USE OF OPTIMIZATION METHODS IN SMALL SATELLITE SYSTEMS ANALYSIS

Ellen Riddle

Ph.D. Candidate, University of Colorado – Boulder
Campus Box 520
University of Colorado
Boulder, Colorado 80309-0520
303-492-4376
eriddle@rodin.colorado.edu

Abstract – This paper describes the mathematical foundation and algorithmic development of a multidisciplinary design optimization technique to provide spacecraft performance optimization in a constrained environment. The method introduced, referred to here as the Early Small Satellite System Analysis Method (ESSAM), incorporates the use optimization algorithms to provide insight into the effect individual technologies have on performance and cost parameters even when the system is at a low definition of design. This high-fidelity knowledge brought to the early stages of the design process allow the spacecraft concept architecture, technology choices, and performance requirements to be adjusted to meet an overall estimated cost goal, thereby enabling spacecraft design to be completed in a more economical and timely manner. The method described in this paper is an extension of previous work done at the University of Colorado in multidisciplinary research modeling and optimization as related to spacecraft design.

Introduction

Spacecraft design has historically been a lengthy, non-structured process, unique to specific missions and institutions, which has succeeded in producing high quality, one-of-a-kind space missions in extensive schedules and at extraordinarily high costs. Current trends at NASA and within the aerospace community require improvements to the spacecraft design process that will produce better space missions in shorter schedules and constrained budgets. With increased scrutiny of government expenditures and profit-driven commercial forces, economics has quickly become the driving force in spacecraft design.[1] In addition, spacecraft are no longer particularly unique, but a variation of past known configurations and designs, with the infusion of new technologies. These trends strongly favor the application of multidisciplinary design optimization (MDO) to improve the conceptual design process related to spacecraft.

MDO is concerned with how to efficiently analyze and optimally design a system governed by multiple coupled disciplines or made up of coupled components. Spacecraft design is a complex, tightly coupled process, involving various disciplines and multiple objectives. In light of fiscal pressures, spacecraft design has become an increasingly iterative process where compromises among conflicting objectives, primarily performance and cost, must be made. Thoroughly understanding these compromises is a lengthy process of trade studies and arbitrary "what-if" analyses. Detailed disciplinary analyses support trade studies in localized and related subsystems but hardly ever provide insight at the system level. System level trades are rarely completed until after a baseline design is already achieved because of the perceived time and effort required for credible analyses. This severely hampers the potential for cost-effective designs because a large percent of total system cost is committed at the beginning of the design process, as initial decisions are made. The application of MDO, when compared to the typical trade study process, offers significant time savings and improved understanding for complex engineering problems by taking into account and exploiting interactions among the design variables.[2] The inherent complexity and nature of spacecraft design, however, hinders it from being a candidate for most classical MDO techniques.

Specifically, the application of MDO to spacecraft design suffers from two major drawbacks. The first is derived from the discrete, nonlinear nature of the design process for which most optimization approaches have yet to be extended to. Spacecraft design consists of a large design space where complex and often non-linear analyses from different disciplines must interact. The coupling between disciplines and the shear dimensionality of full system analyses makes the use of traditional optimization methods impractical. The second drawback in the application of MDO is the reluctance of design teams to incorporate an "automated" decision making procedure into the creative process of innovative design. Design teams are hesitant to use a procedure that provides an "optimal" solution with little or no visibility into the calculations used or the reasons for certain decisions. The mathematical and practical limitations of traditional MDO techniques have led to the development of the Early Small Satellite System Analysis Method (ESSAM) optimization technique described in this paper.

ESSAM integrates subsystem spacecraft analyses, cost estimating relationships (CERs) and MDO to provide an early understanding of how technology trade options and variations in mission parameters impact system cost. The insight afforded by this method allows compromises among multiple objectives, primarily performance and cost, to be made even when the system is at a low definition of design. Dynamic programming, a systematic MDO procedure for determining the optimal combination of a sequence of interrelated decisions, is incorporated to handle the discrete/non-linear nature of the spacecraft design problem and sensitivity analysis is used to provide the design team with additional visibility.

Research associated with the development and application of ESSAM to the design process extends work in the areas of MDO application and spacecraft design at the University of Colorado (CU) and other institutions. The research goal is to provide a structured methodology for use in the design process of small, remote-sensing spacecraft to quickly and reliably asses the effect individual technologies have on performance and cost parameters. In the present study, the impact on spacecraft cost for different power regulation schemes and battery technologies is evaluated as a proof of concept. The goal of this study is to assess the practical limitations and potential impact this methodology would have on the spacecraft design process.

Analytical Approach

Historical Basis

The ESSAM spacecraft design approach is based on recent advancements in the application of MDO and sensitivity analysis to the design process of complex systems. The increased demands of economic competition and the complexity of engineering systems have led to the rapid growth of the MDO field over the past decade.[3] Specifically, MDO has been an emerging discipline within aerospace engineering and has been successfully applied to the design process associated with aircraft,[4,5,6] rotorcraft,[7] launch vehicles,[4] and spacecraft.[1]

Sensitivity analysis, a subset of MDO, has also found its way to the design of aerospace systems. Initial efforts to apply a sensitivity analysis to the conceptual design of a single-stage-to-orbit (SSTO) launch vehicle found it to be an efficient technique for generating sensitivity derivatives in a highly multidisciplinary design environment.[8,9] Sensitivity analysis has also been successfully applied to conceptual aircraft design[4,10] and has proven to have advantages over traditional direct optimization methods.

MDO Approaches to S/C Design

MDO methods can generally be grouped into either traditional or non-traditional approaches. Spacecraft design is a discrete (discontinuous), nonlinear process involving multiple stages and numerous variables not easily solved by traditional techniques. Multistage decision problems can be solved by direct application of classical optimization techniques. However, this requires the functions involved to be continuous and continuously differentiable and the number of variables to be small.[11] Nonlinear programming techniques can be used to solve slightly more complicated multistage decision problems, but their application also requires the variables to be continuous. Dynamic programming on the other hand can deal with discrete variables, as well as non-linear functions.

Dynamic Programming

Dynamic programming has been found to be a very useful mathematical technique for a wide range of complex problems in several areas of decision making.[11] It was originally conceived as an optimization technique for problems involving multiple, sequential decisions. The algorithm formulation as described in Ref. 13, is to divide the problem into stages with a number of states associated with the beginning of each stage. Decisions at each stage transform the state associated with the beginning of the next stage. The solution procedure is to find an optimal policy for the overall problem, beginning by finding the optimal policy for the last stage. A recursive relationship in the form of Eq. (1) or Eq. (2) is employed to identify the optimal policy for stage *n*, given that the optimal policy for stage *n + 1* is available.

$$f_n^*(s_n) = \max_{x_n} f_n(s_n, x_n) \tag{1}$$

$$f_n^*(s_n) = \min_{x_n} f_n(s_n, x_n) \tag{2}$$

A two-dimensional tableau is completed using the recursive relationship with each row corresponding to a specific stage and each column within the row corresponding to a possible state at that stage.

As related to the spacecraft design problem, each stage represents a *disciplinary technology trade area* in the design process. Each state represents a different *technology option* to be evaluated. Decisions (or *trade choices*) at each stage transform the output of the analysis and thus the input variables affecting the next stage. The optimal policy prescribes the optimal trade choice for each possible trade area. The optimal solution prescribes the optimal combination of trade choices for the system. The precise form of the recursive relationship employed differs among dynamic programming problems. For the spacecraft design problem the recursive relationship is given in Eq. (3).

$$f_n^*(s) = \min_{x_n} f_n(s, x_n) = f_n(s, x_n^*) \qquad (3)$$

where

$$f_n(s, x_n) = c_{sx_n} + f_{n+1}^*(x_n) \qquad (4)$$

c_{sx_n} = immediate cost at stage n

$f_{n+1}^*(x_n)$ = minimum future cost at stage n+1,2,..

The values of the immediate cost c_{sx_n} are obtained by contributing analyses (CAs), which transform the design state variables of the trade option into cost variables. Cost variables are parameters associated with an established Cost Estimating Relationship (CER). CERs, derived from historical data and mathematical algorithms (regressing techniques and statistics), are parametric estimates that express cost as a function of specific system or subsystem parameters. Major aerospace contractors and government aerospace organizations routinely use parametric estimates, which have been steadily improving with the explosive growth in the number of practitioners, important methodological improvements, and greatly expanded databases.[12]

In addition to providing an optimal solution, the dynamic programming solution procedure constructs a tableau for each trade area n that describes the optimal decision for every possible trade option. Thus, a policy prescription for every possible circumstance is provided. The additional visibility provided by this procedure can be helpful in a variety of ways, including sensitivity analysis.[13]

Sensitivity Analysis

Sensitivity analysis is used to avoid much of the criticism that MDO has received by the conceptual design community. The additional visibility gained by sensitivity analysis allows the design team to reach an "optimal" design through judgmental modifications. Understanding the relationship between system parameters and design variables of various trade options in different "what-if" scenarios usually requires significant effort. To produce a credible analysis, full system sensitivities must be obtained for every combination of trade options available. Although sensitivity analysis for some kinds of optimization techniques such as linear programming is well developed, sensitivity analysis for discrete or combinatorial problems has hardly been explored. As with all combinatorial problems, analyzing all possible combinations quickly becomes infeasible. This is especially true in sensitivity analysis when there is a lack of gradient information as is often the case in spacecraft design. Without gradient information, obtaining system sensitivities for even one combination of trade choices is impossible except by the computationally intensive finite-differencing method. And although computing capacity has improved dramatically over the last decade, the improvements have mainly been in specialized, single-discipline, detailed analysis, not in the system-level spacecraft analysis needed for finite-differencing.

ESSAM Framework

The optimization procedure proposed in ESSAM uses dynamic programming and sensitivity analysis to improve the conceptual spacecraft design process. Dynamic programming is used to provide an optimal combination of technology trade options that will minimize the cost of the system. Sensitivity analysis provides useful estimates of the influences those trade options have on system parameters. The procedure significantly reduces the cost, time and effort required for understanding the relationship between system parameters and design variables, while increasing the probability of converging on an optimal design. This relationship is very useful and often tends to be obscured in complex systems by conflicting trends and tradeoffs.[5] In addition to the optimal combination of technology options, the relative magnitude as well as the positive or negative nature of the variable influences can be used to further guide the design team towards improvement. A simplified notion of the incorporation of ESSAM into the conceptual design process of spacecraft is illustrated in Fig. 1.

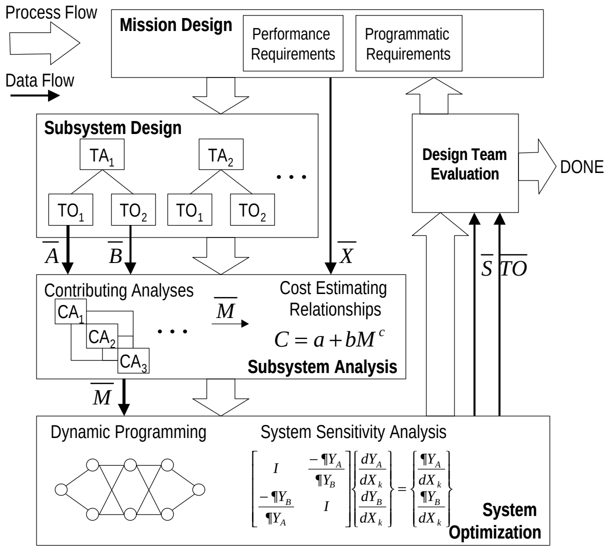

Figure 1: The ESSAM Design Framework

In Fig. 1 the thick arrows represent the flow of the design process, while the thin arrows depict the actual transfer of information. The overall ESSAM process includes:

Step 1: Establishing initial performance requirements (mission lifetime, payload objectives, resolution, etc.) and programmatic requirements (cost, schedule, reliability, etc.).

Step 2: Selection of a set of technology trade options (power source, structural material, guidance and control components, etc.) for each spacecraft subsystem (Attitude Determination and Control, Command and Data Handling, Power, Structure, Thermal, Payload, etc.).

Step 3: Approximation of immediate cost variables by disciplinary analysis of the design variables associated with the trade options.

Step 4: Transformation of the immediate cost variables into an approximate cost for the system using an established CER.

Step 5: Application of the dynamic programming algorithm to provide an optimal combination of trade options that minimize cost.

Step 6: Sensitivity approximation of the system-level influences of the design variables associated with the optimal combination of trade options.

Step 7: Evaluation of the initial approximation of the system by the design team.

Step 8: Acceptance of the conceptual baseline design or suggestions for further improvement.

Application Example

An optimization sub-problem involving the power subsystem is considered here as an illustrative example for the process described in the previous section.

Power Subsystem Problem Formation

The example power subsystem problem operates on two trade studies (T_1 and T_2) with two trade options for each study. Each trade option has a design state vector $(\bar{A}, \bar{B}, \bar{C}, \bar{D})$ consisting of state variables which uniquely describe that option. The two trade studies considered for this example are the power regulation scheme – Direct Energy Transfer (DET) or Peak Power Tracking (PPT) and battery type – Nickel Cadmium (NiCd) or Nickel Hydrogen (NiH2). The state vectors include design variables for power regulation efficiency, and battery specific energy density, depth of discharge, and transmission efficiency.

The CAs used in this example are a combination of physics-based analytical expressions and design estimating relationships obtained from Ref. 14. These equations, comprising the mathematical model of the system, are used for a simple first approximation of the conceptual design and do not depend on the trade options themselves, but rather on the variables associated with them. More extensive analyses can be interchanged, as the system becomes more defined. CA2 through CA6 translate the trade design variables and additional variables from the mission state vector ($\bar{C}$) to immediate cost variables. CA1 relates the immediate cost variables to the cost variable, *M*, used in the CER, Eq. 5. The CER chosen for this example approximates the cost of the spacecraft bus as a function of the mass of the power subsystem.

All of the equations that constitute the CER and CAs are listed in the following tables, which also show the problem notation and the numerical data used for the example.

Notation:

C= Cost of Power System (FY94$M)
M= Mass of Power System (kg)
m_{sa}= Mass of Solar Arrays (kg)
m_{batt}= Mass of Batteries (kg)
m_{pcu}= Mass of Power Control Unit (kg)
$m_{r/c}$= Mass of Regulators/Converters (kg)
m_w= Mass of Wiring (kg)
P_e, P_d= Power required in eclipse, daylight (W)
P_{cont} = Controlled Power (W)
P_{cnv}= Converted Power (W)
sp= Solar Array specific performance (W/kg)
P_{sa}= Power required by Solar Arrays (W)
T_e, T_d = Eclipse, daylight time per orbit (min)
X_e, X_d= Regulation efficiency during eclipse, daylight (%)
C_r= Required capacity (W-hr)
g= Specific Energy Density (W-hr/kg)
DOD= Depth of Discharge (%)
N= Number of batteries
n= Transmission efficiency (%)
M_{dry}= Spacecraft dry weight (kg)

State Vectors:

Mission State Vector:

$$\vec{X} = \left\{ P_e \quad P_d \quad P_{cntr} \quad P_{cnv} \quad sp \quad T_e \quad T_d \quad N \quad M_{dry} \right\}^T$$

Trade Option Design State Vectors:

$$\vec{A}, \vec{B} = \left\{ X_e \quad X_d \right\}^T$$

$$\vec{C}, \vec{D} = \left\{ g \quad DOD \quad n \right\}^T$$

Data:

Mission Variables:	P_e = 500 W	
	P_d = 500 W	
	P_{cntr} = 500 W	
	P_{cnv}= 500 W	
	sp = 25 kg/W	
	T_e = 30 min	
	T_d = 70 min	
	N = 3	
	M_{dry}= 100 kg	
Mission Constants:	Solar Constant = 1358 W/m^2	
Trade Variables:	*DET*	*PPT*
	X_e = 65%	X_e = 60%
	X_d = 85%	X_d = 80%
	NiCd	*NiH$_2$*
	g = 35 W-hr/kg	g = 45 W-hr/kg
	DOD = 20%	DOD = 50%
	n = 9%	n = 9%

CER:

$$C = -3.58 + 1.53 M^{0.702} \qquad (5)^*$$

** developed by The Aerospace Corporation for their Small Satellite Cost Model (SSCM) Version 7.4 [3]*

CAs:

CA1: $M = m_{sa} + m_{batt} + m_{pcu} + m_{r/c} + m_w$

CA2: $m_{sa} = \dfrac{P_{sa}}{sp}$

$$P_{sa} = \frac{\left(\dfrac{P_e T_e}{X_e} + \dfrac{P_d T_d}{X_d} \right)}{T_d}$$

CA3: $m_{batt} = \dfrac{C_r}{g}$

$$C_r = \frac{P_e T_e}{(DOD) Nn}$$

CA4: $m_{pcu} = 0.02 P_{cntr}$

CA5: $m_{r/c} = 0.025 P_{cvr}$

CA6: $m_w = 0.01 M_{dry}$ to $0.04 M_{dry}$

Power Subsystem Solution Method

To explicitly illustrate the dynamic programming solution procedure, this problem is represented as the shortest-path problem shown in Fig. 2. By making the appropriate identification between the stages and states of any dynamic program and the nodes of a network, essentially all deterministic dynamic programming problems can be formulated as equivalent shortest path problems. The directed network is divided into stages corresponding to the different trade areas analyzed for this example. The nodes are representative of the trade options and arc lengths between each node, correspond to the immediate costs.

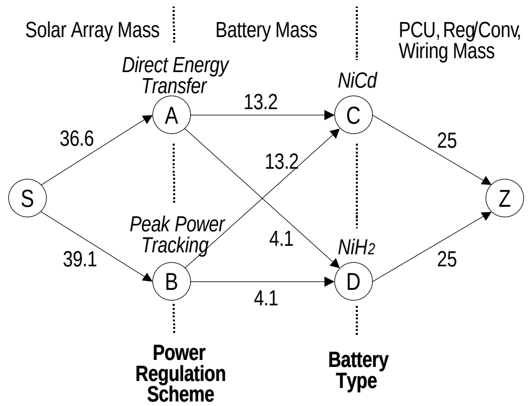

Figure 2: Shortest-Path Network for the Power Subsystem

As related to the dynamic programming formulation and solution procedure summarized above and explicitly outlined in Ref. 13, the objective function is to find the shortest path, $S \to x_1 \to x_2 \to x_3$, through the network. Discrete decision variables x_n (n=1,2,3) represent the selected trade option **A** or **B,** and **C** or **D,** and **Z**. $f_n(s,x_n)$ is the total cost of the optimal policy for the remaining stages, x_n^* denotes any value of x_n that minimizes $f_n(s,x_n)$ and $f_n^*(s)$ is the corresponding minimum value of $f_n(s,x_n)$. The objective function of finding the optimal combination of trade options that will minimize the cost of the system corresponds to finding $f_1^*(\mathbf{S})$ and the associated route. The dynamic programming algorithm finds $f_1^*(s)$ by successively finding $f_3^*(s)$ and $f_2^*(s)$ for each of the possible states and then uses $f_2^*(s)$ to solve for $f_1^*(\mathbf{S})$. The tabular construct of the solution is shown in the following tables:

n=3:

s	$f_3^*(s)$	x_3^*
C	25	Z
D	25	Z

n=2:

x_2	$f_2(s,x_2) = c_{sx_2} + f_3^*(x_2)$			
s	C	D	$f_2^*(s)$	x_2^*
A	38.2	29.1	29.1	D
B	38.2	29.1	29.1	D

n=1:

x_1	$f_1(s,x_1) = c_{sx_1} + f_2^*(x_1)$			
s	A	B	$f_1^*(s)$	x_1^*
S	65.7	68.2	65.7	A

The optimal solution identified from the preceding tables is $S \to A \to D \to Z$, which corresponds to choosing a DET power regulation scheme and NiH_2 batteries. The minimal total mass for the power subsystem is 65.7 kg. Using the CER in Eq. (5) the estimated cost of the example spacecraft is $25.3M.

Selected sensitivity derivatives relating the mission and trade design variables to the mass of the power system and thus the cost of the spacecraft are shown in Table 1. The sensitivities are obtained from direct differentiation of the CAs when possible or through finite-differencing and regression analysis. Approximate sensitivity values are provided to show the magnitude and the positive or negative impact of the variable.

Table 1: Sensitivities of the Power Subsystem

Variable	Sensitivity Derivative
Daylight Power (W)	$\frac{\partial M}{\partial P_d} = 0.0471$ Sensitivity Value: 0.0471 kg/W
Eclipse Power (W)	$\frac{\partial M}{\partial P_e} = 0.0343$ Sensitivity Value: 0.0343 kg/W
Controlled Power (W)	$\frac{\partial M}{\partial P_{cntr}} = 0.02$ Sensitivity Value: 0.020 kg/W
Converted Power (W)	$\frac{\partial M}{\partial P_{cvr}} = 0.025$ Sensitivity Value: 0.025 kg/W
S/C Dry Weight (kg)	$\frac{\partial M}{\partial M_{dry}} = 0.025$ Sensitivity Value: 0.025 kg/kg
Eclipse Time (min)	$\frac{\partial M}{\partial T_e} = 0.0218 T_e - 0.0459$ Sensitivity Value: 0.717 kg/min
Reg. Efficiency (%)	$\frac{\partial M}{\partial X_e} = 71.804 X_e - 88.789$ Sensitivity Value: - 0.295 kg/%

Results

The preceding example illustrates the process by which ESSAM can be used in the conceptual design of spacecraft. Solutions from dynamic programming allow the design team to immediately focus on a baseline design consisting of an optimal combination of technologies. Sensitivity analysis then allows the design team to reevaluate the design with prior knowledge of the effect changes in design variables will have on system parameters. Sensitivity values provide the design team with the ability to very quickly asses different options for a modified design.

For example, suppose a design team decides that having all of the instruments of a spacecraft payload powered during eclipse is desired but not required. In an effort to save mass and potentially cost, the team decides to turn off an instrument suite that requires 200 watts of power during eclipse. Using the sensitivity value from Table 1for Eclipse Power the team can immediately see that a reduction of 200 watts reduces the weight by almost 7 kilograms (*200W x 0.0343kg/W = 6.86kg*) because of reduced battery capacity required, etc. Total weight of the power subsystem is then reduced to 58.8kg resulting in a new cost estimate of $23.1M, a potential cost savings of over $2M dollars. The design team can then use this information in further evaluating the advantages and disadvantages of turning the instrument suite off during eclipse.

Sensitivities can also be used to determine the impact of advances in performance of individual technologies. Again, by the information presented in Table 1, it is easy to see that an increase in the efficiency of the power regulation scheme would substantially reduce the weight of the power subsystem. By quantifying the impact of design variables on overall system parameters, sensitivity analysis provides the means to evaluate the importance of technology advances and concentrate on those advances that would provide the most payoffs.

The simplistic example in this paper was chosen so the intuitive results could provide insight into both the ESSAM algorithm and the ability of the algorithm to perform within the conceptual design process. This example only demonstrates the feasibility of using the ESSAM approach to quickly and effectively perform trade studies given an optimization function such as minimizing cost. The advantage of this procedure becomes more apparent when it is compared to the typical trade study process of the entire spacecraft system. In the spacecraft system, the tight coupling between subsystems and the conflicting objectives of various disciplines often make it extremely difficult to identify the variables that have the most impact on the system. The efficiency of this method, however, is based on the number of trade areas and options employed as well as the coupling between variables. Dynamic programming suffers from a major drawback, known as the curse of dimensionality, where the method becomes costly with a much higher number of design variables. Sensitivity analysis also becomes more difficult in an internally coupled system. A review of research however,[5,9,15,16] provide various algorithms and procedures to overcome these difficulties.

Conclusions

Increased fiscal pressures at NASA and in the aerospace community have led to a critical evaluation of how spacecraft are currently designed. Refined procedures and numerous tools have emerged in an effort to improve the overall spacecraft design process. A common problem encountered in this reengineering effort is the lack of early understanding of the impact disciplinary technology and mission variables have on system cost. This paper provides a methodology that can be used early in the design process to gain a further understanding of these influences while optimizing the overall system. Optimization algorithms are used to quickly and directly express the impact on the spacecraft system of different options in selected technology areas. Dynamic programming is used to provide optimal technology trade combinations and sensitivity analysis allows in-depth knowledge about the relationship between performance variables and cost. Solutions can be used by the design team to characterize the design space about an optimal solution and infer changes in program cost as a result of a design variation without re-optimization or re-analysis of the entire system. The research presented suggests that MDO, and specifically sensitivity analysis, are potentially powerful tools in improving the overall space system design cycle of low cost missions.

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