A PROBABILISTIC METHODOLOGY FOR THE TREATMENT OF SYSTEM-OF-SYSTEMS PROBLEMS AND APPLICATION TO FUTURE AIR TRANSPORTATION ARCHITECTURES

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Keywords: *Probabilistic Design, System-of-Systems, UAV, Package Delivery*

Abstract

In this paper, a problem is studied that extends the motives and goals of multi-"discipline" analysis and design to multi-"system" analysis and design. This transition is important since aerospace engineers and designers are increasingly being posed with "system-of-systems" type problems. Future aviation transportation concepts, future package delivery architectures, and future air-traffic management systems are three prime examples of such emerging system-of-systems. An extension to a novel methodology for conducting design trade-offs is presented, representing a critical part of the system engineering process. The new extension is probabilistic in nature and proceeds under the assumption that both requirement ambiguity and technology uncertainty play a key role in the early design exploration of system-of-systems problems. To simulate the interplay between requirements and technologies, a system-of-systems synthesis capability is needed, to serve in much the same capacity as sizing routines serve in aircraft design. System dynamics modeling, especially including causal loop analysis, is employed for this purpose by representing interaction mechanisms between heterogeneous systems. In this way, the sensitivities of overall system-of-systems responses to both system and inter-system architecture variables can be computed. After an introduction to the problem and a brief survey of related fields, a detailed description of key elements of a new system-of-systems conceptual design method is presented. An example application problem is introduced as the method is presented to further illustrate the approach. This problem involves the design of a package delivery architecture utilizing autonomous, vertical take-off and landing air vehicles.

1. Introduction and Background

1.1. System-of-Systems Overview

System-of-systems problems contain multiple, interacting, non-homogeneous functional elements, each of which may be represented as traditional systems themselves. This collection often exists within multiple hierarchies and is not packaged in a physical unit.

Thus, according to this preliminary definition, an aircraft is a system while a network of vehicles operated for package delivery is a system-of-systems. Other design problems that exemplify the system-of-systems category are numerous. Examples include approaches for increasing the aviation system throughput while maintaining safety, network-centric future combat systems for the military, and solutions for a viable airborne personal transportation capability. The purpose of this paper is to report on design methodology research for this relatively new problem to the aerospace design community, define associated key characteristics and modeling capabilities, and offer some further insights through an example. Particular attention will be given to the formulation and execution of conceptual design methods for such problems.

The increase in complexity brought by these problems challenges the current state-of-the-art in conceptual design methods. In this setting, the increase in complexity over typical single vehicle design is characterized by a number of particular factors, which are summarized in Table 1:

Table 1 : Distinguishing Characteristics of System-of-Systems

Characteristic	*Methodological Challenge*
Heterogeneous models	Individual system models may be of different construction type and fidelity
Uncertainties sources and types	Input parameters and interconnection strengths may be uncertain
Information and Network variables	The number, strength, and direction of connections between constituent systems are important design variables and help define overall complexity
Combinatorial solution space	Network (combinatorial) optimization is needed more than (continuous) optimization methods
Need for synthesis capability-	An ability to "size" a feasible system-of-systems alternative, based on rational analysis of individual systems & their interconnections, is a most pressing need
Emergent behavior at multiple levels	Constituent systems may be simultaneously connected hierarchically and non-hierarchically; thus certain behaviors may not be apparent within a lower hierarchy, but "emerge" in a higher one.

2. Methodology Overview

2.1. Problem Definition and Characterization

The first challenge faced during the problem definition step is identifying the different types of design variables that exist and assessing at what level they interact. Similarly, care must be taken in selecting the value objectives to be tracked, which must be of such a scope that synthesis models can be built to compute them while at the same time be adequate for producing the desired metrics that differentiate good design alternatives from poor ones.

This challenge is more acute for emerging system-of-systems problems, as described in a simplistic way through the notional example in Figure 1. In typical aircraft design problems, the various disciplines are broken down separately as contributing analyses. Disciplines that interact are treated with multidisciplinary analysis and optimization methods. This case appears in the left portion of Figure 1 under the label "System 1" and is described as relatively well understood. In system-of-systems problems, a new layer (or layers) of interactions arise and the resulting relationships amongst constituent systems are typically *not well* understood at the start. Further, unlike the aircraft example, the decomposition is not always hierarchical as sub-systems of different systems may interact directly in affecting the responses. Thus, system information variables may interact with vehicle design variables. This leads to non-hierarchical network problems, and behavior not clearly understood at one level often emerges at another level.

To be sure, very complex models of such system-of-systems exist in numerous fields, such as logistics architecture analysis, financial sector analysis, etc. The challenge that remains elusive, especially in the aerospace system-of-systems sector, is to create modeling approaches appropriate for conceptual level design in which many trade-offs are to be explored. There is a growing need for design-oriented system-of-systems analysis. MA&O researches have developed decomposition tools as well as multi-level optimization routines for systems (aircraft, automobiles, etc). Are these applicable to these complex, heterogeneous problems? This must be determined.

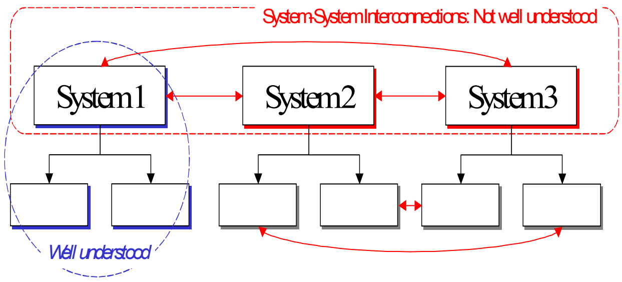

Figure 1: System-of-Systems Decomposition Challenges

2.2. Cross Disciplinary Fertilization- System Dynamics

No longer confined to a focus on the aircraft as the totality of the system, designers need new theories, algorithms, and implementation tools to tackle this new class of problems.

Some of these new, distinguishing characteristics cannot be dealt with properly by existing approaches within the aerospace system design community. Fortunately, unique and valuable insights and tools are available from other engineering disciplines and fields of applied mathematics. In particular, the fields of system dynamics and operations research/network routing optimization offer fertile ground.

The modern field of system dynamics was pioneered by Professor Jay Forrester at the Massachusetts Institute of Technology in the early 1960's. References [1] and [2] are two of the pioneering works that guided what was to follow. During the following 30 years, it has been used in a wide variety of fields to model complex behaviors of systems otherwise not modeled. In recent years, researchers have been focusing on the use of this body of work for business dynamics, emphasizing the identification and improvement of behavior patterns. It the context of this paper, system dynamics, especially as cast in the business dynamics lexicon, is explored as the "sizing" tool which allows the computation of overall system-of-systems alternative cost and performance. This computation should be based on a careful construction of causal relationships between systems, generating a model that, once calibrated, allows the identification of policy options, sensitive parameters, and the range of the parameters for which different policies and scenarios are affected. A review paper by Sterman in Ref. [3] is a particularly comprehensive account of the plethora of applications the system dynamics approach has enjoyed. In addition, exciting research is taking place along various paths concerning network theory and capturing the "network effect", as documented in Ref. [4] and [5]. Such techniques are needed in combination with the system dynamics model as a basis for the study of adaptability and reliability of the system as the network structure changes.

2.3. Refining the Research Objective

The critical nexus for which the aerospace systems design community can serve in this new realm is in the role of *system-of-systems conceptual design synthesis*. This is the research objective and is focused on the creation of engineering simulations that facilitate the performance of sensitivity analyses, trade studies, and robust design studies accounting for uncertainty. A primary use of such a capability is as a guide for technology investment decisions during the early system design exploration phases. This can be done by combining tools from the current field as well as those from related fields, such as linking system dynamics tools with problem decomposition, probabilistic robust design methods, multicriteria optimization, and approximations.

3. Application Problem Set-up & Execution

3.1. Need Definition

To exemplify both the challenges of, and potential solution methods for, system-of-systems design problems, a motivating example is addressed. The unprecedented economic expansion of the last decade combined with the emergence of internet-based commerce has created a growing demand for affordable package shipping services. The demand is projected to accelerate in the future. At the same time, congestion on urban roads and at major hub airports is also increasing and has begun to directly affect the quality of life in terms of increased travel delays, reduced air quality, and other undesirable environmental impacts. The opposing concurrence of this demand for increased (and rapid) parcel delivery with the infrastructure and environmental concerns necessitates the exploration of innovative delivery logistics system-of-systems architectures.

One such class of architectures exploits the advantages of autonomous Vertical Take-off and Landing (VTOL) uninhabited air vehicles (UAVs). The goal of such a concept is to reduce the time and cost currently required to deliver high value-density packages (within certain distance and weight categories) while at the same time having a positive impact on the environment in which it operates. Achieving such a goal would result in a revolutionary delivery system that provides cheaper, more efficient, and more environmentally friendly service to the nation's consumers.

Three major challenges immediately emerge in this endeavor, and they are certainly representative of system-of-systems problems in general. First, a system-of-systems concept alternative generation capability is needed. Second, a *sizing and synthesis model* of the system dynamics over the design space, complete with supporting analyses in key areas, is required. Finally, an intelligent means of exploring and evolving the space of alternatives, under uncertainty, is needed.

System-of-systems problems are still addressed with the classic steps involved in design and decision-making: establish the need, define the problem, establish value objectives, synthesize alternatives, evaluate alternatives against value objectives, and make a decision. For the purposes of this paper, the need definition was quite clearly stated in the previous section. A growing demand for affordable, reliable, environmentally benign, and timely package delivery is present. A key question that requires a new set of engineering design methodologies is whether evolution of the existing system or a totally new architecture is optimal. The remaining steps in the decision-making process are explored next in this context.

3.2. Problem Definition- Informational Design Space

In vehicle design problems, the relationship between disciplines is addressed through the exchange of common variables and constraints (i.e. design space definition). In the system-of-systems problem, while the relationship between systems is also rooted in the information that relates them together, the *characteristics of the information* are also crucially important. How and when this information is transmitted between systems is yet another consideration. Thus, the space is characterized by the nature, distribution, and quantity of information involved in its complex activity.

Clearly, the success of the complex UAV-based package delivery enterprise depends on understanding the interaction of individual systems. Three of the most pertinent system variables in this space appear to be vehicle performance, level of operational autonomy, and the delivery network size/topology. This triad forms the axes of the design space and is depicted in Figure 2. The concept alternatives that reside in the space are collections of vehicles that operate with varying degree of autonomy within a specified network. As indicated in the figure, corners of the design space represent extremely delineated solutions. For example, the corner solution opposite the origin represents a fully distributed network topology in which fully autonomous, fast delivery vehicles determine their own optimal routing and monitor/execute their own servicing. The best alternatives are those that maximize the efficiency and affordability of the entire system-of-systems, i.e. the operational profit, which is the overall objective.

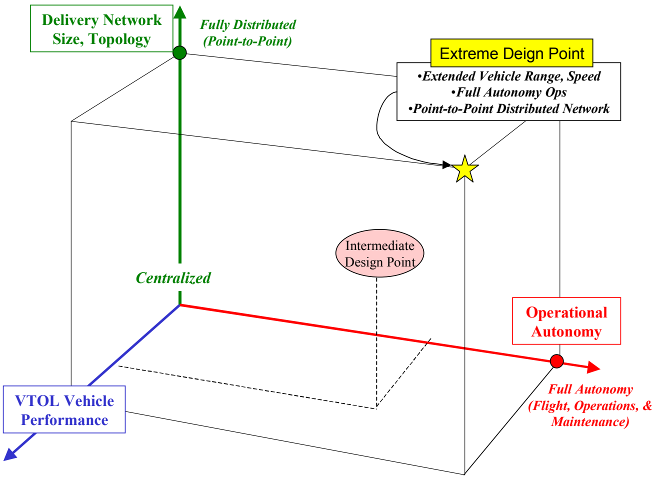

Figure 2: An Example System-of-Systems Informational Design Space

The next priority is to create a capability to hypothesize, synthesize, and evaluate alternatives within the design space.

3.3. Conceptual Alternative Generation

Conceptual level alternative generation cannot be done until sufficient brainstorming and research has been conducted to identify the important functions in the system-of-systems and corresponding options to fulfill those functions. This completion of this task is facilitated by the use of a morphological matrix (Ref. [6]). The morphological matrix can be thought of as an analog to a vehicle configurator. Each row of the matrix has a particular function or system listed in the header column. Subsequent columns in that row contain alternative ways to realize that function or implement that system. Often these options are distinct technology choices. The main output of the morphological matrix is a set of grouped capabilities which comprise a concept alternative.

An example of a morphological matrix for the automated package delivery problem is reported by the authors in Ref. [7]. Several critical functions were identified as needed in order to create and field a successful automated package delivery system-of-systems. Some of these areas include the type of delivery topology (network architecture), the on-board vehicle computing functions (including communication, navigation, and safety), the reliability of autonomous control, the air traffic management (ATM) system integration, and transportation architecture scalability.

3.4. Synthesis of Alternatives via System Dynamics

System dynamics modeling was introduced earlier in this paper as a key body of knowledge that can be brought to bear in tackling system-of-systems design problems. Specifically, research is being conducted to determine how system dynamic modeling may be used to capture the information variables embedded in the concept alternatives generated from the morphological matrix and what values these variables must take to produce a balanced, consistent architecture that meets the stated requirements. This is, again, akin to the role of vehicle sizing and synthesis codes in aircraft design.

An important functionality found in the system dynamics literature is causal loop analysis. In such an analysis, emphasis is placed on determining causal affects of one system upon another. This creates a "main chain" infrastructure. If some outputs of one part of the chain also drive the input of an earlier part, then feedback relationships present. It is these feedback relationships that allow for the study of the time-varying nature of a modeled system, including reinforcing (positive) feedback and dampening (negative) feedback. Underlying this main chain causal model are vehicle models, operational scenarios, and databases, each of which contains key variables present in the causal loop model. The relationship of the causal loop analysis to the system information is depicted in Figure 3.

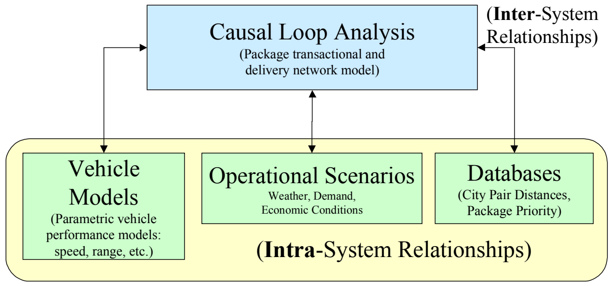

Figure 3: Causal Loop Analysis in System Dynamics Modeling

For the automated package delivery problem, an initial system dynamics framework has been constructed. It serves as a research testbed and is focused primarily on understanding the time and cost performance dynamics of system-of-systems alternatives and on driving an economic sensitivity analyses. This initial cause-and-effect model has been created using Vensim®, a system dynamics modeling software package.

A top-level view of the framework is presented in Figure 4. It currently consists of three major systems: VTOL vehicle configuration, delivery network architecture, and economic/business model. Individual instances of contributing factors and the systems they affect are also shown, such as ATC constraints, cargo demand, and delivery service zones. Also noted is the feedback relationship between the network architecture and the economics model, indicating that the dynamics between these two systems will be especially important.

Within each system are internal parameters and equations that capture the dynamics of that system. The economics model is the last in the main chain, and it contains equations that allow for the final computation of the selected objectives of revenue, cost, and their difference (which is profit), to deliver the load as specified in the cargo model. The cargo model contains package size and pricing information based on actual distributions from today's package delivery sector. The delivery network architecture contains an algorithm that minimizes the number of vehicles needed to deliver packages given the service radius and number of customers. It also estimates the time and distance needed under a particular network topology. The distance information is passed to the vehicle configuration system for total fuel calculation, the result of which is subsequently passed to the economic model.

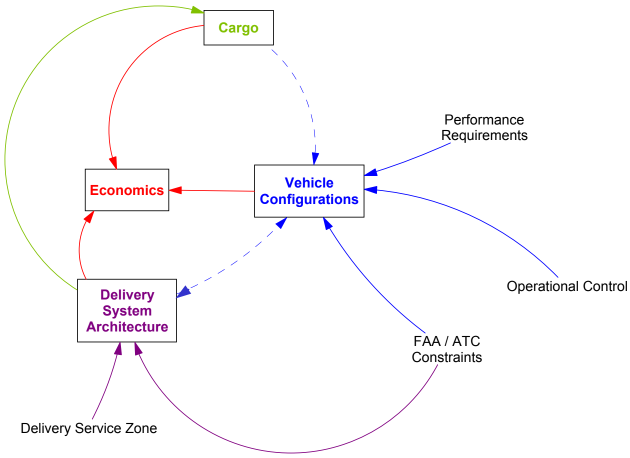

Figure 4: Initial Package Delivery System Dynamics Framework

Individual systems may be modeled in any number of ways, depending on the computational needs and level of fidelity available. For example, a simulation of the delivery network is created for the purpose of obtaining a better estimate of the costs of the assumed network architecture. In this simulation, a point-to-point network is selected with one depot serving all the vehicles in the service zone. Optimizing the paths the vehicles should take when picking up and delivering packages would greatly reduce operating costs. However, this is essentially a travelling salesman problem with many salesmen and with constraints. Fuel and cargo capacity are two of the constraints considered. No optimization method exists yet for this type of problem when the number of points to be visited exceeds approximately 100. Therefore, a heuristic approach to the problem was taken, and a "Savings Algorithm" was implemented into the system (Ref. [8]). This method does not give an optimized solution, but does offer a feasible one.

To avoid embedding the network simulation program in the overall model and to reduce computational burdens, the response surface methodology is employed to create Response Surface Equations (RSEs) for the different outputs. These RSEs are multivariable regression equations that are carefully constructed and optimized to approximate the actual simulation (see Ref.[9]). Once formed, they are inserted into the system dynamics model to obtain the desired results.

Significant research has been conducted concerning the actual design of the VTOL UAV for this application. Currently, a tailsitter design with three shrouded rotors has emerged as a preferred concept, as reported in Ref. [10].

3.5. Evaluate Alternatives: Simulation Results

The system dynamics model shown in Figure 4 simulates the daily delivery of a collection of packages within a specified delivery radius, for a specified number of customers, summed over a one month period and then computes the economics of the enterprise. A set of variables representing the three axes outlined in Figure 2 was selected to demonstrate the techniques used in exploring the requirement and technology dynamics. These variables, their description, and the range of applicable values are summarized in Table 2.

Table 2 : Definition of Design Variables and Responses

DESIGN VARIABLES	
Delivery Network Size	
Service Radius (miles)	100 - 250
# of Customers	400 - 1000
VTOL Delivery Vehicle	
Speed (mph)	115 – 200
Range (miles)	350 – 550
Avg. Vehicle Price ($)	$1000 - $50,000
Fuel Cost ($/gallon)	$0.50 - $1
Autonomous Operations	
Labor Cost ($/person/day)	$50 - $150
Maintenance Cost ($/vehicles/day)	$50 - $150
Maintenance Labor (persons/100 vehicles)	1 - 20
RESPONSES/OBJECTIVES	
Profit / Loss ($M / Month)	(Revenue – Total Cost)
Network Efficiency (⇑ better)	(Package*miles/vehicle)
System Fuel Consumption	Avg. gallons per mile
Operation & Support Cost	($/vehicle/month)

3.5.1. Revolutionary Technology- Near-Autonomous Operations

The delivery network and vehicle variable are sets are self-explanatory. However, the autonomous operations variables are meant to try to capture a revolutionary technology approach to reducing the operations and support (O&S) cost of the system. The concept is quite direct: minimize the required human effort in vehicle flight, loading/unloading, maintenance, and repair. Clearly, this is beyond what is possible today. Specifically, "dynamic" tasks such as fault tolerance, navigation, and mission reconfigurability present a challenge to both today's hardware *and* software technologies. Some of the goals include mid-level coordination for mode switching, reconfigurable fault-tolerant control, demonstration of high-level, mid-level, and low-level control for an autonomous VTOL vehicle, and demonstration of portability of algorithms to other vehicles. Further, all key sub-systems should be line-replaceable units (LRUs) and advanced prognostics and diagnostics are envisioned to determine when a vehicle needs a replacement LRU. This replacement could be done automatically in the same manner as packages are loaded and unloaded automatically. These topics are being explored in on-going research.

3.5.2. Simulation Results

The Response Surface Method is used again in conjunction within a set of simulations for the system dynamics model to create parametric equations for the important responses. These equations are second order polynomials, called Response Surface Equations (RSEs), and enable the powerful capability of answering "What-if" questions and also provide the capability for real-time visualization of sensitivities. RSEs were created for the responses and design variables listed in Table 2 and the sensitivities are displayed in Figure 5. For each response on the left, the minimum and maximum values in the space are displayed while the middle number is the value of the response at the current settings of the design factors. The red dotted lines for each factor can be moved in real time in the software and the value of the responses are updated in real time.

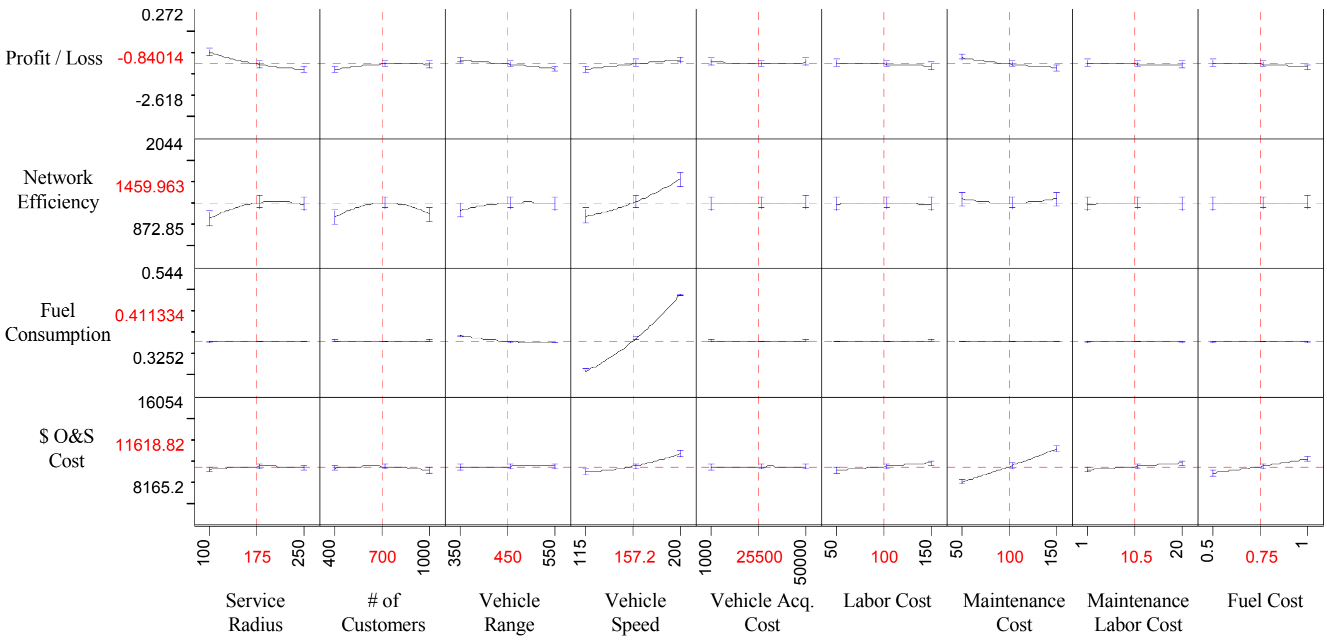

Figure 5 : Response Surface Equations for Design Space

Inspection of the sensitivities shows several interesting behaviors in the system dynamics. First, vehicle speed has a large impact on network efficiency and fuel consumption, as evidenced by the large slopes. However, the effect of vehicle speed on profit/loss is less pronounced, primarily because the increase in network efficiency is counterbalanced by the increase in fuel consumption. This is important information in determining how much R&D should be devoted towards technologies for vehicle speed improvement. Second, the analysis is checked by the fact that some input factors should intuitively have no effect on a response, such as maintenance labor cost on fuel consumption. This is borne out by "flat lines" (meaning no effect) for the economic parameters on fuel consumption. Clearly, all factors have some effect on the bottom line: profit/loss.

Finally, it is noted that the network efficiency response has strong second-order effects from the service radius and #-of-customer factors. The strength (and sometimes even the sign) of these slopes can change, however, when other factors settings are changed. This is due to interactions in the model. For example, as displayed in Figure 6, the optimal number of customers to maximize network efficiency depends on the vehicle range.

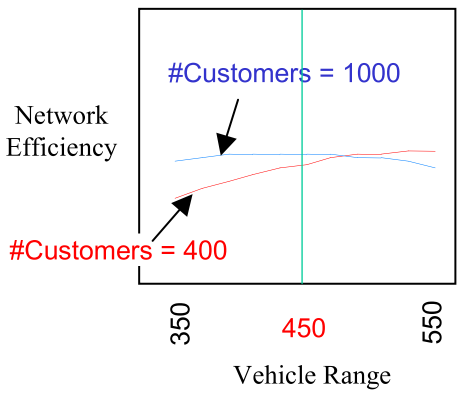

Figure 6: Interaction Effect Between Range and #Customers on network Efficiency Response

3.5.3. Design Space Exploration

Examination of the space of options for the package delivery system shown in Figure 5 indicates that it may be difficult to find settings that result in a profit. To determine just how many feasible solutions may exist, a design space exploration is performed. This is done by assigning uniform probability distributions (see Figure 7) to the network and vehicle design variables (except fuel cost, which will be dealt with later) over their whole range of validity as defined in Table 2, while fixing the operational autonomy variables are their mid-point ranges.

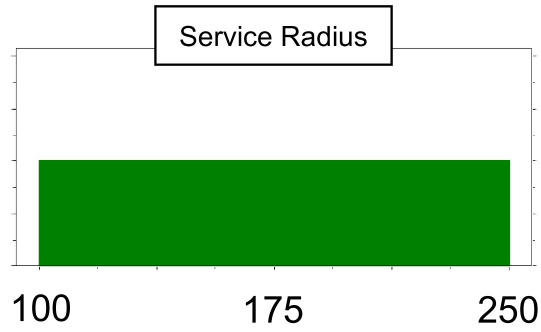

Figure 7: Example Uniform Distribution for Service Radius

Subsequently, a Monte Carlo simulation is performed using these distributions and the RSEs to sample evenly over the space of the six variables and track how many instances of positive profit occur. The result of this probabilistic simulation is displayed in Figure 8 in the form of a cumulative distribution function (CDF) for the profit/loss response. Examination of the profit/loss CDF shows that there is a 0% probability of the system earning a profit as it operates every month!

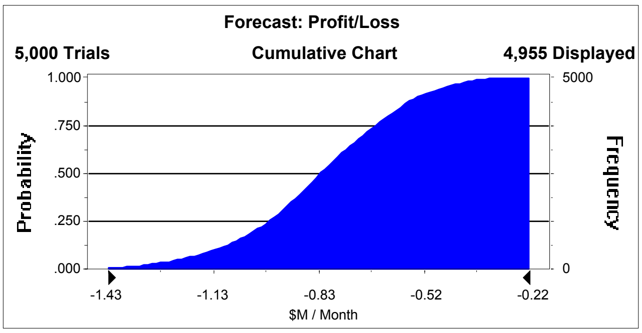

Figure 8: Design Space Exploration- Profit/Loss CDF

3.5.4. Advanced Technology Infusion

Perhaps the most important role for the modeling tools described in this paper is the ability to postulate, represent, and simulate the impact of advanced technology suites on futuristic systems. Clearly, terms such as “futuristic”, “advanced technology”, and “might” indicate that a recognition and accounting of uncertainty must be central in any exercise of the tools for this purpose.

The results of the design space exploration encapsulated in Figure 8 show that, without further technologies, the package delivery system as designed is a money-losing proposition. It is now of interest, then, to examine the operational autonomy technology idea outlined earlier in section 3.5.1.

The implications of the highly automated operation of the fleet of VTOL UAVs include reduced maintenance personnel per vehicle, reduced labor cost for those workers still needed, and, more broadly, a reduced overall maintenance cost due to elimination of a central depot. As such, these three variables from Table 2 are treated as random variables and given distributions that assign most of the probability to low (i.e. reduced) values for these costs to simulate the technology infusion. Fuel cost, a classic uncertain parameter, is included as well. These distributions are shown in Figure 9.

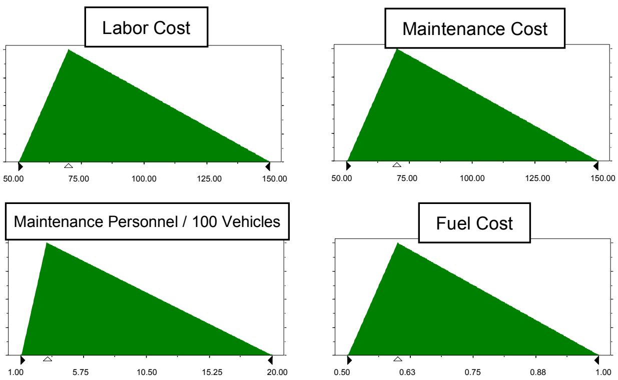

Figure 9: Uncertainty Distributions for Operational Autonomy Technology Variables

A Monte Carlo simulation is again executed, this time using the distributions described in Figure 9 and with the settings of the network and vehicle variables set at their most promising values based on the design space exploration. The results of the simulation are again represented as a CDF on the profit/loss response, as depicted in Figure 10. Compared to Figure 8, it is now noted that the simulated impact, under uncertainty, of the revolutionary operational autonomy concept results in a significant improvement in the probability of having a profitable business enterprise. There is a 25% chance that the system can be operated profitably on a monthly basis.

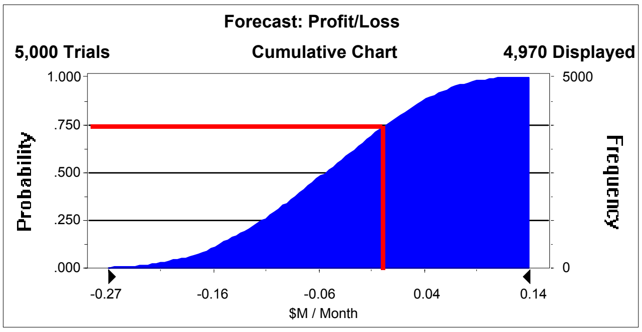

Figure 10: Impact of Operational Autonomy- Profit/Loss CDF Revisiting

Finally, a crucial piece of information remains to be extracted. The knowledge of which uncertain technology parameters have the largest impact on the variability of the response distribution is critical to understanding where technology investment may have the largest payoff. The impact, or leverage, of an uncertain parameter on a response is dependent both on the variability of the random variables and the deterministic sensitivity of the response on the parameter in the first place. For the current study, this information is obtained through a probabilistic sensitivity analysis, the results of which are displayed in Figure 11 for the profit/loss response.

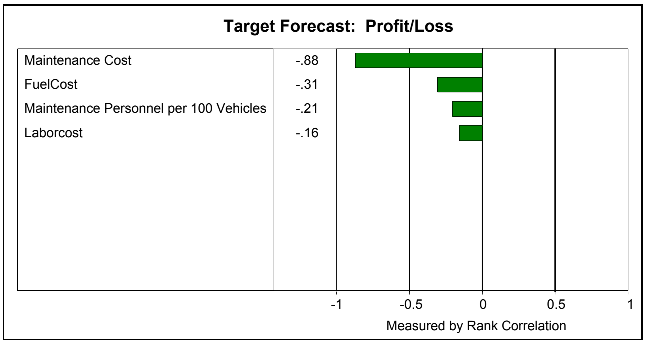

Figure 11: Probabilistic Sensitivity Analysis for Technology Variables

While all sensitivities are negative (indicating their *reduction* results in profit *increase*), the maintenance cost parameter stands out as having the greatest probabilistic sensitivity, due primarily to the larger leverage (slope of sensitivity line in Figure 5) it has compared to the other parameters. Now, if the distributions in Figure 9 change, the relative ranking of the probabilistic sensitivity may also change.

4. Summary

A collection of approaches have been presented and demonstrated for the purpose of modeling and solution of system-of-systems problems. After a description of the key characteristics of these classes of problems, the system dynamics modeling method was introduced to serve the function of system-of-system sizing and synthesis, with particular focus on the potential ability to capture the essential dynamics between constituent systems. To illustrate the technique, a futuristic automated package delivery problem employing VTOL UAVs was formulated and modeled.

System dynamics was found to be a powerful avenue for capturing the interactions between heterogeneous systems such as the vehicle, the delivery network, and the economic concept. The model was exercised to explore the design space, and the initial results indicated that the prospect for positive profit margins appears slim at best. However, a probabilistic approach for computing the degree to which system-of-systems technology alternatives help meet requirements was presented, culminating with an examination of the infusion of operational autonomy technology. Even accounting for uncertainty, the situation is markedly improved primarily by the large reductions in operations costs due to personnel reductions. Further, the uncertainty analysis illustrated that the leverage effect of maintenance cost has a significant impact. *The key points of the whole range of techniques employed is the ease of changing assumptions, the ability to rapidly answer "what-if" questions, and the capability of evolving the model as the concept and market mature.*

While the purpose of the application problem was primarily to elucidate the methodology research ideas, as more insight into the automated package delivery concept was obtained, the prospects for exploring ways to make such a concept profitable increased in interest. The future may yet be bright for such a revolutionary approach to package delivery.

5. Acknowledgements

The authors acknowledge the NASA Institute for Advance Concepts (NIAC) for their sponsorship of this research and the Sikorsky Aircraft Corp. for their partnership in portions of the study.

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