AIAA-2003-2355

Quantitative Assessment of Technology Infusion in Communications Satellite Constellations

Olivier L. de Weck* and Darren D. Chang†

Massachusetts Institute of Technology, Cambridge, MA 02139, USA

Ryutaro Suzuki‡

Communications Research Laboratory, Tokyo, Japan

Eihisa Morikawa§

Next-Generation LEO System Research Center (NeLS), Kanagawa, Japan

A methodology for quantitative assessment of new technologies is presented in the context of communications satellite constellations. The fundamental idea is that new technologies will shift the Pareto-optimal frontier when considering tradeoffs between performance, lifecycle cost and capacity. The suggested process first establishes a baseline by finding a Pareto optimal set of architectures on the basis of mature, state-of-the-art technologies (technology readiness level TRL=8). Lifecycle cost, performance and capacity of each architecture are predicted by a modular software simulation. The fidelity of the simulation is ascertained by benchmarking against existing systems such as Iridium and Globalstar. Next, a set of potential candidate technologies is identified whose TRL is in the range of 5-7. Each of these technologies is modelled and infused individually into the simulation and the effect on the Pareto front is observed, relative to the baseline case. The next step consists of analyzing allowable pairs of technologies to predict their joint effect. The methodology is demonstrated for a set of four technologies applicable to Low Earth Orbit (LEO) communications satellite constellations: optical intersatellite links (OISL), asynchronous transfer mode (ATM), large-scale deployable reflectors (LDR) and digital beamforming (DBF). The proposed methodology is potentially helpful in technology selection as well as in technology portfolio management.

Nomenclature

λ	=	operating wavelength, [m]
τ	=	Technology selection vector
m	=	Number of objectives
$\mathbf{x}$	=	Design vector
CPF	=	Cost per Function, [$/min]
D_A	=	Antenna Diameter, [m]
$\mathbf{J}$	=	Objective vector
P_t	=	Transmitter Power, [W]
T_c	=	Technology compatibility matrix
T_d	=	Technology dependence matrix
Π_i	=	Pareto front with i-th technology

1 Introduction

THE architecture of complex systems and products is defined during conceptual design based on a set of system requirements. In the case of constellations of communications satellites a number of crucial topological decisions regarding the space and ground segments drive the performance, lifecycle cost, capacity and ultimately the likelihood of market success of such systems. Examples of architectural decisions in this context include the constellation type (e.g. polar, Walker or Draim patterns), the use of intersatellite links (ISL) and the multi-access scheme such as frequency division multiplexing (FDMA) versus code division multiplexing (CDMA). In view of the billion dollar class investments required, one should only commit to a particular architecture after careful quantitative evaluation of the underlying combinatorial trade space. It has been argued before that an "optimal" architecture should be selected from a multi-objective Pareto frontier, containing only non-dominated solutions.[1,2] Alternatively, one may argue that an architecture should yield maximum utility, whereby utility is a non-dimensional metric of goodness that reflects stakeholder preferences.

The conceptual designer and system architect faces another challenge. Oftentimes he or she *must select from a portfolio of potentially competing technologies.* Some of these technologies represent alternative im-

*Assistant Professor,Department of Aeronautics and Astronautics, Engineering Systems Division (ESD), Member.

†Research Assistant, Department of Aeronautics and Astronautics, Student Member

‡Senior Research Scientist, Member.

§Senior Research Scientist, Member.

plementations at the intra-satellite subsystem level, e.g. spin-stabilization versus three-axis-inertial attitude control. In other instances emerging technologies, such as radio frequency (RF) or optical inter-satellite links (OISL) will enable new architectures that were not previously realizable or conceivable. Frequently one has to choose between a well established, proven technology versus a set of emerging alternative technologies at various stages of maturity. The field of management of technology (MOT) has attempted to facilitate this technology selection process by means of various frameworks. While helpful in general R&D planning, many of these frameworks remain too general and do not connect well with the more quantitative aspects of conceptual and preliminary design. There is a growing realization that new technologies will simultaneously affect performance, cost and capacity of engineering systems in a multiobjective sense. This leads naturally to the idea of quantitative technology assessment by measuring the effect of candidate technologies on the Pareto-optimal frontier.[3] This is shown conceptually in Figure 1 for a hypothetical cost versus performance/capacity trade space.

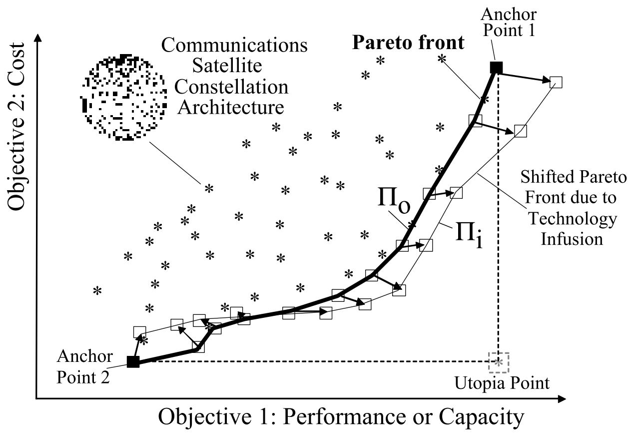

Fig. 1 Notional effect of a new technology on a multiobjective Pareto frontier of cost (J_2) versus performance or capacity (J_1). The utopia point has maximal performance/capacity and minimal cost, but is not achievable.

In Figure 1 each asterisk represents a particular communications satellite constellation architecture. Together these architectures form the trade space. The position of any particular architecture in this objective space, $\mathbf{J} = [J_1 \ J_2]^T$, is predicted by a multidisciplinary simulation that maps the design vector, $\mathbf{x}$ to the vector of objectives, $\mathbf{J}$. The architectures that fall on the Pareto front are of significant interest, since they are not dominated (see below). If one were seeking the optima for J_1 and J_2 alone, i.e. the highest performance/capacity or the lowest cost solution one would find the anchor points 1 and 2, respectively. A hypothetical solution that embodies both optima of J_1 and J_2 represents the non-achievable utopia point. The fundamental premise of this paper is that infusing a new technology or a set of new technologies into the trade space will generally shift the position of one or more architectures in objective space. The effect of this shift on the locus of the Pareto front is of special concern. We propose that quantitative technology assessment metrics can be constructed based on shifted positions of the Pareto front, Π_i, relative to the original Pareto front, Π_o, as characterized by its anchor points and the utopia point.

This paper briefly summarizes previous efforts for characterizing the impact of technologies on system-level metrics. This includes frameworks for technology assessment and selection in the general context of complex engineering systems. A review of the importance of technology selection for communication satellites concludes the literature search. Next, we lay out four associated metrics for quantifying the technology impact: (a) minimum utopia distance δ_{min}, (b) average utopia distance μ, (c) utopia point shift υ as well as (d) the number of Pareto crossings, χ. An application of this assessment method to constellations of communications satellites in Low Earth Orbit (LEO) is developed in detail. The underlying tool is a baseline simulation, whose validity is verified by benchmarking against existing and planned LEO systems such as Iridium and Globalstar. A technology infusion interface (TII) is the means by which information about alternative technologies enters the baseline system simulation.

Four emerging communications satellite technologies are assessed: Optical Intersatellite Links (OISL), Asynchronous Transfer Mode (ATM), Large Deployable Reflectors (LDR) and Digital Beam Forming (DBF). Each of these technologies is quantified according to its anticipated Pareto front impact. The last section discusses the application of this method to technology selection and technology portfolio management. Future work must include the effect of technology readiness levels (TRL) on the uncertainty in Pareto impact prediction as well as the extension to more than two objectives.

2 Previous Work

In this section we will first review previous work in architecture evaluation for constellations of communication satellites, followed by an overview of research on technology assessment and selection, independent of our application domain. This will illustrate the missing link between architecture evaluation and technology assessment.

In order to conduct a quantitative, relative comparison of satellite communications constellations a number of metrics have been proposed. Kelic, Shaw and Hastings proposed a "cost per function" (CPF) metric for satellite-based internet links.[4] In this work five proposed constellations were compared based on a "cost per T1 minute" metric that took into account the lifecycle cost of a satellite-based T1 internet link at a data rate of 1.544 Mbps. The cost in that paper, however is not the cost to the operator, but rather the price of a T1-minute to the customer that will ensure a 30% internal rate of return. This contribution built upon earlier work by Hastings, Gumbert[5] and Violet.[6] Shaw extended this work, enabling the modeling of most distributed satellite systems (DSS) as information processing networks. The methodology proposed by Shaw is called the Generalized Information Network Analysis (GINA) methodology.[7] Jilla and Miller have extended this methodology to include multidisciplinary design optimization (MDO),[1] i.e. the use of optimization to find a subset of good architectures in a very vast design space. The framework of multiobjective architecture tradespace evaluation and selection was subsequently applied to constellations of LEO communications satellites by de Weck and Chang,[2] including benchmarking against Iridium and Globalstar. Suzuki and coworkers[8,9]describe a set of key technologies that are under development as enablers of a next-generation global multimedia mobile satellite communications system in Low Earth orbit in Japan. These technologies include active phased array antennas, digital beam forming, large scale deployable antennas and optical intersatellite links.

The next question that arises naturally is *how new technologies can potentially impact the position of architectures in objective space.* Specifically, we are interested in observing changes in the position of non-dominated architectures along the Pareto front. This is the main question of the present paper.

Historically, technology assessment has been the focus of the Management of Technology (MOT) community. Utterback has observed the evolution of technologies over time and derived a model of the dynamics of technological and industrial evolution from it.[10] Tschirky discusses technology assessment as an integral function of technology and general management[11] and describes it as the *systematic identification and estimation of present and future impact of technology application in all areas of society.* Technology classification has been proposed by van Wyk.[12] Gordon and Stower make an explicit connection between technology forcasting and complex system simulation.[13] One way to distinguish between incremental, architectural, modular and radical innovation has been proposed by Henderson and Clark.[14] While architectural innovation changes only the linkages between core concepts and components but keeps the technologies the same, modular innovation keeps the linkages the same, but substitutes new technologies within the architecture. Radical innovation overturns both the architecture and technologies at the same time. The approach presented in this paper is most applicable to *modular innovation.*

More recently a systematic approach to technology selection for infusion in complex systems has been proposed by Mavris, DeLaurentis and co-workers.[15] This approach is called *Technology Identification, Evaluation and Selection* (TIES) and is useful for sorting through a large set of candidate technologies to be infused in aircraft systems. The technology selection problem is treated as a bi-level optimization problem. The present paper uses the impact of technologies on the Pareto front as a measure of technology effectiveness. This differs from previous work in the sense that there is no attempt to develop a single scalar metric of technology effectiveness. It will become clear that there are subtleties in technology infusion that are lost by converting to a single measure of effectiveness. The treatment of the Pareto frontiers, representing the best tradeoff between system performance and capacity versus cost, is inspired by the s-Pareto Frontier approach developed by Messac and Mattson.[16]

One crucial aspect in determining the predictive accuracy of technology assessment is the stage of maturity of technologies under consideration. We refer to NASA's technology readiness level (TRL) scale[17] to estimate the uncertainty in these predictions in future work.

3 Quantitative Technology Infusion Assessment Methodology

Key Assumptions

The methodology proposed here assumes that it is possible to create useful models of complex engineering systems such as satellite communication constellations during the conceptual phase of design. These models capture the relationship between design inputs and system behavior as the outputs. The inputs are architectural design variables such as constellation type and altitude, satellite transmitter power level, multiaccess scheme and the presence of intersatellite links, among others. The outputs are the expected capacity and lifecycle cost subject to a fixed per-channel performance requirement. Benchmarking against existing systems gives confidence in the validity of such models. The architectural design space is first explored and the best tradeoff architectures (Pareto-optimal surfaces) are identified based on existing technologies.[2]

General Methodology

This section introduces the proposed methodology for quantitative technology assessment. The process is composed of six sequential steps and is illustrated in Figure 2.

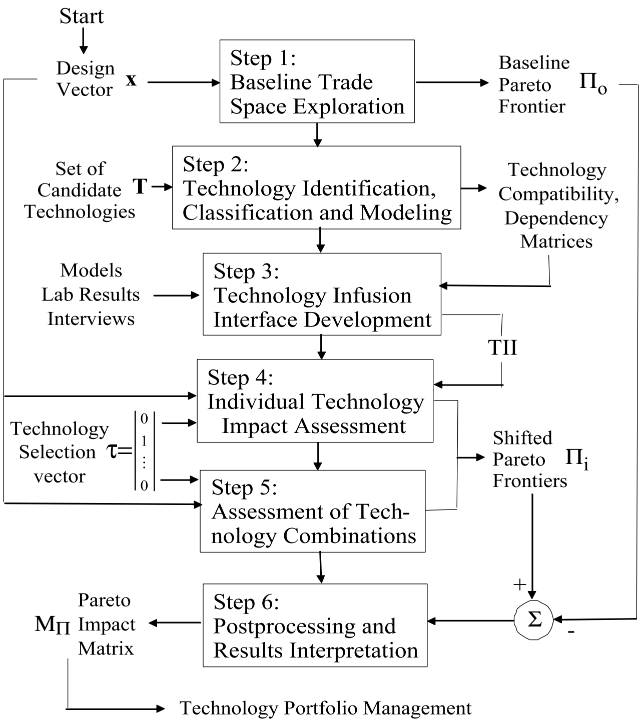

Fig. 2 Quantitative Technology Assessment Method - Process Diagram

Step 1: Baseline Trade Space Exploration

The first step is the exploration of a baseline trade space, using only mature, state-of-the-art technologies. The procedure for doing this was documented in previous work.[1,2] The result from this step is a set of corresponding objective vectors, $\mathbf{J}_i(\mathbf{x}_i)$ from which one finds the Pareto set, Π_o, of non-dominated architectures, $\mathbf{x}^*$.

Fundamentally the architectural choices are captured by a "design vector" $\mathbf{x}$ and the metrics by which the merits of a particular LEO system architecture are assessed are contained in the objective vector $\mathbf{J}$. Other inputs are vectors containing constant parameters, $\mathbf{c}$, and requirements, $\mathbf{r}$. Thus, there is a mapping from decision space to objective space:

$$\mathbf{x} \mapsto \mathbf{J} = f\left(\mathbf{x},\mathbf{c},\mathbf{r}\right) \tag{1}$$

The set of feasible vectors $\mathcal{X}$, where $\mathbf{x} \in \mathcal{X}$, defines an architectural design space. The problem is to find, which corresponding objective vectors, $\mathbf{J} = [J_1, J_2, ..., J_m]^T$, are non-dominated in objective space $\mathcal{J}$, where $\mathbf{J} \in \mathcal{J}$.

Dominance is defined by Steuer[18] as follows: Let $\mathbf{x^1}$ and $\mathbf{x^2}$ be two alternative architectures represented by their objective vectors $\mathbf{J^1}$ and $\mathbf{J^2}$, respectively. Note that

$$\mathbf{J^1}, \mathbf{J^2} \in \mathbb{R}^m$$

Then $\mathbf{J^1}$ dominates $\mathbf{J^2}$ (weakly) iff

$$\mathbf{J^1} \geqslant \mathbf{J^2} \text{ and } \mathbf{J^1} \neq \mathbf{J^2} \tag{2}$$

or more precisely,

$$J_i^1 \geqslant J_i^2 \;\forall\; i \text{ and } J_i^1 > J_i^2 \text{ for at least one } i \tag{3}$$

Architecture 1 ($\mathbf{J^1}$) strongly dominates architecture 2 ($\mathbf{J^2}$) if and only if

$$J_i^1 > J_i^2 \;\forall\; i \tag{4}$$

In other words, if two architectures provide the same data rate, bit-error-rate and link margin per channel, but one achieves this at a higher capacity (greater number of channels or throughput) and lower lifecycle cost than the other, it would be considered to be non-dominated. The set of all non-dominated architectures, $\mathbf{x}^* \in \mathcal{X}$, forms what is known as the Pareto frontier in $\mathcal{J}$. It is this set, Π_o, of architectures that we are seeking during conceptual design.

Step 2: Technology Identification, Classification and Modelling

The second step consists of identifying new technologies that can potentially be infused in the system of interest, $\mathbf{T} = [T_1\; T_2\; \ldots\; T_t]^T$. The maturity of each technology must be assessed and NASA's technology readiness levels (1-8) form a well established scale. Matrices showing the relative relationships of technologies with respect to each other can be assembled.[15] The technology compatibility matrix, T_c, is symmetric and has zero entries for technologies that are compatible and a 1 for technologies that are mutually exclusive. An example of mutually exclusive technologies in spacecraft are gravity gradient stabilization and high-angular resolution optical payloads.

$$T_c = \begin{bmatrix} - & 1 & 0 & 0 \\ & - & 0 & 1 \\ & & - & 0 \\ & & & - \end{bmatrix} \tag{5}$$

In the above matrix technologies T_1 and T_2 cannot be selected together, the same is true for T_2 and T_4, all other combinations are allowed. Finally, one technology may be implemented only after the other is implemented. This represents a technology dependence, as represented by the technology dependence matrix, T_d.

$$T_d = \begin{bmatrix} - & 0 & 1 & 0 \\ 0 & - & 0 & 0 \\ 1 & 0 & - & 0 \\ 1 & 0 & 1 & - \end{bmatrix} \tag{6}$$

Here Technology T_1 requires simultaneous implementation of T_3, T_2 depends on no other technology, implementation of T_3 requires T_1 and T_4 requires T_1 and T_3.

Each technology must be modelled quantitatively. There are three options for generating such a technology model:

1. Physics-based first principles
2. Data from prototype/benchtop tests
3. Empirical relationships based on expert interviews

Step 3: Technology Infusion Interface Development

The technology infusion interface (TII) infuses new technologies into the system simulation and evaluates their effects on intermediate variables during the simulation. This is shown graphically in Figure 3.

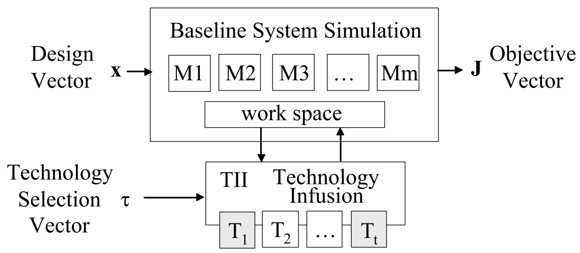

Fig. 3 Technology Infusion Interface

The key idea is that the TII is modular and does not require recoding of the previous system simulation every time a new technology needs to be investigated. The outputs of the TII are the impacts of the new technologies on intermediate variables during the simulation.

Step 4: Individual Technology Assessment

In this phase technologies can be selected individually, by setting the corresponding i-th entries in the technology selection vector, τ, to “1” or “0”. Three potential outcomes arise as discussed in Step 6. If the Pareto front, Π_i, recedes compared to the baseline case, Π_o, the proposed technology shows little promise for the particular system under consideration. If the entire Pareto front, Π_i, is moved towards the utopia point, the technology shows a high degree of promise and might be considered as disruptive (see Utterback[10]). The third case is the most common case, where one or more crossovers between the old and new Pareto fronts occur. In this case the new technology offers advantages, but only in certain areas of the trade space, for example for high capacity systems.

Step 5: Assessment of Combinations of Technologies

Next, combinations of technologies can be selected to observe their joint effect. The set of allowable technology combinations is established from the matrices T_c and T_d, respectively. This paper focuses on pairwise combinations of new technologies. It is rare that more than two new, unproven technologies will be deployed in any system.

Step 6: Relative Comparison and Interpretation

In order to compare the relative benefit of technologies on a common scale, we define four metrics of technology impact, that are derived from the shift in the baseline Pareto frontier, Π_o relative to a perturbed Pareto frontier, Π_{ij}. This is shown graphically in Figure 4. The four metrics, $\delta_{min}, \mu, \upsilon$ and χ are computed in normalized objective space $J_i/J_{i,max}$.

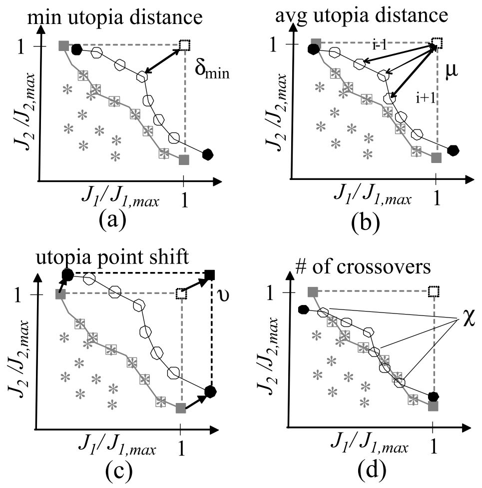

Fig. 4 Pareto Impact Metrics

The first metric is the normalized, minimum distance of the Pareto frontier to the utopia point determined in the baseline case.

$$\delta_{\min} = \min\left(\left[\sum_{i=1}^{m}\left(1-\frac{J_i\left(\mathbf{x}_k\right)}{J_{i,\max}}\right)^2\right]^{\frac{1}{2}}\right) \;\forall\; k=1,2,\ldots,N \tag{7}$$

The second scalar metric is the averaged distance, μ, from the utopia point, which is found by integrating (summing) along the Pareto frontier between anchor points. Note that N is the number of solutions in the perturbed Pareto set.

$$\mu = \frac{1}{N}\sum_{k=1}^{N}\left[\sum_{i=1}^{m}\left(1-\frac{J_i\left(\mathbf{x}_k\right)}{J_{i,\max}}\right)^2\right]^{\frac{1}{2}} \tag{8}$$

The third metric captures the shift between the baseline utopia point and the technology-perturbed utopia point. This is captured as the vector from the baseline utopia point to the perturbed utopia point in normalized objective space. This captures the ability of a new technology to extend the current state-of the art.

$$\upsilon = \begin{bmatrix} \frac{J_{1,\max}(\tau) - J_{1,\max}}{J_{1,\max}} & \dots & \frac{J_{m,\max}(\tau) - J_{m,\max}}{J_{m,\max}} \end{bmatrix}^T \tag{9}$$

Another way to evaluate the technologies is to analyze the geometric relation between the Pareto front of the design with the new technology and the baseline Pareto front. When the two Pareto fronts cross each other, a technology is surpassing the other in becoming closer to the utopia point. When this crossing happens several times for two designs, it means a technology is superior in some ranges of the design space and the other technology is superior in the other ranges. Thus, the number of crossover points is the fourth Pareto impact metric, χ.

4 Application to Satellite Communications Constellations

A LEO communications satellite simulator was created previously and has been continuously refined since 2001.[2] The simulator can test a large number of designs in a relatively short amount of time. Fundamentally it takes in a vector of design variables, $\mathbf{x}$, and predicts system performance, capacity and cost in the form of the objective vector, $\mathbf{J}$. This is shown schematically in Figure 5 with the simulator as a "black box".

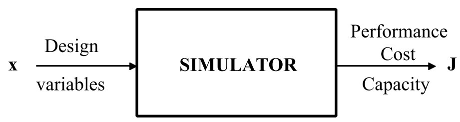

Fig. 5 Simulator Black Box

A more detailed block diagram of the simulator is shown in Figure 6.

It can be seen that the technology infusion interface (TII) is implemented in two separate modules here. The quality of a simulation must be assured by benchmarking against a set of real systems. The benchmarking compares the real systems of Iridium and Globalstar with the predictions from the simulation. The result shows that deviation of key system parameters between the real systems and the simulations are typically below 20%. Although not perfect, the fidelity of the simulator satisfies the need of the system studies we will conduct, since we are mainly interested in meaningful relative predictions. Figures 7 and 8 show sample benchmarking results for Iridium and Globalstar as well as Orbcomm and Skybridge, respectively.

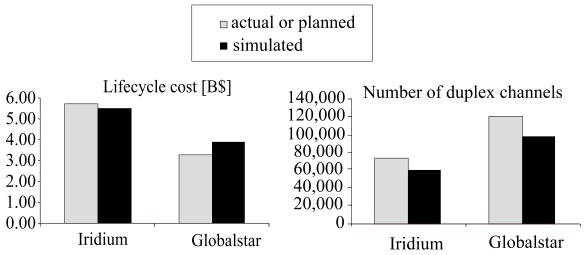

Fig. 7 Iridium and Globalstar Benchmarking Results

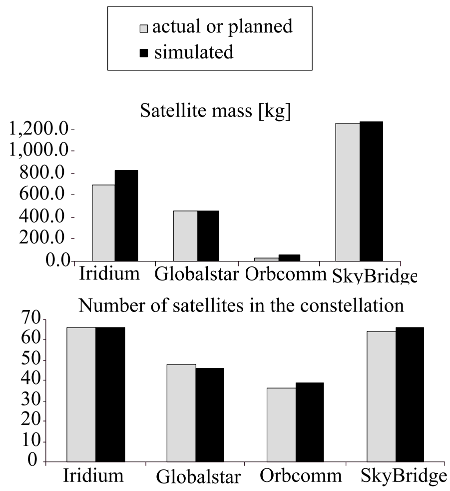

Fig. 8 Simulator Benchmarking Results

A table of simulator benchmarking results is available in Table 6. Generally the simulation predicts system level variables well within 20 %.

Step 1: Baseline Analysis

As discussed in the previous section we first carry out a baseline analysis. We assume that only existing, mature technologies are used in the system. We set two simultaneous objectives: maximize J_1 = total data flow (throughput) over the system lifetime in [MB] and at the same time minimize J_2= lifecycle cost in [B$]. We further assume a fixed communications performance at a data rate of 4.6 [kbps] per duplex channel, a bit-error-rate of 10^{-3} and a link fading margin of 16 [dB].[1]. An interest rate of 15 % is used to compute the net present lifecycle cost, normalized to fiscal year 2002 in U.S. $. For the baseline case, that is, the system without any of the new technologies, several different values are assigned to each design variable to form a full factorial trade space of

[1]The actual data rate, BER and margin are adjusted internally depending on the multiple access scheme and diversity

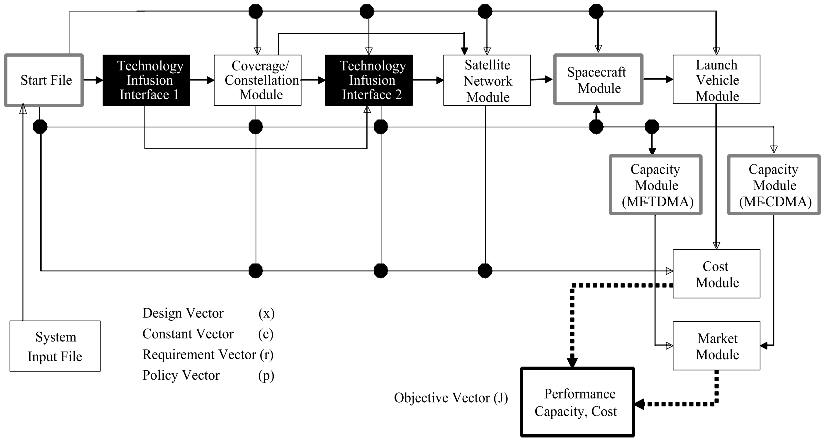

Fig. 6 Simulator Block Diagram

1728 possible designs. The values of the design variables, $\mathbf{x} = [x_1\ ...\ x_i\ ...\ x_{10}]^T$ are defined in Table 1.

i	Design Variable	Possible Values
1	constellation type	polar,walker
2	orbital altitude,[km]	500,1000,1500
3	minimum elevation,[^{o}]	8,10
4	diversity	1,2,3
5	satellite transmitter power,[W]	200,400,600
6	satellite transmitter gain in edge cell,[dBi]	15,25
7	intersatellite link	yes,no
8	multiple access scheme	MF-TDMA MF-CDMA
9	satellite lifetime ,[years]	5,8
10	on-board processing	yes

Table 1 Design Variable Values, x_i, for the Full Factorial Trade Space

The results for the 1728 runs are shown by plotting J_2 versus J_1 in Figure 9. The figure also shows the iso-CPF lines for 0.1, 1.0, 10.0 and 100 [$/MB]. CPF is the cost per function and is the ratio of the total lifecycle cost, LCC over the total data flow (TDF), i.e. the system throughput over the life of the system in [MB]. As such the CPF is similar to the metric developed by Kelic and Hastings,[4] except that is does not contain a fixed rate of return.

Figure 9 shows the Pareto front (using weak dominance) according to Equation (2). All designs along this line are non-dominated. An overview of these architectures is shown at the end of the paper in Table 7 - high altitude low power constellations dominate the low capacity end, while low altitude high power constellations, featuring many satellites, characterize the large capacity end. Several interesting observations can be made. First, even for a small throughput (capacity), one has to invest on the order of B$ 2.0 in order to launch a viable satellite constellation, which provides global coverage. Initially additional throughput comes at a modest increase in cost, but above roughly 10^9 [MB] the cost of satellite constellations starts to increase sharply. One may hypothesize that the baseline technologies do not allow the system to be scaled up easily to high throughput levels such as the ones required by the next generation LEO system proposed by NeLS and CRL. The lowest lifecycle cost is 1.85 [B$], while the largest throughput is 48.8 billion [MB]. These two architectures define the *anchor points* of the trade space and therefore define the utopia point in the lower right hand corner of Figure 9. These values are also used for subsequent normalization. The intermediate architecture #251 achieves the lowest cost per function (CPF) at 0.248 [$/MB], see Table 7.

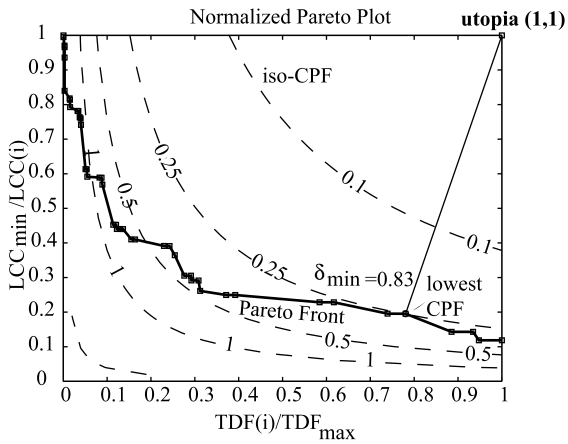

Fig. 10 Normalized Pareto plot with iso-CPF lines

The highest data flow rate and the lowest life-cycle cost of all the designs define the utopia point. This utopia point will be used to normalize the runs with new technologies infused.

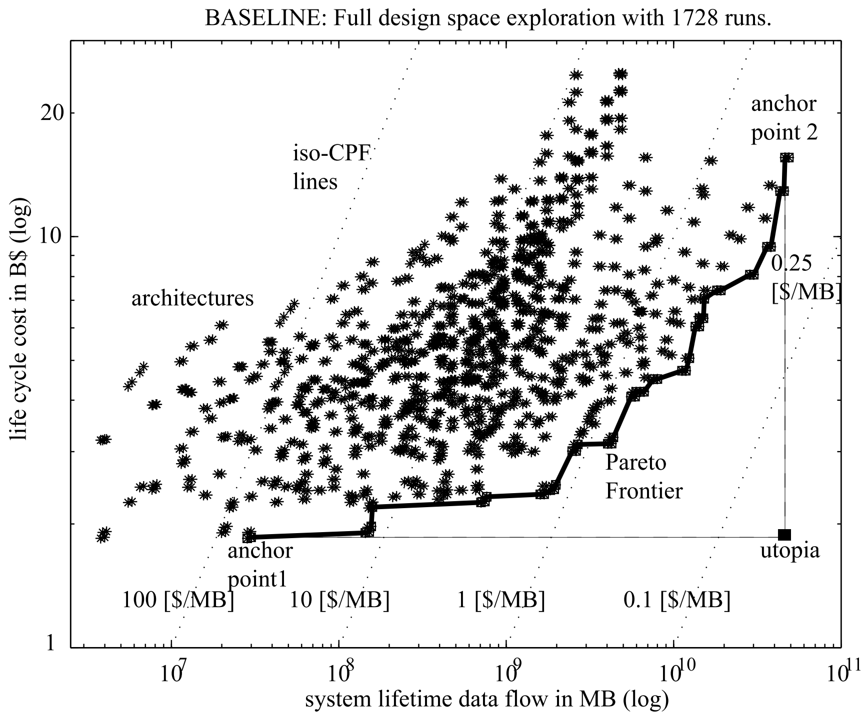

Fig. 9 Baseline Case: Full factorial run of lifecycle cost [b$] versus the total data flow over system life time [MB].

Step2: Technology Identification

In this section a set of specific new communication satellite technologies are examined. These technologies are currently under development at NeLS and CRL and are targeted for deployment in future broadband LEO communication satellite constellations. The candidate technologies are:

- T1: Optical Inter-Satellite Links (OISL)
- T2: Asynchronous Transfer Mode (ATM)
- T3: Large Deployable Reflectors (LDR)
- T4: Digital/Analog Beam Forming (DBF)

The technologies selected for this study are mutually compatible. No use of one technology excludes the use of any other technology. The technology compatibility matrix is shown in Table 2.

	T1	T2	T3	T4
T1	0	0	0	0
T2		0	0	0
T3			0	0
T4				0

Table 2 Technology Compatibility Matrix

The dependency relations of the technologies are shown in Table 3. If a cell is 1, the technology of that column depends on the technology of that row. Large deployable reflectors (LDR) will increase the gain of a spotbeam, decrease its beamwidth, θ, and thus reduce the footprint size of the spotbeam on the ground. Sometimes this footprint becomes so small that user handover between spotbeams becomes difficult. In this situation, the implementation of digital beam forming (DBF) is required to "anchor" the spotbeam on the ground so that handover between the spotbeams of the same satellite is not necessary. The implementation of LDR, therefore, depends on the implementation of DBF first. So the entry of "1" in the T3-column and T4-row is used to signal this dependency.

	T1	T2	T3	T4
T1	0	1	0	0
T2	0	0	0	0
T3	0	0	0	0
T4	0	0	1	0

Table 3 Technology Dependency Table

A series of interviews were conducted with leading developers of these technologies in Japan during the summer of 2002. Based on these interviews some reasonable scaling relationships were developed to estimate the effect that implementation of the technologies would have on system level variables. New technologies are often in the process of being developed, ranging anywhere from conceptual design to prototype testing (see NASA TRL scale). Their technical details are uncertain and yet maturing. This increases the difficulty in modelling them in computer simulations. In addition, different from mature technologies, the information on technical details of these new technologies is often at least partially proprietary. A technology summary was drafted at the end of the interviews, as shown in Table 4.

Step 3: Technology Infusion Interface

To simulate the implementation of these new technologies in the system, a Technology Infusion Interface (TII) was created, as illustrated in Figure 11. The TII has two types of inputs: the technology selection vector, τ, and relevant system-level variables. The technology selection vector allows individual technologies or allowable combinations of technologies to be turned "on" or "off".

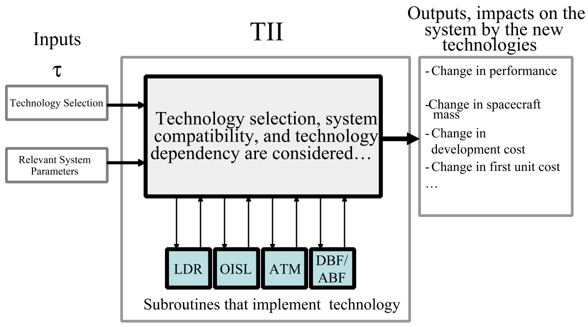

Fig. 11 Diagram of the technology infusion interface (TII).

The technology selection vector,τ, technology compatibility, T_c, and technology dependency matrix, T_d, together determine which new technologies can be implemented. Then sub-routines representing each technology are called into action. An example of a simplified technology model is given for the large deployable reflectors (LDR) as shown on the ETS-VIII test satellite in Figure 12.

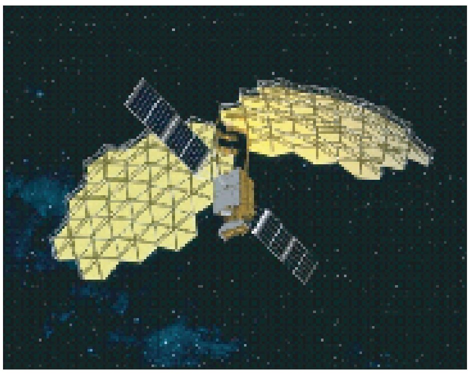

Fig. 12 Japanese Engineering Test Satellite ETS-VIII with Large Deployable Reflector (LDR) Antenna

The contents of a function *LDR* contain the following scaling relationships, among others. The antenna gain with LDR is computed as

$$G_{T,LDR} = 10 \cdot log10\left(\eta\left(\frac{\pi \cdot D_A}{\lambda}\right)^2\right) \qquad (10)$$

in units of [dBi], where η is the antenna efficiency. The additional development cost is estimated as M$ 20.3 and is included in the lifecycle cost. The first unit cost is estimated as the mean of two cost estimates. The first is based on historical data[17] and scales with antenna mass, M_A:

$$TFU_{LDR,1} = 20 + 230 \cdot M_A^{0.59} \qquad (11)$$

The second cost estimation relationship (CER) scales with antenna diameter according to the following equation in [k$]:

$$TFU_{LDR,2} = 2120 \cdot \left(\frac{D_A}{5}\right) \qquad (12)$$

For $D_A = 6$ [m] we obtain $TFU_{LDR} = 2.45$ [M$], $G_T \sim 39$ [dBi] for $\lambda = 0.1875$ [m] and $M_A = 70.7$ [kg]. These quantities would then be returned to the main simulation and either replace previous intermediate system variables, be added to them or be applied as a multiplicative factor, assuming that the "LDR" technology is turned "on". The other technologies are modelled analogously.

To smooth the interaction between TII and the simulator, these impacts are simplified to the form of the changes in performance parameters, in system parameters, in spacecraft mass, in development cost, and in first unit cost, etc. These changes are directly fed to the other modules of the simulator and join the computations in each module. For example, OISL will increase the ISL bandwidth from its original value to a typical value of 10 [Gbps], meanwhile reducing the overall mass of the spacecraft if radio-frequency (RF) ISL was originally installed, or increase the spacecraft mass by slightly more than $\approx$ 100 kg if no ISL was originally installed. Similarly, different changes in development cost and first unit cost caused by OISL will be added depending on the original state of the ISL design variable.

Step 4: Individual Technology Assessment

At this point, the impact of each technology on the system is estimated individually. The full factorial run (1728) of each technology uses the same design variable combination as the baseline case, see Table 1. The results are compared against the baseline results, and the new Pareto frontier, Π_i is judged in relation to the baseline Pareto frontier, Π_o. The effect of using LDR on the design space is shown in Figure 13.

One can see that there is a large effect of using LDR and the architectures in objective space are generally

Table 4 Technology Overview. Column Descriptions: Tech. - technology acronym, Description - main feature, Satellite - example prototype implementation in space, Advantage- key benefit, R&D - estimated additional research and development cost in M$, TFU - theoretical first unit cost in M$, Drawbacks - key disadvantage

Tech.	Description	Satellite	Advantage	R&D	TFU	Drawbacks
OISL	Replaces RF ISL	Spot-4	Datarate 10Gbps	25	16.7	pointing accuracy
ATM	packet/circuit switched	NASA ACTS	flexibility, efficiency	40	10-15	mass penalty
LDR	D_A up to 20 m	ETS-VIII	Gain $\approx$ 38-45 dBi	20.3	> 2.12	large stowed volume
DBF	Ground fixed cells	TBD	higher gain	7-10	3.6	increased complexity

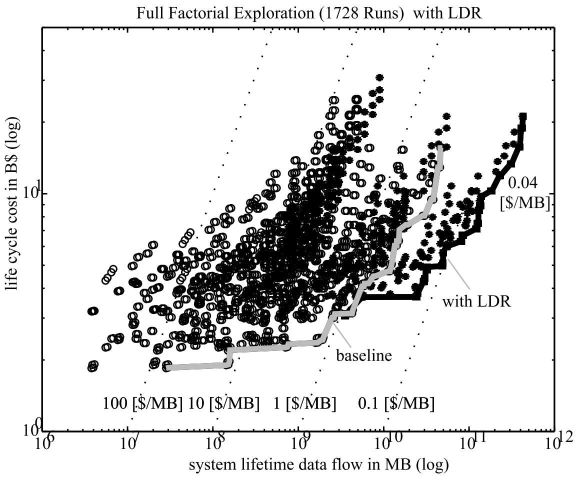

Fig. 13 Full factorial run of the total data flow over system life time, LDR implemented.

shifted towards higher throughput, but also higher lifecycle cost. This can be explained by the fact that LDRs significantly increase antenna gain, G_T (Eq. 10), while at the same time imposing a mass and cost penalty according to Equation (11). The relative effect of LDR can be measured by applying the metrics from Figure 4 to the new Pareto front, see Figure 14.

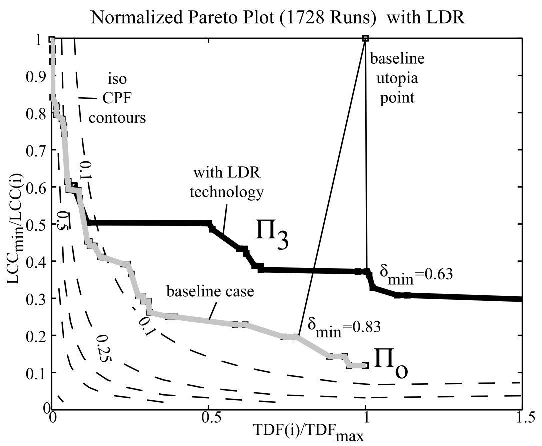

Fig. 14 Normalized Pareto plot, LDR implemented.

The other technologies that were examined individually are OISL and ATM.

Step 5: Assessment of Combinations of Technologies

Three combinations of technologies were examined. They are OISL+ATM, ATM+LDR, and OISL+LDR. The effect on the Pareto frontier is summarized in Table 5. The technology dependency in Table had to be taken into account. Thus, digital beam forming (DBF) is automatically turned on whenever the time between handovers drops below 30 sec in the simulation.

Step 6: Relative Comparison and Interpretation

A relative comparison between technologies is shown in Table 5.

Table 5 Pareto Impact Matrix M_Π. Legend: CPF: minimum cost per function of any architecture [$/min]

Case	δ_{min}	μ	$\upsilon(1)$	$\upsilon(2)$	χ	CPF
Baseline	0.83	0.98	1.0	1.0	-	0.248
OISL	0.89	1.04	1.80	0.52	1	0.287
ATM	0.84	1.02	2.37	0.65	5	0.167
LDR	0.63	2.2	8.79	0.6	2	0.040
OISL+ATM	0.84	1.19	3.00	0.40	0	0.200
ATM+LDR	0.64	4.10	14.3	0.45	1	0.032
LDR+OISL	0.73	3.15	9.83	0.39	1	0.058

A critical analysis of this table shows that the minimum distance to the utopia point is decreased for all cases that use *LDR*, either alone or in combination with other technologies. None of the technologies decreased the mean distance from the utopia point, μ, while all technologies lead to a shift of the utopia point in the direction of higher throughput and higher lifecycle cost. This confirms the effectiveness of these technologies in the context of high bandwidth systems such as the Mobile Multimedia Next Generation LEO system described by Suzuki and coworkers.[9] All four technologies $T_1 ... T_4$ can be described as enabling of high throughput, based on their Pareto effect. One may speculate that technologies designed *to improve efficiency alone* would reduce Pareto distance metrics, without significantly shifting the utopia point.

Based on this information designers can select favorable technologies depending on the desired total capacity or throughput of the system. Very often this judgement is assisted by prediction of the market demand. A trend we have found is that these new technologies tend to do better (closer to the utopia point) in ranges of higher system capacity.

5 Conclusions and Future Work

The methodology presented in this paper quantitatively assesses the effectiveness of technology infusion in the context of communications satellite constellations. This is useful for two particular situations:

1. Choosing between mature technologies (e.g. RF intersatellite links) versus a newly emerging technology (e.g. optical intersatellite links) when implementing a particular system.

2. Assembling a technology portfolio and making technology investment decisions. Given a fixed budget for technology research one may find the incremental performance, capacity and cost impact of each technology relative to its anticipated development and deployment cost. Naturally, such predictions will be quite uncertain, but the process of quantitative impact assessment is useful in itself.

Future work needs to focus on situations where multiple missions or systems are under consideration at once. It is possible that a technology will show a significant advantage in one scenario, e.g. broadband, broadcast systems, but no advantage in a different situation, e.g. personal, mobile voice communications. Also, the uncertainty in predictions such as the ones shown in Table 5 will increase with decreasing technology readiness level; this must be investigated further. The Pareto impact metrics, particularly, χ, have to be extended to more than two objectives. Finally, it would be interesting to investigate - a-posteriori - what turned out to be disruptive technologies based on historical data that would allow to reconstruct the evolution of the Pareto frontier over time.

6 Acknowledgments

This paper is a joint effort of the Massachusetts Institute of Technology (MIT) of the United States, the Communications Research Laboratory (CRL) of Japan as well as the Next-Generation LEO System Research Center (NeLS) of Japan. The methodology, simulator and technology infusion interface were developed at MIT; the new communications satellite technologies used as hypothetical evaluation examples are proposed and developed jointly by CRS and NeLS. This research was funded by the Alfred P. Sloan Foundation under grant number 2000-10-20 with Dr. Gail Pesyna serving as the program monitor, Prof. Richard de Neufville and Dr. Joel Cutcher-Gershenfeld serving as project managers and Mrs. Ann Tremelling of the Engineering Systems Division (ESD) serving as the fiscal officer.

Table 7 Selection of Pareto-optimal architectures, Π_o, in the baseline case, Π_o

#	h [km]	ϵ [deg]	diversity	P_t [W]
1444	1500	8	1	200
1595	1500	10	1	200
1491	1500	8	2	200
1643	1500	10	2	200
1212	1000	8	2	200
1548	1500	8	3	200
1691	1500	10	3	200
1228	1000	8	2	400
1371	1000	10	2	400
1260	1000	8	3	200
1403	1000	10	3	200
1276	1000	8	3	400
1419	1000	10	3	400
924	500	8	2	200
396	1000	8	3	200
972	500	8	3	200
1115	500	10	3	200
988	500	8	3	400
60	500	8	2	200
1003	500	8	3	600
204	500	10	2	200
108	500	8	3	200
251	500	10	3	200
268	500	10	3	400
284	500	10	3	600
283	500	10	3	600

References

[1] Cyrus Jilla and David W. Miller. A Multiobjective, Multidisciplinary Design Optimization Methodology for the conceptual design of distributed satellite systems. In *9th AIAA/ISSMO Symposium on Multidisciplinary Analysis and Optimization*, number Paper No. AIAA-2002-5491, September 4-6 2002. Atlanta, Georgia.

[2] Olivier L. de Weck and Darren D. Chang. Architecture Trade Methodology for LEO Personal Communication Systems. In *20th AIAA International Communications Satellite Systems Conference*, number Paper No. AIAA-2002-1866, May 12-15 2002. Montréal, Québec, Canada.

[3] Hirotaka Nakayama Yoshikazu Sawaragi and Tetsuzo Tanino. *Theory of Multiobjective Optimization*, volume 176 of *Mathematics in Science and Engineering*. Academic Press Inc., London, United Kingdom, i edition, 1985.

[4] Andjelka Kelic, Graeme B. Shaw, and Daniel E. Hastings. Metric for systems evaluation and design of satellite-based internet links. *Journal of Spacecraft and Rockets*, 35(1):73–81, January-February 1998.

[5] C. Gumbert. Assessing future growth potential of mobile satellite systems using a cost per billable minute metric. Master's thesis, Massachusetts Institute of Technology, Department of Aeronautics and Astronautics, August 1995.

Table 6 LEO Simulator Benchmarking Results. Legend: CH - number of simultaneous channels in the constellation, LCC=lifecycle cost, CH/sat= number of simultaneous channels per satellite, M_{sat} = satellite wet mass, N_{sat} = number of satellites in the constellation, N_{spot}= number of spot beams per satellite.

metric	CH	total life data flow	LCC	CH/sat	M_{sat}	N_{sat}	N_{spot}
units	[-]	[MB]	[B$]	[-]	[kg]	[#]	[#]
Iridium actual	72,600	638,050,000	5.70	1,100	689	66	48
Iridium simulated	59,730	524,940,000	5.48	905	829.7	66	44
Globalstar actual	120,000	825,360,000	3.30	2,500	450.0	48	16
Globalstar simulated	96,876	666,310,000	3.91	2,106	458.9	46	18
Orbcomm actual	N/A	N/A	0.5+	N/A	41.7	36	1
Orbcomm simulated	8,424	59,228,000	1.55	216	60.9	39	1
Skybridge designed	N/A	N/A	6.6+	N/A	1,250.0	64	18
Skybridge simulated	50,556	1,545,400,000,000	9.63	766	1,269.7	66	30

[6] M. Violet. The development and application of a cost per minute metric for the evaluation of mobile satellite systems in a limited-growth voice communications market. Master's thesis, Massachusetts Institute of Technology, Department of Aeronautics and Astronautics, August 1995.

[7] Graeme Shaw. *The Generalized Information Network Analysis Methodology for Distributed Satellite Systems*. PhD thesis, Massachusetts Institute of Technology, 1999.

[8] Ryutaro Suzuki, Keiichi Sakurai, Shinichi Ishikawa, Iwao Nishiyama, and Yasuhiko Yasuda. A Study of Next-Generation LEO System for Global Multimedia Mobile Satellite Communications. *AIAA*, (AIAA-2000-1102), 2000.

[9] Ryutaro Suzuki, Iwao Nishiyama, Shigeru Motoyoshi, Eihisa Morikawa, and Yasuhiko Yasuda. Current Status of NeLS Project: R&D of Global Multimedia Mobile Satellite Communications. In *20th AIAA International Communication Satellite Systems Conference and Exhibit*, number AIAA 2002-2038, May 2002. Montréal, Québec, Canada.

[10] James M. Utterback. *Mastering the Dynamics of Innovation*. Harvard Business School Press, Boston, Massachusetts, 1 edition, 1994.

[11] Hugo Tschirky. Technology Management: An Integrated Function of General Management. In *Portland International Conference on Management of Engineering and Technology*, October 27-31 1991. Portland, Oregon, USA.

[12] Rias J. van Wyk. Management of technology: New frameworks. *Technovation*, (7):341–351, 1988.

[13] TH. J. Gordon and J. Stover. Using perceptions and data about the future to improve the simulation of complex systems. *Technological Forcasting & Social Change*, (12), 1978.

[14] R. Henderson and K.B. Clark. Architectural innovation: The reconfiguration of existing product technologies and the failure of established firms. *Administrative Science Quarterly*, 35:9–30, 1990.

[15] D. DeLaurentis A. Utturwar, S. Rallabhandi and D. Mavris. A Bi-Level Optimization Approach for Technology Selection. In *9th AIAA/ISSMO Symposium on Multidisciplinary Analysis and Optimization*, number Paper No. AIAA-2002-5426, September 4-6 2002. Atlanta, Georgia.

[16] Christopher Mattson and Achille Messac. Concept Selection in n-Dimension using s-Pareto Frontiers and Visualization. In *9th AIAA/ISSMO Symposium on Multidisciplinary Analysis and Optimization*, number Paper No. AIAA-2002-5418, September 4-6 2002. Atlanta, Georgia.

[17] W. J. Larson and J. R. Wertz, editors. *Space Mission Analysis and Design*. Microcosm, Inc. and Kluwer Academic Publishers, 2 edition, 1992.

[18] R.E. Steuer. *Multiple Criteria Optimization*. John Wiley & Sons Inc., New York, 1986.