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Managing Operational Uncertainty with Real Options

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Abstract

The operation of a complex system in a high stakes environment can lead to unacceptable levels of risk. The unintended consequences of system failure or under-performance make it imperative to understand and manage operational uncertainty during the design phase. In order to manage operational uncertainty, this paper presents the application of real options analysis in design. Our approach first identifies beneficial insertion points in the original design for mechanisms that add operational flexibility. We then use a binomial lattice options pricing model to value one or more options in the context of possible operational scenarios and outcomes. Finally, if the benefit of an option is greater than its additional cost, our approach will recommend the option. We present a hypothetical design example that finds a positive value for the addition of a flexible battery pack that can be deployed with a large micro air vehicle (MAV) fleet.

Introduction

Complex systems are subject to many lifecycle uncertainties that may lead to suboptimal performance or even mission failure if unmanaged. In particular, we define operational uncertainties as factors that may change during the operational life of the system, such that they have a potential impact on the requirements, capabilities or performance of the system. Examples include changes in the operational environment or context, and system degradation. Operational uncertainties differ from other lifecycle uncertainties in that they directly concern the end user of a system. We present a method for managing operational uncertainties through the application of real options analysis. We define an operational option as a real option for managing operational uncertainty by the end user, through the opportunity, but not the obligation, to execute the option during the operational life of the system.

In this paper, we use a hypothetical MAV example to demonstrate the process of managing operational uncertainty by first identifying where operational options could be embedded in the design, and then valuing the options.

Example Scenario: In recent years, there has been a growing interest in the development of networks of multiple unmanned micro air vehicles (MAV) as sensor networks for the purpose of coordinated monitoring, surveillance and rapid emergency response. Given the dynamic, fast-changing pace of the MAV industry, it is critical to design the MAVs to operate in the face of uncertain future demands and mission requirements. In general, the design of the MAV must incorporate "enough" flexibility to adapt to uncertainties that arise during operation. Some important operational uncertainties that may affect the value of the system performance include properties of the operational environment in which the system will operate (for example, whether a map of the terrain is available and the types of obstacles and hazards present in the environment.), and internal faults that cause the MAV to break. We will consider the major uncertainty in our analysis to be the flight duration per MAV mission. The flight duration requirement will likely reflect the many uncertainties in the operational environment.

Operational Uncertainties

In this project we will consider design options for a surveillance MAV that will operate in an uncertain terrain. The MAV may operate in terrains with different density of obstacles, and the size of the terrain to be traversed may vary. Such factors impact the time required by the MAV to traverse a terrain, and must therefore be considered in designing MAVs for operation across different terrains. Furthermore, the required time of flight for the MAVs may change based on a particular mission type. An emergency surveillance request may have more stringent deadlines than a periodic monitoring task. Uncertainties in the operational environment may lead to changing mission requirements (such as flight duration) over the long term. The problem then is how to design and deploy MAV technology to provide flexibility in the face of such operational uncertainties.

Mission uncertainties discussed above (density of hazards, area of the terrain and the emergency of the mission) impose similar demands on the design. We therefore combine all these ‘mission’ characteristics and formulate the mission uncertainty in terms of the **required flight duration of the mission**. The success of a mission is determined by the percentage of the mission that can be completed, based on the endurance of the MAV. For this paper, we analyze MAVs have relatively small weight (up to 10 lb) and can operate at an altitude less than 1200 ft. Current MAV missions have typical flight durations **ranging from a few minutes to 2 hours**. Longer flight durations may demand bigger UAVs which will not be considered in this example. The uncertainty in the flight duration is not necessarily random because it may depend on the particular application of the MAV. For example, an urban surveillance mission may demand relatively longer flight durations (due to hazards/obstructions) than an agricultural application in an open field. Historical data on MAV missions may be unavailable or classified. Therefore, it is reasonable to analyze several different mission scenarios. In particular, we divide the required flight duration into two categories: short duration missions that take less than one hour, and long duration missions that have a flight time between one and two hours.

Identifying where to Insert Real Options

Requirements “creep” is a challenge for systems architects during development. Once architecture is approved, it is usually quite difficult and costly to make desired changes. Thus, the creation of options “in” the technical design is desirable, but identifying where to place options is a complicated problem.

In order to determine how operational uncertainties will affect the engineering system, one must develop a model that captures the salient variable and interactions between variables. For this research, we chose to use an Engineering Systems Matrix (ESM) methodology proposed by Bartolomei to organize the information about the MAV system. (Bartolomei 2006). The ESM methodology uses a mixture of social science and engineering science research methods to construct a model of the MAV system that includes information about the social network, technical architecture, and environmental variables. The parameters and relationships are organized in a database and can be represented in Figure 1.

(see Figure 1)

The ESM contains information about the stakeholders in the system, the objectives of the system, the functions, objects, and processes designed to meet the system objectives and the interactions within these different classes of information. This information is represented within the adjacency matrices located along the diagonal. The off-diagonal blocks represent incidence matrices representing interactions between classes of elements. The lower triangle represents feed forward relations, while the upper triangle represents feedback relations. Lastly, the ESM explicitly considers exogenous variables and represents this information in the matrix labeled "systems drivers".

In the hypothetical example used for this problem, the key stakeholders a specified user who has the objective to maximize system endurance. The objective to maximize systems endurance is decomposed into the functions to be performed by the system. These functions are traceable to specific subsystems located in the "objects" matrix. As mentioned previously, it was suggested that due to the different operational environments there was uncertainty in the stability of the endurance requirement for the MAV system. By using the ESM, it was easy to identify the elements that would be affected by changing the endurance requirement.

A physics based model constructed by the USAF Academy was used to model the aerodynamic performance of the existing MAV design configuration. From the physics based model, it was shown that the endurance performance of the system was particularly sensitive to several design variables. These variables included wing geometry and the size of the batteries/battery power. In this example, we chose to focus on evaluating options for the battery pack.

Cost and Energy Density of MAV batteries: The choice of battery technology is crucial for the MAV design, since it affects both the endurance performance and cost of the MAVs. Only rechargeable Lithium ion batteries will be considered in this project, due to their advantages (such as higher energy density, safety) over Nickel based and primary (non-rechargeable) batteries. Figure 2 shows historical data of Li-ion battery prices in the past 15 years. The battery price shows an overall declining trend, while energy density is improving.

(see Figure 2)

Once we identified where to lay options into the system, we then identify and valuate the real options.

System Designs to be Analyzed

Given the above operational uncertainties, the problem is to design an MAV power system that maximizes the success of MAV missions over hundreds of missions. We consider two types of system design:

Fixed Design: we consider two fixed designs that optimize the weight of the battery for long duration (two hours) and short duration (one hour) flights. We refer to these designs as Fixed L (long mission) and Fixed S (short mission). We assume that the MAV mission duration requirement does not exceed ~ 2 hours.

Flexible Design: the flexible design has a relatively lightweight battery, along with the option to add an extra battery into the modular payload bay of the MAV. The weight of the batteries in this case is optimized for a combination of short and long flights. The flexible design has more wiring in the payload bay of the MAV, in order to provide the dual function of accommodating either an extra battery or payload. This extra structure in the flexible design comes at a cost, which is modeled according to the weight of the extra structures. The cost model for the MAV is based on the weight of the MAV, and is discussed further in the following subsection. Besides the structural changes in the payload bay, the fixed and flexible designs have the same structural design (wing, payload, etc.)

The main design variables considered are the mass and energy density of the battery. The energy density is limited by the technical capabilities to date. Li-ion batteries currently have a specific **energy density as high as 200 Wh/kg** (see Figure 2). Future advances in battery technology will likely improve the energy density. Such changes may be incorporated at a future time into all designs that we will consider. It is also possible to make Li-ion batteries into any shape necessary to fit an application. Therefore, we focus on the **mass budget** of the MAV batteries.

The following subsections discuss the design parameters obtained using an Excel spreadsheet of MAV technical models, as well as cost and revenue estimates obtained using a separate Excel spreadsheet of cost and revenue models.

Cost and revenue models: Empty weight cost is a commonly used metric for aircraft cost estimation. The cost of an MAV in $FY02 is roughly $1500 per pound of empty weight and $8000 per pound of payload capacity, as shown in Figure 3. The current costs are assumed to be equivalent to $FY02, as component costs are assumed to decline at the inflation rate.

(see Figure 3)

There is a necessary tradeoff between longer flight time (better endurance) and lower weight design (better aerodynamic performance as a result of reduction in induced drag caused by added mass.) We assume that all the designs compared in this project have equivalent payload capability and therefore equivalent payload costs. Therefore, payload costs are excluded from the cost model.

We divide the cost of a single MAV, excluding the payload cost, into two elements: the empty weight cost of the MAV and the cost of the batteries. The former is assumed to be $1500/lb for the current year. The cost of the Li-ion battery cells (capacity of 0.2 W.hr/gm) is estimated using the chart in Figure 2, as 0.2 W.hr/gm * $0.28/W.hr = $0.056/gm. We estimate the price of the finished battery product to be five times that of the raw Li-ion cell price, i.e. 5*$0.056/gm = $0.28/gm.

Table 1 lists the three designs considered, along with the estimated cost/MAV for each design. The battery mass, total MAV mass and endurance are obtained using a technical Excel spreadsheet for MAV design. The payload is set at 50 gm and a 100W motor is used for all cases. In Table 1, the flexible design has a lightweight battery of 88gm, with the option to add an extra battery of mass 132 gm for long duration flights of up to 2 hours. The cost per MAV for a flexible design is lower than the Fixed L design if the extra battery is not bought, but higher with the extra battery. In both cases, the flexible design costs more than the Fixed S design.

(see Table 1)

For the analysis that follows, we evaluate the design and deployment of 1,000,000 MAVs. This quantity is hypothetical. Table 2 lists the costs, revenues and profits generated by a million MAVs per short duration and long duration mission.

(see Table 2)

In the cost model, the MAV cost per mission is obtained by dividing the cost/MAV estimate by the number of missions a MAV can perform before extra costs are incurred. The number of missions/MAV is estimated at 200. Many factors may affect the number of missions/MAV, including the type of battery, battery depth of discharge, capacity fading, number of recharge cycles, and frequency and duration of missions. It is reasonable to assume that the batteries will be recharged at the beginning of each new mission. The small Li-ion rechargeable batteries typically have a few hundred recharge cycles. A conservative estimate is 200 recharge cycles and hence an estimated 200 missions/MAV. Note that the MAV itself may fail or break due to potential hazards.

In order to perform the analysis in monetary terms, a revenue model is used to value the benefits from an MAV mission. Two types of missions are distinguished: a short mission of one hour duration, and a long mission of two hour duration. The value per mission is assumed to be $10 per hour of flight, i.e. $10/short mission and $20/long mission. These values may be reasonable for the analysis and relative ranking of designs, given that we only consider the cost of the initial investment to purchase the MAVs, thereby ignoring operational costs. Profit is equal to revenue minus costs.

(see Table 3)

An average profit for each design can be calculated based on the percentage of long and short duration missions. Table 3 shows the weighted average profit per design for different scenarios characterized by the percentage of long duration missions. The Fixed S design has a constant profit across all scenarios, because it fails to profit from long mission opportunities due to limited endurance. The Fixed L and Flexible designs generate better profits than fixed S for all cases except when 100% of the missions have short duration. Figure 4 shows a graph of the difference in average profit between the Flexible and Fixed L designs. The break-even point for these designs occurs when ~ 70% of missions have long duration. The Fixed L design is optimized for long mission durations, and therefore generates most profit when the percentage of long duration missions is greater than 70%. The flexible design would outperform the fixed designs for all other scenarios.

(see Figure 4)

Lattice Model of Uncertainty

Lattice analysis will be performed for the evolution of the major uncertainty in the duration of MAV flights, which is characterized by the percentage of long duration flights. The lattice is developed for five time periods. The starting percentage of long duration flights is assumed to be 25%. This percentage is not likely to grow, in fact it may even decrease, due to the growing interest in deploying swarms of collaborative MAVs. Such a distributed architecture will likely provide better surveillance capability by taking images from several viewpoints, as well as increase the robustness of the overall architecture by not relying on a single MAV, thereby shortening the required flight duration per MAV through the option to deploy multiple MAVs at various times during the mission. Therefore, the growth rate of the required flight time will be taken to be zero in the following analysis. The variation in the flight durations will be modeled as volatility around the assumed mean value of 25%. The volatility will be modeled by an assumed standard deviation of 30%. We use the following values to calibrate the lattice model:

S = starting percentage of long duration flights = 25%
v = growth rate per period = 0%
dt = 1 period
sigma = standard deviation of percentage of long flights = 30%

Using the above values, we calculate u, d and p values for the lattice using the following equations (Copeland et al, 2003), where "u" is an upside multiple by which each node value in the lattice increases in the subsequent step; "d" is a downside multiple by which each node value in the lattice decreases in the subsequent step; "p" is the probability of transitioning to an upside value from a given node.

u = e exp(sigma*(dt)^1/2) = e exp(0.3) = **1.35**
d = e exp(- sigma*(dt)^1/2) = 1/u = **0.74**
p = 0.5 + 0.5*(v/sigma)*(dt)^1/2 = 0.5 + 0.5*(0/0.3) = **0.5**

Since the outcome value can not exceed 100% in the lattice model, the outcome is set to 1 (i.e. 100%) if the value of the outcome in the lattice model exceeds 1.

The <u>outcome lattice</u> is:

OUTCOME LATTICE

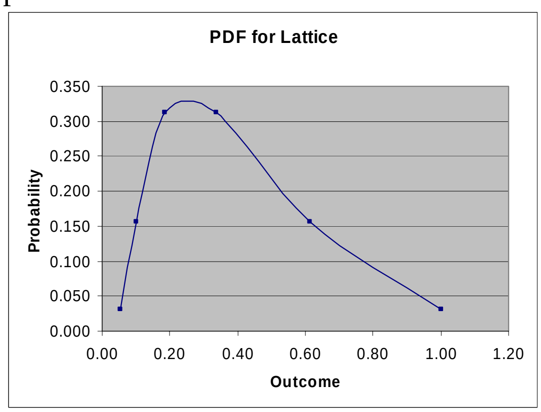
0.250	0.338	0.456	0.615	0.830	1.000
	0.185	0.250	0.337	0.455	0.614
		0.137	0.185	0.250	0.337
			0.101	0.137	0.185
				0.075	0.101
					0.055

The <u>probability lattice</u> is:

PROBABILITY LATTICE

1.000	0.500	0.250	0.125	0.063	0.031
	0.500	0.500	0.375	0.250	0.156
		0.250	0.375	0.375	0.313
			0.125	0.250	0.313
				0.063	0.156
					0.031

The <u>resulting distribution</u> of outcomes and probabilities:



Valuing Real Options using Lattice

The lattice model of evolution of the major uncertainty (percentage of long duration flights) is used in the valuation of the different designs: fixed small, fixed large and flexible. The flexible design considered for this project is equivalent to the small design, with the option to add an extra battery in the payload bay of the MAV, thus providing the capability for longer duration flight. Note that the flexibility in this case is a “reversible” option that may be exercised more than once, i.e. the flight duration may be shortened or lengthened by removing or adding the extra battery.

For each design, the profit is calculated as the weighted average of the profit per long duration flight and the profit per short duration flight. The weights are the percentage of long flights and percentage of short flight, respectively. The profit/mission values are listed in Table 2. Based on the outcomes lattice (percentage of long duration flights) above, the profit lattices in Table 4 are calculated for each design. Note that the Fixed S design can not take advantage of potential revenues from long duration flights, thus the profits stay constant.

(see Tables 4 and 5)

The NPV lattice is calculated for each design using a discount rate of 12%. The results are shown in Table 5. The NPV lattice is calculated using the binomial lattice valuation algorithm by moving backward through the lattice starting at the last time period. The NPV value at each node of the lattice is the profit for that node plus the discounted expected value of future profits (upside and downside from current node) weighted by the probabilities of the future outcomes shown in the probability lattice (in the section on modeling uncertainty.)

Comparison of NPVs across all designs in Table 5 shows that the flexible design has the best NPV of $29,832,131. The value of the flexible option is evaluated with respect to the Fixed L design that has the next best NPV. The value of the flexible option to add/remove an extra battery compared to the Fixed L design is $29,832,131 - $29,450,373 = **$381,758**

The particular application in this project relates to the design of the battery subsystem. It is possible to extend the analysis to many more uncertainties and design variables. Furthermore, the paper describes the application of the binomial lattice method for option valuation. It is possible to value the options using other techniques, such as decision analysis.

Conclusion

Real options analysis in the context of a hypothetical MAV application shows that flexibility enables better performance under uncertainty. The paper outlines a methodology for managing operational uncertainty through the following process: 1) identification of operational uncertainties, 2) identification of where to insert real options in system design based on operational uncertainties, and 3) valuation of the options using real options analysis techniques such as the binomial lattice model. The application of the methodology to a sample MAV problem has shown that real options is a generally important way of thinking about engineering system performance and value under operational uncertainty. Although the above example considers a single option in system design, it is possible to consider multiple options simultaneously (Copeland et al, 2003.) Future work includes the application of this methodology to the architecture of a swarm of MAVs.

References

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Biography

Tsoline Mikaelian is a doctoral student in the Department of Aeronautics and Astronautics at MIT. She has a Master of Science degree in Aeronautics and Astronautics from MIT and a Bachelor of Science degree in space and communication sciences from York University, Canada.

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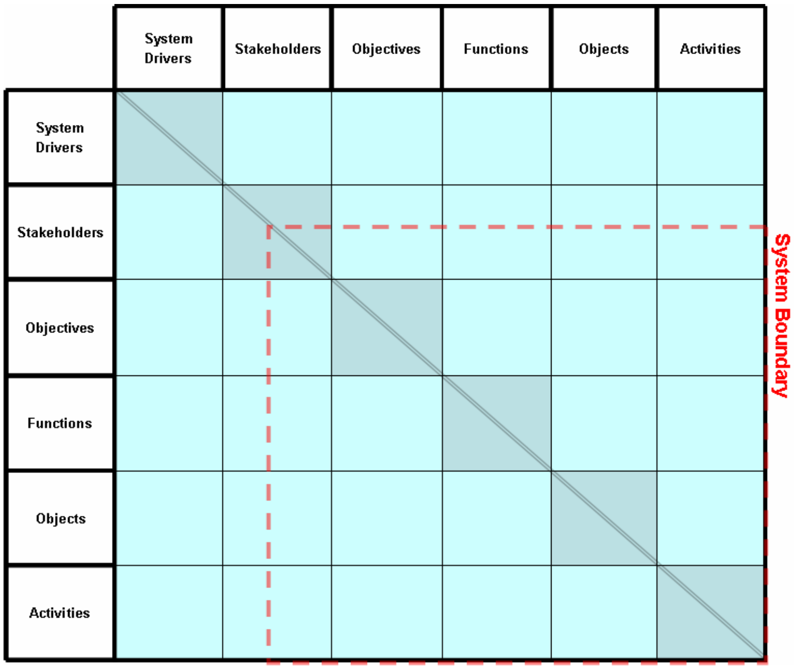
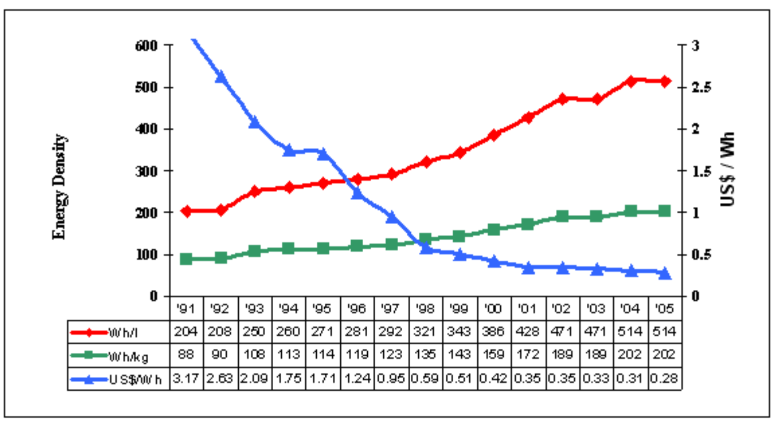


Figure 1 Engineering Systems Matrix



	'91	'92	'93	'94	'95	'96	'97	'98	'99	'00	'01	'02	'03	'04	'05
Wh/l	204	208	250	260	271	281	292	321	343	386	428	471	471	514	514
Wh/kg	88	90	108	113	114	119	123	135	143	159	172	189	189	202	202
US$/Wh	3.17	2.63	2.09	1.75	1.71	1.24	0.95	0.59	0.51	0.42	0.35	0.35	0.33	0.31	0.28

Figure 2 Historical data for Li-ion battery prices and energy density.

(Source: http://www.batteryuniversity.com/parttwo-55.htm)

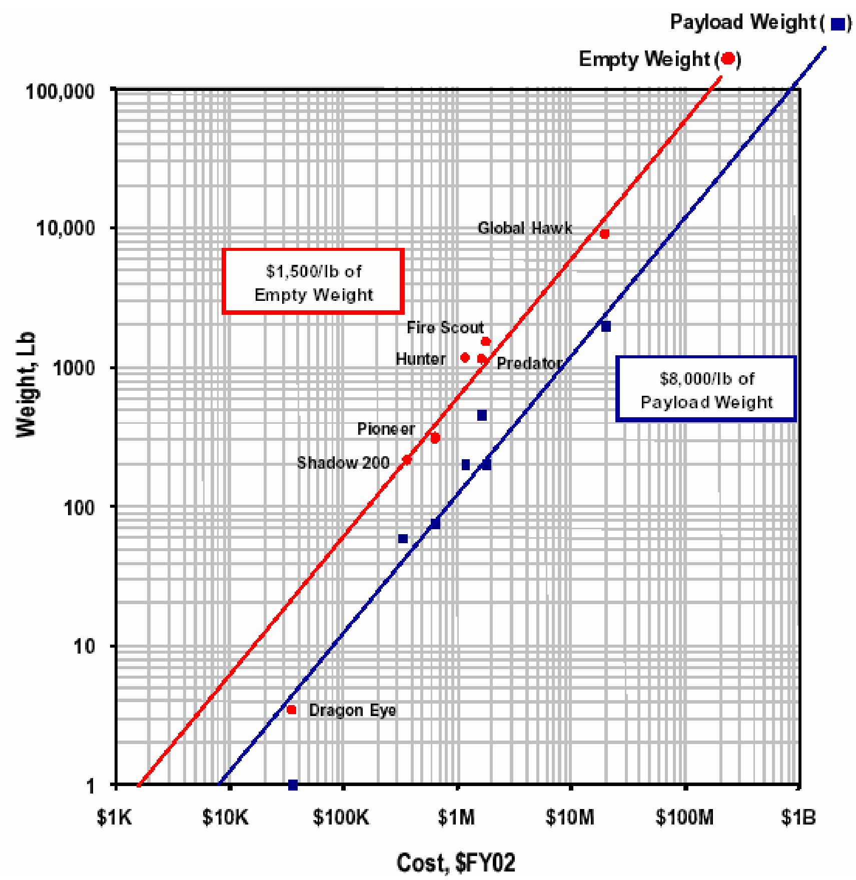


Figure 3 Cost versus weight of uninhabited air vehicles. (Source: http://www.uavforum.com/library/uav_roadmap_2005.pdf)

Table 1 Designs considered: Fixed S for short mission, Fixed L for long mission, and Flexible. Payload = 50 gm for each case.

Design	Battery Mass (gm)	Total Mass (gm)	Endurance (hr)	Cost/MAV
Fixed S	88	504	1.005	$1,234.96
Fixed L	219	635	2.004	$1,271.64
Flexible	88	507	0.999	$1,244.88
	extra 132	639	2.001	$1,281.84

Table 2 Cost, revenue and profit for deployment of 1,000,000 MAVs; cost is amortized across 200 missions per MAV. Revenue is $10/hr/MAV. S = short

Design	Cost	Revenue/S	Revenue/L	Profit/S	Profit/L
Fixed S	$6,174,785	$10,000,000	$10,000,000	$3,825,215	$3,825,215
Fixed L	$6,358,185	$10,000,000	$20,000,000	$3,641,815	$13,641,815
Flexible	$6,224,390	$10,000,000	$20,000,000	$3,775,610	$13,590,810
	$6,409,190				

Table 3 Weighted average profit per mission for a fleet of million MAVs, for each of three designs and for different scenarios characterized by the percentage of long duration missions.

	Average Profit		
% Long Missions	Fixed S	Fixed L	Flexible
0%	$3,825,215.00	$3,641,815.00	$3,775,610.00
10%	$3,825,215.00	$4,641,815.00	$4,757,130.00
20%	$3,825,215.00	$5,641,815.00	$5,738,650.00
30%	$3,825,215.00	$6,641,815.00	$6,720,170.00
40%	$3,825,215.00	$7,641,815.00	$7,701,690.00
50%	$3,825,215.00	$8,641,815.00	$8,683,210.00
60%	$3,825,215.00	$9,641,815.00	$9,664,730.00
70%	$3,825,215.00	$10,641,815.00	$10,646,250.00
80%	$3,825,215.00	$11,641,815.00	$11,627,770.00
90%	$3,825,215.00	$12,641,815.00	$12,609,290.00
100%	$3,825,215.00	$13,641,815.00	$13,590,810.00

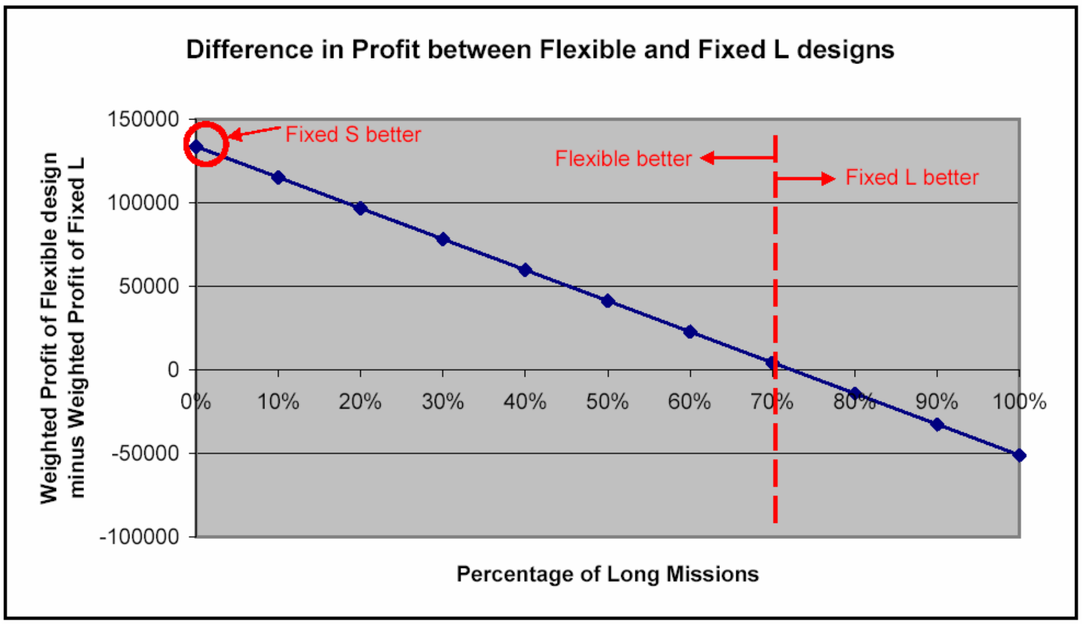


Figure 4 Difference in weighted average profit between flexible and Fixed L designs. Break-even point occurs at 70% long duration missions.

Table 4 Weighted average profit per mission for each design.

Profit for Fixed S:	0	1	2	3	4	5
	3,825,215	3,825,215	3,825,215	3,825,215	3,825,215	3,825,215
		3,825,215	3,825,215	3,825,215	3,825,215	3,825,215
			3,825,215	3,825,215	3,825,215	3,825,215
				3,825,215	3,825,215	3,825,215
					3,825,215	3,825,215
						3,825,215

Profit for Fixed L:	0	1	2	3	4	5
	6,141,815	7,016,815	8,198,065	9,792,753	11,945,581	13,641,815
		5,491,815	6,139,315	7,013,440	8,193,509	9,786,602
			5,010,815	5,489,965	6,136,818	7,010,068
				4,654,875	5,009,446	5,488,117
					4,391,479	4,653,862
						4,196,567

Profit for Flexible:	0	1	2	3	4	5
	6,229,410	7,088,240	8,247,661	9,812,878	11,925,922	13,590,810
		5,591,422	6,226,956	7,084,927	8,243,188	9,806,841
			5,119,311	5,589,606	6,224,505	7,081,618
				4,769,949	5,117,967	5,587,792
					4,511,421	4,768,954
						4,320,110

Table 5 NPV lattice for each design.

NPV for Fixed S:	0	1	2	3	4	5
	17,614,259	15,443,729	13,012,736	10,290,024	7,240,586	3,825,215
		15,443,729	13,012,736	10,290,024	7,240,586	3,825,215
			13,012,736	10,290,024	7,240,586	3,825,215
				10,290,024	7,240,586	3,825,215
					7,240,586	3,825,215
						3,825,215

NPV for Fixed L:	0	1	2	3	4	5
	29,450,373	29,416,513	28,755,896	26,800,216	22,404,695	13,641,815
		22,794,658	21,419,428	19,249,327	15,692,022	9,786,602
			17,338,940	14,978,126	11,716,364	7,010,068
				12,636,874	9,537,115	5,488,117
					8,342,564	4,653,862
						4,196,567

NPV for Flexible:	0	1	2	3	4	5
	29,832,131	29,684,790	28,908,581	26,845,905	22,371,302	13,590,810
		23,185,306	21,707,690	19,434,557	15,782,679	9,806,841
			17,702,610	15,242,288	11,880,492	7,081,618
				12,944,303	9,741,515	5,587,792
					8,569,039	4,768,954
						4,320,110