m_{\text{gps}}, m_{\text{position_sensor}}, m_{\text{sun_sensor}}, n_{\text{gps}}, n_{\text{position_sensor}}, n_{\text{sun_sensor}}$

Systems:

$m_{\text{total_adacs}}, \Gamma_{\text{adacs}}$

Thermal:

$P_{\text{avg_adacs_phase_i}}, P_{\text{peak_adacs_phase_i}}$

E. Telecom Discipline

Michael Magnin (& Gan Cheng Rui Calvin)

The telecommunications subsystem model determines telecommunications specific component masses (e.g., antennas, filters, diplexers, transmitters, etc.), power requirements by phase, temperature tolerances, and pointing requirements.

Major Model Assumptions

- Assumes use of both high- and low-gain antennas
- Low-gain antenna is for engineering telemetry
- High-gain antenna is for payload data transfer
- Rain attenuation is represented as an uncertainty described by a normal distribution

References Used

Telecom discipline based on one reference:

- Wertz, J. and Larson, W., *Space Mission Analysis and Design*, 3rd ed., Microcosm, Torrance, CA, USA, 1999.

Files Used

Telecom specific (9 files):

horn_mass.m, link_budget_hga.m, link_budget_lga.m, main_telecom.m, parabolic_antenna.m, telecom_mass_summary.m, telecom_outputs.m, telecom_power.m, transmitter_determination.m

Systems/Databases (3 files):

horn_antenna_data.m, parabolic_dish_data.m, telecom_components.xls

Telecom Model Flow Chart

Fig. E.1 Telecom subsystem model flowchart

- Subsystem input variables are listed in sections: Uncontrollable Design Variables, Constant Input Variables, and Controllable Input Variables and Their Constraints
- Multidisciplinary variables are listed in section: Inputs from Other Subsystems
- Telecom outputs are listed in section: Outputs to Other Subsystems

Telecom Nomenclature

Table E.1 Telecom-related variables nomenclature

Symbol	Definition
d	diameter
D	data rate
E_b/N_0	energy per bit to noise power spectral density ratio
f	frequency
h	height
k	factor
m	mass
n	quantity or number
P	power
T	temperature
w	width
Γ	technology readiness level
θ	angle
η	efficiency
τ	type

Table E.2 Telecom-related subscript nomenclature

Symbol	Definition
hga	high-gain antenna
lga	low-gain antenna

Inputs from Other Subsystems (9)

- Note that subscript $i = \{1, 2, 3, 4, 5, 6, 7, 8\}$ and represents the phase number

Payload:

D_i , $h_{\text{slant_max}}$

Uncontrollable Design Variables (16)**Table E.3 Telecom model uncertainties assumed**

Parameter	Units	Distribution type and parameters
$D_{\text{downlink_lga}}$	Mbps	Normal(0.5,0.02)
$D_{\text{uplink_hga}}$	Mbps	Normal(2,0.1)
$D_{\text{uplink_lga}}$	Mbps	Normal(0.5,0.05)
$d_{\text{ground_antenna}}$	m	Normal(5,0.15)
E_b/N_0	dB	Uniform(7.25,13.25)
$k_{\text{line_loss}}$	dB	Normal(1,0.05)
$k_{\text{rain_attenuation}}$	dB	Normal(4.5,0.1)
m_{duplexer}	kg	Uniform(0.5,1.5)
m_{filter}	kg	Uniform(0.5,1.5)
$m_{\text{total_telecom}}$	kg	Uniform(-0.5,1.5)
$T_{\text{system_noise_downlink}}$	K	Normal(150,5)
$T_{\text{system_noise_uplink}}$	K	Normal(615,10)
$\theta_{\text{pointing_error}}$	degrees	Normal(1,0.01)
η_{hga}	n/a	Normal(0.55,0.02)
η_{lga}	n/a	Normal(0.55,0.02)
$\tau_{\text{transmitter}}$	n/a	Custom

Constant Input Variables (12)**Table E.4 Telecom constant input variables**

Parameter	Value	Units
$d_{\text{lga_input_feed}}$	m	0.005
d_{lga}	m	0.1
f_{hga}	GHz	2
f_{lga}	MHz	1000
n_{duplexer}	n/a	1
n_{filter}	n/a	1
n_{hga}	n/a	1
n_{lga}	n/a	1
$n_{\text{transmitter_hga}}$	n/a	1
$n_{\text{transmitter_lga}}$	n/a	1
T_{hga}	n/a	1
T_{lga}	n/a	1

Controllable Input Variables (1) and their Constraints

d_{hga} : $d_{\text{hga}} \in \{0.30, 0.35, \dots, 0.60, 0.65\}$

Outputs to Other Subsystems [31]

Cost:

$D_{\text{hga}}, m_{\text{total_telecom}}, \Gamma_{\text{telecom}}$

Power:

$P_{\text{avg_telecom_phase_i}}, P_{\text{peak_telecom_phase_i}}$

Structures:

$m_{\text{hga}}, m_{\text{lga}}, m_{\text{diplexer}}, m_{\text{filter}}, m_{\text{transmitter_hga}}, m_{\text{transmitter_lga}}, n_{\text{hga}}, n_{\text{lga}}, n_{\text{diplexer}}, n_{\text{filter}}, n_{\text{transmitter_hga}}, n_{\text{transmitter_lga}}$

Systems:

$m_{\text{total_telecom}}, \Gamma_{\text{telecom}}$

F. Command & Data Handling Discipline

Michael Magnin (&Leong Yoke Fun Hannah)

The command and data handling (C&DH) subsystem model determines masses of the processor and solid-state recorder, power requirements by phase, temperature tolerances, and onboard data-storage capacity.

Major Model Assumptions

- Simple processor is selected if data rate is below a certain threshold value; complex processor is selected if data rate is above a certain threshold value
- Data rate threshold is modeled as an uncertainty
- Smaller solid state recorder is selected if data rate is below a certain threshold value; larger solid state recorder is selected if data rate is above a certain threshold value
- Data capacity threshold is modeled as an uncertainty
- Two possible processors (simple, complex)
- Two possible solid state recorders (small, large)

References Used

C&DH discipline based on one reference:

- Wertz, J. and Larson, W., *Space Mission Analysis and Design*, 3rd ed., Microcosm, Torrance, CA, USA, 1999.

Files Used

C&DH specific (5 files):

cdh_determination.m, cdh_outputs.m, cdh_power.m, cdh_trl.m, main_cdh.m

Systems/Databases (3 files):

cdh_components.xls, processor_data.m, ssr_data.m

C&DH Model Flow Chart

Fig. F.1 C&DH subsystem model flowchart

- Subsystem input variables are listed in sections: Uncontrollable Design Variables, Constant Input Variables, and Controllable Input Variables and Their Constraints
- Multidisciplinary variables are listed in section: Inputs from Other Subsystems
- C&DH outputs are listed in section: Outputs to Other Subsystems

C&DH Nomenclature**Table F.1 C&DH-related variables nomenclature**

Symbol	Definition
D	data rate
h	height
l	length
L	source lines of code
m	mass
n	quantity or number
P	power
q	data capacity
T	temperature
w	width
Γ	technology readiness level
τ	type

Table F.2 C&DH-related subscript nomenclature

Symbol	Definition
max	maximum
min	minimum
ssr	solid state recorder

Inputs from Other Subsystems (17)

- Note that subscript $i = \{1, 2, 3, 4, 5, 6, 7, 8\}$ and represents the phase number

Mission design:

t_i

Payload:

$D_i, \tau_{\text{payload}}$

Uncontrollable Design Variables (4)**Table F.3 C&DH model uncertainties assumed**

Parameter	Units	Distribution type and parameters
$D_{\text{threshold}}$	Mbps	Lognormal(3.9,0.07)
L	kilo-lines	Normal(11,1)
$m_{\text{uncertainty_cdh_total}}$	kg	Uniform(-0.5,2)
$q_{\text{threshold}}$	Gb	Lognormal(3.1,0.1)

Constant Input Variables (0)

Controllable Input Variables (0) and their Constraints

Outputs to Other Subsystems [34]

Cost:

$q_{\text{total}}, m_{\text{total_cdh}}, L, \Gamma_{\text{cdh}}$

Power:

$P_{\text{avg_cdh_phase_i}}, P_{\text{peak_cdh_phase_i}}$

Structures:

$m_{\text{processor}}, m_{\text{ssr}}, n_{\text{processor}}, n_{\text{ssr}}$

Systems:

$m_{\text{total_cdh}}, \Gamma_{\text{cdh}}$

Thermal:

$h_{\text{cdh_component_1}}, h_{\text{cdh_component_2}}, l_{\text{cdh_component_1}}, l_{\text{cdh_component_2}}, P_{\text{avg_cdh_phase_i}}, P_{\text{peak_cdh_phase_i}},$
 $T_{\text{max_cdh_component_1}}, T_{\text{max_cdh_component_2}}, T_{\text{min_cdh_component_1}}, T_{\text{min_cdh_component_2}},$
 $w_{\text{cdh_component_1}}, w_{\text{cdh_component_2}}$

G. Power Discipline

Michael Magnin (& Aditya Mahesh Khatri)

The power subsystem model determines power specific component (e.g., batteries, solar array, distributor, pyrotechnic charges, etc.) masses, battery capacities, solar-array area, and component temperature tolerances

Major Model Assumptions

- Both primary and secondary batteries are used
- Primary battery supplies power during Launch, Orbit Insertion, and De-orbit phases (phases 1, 2, and 7)
- Secondary battery supplies power during Night-time Data Collection/Transmission, Night-time Silent, and Emergency phases (phases 5, 6, and 8)
- Solar flux is treated as an aleatory uncertainty
- Solar array sizing is based on power generation during a worst-case scenario (i.e., when the incidence angle with the Sun is at a minimum)
- Eight possible solar array cell types
- Nine possible primary battery types
- Twelve possible secondary battery types

References Used

Power discipline based on two references:

- Griffin, M. and French, J., *Space Vehicle Design*, 2nd ed., AIAA Education Series, Reston, VA, USA, 2004.
- Wertz, J. and Larson, W., *Space Mission Analysis and Design*, 3rd ed., Microcosm, Torrance, CA, USA, 1999.

Files Used

Power specific (11 files):

array_determination.m, generate_avg_power_vector.m, generate_duration_vector.m, generate_peak_power_vector.m, main_power.m, power_dimension_summary.m, power_outputs.m, power_temperature_summary.m, power_trl.m, primary_battery.m, secondary_battery.m

Systems/Databases (4 files):

primary_battery_data.m, power_components.xls, secondary_battery_data.m, solar_cell_data.m

Power Model Flow Chart

Fig. G.1 Power subsystem model flowchart

- Subsystem input variables are listed in sections: Uncontrollable Design Variables, Constant Input Variables, and Controllable Input Variables and Their Constraints
- Multidisciplinary variables are listed in section: Inputs from Other Subsystems
- Power outputs are listed in section: Outputs to Other Subsystems

Power Nomenclature**Table G.1 Power-related variables nomenclature**

Symbol	Definition
A	area
C	coefficient
h	height
k	factor
l	length
m	mass
n	quantity or number
P	power
Q	charge
t	time or duration
T	temperature
w	width
Γ	technology readiness level
θ	angle
τ	type
Φ	flux

Table G.2 Power-related subscript nomenclature

Symbol	Definition
avg	average
batt	battery
bol	beginning of life
conv	converter
dist	distributor
eff	efficiency
eol	end of life
harn	harness
max	maximum
md	multidisciplinary
min	minimum
op	operational
uv	ultraviolet

Inputs from Other Subsystems (127)

- Note that subscript $i = \{1, 2, 3, 4, 5, 6, 7, 8\}$ and represents the phase number

ADACS:

$P_{\text{avg_adacs_phase_i}}, P_{\text{peak_adacs_phase_i}}, t_{\text{slew}}$

C&DH:

$P_{\text{avg_cdh_phase_i}}, P_{\text{peak_cdh_phase_i}}$

Mission design:

$n_{\text{phase}}, t_{\text{mission}}, t_i$

Payload:

$P_{\text{avg_payload_phase_i}}, P_{\text{peak_payload_phase_i}}, \theta_{\text{look_max}}$

Propulsion:

$P_{\text{avg_propulsion_phase_i}}, P_{\text{peak_propulsion_phase_i}}$

Structures:

$h_{\text{bus}}, l_{\text{bus}}, P_{\text{avg_structures_phase_i}}, P_{\text{peak_structures_phase_i}}, w_{\text{bus}}$

Telecom:

$P_{\text{avg_telecom_phase_i}}, P_{\text{peak_telecom_phase_i}}$

Thermal:

$P_{\text{avg_thermal_phase_i}}, P_{\text{peak_thermal_phase_i}},$

Uncontrollable Design Variables (21)

Table G.3 Power model uncertainties assumed

Parameter	Units	Distribution type and parameters
$h_{\text{solar_panel}}^c$	m	Uniform(25,35)
$k_{\text{assembly_mismatch}}$	n/a	Beta(1000,20)
$k_{\text{batt_to_conv}}$	n/a	Beta(1000,110)
$k_{\text{batt_to_dist}}$	n/a	Beta(10000,50)
$k_{\text{conv_eff}}$	n/a	Beta(1000,110)
$k_{\text{conv_to_harm}}$	n/a	Beta(10000,50)
$k_{\text{coverglass_coating}}$	n/a	Beta(1000,20)
$k_{\text{dist_to_load}}$	n/a	Beta(1000,11)
$k_{\text{fuse_to_load}}$	n/a	Beta(10000,50)
$k_{\text{harm_to_fuse}}$	n/a	Beta(10000,50)
$k_{\text{meteoroid_damage}}$	n/a	Beta(1000,20)
k_{packing}	n/a	Beta(1000,110)
$k_{\text{propellant_contamination}}$	n/a	Beta(1000,20)
$k_{\text{shadowing}}$	n/a	Beta(1000,250)
k_{uv}	n/a	Beta(1000,30)
k_{voltage}	n/a	Beta(190,4)
$m_{\text{power_dist}}^a$	kg	Uniform(3,5)
$m_{\text{uncertainty_power_total}}^a$	kg	Uniform(-1,3.5)
$m_{\text{pyro_charge}}^a$	kg	Uniform(0.1,0.2)
Φ_{solar}^b	W/m ²	Normal(1386.5,35)
$\tau_{\text{primary_battery}}$	n/a	Custom ^d
$\tau_{\text{solar_cell}}$	n/a	Custom ^d
$\tau_{\text{solar_cell}}$	n/a	Custom ^d

Constant Input Variables (10)**Table G.4 Power constant input variables**

Parameter	Value	Units
$C_{\text{temperature}}$	0.005	n/a
$n_{\text{power_dist}}$	1	n/a
$n_{\text{solar_panels}}$	2	n/a
t_{recharge}	15	hours
$T_{\text{op_max_array_drive}}$	334	K
$T_{\text{op_min_array_drive}}$	243	K
$w_{\text{array_drive}}$	0.1	m
θ_{sun}	23.5	degrees
$\tau_{\text{array_load}}$	1	n/a
$\tau_{\text{secondary_battery}}$	4	n/a

Controllable Input Variables (2) and their Constraints

$\tau_{\text{primary_battery}}$: $\tau_{\text{primary_battery}} \in \{1, 2, 3, \dots, 9\}$

$\tau_{\text{solar_cell}}$: $\tau_{\text{solar_cell}} \in \{1, 2, 3, \dots, 8\}$

Table G.5 Primary battery types

Primary battery number	Primary battery type
1	LeClanche
2	Alkaline MnO ₂
3	Mercury
4	Zn/Ag ₂ O
5	Zn/Air
6	Li/MnO ₂
7	Li/SO ₂
8	Li/SOCl ₂
9	Li(CF) _n

Table G.6 Solar cell types

Solar cell number	Solar cell type
1	Silicon
2	3 mil High Efficiency Si
3	GaAs
4	InGaP/GaAs
5	GaInP ₂ /GaAs/Ge
6	Quadruple Junction
7	Amorphous Si
8	CuInSe (in concentrator arrays)

Outputs to Other Subsystems [33]

ADACS:

 $A_{\text{solar_array}}, \Phi_{\text{solar}}, \theta_{\text{sun}}$

Cost:

 $A_{\text{solar_array}}, m_{\text{total_power}}, n_{\text{secondary_battery}}, P_{\text{bol}}, P_{\text{eol}}, Q_{\text{capacity_primary_battery}}, Q_{\text{capacity_secondary_battery}}, \Gamma_{\text{power}}$

Mission design:

 $A_{\text{solar_array}}$

Structures:

 $h_{\text{solar_array}}, k_{\text{panel}}, l_{\text{solar_array}}, m_{\text{battery_primary}}, m_{\text{battery_secondary}}, m_{\text{power_dist}}, m_{\text{pyro_charge}}, m_{\text{solar_array}}, n_{\text{battery_primary}}, n_{\text{battery_secondary}}, n_{\text{power_dist}}, n_{\text{pyro_charge}}, n_{\text{solar_array}}, w_{\text{solar_array}}$

Systems:

 $m_{\text{total_power}}, \Gamma_{\text{power}}$

Telecom:

 $h_{\text{slant_max}}$

Thermal:

 $h_{\text{power_component_1}}, h_{\text{power_component_2}}, l_{\text{power_component_1}}, l_{\text{power_component_2}}, T_{\text{op_max_power_component_1}}, T_{\text{op_max_power_component_2}}, T_{\text{op_min_power_component_1}}, T_{\text{op_min_power_component_2}}, w_{\text{power_component_1}}, w_{\text{power_component_2}}$

H. Structures & Mechanisms Discipline

Michael Magnin (& Ng Bing Feng)

The structures and mechanisms (or simply structures) subsystem model determines structure masses, mechanism masses, power requirements by phase, and spacecraft-bus dimensions.

Major Model Assumptions

- Structure masses based on rules of thumb
- Density factors offset the center of mass from the geometric center
- Rectangular-box shape is assumed for the spacecraft bus
- Moment-of-inertia calculations are performed under the assumption that the bus mass is uniformly distributed
- Load calculations for the spacecraft bus are not performed
- Three possible bus material types

References Used

Structures subsystem based on three references:

- Rimrott, F., *Introductory Attitude Dynamics*, Springer-Verlag, New York, NY, USA, 1989.
- Sercel, J., *AE125 Class Notes V.7*, California Institute of Technology, Pasadena, CA, USA, October, 2000.
- Wertz, J. and Larson, W., *Space Mission Analysis and Design*, 3rd ed., Microcosm, Torrance, CA, USA, 1999.

Files Used

Structures specific (6 files):

bus.m, ***main_structures.m***, *mech.m*, *moment_inertia.m*, *struct_dimensions.m*, *structures_outputs.m*

Systems/Databases (0 files)

Structures Model Flow Chart

Fig. H.1 Structures subsystem model flowchart

- Subsystem input variables are listed in sections: Uncontrollable Design Variables, Constant Input Variables, and Controllable Input Variables and Their Constraints
- Multidisciplinary variables are listed in section: Inputs from Other Subsystems
- Structures outputs are listed in section: Outputs to Other Subsystems

Structures Nomenclature

Table H.1 Structures-related variables nomenclature

Symbol	Definition
A	area
h	height
k	factor
l	length
m	mass
n	quantity or number
P	power
V	volume
w	width
Γ	technology readiness level
ρ	density
τ	type

Table H.2 Structures-related subscript nomenclature

Symbol	Definition
comp	component
dist	distributor
gps	global positioning system
hga	high-gain antenna
lga	low-gain antenna
lv	launch vehicle
mli	multilayer insulation
sc	spacecraft
scdsa	spacecraft, deployed solar array
scusa	spacecraft, undeployed solar array
ssr	solid state recorder

Inputs from Other Subsystems (55)

- Note that subscript $i = \{1, 2, 3, 4, 5, 6, 7, 8\}$ and represents the phase number

ADACS:

$m_{\text{gps}}, m_{\text{position_sensor}}, m_{\text{sun_sensor}}, n_{\text{gps}}, n_{\text{position_sensor}}, n_{\text{sun_sensor}}$

C&DH:

$m_{\text{processor}}, m_{\text{ssr}}, n_{\text{processor}}, n_{\text{ssr}}$

Mission design: η_{lv} **Payload:** $m_{\text{imager}}, n_{\text{imager}}$ **Power :** $h_{\text{solar_array}}, k_{\text{panel}}, l_{\text{solar_array}}, m_{\text{battery_primary}}, m_{\text{battery_secondary}}, m_{\text{power_dist}}, m_{\text{pyro_charge}}, m_{\text{solar_array}},$
 $n_{\text{battery_primary}}, n_{\text{battery_secondary}}, n_{\text{power_dist}}, n_{\text{pyro_charge}}, n_{\text{solar_array}}, W_{\text{solar_array}}$ **Propulsion:** $m_{\text{oxidant_tank}}, m_{\text{pressurant_tank}}, m_{\text{propellant_tank}}, m_{\text{thruster}}, n_{\text{oxidant_tank}}, n_{\text{pressurant_tank}}, n_{\text{propellant_tank}},$
 n_{thruster} **Systems:** $m_{\text{total_sc_dry}}, m_{\text{total_sc_wet}}$ **Telecom:** $m_{\text{hga}}, m_{\text{lga}}, m_{\text{diplexer}}, m_{\text{filter}}, m_{\text{transmitter_hga}}, m_{\text{transmitter_lga}}, n_{\text{hga}}, n_{\text{lga}}, n_{\text{diplexer}}, n_{\text{filter}}, n_{\text{transmitter_hga}},$
 $n_{\text{transmitter_lga}}$ **Thermal:** $m_{\text{louver}}, m_{\text{mli}}, m_{\text{radiator_body_mount}}, n_{\text{louver}}, n_{\text{mli}}, n_{\text{radiator_body_mount}}$

Uncontrollable Design Variables (29)

Table H.3 Structures model uncertainties assumed

Parameter	Units	Distribution type and parameters
$k_{\text{advanced_materials}}$	n/a	Normal(0.83,0.03)
k_{aluminum}	n/a	Normal(1.12,0.03)
k_{ballast}	n/a	Beta(175,17000)
$k_{\text{composite}}$	n/a	Normal(1,0.03)
$k_{\text{density_x}}$	n/a	Uniform(0.9,1.1)
$k_{\text{density_y}}$	n/a	Uniform(0.9,1.1)
$k_{\text{density_z}}$	n/a	Uniform(0.9,1.1)
$k_{\text{distributed_comp}}$	n/a	Beta(175, 700)
$k_{\text{external_mounted_comp}}$	n/a	Beta(175, 1000)
$k_{\text{external_supplementary_comp}}$	n/a	Beta(175, 2300)
$k_{\text{high_density_comp}}$	n/a	Beta(175, 3300)
$k_{\text{integrated_hardware}}$	n/a	Beta(175, 1575)
$k_{\text{lv_interface}}$	n/a	Beta(175, 3300)
$k_{\text{lv_interface_on_sc}}$	n/a	Beta(175, 520)
$k_{\text{primary_structure}}$	n/a	Beta(175, 1000)
$k_{\text{strengtheners}}$	n/a	Beta(175, 4200)
k_{wiring}	n/a	Beta(175, 2000)
$m_{\text{array_drive}}$	kg	Uniform(1.5,3.5)
$m_{\text{gimbal_hga}}$	kg	Uniform(1,1.5)
$m_{\text{mech_array_deploy}}$	kg	Uniform(0.5,1)
$m_{\text{mech_array_unfolding}}$	kg	Uniform(0.5,1)
$m_{\text{uncertainty_structures_total}}$	kg	Uniform(-2,6)
$P_{\text{avg_array_drive}}$	W	Uniform(0.5,1)
$P_{\text{avg_gimbal_hga}}$	W	Uniform(0.5,1)
$P_{\text{avg_mech_array_deploy}}$	W	Uniform(0.5,1)
$P_{\text{peak_array_drive}}$	W	Uniform(1,2)
$P_{\text{peak_gimbal_hga}}$	W	Uniform(1,2)
$P_{\text{peak_mech_array_deploy}}$	W	Uniform(1,2)
ρ_{sc}	kg/m ³	Normal(350,20)

Constant Input Variables (3)**Table H.4 Structures constant input variables**

Parameter	Value	Units
$n_{\text{array_drive}}$	2	n/a
$n_{\text{gimbal_hga}}$	1	n/a
$n_{\text{mech_array_deploy}}$	2	n/a

Controllable Input Variables (1) and their Constraints

$\tau_{\text{structure}}: \tau_{\text{structure}} \in \{1, 2, 3\}$

Table H.5 Structure types

Structure type number	Structure type
1	Composite
2	Aluminium
3	Advanced materials

Outputs to Other Subsystems [30]

ADACS:

$h_{\text{bus}}, I_{xx_scdsa}, I_{xx_scusa}, I_{yy_scusa}, I_{yy_scdsa}, I_{zz_scusa}, I_{zz_scdsa}, l_{\text{bus}}, w_{\text{bus}}$

Cost:

$m_{\text{total_structures}}, V_{\text{sc}}, \Gamma_{\text{structures}}$

Mission design:

$h_{\text{bus}}, l_{\text{bus}}$

Power:

$h_{\text{bus}}, l_{\text{bus}}, P_{\text{avg_structures_phase_i}}, P_{\text{peak_structures_phase_i}}, w_{\text{bus}}$

Systems:

$m_{\text{lv_interface_off_sc}}, m_{\text{total_structures}}, \Gamma_{\text{structures}}$

Thermal:

$A_{\text{surface_spacecraft}}, h_{\text{bus}}, l_{\text{bus}}, P_{\text{avg_structures_phase_i}}, P_{\text{peak_structures_phase_i}}, w_{\text{bus}}$

I. Thermal Control Discipline

Michael Magnin (& Kong Kian Shing)

The thermal control subsystem model determines thermal specific component (e.g., radiator, louver, heaters, etc.) masses, radiator area, and power requirements by phase. The model computes a worst-case maximum-spacecraft temperature and sizes a radiator to ensure that an energy balance is achieved.

Major Model Assumptions

- The temperature of the spacecraft is analyzed only at specific extreme-case intervals of the orbit
- View factors [Wertz & Larson, 1999] are assumed for each of the six spacecraft faces
- The inclusion of multi-layer insulation (MLI) is assumed
- The inclusion of radiators is assumed

References Used

Thermal discipline based on two references:

- Gilmore, D., *Satellite Thermal Control Handbook*, 1st ed., The Aerospace Corporation, El Segundo, CA, USA, 1994.
- Wertz, J. and Larson, W., *Space Mission Analysis and Design*, 3rd ed., Microcosm, Torrance, CA, USA, 1999.

Files Used

Thermal specific (8 files):

heater.m, main_power.m, mli.m, radiator.m, temp_range.m, thermal_mass_summary.m, thermal_outputs.m, thermal_trl.m

Systems/Databases (2 files):

Surface_finish_data.m, thermal_components.xls

Thermal Model Flow Chart

Fig. I.1 Thermal subsystem model flowchart

- Subsystem input variables are listed in sections: Uncontrollable Design Variables, Constant Input Variables, and Controllable Input Variables and Their Constraints
- Multidisciplinary variables are listed in section: Inputs from Other Subsystems
- Thermal outputs are listed in section: Outputs to Other Subsystems

Thermal Nomenclature

Table I.1 Thermal-related variables nomenclature

Symbol	Definition
A	area
g	flag
h	height
k	factor
l	length
m	mass
n	quantity or number
P	power
T	temperature
w	width
α	absorptivity
Γ	technology readiness level
ϵ	emissivity
η	efficiency
κ	mass per unit length
π	mass per unit area
τ	type
Φ	flux

Table I.2 Thermal-related subscript nomenclature

Symbol	Definition
adacs	attitude determination and control
avg	average
cdh	command and data handling
bol	beginning of life
eol	end of life
ir	infrared
max	maximum
min	minimum
mli	multi-layer insulation
op	operational

Inputs from Other Subsystems (131)

- Note that subscript $i = \{1, 2, 3, 4, 5, 6, 7, 8\}$ and represents the phase number

ADACS:
 $P_{\text{avg_adacs_phase_i}}, P_{\text{peak_adacs_phase_i}}$
C&DH:
 $h_{\text{cdh_component_1}}, h_{\text{cdh_component_2}}, l_{\text{cdh_component_1}}, l_{\text{cdh_component_2}}, P_{\text{avg_cdh_phase_i}}, P_{\text{peak_cdh_phase_i}},$
 $T_{\text{max_cdh_component_1}}, T_{\text{max_cdh_component_2}}, T_{\text{min_cdh_component_1}}, T_{\text{min_cdh_component_2}},$
 $w_{\text{cdh_component_1}}, w_{\text{cdh_component_2}}$
Mission design:
 $h_{\text{altitude_orbital}}$
Payload:
 $h_{\text{payload_component_1}}, h_{\text{payload_component_2}}, l_{\text{payload_component_1}}, l_{\text{payload_component_2}}, P_{\text{avg_payload_phase_i}},$
 $P_{\text{peak_payload_phase_i}}, T_{\text{op_max_payload_component_1}}, T_{\text{op_max_payload_component_2}},$
 $T_{\text{op_min_payload_component_1}}, T_{\text{op_min_payload_component_2}}, w_{\text{payload_component_1}}, w_{\text{payload_component_2}}$
Power:
 $h_{\text{power_component_1}}, h_{\text{power_component_2}}, l_{\text{power_component_1}}, l_{\text{power_component_2}},$
 $T_{\text{op_max_power_component_1}}, T_{\text{op_max_power_component_2}}, T_{\text{op_min_power_component_1}},$
 $T_{\text{op_min_power_component_2}}, w_{\text{power_component_1}}, w_{\text{power_component_2}}$
Propulsion:
 $P_{\text{avg_propulsion_phase_i}}, P_{\text{peak_propulsion_phase_i}}$
Structures:
 $A_{\text{surface_spacecraft}}, h_{\text{bus}}, l_{\text{bus}}, P_{\text{avg_structures_phase_i}}, P_{\text{peak_structures_phase_i}}, w_{\text{bus}}$
Telecom:
 $P_{\text{avg_telecom_phase_i}}, P_{\text{peak_telecom_phase_i}}$

Uncontrollable Design Variables (15)**Table I.3 Thermal model uncertainties assumed**

Parameter	Units	Distribution type and parameters
k_{albedo}	n/a	Normal(0.3,0.02)
$k_{\text{louver_emitting}}$	n/a	Normal(0.85,0.02)
$k_{\text{louver_emitting_closed}}$	n/a	Normal(0.15,0.02)
$l_{\text{heat_pipe}}$	m	Uniform(2,4)
$m_{\text{thermal_total}}$	kg	Uniform(-1,1.5)
π_{louver}	kg/m ²	Normal(1.95,0.1)
π_{mli}	kg/m ²	Normal(0.05,0.005)
$\pi_{\text{radiator_body}}$	kg/m ²	Normal(3.3,0.3)
$\pi_{\text{radiator_deployed}}$	kg/m ²	Normal(12.2,0.5)
$K_{\text{heat_pipe}}$	kg/m	Beta(175,1000)
α_{louver}	n/a	Normal(0.16,0.02)
$\epsilon_{\text{mli_bol}}$	n/a	Beta(175,17500)
$\epsilon_{\text{mli_eol}}$	n/a	Beta(175,8500)
$\eta_{\text{power_dissipation}}$	n/a	Normal(0.1,0.01)
Φ_{ir}	W/m ²	Normal(230,10)

Constant Input Variables (12)**Table I.4 Thermal constant input variables**

Parameter	Value	Units
$g_{\text{mli_cdh_component_1}}$	0	n/a
$g_{\text{mli_cdh_component_2}}$	0	n/a
$g_{\text{mli_payload_component_1}}$	0	n/a
$g_{\text{mli_payload_component_2}}$	0	n/a
$g_{\text{mli_power_component_1}}$	0	n/a
$g_{\text{mli_power_component_2}}$	0	n/a
$P_{\text{avg_louver}}$	1	W
$P_{\text{peak_louver}}$	1	W
$n_{\text{layer_mli}}$	10	n/a
n_{louver}	1	n/a
n_{radiator}	1	n/a
τ_{heater}	1	n/a

Controllable Input Variables (3) and their Constraints

τ_{mli} : $\tau_{\text{mli}} \in \{1,2,3,4,5,6,7,8,9,10,11,12,13,14,15\}$

$\tau_{\text{surface_finish_louver}}$: $\tau_{\text{surface_finish_louver}} \in \{1,2,3,4,5,6,7,8,9,10,11,12,13,14,15\}$

$\tau_{\text{surface_finish_radiator}}$: $\tau_{\text{surface_finish_radiator}} \in \{1,2,3,4,5,6,7,8,9,10,11,12,13,14,15\}$

Table I.5 Surface finish types

Surface finish number	Surface finish type
1	OSR 5 mil Silvered Teflon
2	OSR 6 mil Uncoated Quartz Mirror
3	Teflon (Aluminum Backing) 5 mil
4	Indium Oxide Coated OSR
5	White S13G-LO Silicone Paint, 10 mil
6	Chemglaze Black Paint Z306
7	3M Black Velvet Paint
8	Black Z306 Polyurethane Paint, 3 mil
9	1 mil Aluminized Kapton
10	2 mil Aluminized Kapton
11	5 mil Aluminized Kapton
12	Polished Aluminum
13	Clad 7075 Aluminum
14	Polished Gold
15	Solar Cell-Fused Silica Cover

- Table I.5 provides surface finish options for the louvers, radiators and MLI

Outputs to Other Subsystems [24]

Cost:

$m_{\text{total_thermal}}$, Γ_{thermal}

Power:

$P_{\text{avg_thermal_phase_i}}$, $P_{\text{peak_thermal_phase_i}}$

Structures:

m_{louver} , m_{mli} , $m_{\text{radiator_body_mount}}$, n_{louver} , n_{mli} , $n_{\text{radiator_body_mount}}$

J. Systems Engineering Discipline

Michael Magnin

The systems engineering discipline provides all the general purpose functions required in the iteration process.

Major Model Assumptions

- Single spacecraft
- Technology readiness level (TRL) of the spacecraft is an average of the average TRL of each subsystem (average TRL of a subsystem is based on the TRL of the components within the given subsystem)

References Used

Systems discipline based on one reference:

- Wertz, J. and Larson, W., *Space Mission Analysis and Design*, 3rd ed., Microcosm, Torrance, CA, USA, 1999.

Files Used

Systems specific (4 files):

define_phase.m, *sc_mass_summary.m*, *sc_trl.m*, *spacecraft.m*

Systems/Databases (0 files):

Systems Model Flow Chart

Fig. J.1 Systems discipline model flowchart

- Subsystem input variables are listed in sections: Uncontrollable Design Variables, Constant Input Variables, and Controllable Input Variables and Their Constraints
- Multidisciplinary variables are listed in section: Inputs from Other Subsystems

Systems Nomenclature

Table J.1 Systems-related variables nomenclature

Symbol	Definition
m	mass
R	resolution
t	time
Δv	change in velocity
Γ	technology readiness level
$\$$	cost

Table J.2 Systems-related subscript nomenclature

Symbol	Definition
adacs	attitude determination & control subsystem
cdh	command and data handling
lv	launch vehicle
sc	spacecraft

Inputs from Other Subsystems (33)

ADACS:

$m_{\text{total_adacs}}$, Γ_{adacs}

C&DH:

$m_{\text{total_cdh}}$, Γ_{cdh}

Cost :

$\$_{\text{adacs}}$, $\$_{\text{cdh}}$, $\$_{\text{lv}}$, $\$_{\text{payload}}$, $\$_{\text{power}}$, $\$_{\text{propulsion}}$, $\$_{\text{structures}}$, $\$_{\text{telecom}}$, $\$_{\text{thermal}}$, $\$_{\text{total_deployment}}$, $\$_{\text{wraps}}$

Mission design:

Δv_{total} , t_{coverage} , t_{orbit}

Payload:

$m_{\text{total_payload}}$, R , Γ_{payload}

Power :

$m_{\text{total_power}}$, Γ_{power}

Propulsion:

$m_{\text{propulsion_total}}$, $m_{\text{total_propellant}}$, $\Gamma_{\text{propulsion}}$

Structures:

$m_{lv_interface_off_sc}$, $m_{total_structures}$, $\Gamma_{structures}$

Telecom:

$m_{total_telecom}$, $\Gamma_{telecom}$

Thermal:

$m_{total_thermal}$, $\Gamma_{thermal}$

Uncontrollable Design Variables (0)

Constant Input Variables (0)

Controllable Input Variables (0) and their Constraints

Outputs to Other Subsystems [3]

Cost:

$m_{total_sc_dry}$

Mission design:

$m_{injected}$, $m_{total_sc_dry}$, $m_{total_sc_wet}$

Propulsion:

$m_{sc_total_wet}$

Structures:

$m_{total_sc_dry}$, $m_{total_sc_wet}$

K. Cost Discipline

Michael Magnin

The cost model determines the final cost of the spacecraft. Cost estimating relationships (CER) are used to determine the cost.

Major Model Assumptions

- Based on the small-spacecraft cost model [Wertz & Larson, 1996; Wertz & Larson, 1999] Primary battery supplies power during Launch, Orbit Insertion, and De-orbit phases (phases 1, 2, and 7)
- In cases where more than one CER is provided to determine the cost of a subsystem, a weighted average is taken of all available CERs
- Weights are inversely proportional to the square of the standard error of the CER
- Assume cost estimating relationships are valid for all possible designs
- All cost calculations are made in US\$ for fiscal year 2007

References Used

Cost discipline based on two references:

- Wertz, J. and Larson, W., *Reducing Space Mission Cost*, 1st ed., Microcosm, Torrance, CA, USA, 1996
- Wertz, J. and Larson, W., *Space Mission Analysis and Design*, 3rd ed., Microcosm, Torrance, CA, USA, 1999.

Files Used

Power specific (3 files):

cer.m, *cost_outputs.m*, ***main_cost.m***

Systems/Databases (0 files):

Cost Model Flow Chart

Fig. K.1 Cost discipline model flowchart

- Subsystem input variables are listed in sections: Uncontrollable Design Variables, Constant Input Variables, and Controllable Input Variables and Their Constraints
- Multidisciplinary variables are listed in section: Inputs from Other Subsystems
- Cost outputs are listed in section: Outputs to Other Subsystems

Cost Nomenclature

Table K.1 Cost-related variables nomenclature

Symbol	Definition
A	area
D	data rate
k	factor
L	source lines of code
m	mass
n	quantity or number
P	power
q	data capacity
Q	charge
V	volume
Γ	technology readiness level
θ	angle
$\$$	cost

Table K.2 Cost-related subscript nomenclature

Symbol	Definition
adacs	attitude determination & control subsystem
bol	beginning of life
cdh	command and data handling
cer	cost estimating relationship
eol	end of life
gse	ground support equipment
hga	high-gain antenna
iat	integration, assembly, and testing
loos	launch and orbital operations support
lv	launch vehicle
sc	spacecraft

Inputs from Other Subsystems (29)

ADACS:

 $m_{\text{total_adacs}}, \theta_{\text{pointing_accuracy}}, \theta_{\text{pointing_knowledge}}, \Gamma_{\text{adacs}}$

C&DH:

 $q_{\text{total}}, L, m_{\text{total_cdh}}, \Gamma_{\text{cdh}}$

Mission design:

 $\$_{\text{lv}}$

Payload:

 Γ_{payload}

Power :

 $A_{\text{solar_array}}, m_{\text{total_power}}, n_{\text{secondary_battery}}, P_{\text{bol}}, P_{\text{eol}}, Q_{\text{capacity_primary_battery}}, Q_{\text{capacity_secondary_battery}}, \Gamma_{\text{power}}$

Propulsion:

 $n_{\text{thrusters}}, \Gamma_{\text{propulsion}}$

Structures:

 $m_{\text{total_structures}}, \Gamma_{\text{structures}}, V_{\text{sc}}$

Systems :

 $m_{\text{total_sc_dry}}$

Telecom:

 $D_{\text{hga}}, m_{\text{total_telecom}}, \Gamma_{\text{telecom}}$

Thermal:

 $m_{\text{total_thermal}}, \Gamma_{\text{thermal}}$ **Uncontrollable Design Variables (25)****Table G.3 Cost model uncertainties assumed**

Parameter	Units	Distribution type and parameters
$\$_{\text{adacs_mass_cer_uncertainty}}$	\$K	Normal(0,371)
$\$_{\text{adacs_pointing_accuracy_cer_uncertainty}}$	\$K	Normal(0,501.7)
$\$_{\text{adacs_pointing_knowledge_cer_uncertainty}}$	\$K	Normal(0,598.3)
$\$_{\text{cdli_D_cer_uncertainty}}$	\$K	Normal(0,415.3)
$\$_{\text{cdh_mass_cer_uncertainty}}$	\$K	Normal(0,209.7)
$\$_{\text{gse_cer_uncertainty}}$	\$K	Normal(0,81.3)
$\$_{\text{iat_cer_uncertainty}}$	\$K	Normal(0,171.3)
$\$_{\text{loos_cer_uncertainty}}$	\$K	Normal(0,75)
$\$_{\text{payload_cer_uncertainty}}$	\$K	Normal(0,492.7)
$\$_{\text{power_array_cer_uncertainty}}$	\$K	Normal(0,549)
$\$_{\text{power_battery_cer_uncertainty}}$	\$K	Normal(0,518)
$\$_{\text{power_bol_cer_uncertainty}}$	\$K	Normal(0,528.3)
$\$_{\text{power_eol_cer_uncertainty}}$	\$K	Normal(0,534.3)
$\$_{\text{power_mass_cer_uncertainty}}$	\$K	Normal(0,303.3)
$\$_{\text{program_cer_uncertainty}}$	\$K	Normal(0,282)
$\$_{\text{propulsion_mass_cer_uncertainty}}$	\$K	Normal(0,103.3)
$\$_{\text{propulsion_thruster_cer_uncertainty}}$	\$K	Normal(0,278)
$\$_{\text{propulsion_volume_cer_uncertainty}}$	\$K	Normal(0,132.7)
$\$_{\text{structures_cer_uncertainty}}$	\$K	Normal(0,39.6)
$\$_{\text{telecom_D_cer_uncertainty}}$	\$K	Normal(0,415.3)
$\$_{\text{telecom_mass_cer_uncertainty}}$	\$K	Normal(0,209.7)
$\$_{\text{thermal_mass_cer_uncertainty}}$	\$K	Normal(0,39.7)
$\$_{\text{thermal_power_cer_uncertainty}}$	\$K	Normal(0,42.3)
$\$_{\text{bus_cer_uncertainty}}$	\$K	Normal(0,1232)
$k_{\text{contractor}}$	n/a	Uniform(1.08,1.12)

Constant Input Variables (1)**Table K.4 Cost constant input variables**

Parameter	Value	Units
$k_{\text{inflation}}$	1.148	n/a

Controllable Input Variables (0) and their Constraints**Outputs to Other Subsystems [11]**

Systems:

$\$_{\text{adacs}}$, $\$_{\text{cdh}}$, $\$_{\text{lv}}$, $\$_{\text{payload}}$, $\$_{\text{power}}$, $\$_{\text{propulsion}}$, $\$_{\text{structures}}$, $\$_{\text{telecom}}$, $\$_{\text{thermal}}$, $\$_{\text{total_deployment}}$, $\$_{\text{wraps}}$

L. Simulated Annealing Code

```
function [ANNEAL SPACECRAFT_OUTPUTS] =
sim_anneal(SIM_ANNEAL_INPUTS,...

Sim_anneal_inputs,MD_VARIABLES,Md_variables,DATABASE,PAYLOAD_INPUTS,.
..
    Payload_inputs,MISSION_INPUTS,Mission_inputs,PROP_INPUTS,...

Prop_inputs,ADACS_INPUTS,Adacs_inputs,TELECOM_INPUTS,Telecom_inputs,.
..

CDH_INPUTS,Cdh_inputs,POWER_INPUTS,Power_inputs,STRUCTURES_INPUTS,...
    Structures_inputs,THERMAL_INPUTS,Thermal_inputs,COST_INPUTS,...
    Cost_inputs,max_iteration,mass_differ_criterion,Range,i)

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%
%
% Main Program for Simulated Annealing
%
%
% Author:           Michael Magnin
%
% Date Created:      December 1, 2006
%
% Date Modified:     July 24, 2007
%
%
% This is the main program for performing the simulated annealing
% algorithm.
%
%
%
%
% Note the general format for variables in this file and all other
% associated m-files:
%
%
% lower_case = individual variable
%
% Capitalized = vector or array or cell
%
% ALL_CAPS   = structure
%
%
% note: attribute_product format for all variables ... e.g.
density_tank %
```

```

% insofar as possible.
%
%
%
%
%
%
%
%
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

%initialize inputs
dof = Sim_anneal_inputs(index_var(SIM_ANNEAL_INPUTS,'dof'));
lambda = Sim_anneal_inputs(index_var(SIM_ANNEAL_INPUTS,'lambda'));
iteration_limit = Sim_anneal_inputs(index_var(SIM_ANNEAL_INPUTS,...
    'iteration_limit'));
temperature = Sim_anneal_inputs(index_var(SIM_ANNEAL_INPUTS,...
    'temperature'));
temperature_final = Sim_anneal_inputs(index_var(SIM_ANNEAL_INPUTS,...
    'temperature_final'));

%determine an initial input vector which outputs Input_vector_i
itry = 1;

[OUTPUT_VARIABLES Md_variables Sol_1] = spacecraft(MD_VARIABLES,...
Md_variables,DATABASE,PAYLOAD_INPUTS,Payload_inputs,MISSION_INPUTS,...
.
Mission_inputs,PROP_INPUTS,Prop_inputs,ADACS_INPUTS,Adacs_inputs,...
TELECOM_INPUTS,Telecom_inputs,CDH_INPUTS,Cdh_inputs,POWER_INPUTS,...
Power_inputs,STRUCTURES_INPUTS,Structures_inputs,THERMAL_INPUTS,...
    Thermal_inputs,COST_INPUTS,Cost_inputs,max_iteration,...
    mass_differ_criterion,i);

SPACECRAFT_OUTPUTS.Md_variables(:,itry) = Md_variables(:,i);

%To determine the range
OPTIMIZATION_CONSTRAINTS =
load_constraints('optimization_constraints',...
    'inputs');

%Generate constraints vectors
m = size(OPTIMIZATION_CONSTRAINTS,1);
for j = 1:m
    Data = OPTIMIZATION_CONSTRAINTS(j).data;
    unit_type = OPTIMIZATION_CONSTRAINTS(j).unit_type;
    unit = OPTIMIZATION_CONSTRAINTS(j).unit;
    Discretization(j,:) = unit_convert(unit_type,Data(1),...
        unit,default_si(unit_type));
    Lower_bound(j,:) = unit_convert(unit_type,Data(2),...
        unit,default_si(unit_type));
    Upper_bound(j,:) = unit_convert(unit_type,Data(3),...
        unit,default_si(unit_type));
end

%Generate an initial vector of the optimization variables
Optimization_inputs_1 = generate_optimization_vector(...

```

```

OPTIMIZATION_CONSTRAINTS, PAYLOAD_INPUTS, Payload_inputs, ...

MISSION_INPUTS, Mission_inputs, PROP_INPUTS, Prop_inputs, ADACS_INPUTS, ...

Adacs_inputs, TELECOM_INPUTS, Telecom_inputs, CDH_INPUTS, Cdh_inputs, ...
    POWER_INPUTS, Power_inputs, STRUCTURES_INPUTS, Structures_inputs, ...
    THERMAL_INPUTS, Thermal_inputs, i);

Pareto_cand_sol = Sol_1;
All_sol = Sol_1;
Pareto_cand_input = Optimization_inputs_1';
All_inputs = Optimization_inputs_1';
size_P = 1;
size_Q = 1;
temperature = lambda * temperature;

%Simulated annealing algorithm loop

while temperature > temperature_final
    for j = 1:iteration_limit
        itry = itry + 1;

        %Perturb the optimization vector
        Optimization_inputs_2 =
perturb_binomial(Optimization_inputs_1, ...
                Upper_bound, Lower_bound, dof, Discretization);

        [Payload_inputs Mission_inputs Prop_inputs Adacs_inputs...
            Telecom_inputs Cdh_inputs Power_inputs
Structures_inputs...
            Thermal_inputs] =
update_inputs(OPTIMIZATION_CONSTRAINTS, ...

PAYLOAD_INPUTS, Payload_inputs, MISSION_INPUTS, Mission_inputs, ...
    PROP_INPUTS, Prop_inputs, ADACS_INPUTS, Adacs_inputs, ...
    TELECOM_INPUTS, Telecom_inputs, CDH_INPUTS, Cdh_inputs, ...
    POWER_INPUTS, Power_inputs, STRUCTURES_INPUTS, ...
    Structures_inputs, THERMAL_INPUTS, Thermal_inputs, ...
    Optimization_inputs_2, i);

        %Evaluate new solution
        [OUTPUT_VARIABLES Md_variables Sol_2] =
spacecraft(MD_VARIABLES, ...
            Md_variables, DATABASE, PAYLOAD_INPUTS, Payload_inputs, ...
            MISSION_INPUTS, Mission_inputs, PROP_INPUTS, Prop_inputs, ...

ADACS_INPUTS, Adacs_inputs, TELECOM_INPUTS, Telecom_inputs, ...
    CDH_INPUTS, Cdh_inputs, POWER_INPUTS, Power_inputs, ...
    STRUCTURES_INPUTS, Structures_inputs, THERMAL_INPUTS, ...
    Thermal_inputs, COST_INPUTS, Cost_inputs, max_iteration, ...
    mass_differ_criterion, i);
        SPACECRAFT_OUTPUTS.Md_variables(:, itry) = Md_variables(:, i);
        xchi = random('unif', 0, 1);
        delt = delta(Sol_1, Sol_2, Range);

        if compare(Pareto_cand_sol, Sol_2) == 1
            %if solution is a Pareto candidate accept it into the
candidate

```

```

        %set
        size_P = size_P + 1;
        size_Q = size_Q + 1;
        Pareto_cand_sol(size_P,:) = Sol_2;
        Pareto_cand_input(:,size_P) = Optimization_inputs_2';
        All_inputs(:,size_Q) = Optimization_inputs_2';
        All_sol(size_Q,:) = Sol_2;
        Location_cand_sol(size_P) = itry+1;
        Sol_1 = Sol_2;
        Optimization_inputs_1 = Optimization_inputs_2;
    elseif xchi <= exp((-delt)/temperature)
        %if solution is not a Pareto candidate, compare it to the
        %acceptance criterion
        size_Q = size_Q + 1;
        Sol_1 = Sol_2;
        Optimization_inputs_1 = Optimization_inputs_2;
        All_inputs(:,size_Q) = Optimization_inputs_2';
        All_sol(size_Q,:) = Sol_2;
    else
        %otherwise discard the solution
        size_Q = size_Q + 1;
        All_inputs(:,size_Q) = Optimization_inputs_2';
        All_sol(size_Q,:) = Sol_2;
    end %end if

end %end for

%reduce the system temperature
temperature = lambda * temperature;
end %end while

%Extract the final Pareto set from the Pareto candidate set
j = size(Pareto_cand_sol,1);
size_s = 0;
for k = 1:j
    z = 1;
    flag = 1;
    while (z <= j) && (flag == 1)
        if ~(z == k)
            if sum(Pareto_cand_sol(z,:) <= Pareto_cand_sol(k,:))
==...
                length(Pareto_cand_sol(z,:))
                discard(z) = 1;
                flag = 0;
            else
                discard(z) = 0;
            end
        elseif z == k
            discard(z) = 0;
        end
        z = z + 1;
    end

    if sum(discard) == 0
        size_s = size_s + 1;
        Pareto_set(size_s,:) = Pareto_cand_sol(k,:);
        Pareto_input(:,size_s) = Pareto_cand_input(:,k);
        Location_solution(size_s) = Location_cand_sol(k);
    end
end

```

end

```
ANNEAL.All_inputs = All_inputs';
ANNEAL.All_sol(:,1) = -All_sol(:,1);
ANNEAL.All_sol(:,2) = All_sol(:,2);
ANNEAL.All_sol(:,3) = All_sol(:,3);
ANNEAL.Pareto_cand_sol(:,1) = -Pareto_cand_sol(:,1);
ANNEAL.Pareto_cand_sol(:,2) = Pareto_cand_sol(:,2);
ANNEAL.Pareto_cand_sol(:,3) = Pareto_cand_sol(:,3);
ANNEAL.Pareto_cand_input = Pareto_cand_input';
ANNEAL.Pareto_input = Pareto_input';
ANNEAL.Pareto_set(:,1) = -Pareto_set(:,1);
ANNEAL.Pareto_set(:,2) = Pareto_set(:,2);
ANNEAL.Pareto_set(:,3) = Pareto_set(:,3);
```