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Acquisition Management for Systems-of-Systems: Affordability through Effective Portfolio Management

DeLaurentis, Daniel A.; Davendralingam, Navindran; Neema, Kartavya

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12 May 2014

Daniel A. DeLaurentis, Professor,
Navindran Davendralingam, Senior Research Associate, and
Kartavya Neema, PhD Candidate

School of Aeronautics and Astronautics

Purdue University

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Abstract

Promoting *affordability* and a 'Should Cost' policy in defense acquisitions involves a series of decision epochs that lead up to end procurement of a desired sustainable capability. Often times the number of decision variables, coupled with programmatic uncertainties, leads to a decision problem that can quickly exceed the mental faculties of the decision-maker. Yet these decision problems, especially early on, directly impact cost, schedule and performance in subsequent decision-epochs. Our research under this grant leverages techniques from the fields of operations research towards improving multi-period decision-making in defense acquisitions. Our work extends prior developed portfolio tools to include a framework that can handle complex interdependencies between technical and programmatic dimensions of acquisitions, bearing multi-epoch consideration in mind. We provide representative case study analyses to illustrate application of methods in identifying optimal acquisition strategies and investment policies.

Keywords: affordability, defense acquisition, system-of-system, operations

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About the Authors

Daniel A. DeLaurentis—is an associate professor in Purdue's School of Aeronautics & Astronautics in West Lafayette, IN. He is director of the Center for Integrated Systems in Aerospace (CISA), which is home to over 15 additional faculty and staff, and leads the System-of-Systems Laboratory (SoSL) which includes graduate and undergraduate students as well as professional research staff. His primary research interests are in the areas of problem formulation, modeling and system analysis methods for aerospace systems and systems-of-systems (SoS), with particular focus on network analysis and agent-driven models.

Daniel A. DeLaurentis
School of Aeronautics and Astronautics
Purdue University
701 W. Stadium Ave
West Lafayette IN 47907
Tel: (765) 494-0694
E-mail: ddelaure@purdue.edu

Navindran Davendralingam—is a senior research associate in the School of Aeronautics and Astronautics at Purdue University. He received his PhD from Purdue University in Aerospace Engineering in 2011. He is currently conducting research in the Center for Integrated Systems in Aerospace (CISA) led by Dr. Daniel DeLaurentis.

Navindran Davendralingam
School of Aeronautics and Astronautics
Purdue University
701 W. Stadium Ave
West Lafayette IN 47907
E-mail: davendra@purdue.edu

Kartavya Neema—is a Ph.D. candidate in the School of Aeronautics and Astronautics, Purdue University. His current research interest includes consensus control, target tracking, distributed optimization and system complexity measures. Kartavya is a student member of International Council on Systems Engineering (INCOSE) and American Institute of Aeronautics and Astronautics (AIAA).

Kartavya Neema
School of Aeronautics and Astronautics
Purdue University
701 W. Stadium Ave
West Lafayette IN 47907

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Executive Summary

The US Department of Defense (DoD) has emphasized a need for Better Buying Power initiatives in tackling issues of increasing costs, schedule growths and programmatic failures that stem from complex cascading failures across highly interdependent military assets. The management of warfighting portfolios through a ‘Should Cost’ technique becomes increasingly difficult as acquisition practitioners leverage performance against various measures of risk, bearing military asset interdependencies in mind.

Balancing support warfighter activities whilst maintaining affordability of programs throughout the acquisition lifecycle is a challenge. The need to reduce cost and promote adequate competition and growth of technological options in developing military capabilities has further increased the complexity of the acquisition process. This increase in complexity now includes the need to account for competitive elements in contracting, improving productivity and reducing unnecessary redundancies. Prior research by the authors has employed financial engineering tools to establish a robust investment portfolio approach as a means of exploring acquisition trade space by balancing capability and cost of a ‘portfolio’ of military assets against various metrics of acquisition risk. The risk measure in the portfolio framework addresses cascading effect of interdependencies that exist between interconnected systems. The presented research extends the prior work and supports the Better Buying Power (BBP) initiative by incorporating decision-support strategies from system of systems engineering, financial engineering and operations research to support the sequential nature of acquisition decision-making that typically exists in managing portfolios of military assets. Three techniques are explored1) policy construction for cost and schedule overruns using *mechanism design* 2) a strategic level *robust multi-period portfolio problem* and 3) a multi-period portfolio formulation that leverages d*ecision epoch updates for sequential decision-making*. The proposed strategies support acquisitions, both in the pre- and post-milestone B phases, and exploit current initiatives such as open architecture (OA) and competitive contracting (e.g. Fixed Price Initiatives) in supporting ‘Should Cost’ based management decisions to improve affordability and capabilities whilst preserving adaptive traits in view of evolving military requirements.

Nomenclature

J_i :	set of coefficients with parameter uncertainty
p_j, y_j, z :	Dual variables of non-linear primal
x_i :	decision vector of policies (i)
U_{pi} :	Utility of policy (i) on participant (p)

C_{pi}:	cost of policy (i) on participant (p)
u_j, l_j:	Upper and lower variable bounds
$R_{corr}P_{ratei}$:	Product of correlation matrix and 'performance due to policy (i)'
Γ:	level of conservatism
w :	weighting factor
R_c :	baseline capability level for each of the capabilities that contribute to index
$C^B_{q,t}$:	cost of acquiring system (*q*) at time (*t*)
C^S_t :	cost of retiring system (*q*) at time (*t*)
$X^B_{q,t}$:	Decision vector
$U^B_{q,t}$ and $V^B_{q,t}$:	decision to acquire and remove system (q) at time (t)
$\bar{\eta}_{ik}$:	Independent and symmetric random variable
Sqc:	Numerical value for system (q) capability type (c)
q:	system

Abbreviation

DoD:	Department of Defense
OA:	Open Architecture
VCG:	Vickerey-Clark-Groves
P2P:	Peer to Peer
SoS:	System of Systems
LCS:	Littoral Combat Ship
LP:	Linear Program
MISDP:	mixed integer semi definite programming
MIW:	Mine Warfare
ASW:	Anti-Submarine Warfare
SUW:	Surface Warfare
MCM:	Mine Counter Measures

Outreach and Collaboration

Work documented in this report has resulted in a conference publication at the 10th NPS Acquisition Research Symposium 2013, the IEEE Conference on System of Systems and the 11th NPS Acquisition Research Symposium 2014. Resulting interactions at attended conferences have produced very valuable insights into the applicability of method(s) developed towards defense acquisitions research. The presentation and interactions at the IEEE System of Systems Engineering (SoSE) conference has resulted in feedback and additional input on the merits of our current results and potential further development of the portfolio approach in this report. The presentation of research material at the conference especially allowed us to foster closer academic ties and exchanges with various members of the broader community for collaboration and exchange of ideas. The work has also informed and enhanced related work we are conducting under the DoD SERC UARC in the area of analytic methods for system of systems planning and evolution.

Introduction

Our research seeks to introduce innovations formed at the intersection of system-of-system engineering, operations research and financial engineering towards dealing with technical and programmatic complexities of managing acquisition and development of a portfolio of defense capabilities. More specifically, our work seeks to extend prior funded NPS efforts (ref) in the application of portfolio-based approaches to managing cost, schedule and risk, by considering policy and multi-epoch decision impacts within a quantitative framework. The quantitative frameworks we present do not seek to replace decision-maker authority, but rather, complement him/her with tools that offer quantitatively based insights of the complex acquisition trade-space for more informed decision-making. Effectively, the idea is to reduce decision-making difficulties, by allowing mathematical programming to account for the combinatorial and uncertainty aspects of the problem, whilst delegating the decision-making and trade-space control to that of the human decision-maker. We accomplish this through a portfolio-based technique in dealing with programmatic acquisition complexities. In this body of work, we adopt mathematical programming techniques to deal with issues in 1) policy construction for cost and schedule overruns using *mechanism design* 2) a strategic level *robust multi-period portfolio problem* and 3) a multi-period portfolio formulation that leverages d*ecision epoch updates for sequential decision-making*. Concept application problems illustrate the aforementioned methods that address facets of the complex decision-making associated with multi-period decision epochs.

Motivation

The US Department of Defense (DoD) has emphasized a need for Better Buying Power (BBP) initiatives in tackling issues of increasing costs, schedule growths and programmatic failures. Dr. Ashton Carter, Under Secretary of Defense for Acquisitions, Technology and Logistics, in a series of memo issues (ref), has called for a need for ‘Should Cost’ policies to promote affordability in defense acquisitions. ‘Should Cost’ policies involve a practical approach to reducing costs of defense portfolios through targeting of cost growths, incentivizing productivity and innovation, reducing redundant processes, promotion of real competition and improvement of tradecraft in acquisition of services. The spirit of the move towards affordability is to promote the identification and acquisition of sensible technologies (or programs) at an acceptable cost and at minimum schedule risk. Policy levers (e.g. incentivized contracting) are used to promote innovation, while at the same time, reducing cost growths and redundancies in the capabilities of the warfighter portfolio. The reduction in technical and programmatic redundancies is in line with the US military's vision of promoting adaptability and resilience in capabilities where systems and assets can adapt, through reconnections and redeployment of existing assets, towards meeting the needs of a changing warfighter scenario.

Additionally, there have been significant efforts in promoting competitive innovation through Open Architecture (OA) and rapid prototyping initiatives. OA establishes set standards that enable the leveraging of technological innovations, with emphasis on Small Business Innovation research (SBIR) and Small Business Technology Transfer (STTR) mechanisms that can readily interface with existing platforms, based on set interface standards. More specifically, OA involves the design and implementation of systems that conform to a common and unified set of technical interfaces and business standards. This form of 'open architecture' tests and broadens potential innovations to a much larger scope than traditional acquisition processes. Rapid prototyping on the other hand complements efforts such as the OA to enable rapid proof-of-concept testing and fielding in warfighter test environments. Rapid prototyping and testing of new, yet-to-be introduced systems naturally provides objective information on the potential operational value of individual systems early on in the platform lifecycle.

The current needs of the US military still challenges the effectiveness of BBP policies in acquiring 'capabilities' rather than localized acquisition of an individual system. The acquisition of 'capabilities', in an overarching sense, presents unique complexities that exist between yet-to-be acquired and existing system capabilities. BBP policies, OA and rapid prototyping are examples of policies that serve to determine the value of yet-to-be introduced systems. However, these policies are more of general guidelines and cannot deal with the technical and programmatic complexities of the overarching collection of systems or 'system of systems' as a whole that contribute collectively to a desired capability. Furthermore, the decision-spaces associated with evaluating the connectivity, capabilities and development schedule impacts under uncertainty, can involve a large number of variables that can often go beyond the immediate mental faculties of the decision-maker. The problem in size of the decision space exacerbates the difficulty of decision-making in situations where early on acquisition decisions can have an impact on subsequent decision-epochs of an acquisition strategy. The current guidelines in the Department of Defense (DoD Acquisitions Guidebook (DAG), and the DoD System of Systems Engineering (SoSE) Guidebook do not provide distinct methodologies in managing the quantitative complexities that can manifest across technical and programmatic dimensions of development. The need for necessary quantitative tools and frameworks towards supporting effective decision-making across measures of cost, risk and schedule for defense acquisitions, motivates our body of research.

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Methods of Approach

This section covers the three methods of approach that we have investigated towards dealing with issues in 1) policy construction for cost and schedule overruns using *mechanism design* 2) a strategic level *robust multi-period portfolio problem* and 3) a multi-period portfolio formulation that leverages d*ecision epoch updates for sequential decision-making*.

Method 1: A Mechanism Design Approach to Policy Design

This thrust of our research examines *mechanism design* of auctions for modeling behaviors and effecting policy interventions that are intended to improve overall programmatic performance when acquiring independently managed systems of systems. Previous models and empirical studies provide an understanding of the behavioral aspects of the acquisition process. A method inspired by *mechanism design* incorporates the insights and data from these studies to formulate a probabilistic optimization framework for constructing interventions that enhance the probability of meeting cost and schedule goals when acquiring a system of systems. The method follows a myopic policy in multi-epoch decision-making and can be utilized at each strategic epoch of acquisition process with the goal of reducing cost and schedule overruns.

Overview of Acquisition Models and Studies and Mechanism Design

Models of the system of systems acquisition process provide a structure for investigating the impact of interventions that incentivize the managers of the systems that comprise a system of systems to change their behavior. Empirical studies of the acquisition process identify the key behavioral aspects of the acquisition process and analysis of its empirical data can yield estimates of quantitative relationships between behaviors and their effects on programmatic measures such as cost and schedule. Mechanism design methods can be used to formulate a probabilistic optimization framework for evaluating the effects of interventions that enhance the probability of meeting cost and schedule goals when acquiring a system of systems.

Models and Studies of the Acquisition Process

The trapeze model (Dahmann J. e., 2011)for system of systems describes seven interacting core elements, or activities, that accomplish systems engineering for systems of systems. The wave model unwinds the trapeze model to define an iterative, dynamic model that accomplishes the goals of the seven elements in the trapeze model by employing six steps: initiation, initial analysis, architecting, planning, implementation, and continuing analysis. The last four steps can be repeated indefinitely as the system of systems evolves in response to changes in the external environment and the results of the managerial and operational behaviors exhibited by the participating systems. In this research, acquisition cost and schedule are the key measures of the results of managerial behavior; and technical performance capability is the key measure of the results of operational behavior.

The six activities of the wave model have been used to define an agent-based model of system of systems development (Acheson, et al., 2012). The model simulates iteration of designing, planning, implementation, and continuing analysis. The agent-based wave model defines the set of prerequisite activities that must be completed prior to advancing the epoch and beginning a new iteration of an activity. The agent-based model uses a genetic algorithm to simulate generation of initial system of systems architectures, and it uses a fuzzy assessor model to simulate selection of the desired system of systems architecture for the next epoch based on four attributes associated with each system: performance, affordability, robustness, and flexibility. Each system communicates if it is going to participate in the next epoch based on its ability and willingness to cooperate.

Wirthlin (Wirthlin, 2009) used empirical data to model the US defense acquisition system as three interdependent processes: budgeting (how much and when to buy), requirements development (why and what to buy), and acquisition (how to buy). He defined five key characteristics of the acquisition system: cost, schedule, quality, transparency, and flexibility. He concluded that flexibility, transparency, and quality are the most valued and are essentially non-negotiable, whereas cost and schedule are negotiable. He describes the behaviors and results that occur from valuing these three characteristics as follows:

> If flexibility is valued, e.g. being able to start programs at will, rush things through, jump ahead of other programs in development cycle, then the system must be able to deal with the funding instability that ensues. If transparency is valued, e.g. process checking, error proofing, consensus-building, then the system must maintain process reviews and levels of approval and accept expensive use of calendar time. If quality is valued, e.g. not giving relief for technical requirements, capabilities and performance expectations, then expect

program delays and cost increases to develop and mature the necessary technologies, or deliver the expected capabilities, etc.

There is empirical data from other studies that support the assertion that cost and schedule should be considered as negotiable, dependent variables (Oehmen, Olechowski, Kenley, & Ben-Dayac, 2012), (Conrow, 1997).

Using a survey instrument, Sheard (Sheard, 2012) confirmed a hypothesis regarding three measures of complexity for system development efforts: “Projects characterized by higher numbers of ‘difficult’ requirements, higher cognitive overload, and more complex stakeholder relationships demonstrate significantly higher performance issues (cost overrun, schedule delay, and performance shortfall).” Difficult requirements are considered to be difficult to implement or engineer, are hard to trace to the source, and have a high degree of overlap with other requirements. Higher cognitive overload exists when the project frequently finds itself in a fog of conflicting data and information overload combined with multitasking and interruptions. Complexity in stakeholder relationships is measured according to an ordinal scale as follows: (1) relationships stable; (2) new relationships; and (3) resistance to changing relationships.

To gain an understanding of the causes of failure in acquisition programs in the US Air Force, Marticello (Martcello, Jr., 2012) applied the conceptual framework that complexity emerges from two elements, the diversity of things to be done and the coordination required to get them done (Tainter, 1988). Marticello reviewed three areas that provide evidence of complexity in the Air Force acquisition system: significant differentiation that exists in personnel specialization and organizational structure, the large number of actions required to manage financial resources, and the need to comply with a large number of regulatory guidelines and policies.

McNew (McNew, 2011) used behavior archetypes to structure a survey on the prevalence of certain behaviors in acquisition and their relationship to cost or schedule growth and to root causes of the behaviors. McNew surveyed 65 program managers who were asked to confirm the presence or absence of the behaviors on specific programs. If a behavior was present, the respondents indicated if the behavior was a cause of cost or schedule growth, and the root causes that contributed to the presence of the behavior. **Error! Reference source not found.** shows the influence diagram for the survey, which indicates the probabilities that can be estimated directly from the survey results, *P{Behavior}*, *P{Management Outcome* **|** *Behavior}*, and *P{Root Cause* **|** *Behavior}*. By applying Bayes’ rule to these estimates, *P{Management Outcome* **|** *Root Cause}* and *P{Root Cause}* can be determined.

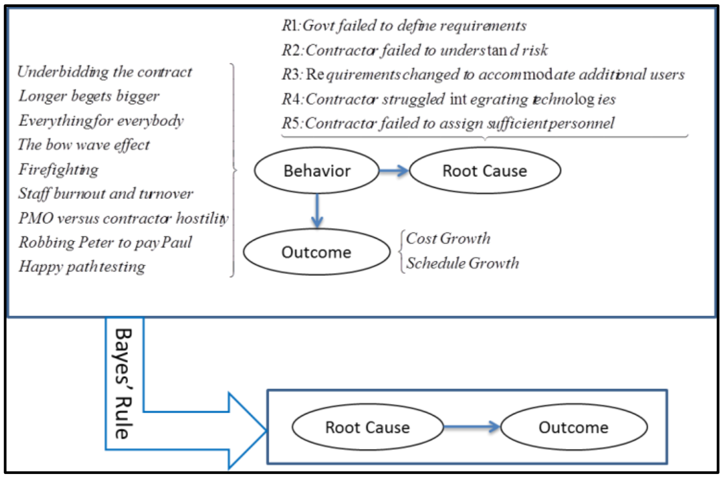

Figure 1. Behavior Archetypes Influence Diagram

Table 1 shows summary statistics from using McNew's survey data in order of the estimate prevalence (P) of the root causes. The very high correlation between schedule growth and cost growth are typical and explained by the fact that the majority of the cost incurred in most projects is for salaries of personnel who remain on the project until it is completed. The correlations between the root causes and the cost and schedule outcomes represent the "dose-response" relationship that measures the effect that a change in the probability of occurrence of a root cause can have on the probability of occurrence of an cost and schedule outcomes. Our mechanism design framework uses the Bayesian network to capture the correlations and the estimated probabilities based on the survey as inputs to specify the baseline dose-response behavior for individual systems within a system of systems. The mechanism design aims to optimize the effect on outcomes that result from changing *P{Root Cause}* via policy changes or other interventions.

Table 1. Summary Statistics for McNew Survey

	Correlation							
	R1	R2	R3	R4	R5	SG	CG	P
R1	1.0	0.3	0.4	0.2	0.1	0.5	0.5	0.4
R2		1.0	0.4	0.4	0.2	0.4	0.5	0.3
R3			1.0	0.1	0.1	0.4	0.5	0.3
R4				1.0	0.3	0.4	0.3	0.3
R5					1.0	0.3	0.3	0.3
SG						1.0	0.8	0.6
CG							1.0	0.6

Mechanism Design

Mechanism design, also known as 'reverse game theory', refers to the construction of governing rules of interaction among participating agents, to result in a desired global outcome. The fundamentals of mechanism design derive from game theory and typically aim at motivating agents to disclose truthful private information, while seeking to maximize their respective utilities. An intuitive example is the case of auctions where the implementation of specific auction rules, can be theoretically shown (under certain assumptions) to result in optimal utility for participating agents, only if the agents disclose truthful valuations of the items being auctioned. One such auctioning mechanism is the Vickerey-Clark-Groves (VCG) mechanism (Vickrey, 1061) (Clarke, 1971) (Groves, 1973), that considers the optimal design of an auction for a single item case where bidders have unlimited budgets. The method is based on the idea that there are observed, common knowledge distributions on prior valuations by each bidder. The main properties that drive the design of auctions are related to knowledge and assumptions on bidder budgets and include the following conditions (Bandi, Tractable stochastic analysis in high dimensions via robust optimization , 2012):

1. *Individual Rationality:* Buyers do not achieve negative utility with truthful bids.
2. *Budget Feasibility:* Buyers are constrained by resource budgets in bidding.
3. *Incentive Compatibility:* Bidders fare best (optimal utility) when truthfully disclosing information.

In general, the conditions listed in (a-c) above are not all achievable in auctions. For example, Dobzinski (Dobzinski, 2008) proves the impossibility of an incentive-compatible auction that is always Pareto-optimal, in the case of a multi-unit auction with private information budget limits.

Computational mechanism design is the application of mechanism design principles to the case of computer agents that act on the behalf of human counterparts. In lieu of controlling interactions on large-scale systems, (e.g. the internet, P2P, e-commerce, bandwidth allocation), *computational mechanism design* provides a powerful, game-theoretic framework for the control and administration of multi-agent systems within a decentralized framework (Dash, 2003). There have been many practical applications of mechanism design that include, tactical sensor allocation (Klein, 2008), electricity markets, and even Google's advertising revenue management systems (Edeleman, 2005).

The myriad of interactive conditions that exist in current real world systems have prompted the development of a range of theoretical and algorithmic work that address varied assumptions and conditions for auction mechanisms. Recent research has adopted robust optimization methods to design a multi-item multi-bidder auction under budget constraints; the core tenet of the work replaces

Kolmogorov axioms of probability with the notion of uncertainty sets that derive from asymptotic implications of probability theory (Bandi, 2012). This robust formulation allows for a numerically tractable approach for large-scale auction design that leads to improved revenue generation for the auctioneer, even under conditions of uncertainty in valuations and past distributions.

Mechanism Design for Acquisitions

In a system of systems, the interacting operationally and managerially independent entities gives rise to complex dynamics that can either benefit architectural evolution or, conversely, generate systemic failures. The selection of an appropriate set of interaction rules (policies) for participating agents that interact in the system of systems acquisition process is naturally important in ensuring that key performance goals of the overarching architectural gamut are fulfilled while preserving preferences on maximizing individual agent utilities and reflect the utility seeking behaviors of entities in a system of systems. Mechanism design strategies can potentially be useful in the construction of incentive-compatible policies that establish the potential for individual agents to maximize utility under budget constraints. Figure 2 shows the general feedback loop for sequential policy-making epochs.

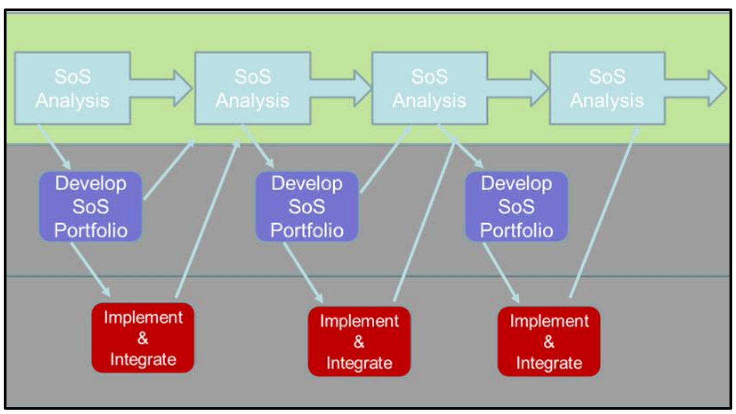

Figure 2. Policy mechanism feedback for system of systems acquisitions.

Figure 2 is adapted from the wave model (Dahmann, Rebovich, Lane, Lowry, & Baldwin, 2011) and illustrates the mechanistic feedback process where information gains at the end of each decision epoch (e.g. through the McNew data at the post ‘implement and integrate’ phase) are used to perform acquisition policy changes that support conducive participant behaviors in minimizing contributors of cost and schedule overruns. The combination of a Bayesian Network approach in estimating the effects of propagation, and optimization driven decision-making (under uncertainty) can be a valuable tool in orchestrating a feedback control that identifies optimal policy vectors. In effect, the decisions set the stage for a sequential ‘auction’ between the organizations responsible for the system of systems and participating agencies. The consideration of the policy vector as binary choices allows for the quantitative aspects of the problem to be addressed within the context of a discrete optimization problem.

Optimization Problem Formulation and Solution

We motivate our mechanism design approach with a conceptual problem that seeks to determine the optimal set of discrete policies that minimizes the effects (probabilities) of cost and schedule related root causes occurring within a system of systems acquisitions context. The treatment of policies as discrete actions (such as the reward system for acquisition program office personnel and the contracting terms with system developers) allows for a large variety of types of policies to be considered. The idea is to use *a priori* information, such as that garnered from the McNew survey data in this research, to reduce cost and schedule growth through effective policy management. We adopt an operations research perspective to dealing with optimal selection of policies, and seek to maximize the performance (minimize cost and schedule growth) of an overarching system of systems acquisition.

The approach is based on extension of a relatively simple combinatorial auction problem where the objective of the auctioneer is to maximize revenue subject to receiving a set of bids for auctioned items ((Tutuncu, Combinatorial Auctions, 2007)). This parallels, in a simple sense, the dynamics of acquisition interactions where the policies for acquisitions (‘items of auction’) result in a net performance (root cause manifestations (‘bids’) from participants of the auction, namely the systems that are participating in a system of systems acquisition. The idea is thus to dynamically adapt and minimize cost and schedule growth, through the feedback mechanism as depicted in Figure (2), while considering the uncertainties in associated estimated quantities (e.g. *P (root causes)).*

The resulting robust optimization problem, following the Bertsimas-Sim method of formulation (Bertsimas, 2004), becomes the following:

$$\max\ t \tag{1}$$

subject to:

$$R_{corr} P_{ratei} x_i - z\Gamma - \sum_{j \in J_i} p_j \geq t \tag{2}$$

$$z + p_j \geq R_{corr} P_{rate} \mathrm{y}_j \qquad y_j \forall j \in J_i \tag{3}$$

$$-y_j \leq x_j \leq y_j \quad y_j \forall j \in J_i \tag{4}$$

$$l_j \le x_j \le u_j \qquad y_j \forall j \in J_i \tag{5}$$

$$p_j \ge 0, y_j \ge 0, z \ge 0 \tag{6}$$

$$x_1 + x_5 \le 1 \tag{7}$$

$$x_2 + x_6 \le 1 \tag{8}$$

$$\left(U_{pi} - C_{pi}\right) x_i \ge 0 \tag{9}$$

$$\sum_i C_{pi} x_i \le Budget_p \tag{10}$$

$$x_i \in [0,1] \qquad \text{(policy vector)} \tag{11}$$

where:

J_i :	set of coefficients with parameter uncertainty
p_j, y_j, z :	dual variables of non-linear primal (see reference (Bertsimas, 2004))
x_i :	decision vector of policies (i)
U_{pi} :	utility of policy (i) on participant (p)
C_{pi} :	cost of policy (i) on participant (p)
u_j, l_j :	upper and lower variable bounds
$R_{corr} P_{ratei}$:	product of correlation matrix and 'performance due to policy (i)'
Γ:	level of conservatism

Equations (1-3), represent the robustified objective of maximizing performance, that is quantified by $R_{corr} P_{ratei} x_i$. ; The first two terms, R_{corr} and P_{ratei} , relate to the estimated effect that the decision to introduce policies x_i will have in reducing the probabilities of root causes occurring (R1-R5) as described in Figure 1. We assume an estimation uncertainty that exists in the coefficients of the matrix product of $R_{corr} P_{rate}$, and assume it to exist in the nominal interval of [$R_{corr} P_{rate} + R_{corr} P_{rate}$, $R_{corr} P_{rate} - R_{corr} P_{rate}$]. The robust formulation that uses the Bertsimas-Sim approach ensures that is able to withstand the coefficient uncertainties with probabilistic guarantees based on a chosen level of conservatism. Equations (2 - 6) employ the use dual variables from the original non-linear formulation (see reference

(Bertsimas, 2004)) variables in the robustification of the resulting optimization problem. Equations (7 and 8) enforce compatibility constraints for policies. In this case, policies 1 and 5, and, 2 and 6 are mutually exclusive. Equation (9) ensures that the policies selected result in a net utility for each stakeholding participant entity in the system of systems architecture. The cost and utility to participant p, $U_{pi,}$ and $C_{pi,}$ due to the implementation of policy x_i are estimated quantities that can reflect, say, monetary valuations of policy decisions. Equation (10) ensures budget feasibility of the policy for participating agents. While Equations (9) and (10) address the requirements of budget feasibility and individual rationalities in a very simplistic sense, this may not always be achievable due to the nature of the set policies available. For example, the implementation of any combination of a finite set of policies may favor specific groups of system development programs more than others and present negative net utilities; this condition may require relaxations to be enforced and a consideration of utility frontiers that address tradeoffs between participating agents. Equation (11) describes the decision variables as binary integers; the linear formulation of the optimization problem, with these binary variables makes it a binary integer-programming problem. Although the formulation is built on a myopic policy, we partially address the multi-period nature of the acquisition feedback loop as shown in Figure (2) by considering the uncertainties of each decision epoch.

Results for Mechanism Design Policy Generation

We solve the optimization problem of Equations (1 – 11) using values of Γ, varied between 0.1 and 2.5; this allows for the construction of a trade-off frontier between performance and conservatism (probability of constraint violation), as shown in Figure (3) and Figure (4) respectively. Although there are 25 discrete optimization runs, there are however, only three unique ‘portfolios’ of policies x_i as presented in Table 2. These correspond to the circled points in Figures (3) and (4), at prescribed levels of conservatism, Γ. The discrete nature of the decision variables allows for a fixed vector of policies (x_i) to range of probabilities until the next ‘optimal’ configuration of policies; the probabilities of constraint violations are thus lower bounds for each discovered optimal solution.

While the natural instinct would be to assume policies with the lowest probabilities of constraint violation, the associated tradeoff with performance and cost, (among other potential metrics) in performing the policies, may offset the potential gains. The ‘cost-benefit’ analysis on the range of optimal policies can be performed by the policymaker to determine a suitable policy vector that attempts to minimize the probability of root causes that directly contribute to overall cost and growth overruns. The robust approach adopted in this section is an initial step towards construction of a probabilistic optimization framework that can assist in the construction of appropriate policies, over decision epochs of the system of systems acquisitions problem, but can be used as a policy control tool over each period of policy decision-making.

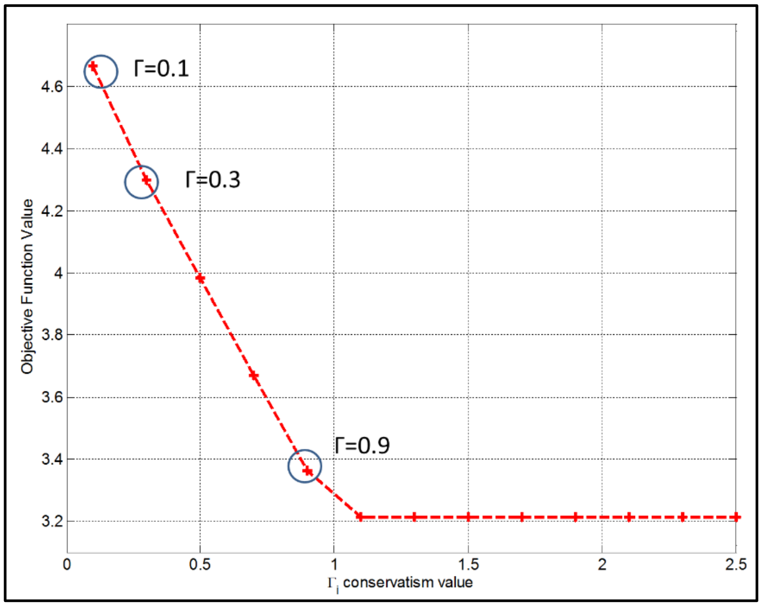

Figure 3. Tradeoff between objective and conservatism in robustness. Γ is the adjustable conservatism constant.

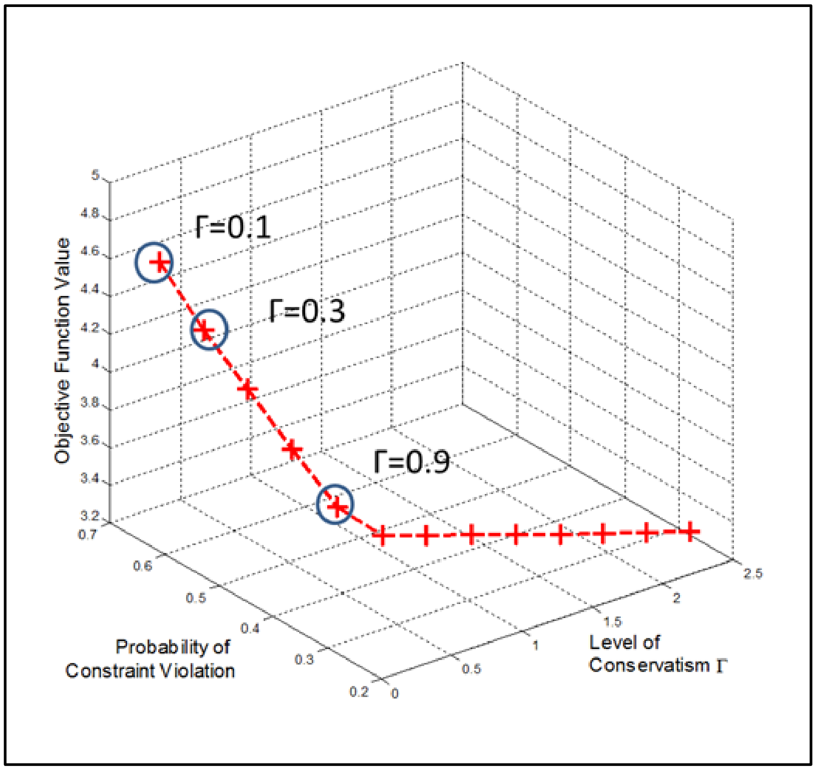

Figure 4. Probability of constraint violation at varying levels of constraint conservatism Γ.

Table 2. Policy selection based on conservatism

	Unique Portfolios		
Policy 1	1	-	-
Policy 2	1	1	-
Policy 3	1	1	1
Policy 4	1	-	-
Policy 5	-	1	1
Policy 6	-	-	1
Policy 7	1	1	1
Policy 8	1	1	1
Conservatism (Γ)	0.1	0.3	0.9
P(Constraint Viol)	0.64	0.61	0.52

Our work in mechanism design presents an initial framework for constructing approach to applying mechanism design to system of systems acquisition management. It can be used to extend the agent-based model of system of systems development (Acheson, et al., 2012) to allow for evaluating the impact of interventions that change the behavior of the managers of the participating (and non-participating) systems. Additional surveys may provide further insights and empirical data to enhance the applicability and realism of the agent-based model. Furthermore, extensions to the optimization framework will include more explicit integration of Bayesian measures in the optimization process, to promote an optimal balance of performance maximization and policy information gain using available methods from literature (Ryzhov, 2012)

Method 2: A Robust Multi-Period Decision Framework

Portfolio management techniques have been successfully applied to the management of strategic 'portfolios of systems' in military acquisitions; this includes application of Real Options (RO) theory and metrics such as Knowledge-Value Added (KVA) that account for the value added by human and IT investments (Komoroski, 2006). Work by Mun (2005) (Mun, 2005)has developed an eight phase process to addressing portfolio management of strategic assets. Work by Giachetti (2012) (Giachetti, 2012)has applied stochastic techniques to managing military investments. Previously funded research by the Naval Postgraduate School (NPS), presented at the 2012 NPS Acquisition Research Symposium (Davendralingam, 2012), has focused on a robust portfolio management problem of maximizing a warfighter system of systems portfolio performance index while preserving budgetary and compatibility constraints of underlying military assets.

Risks and capabilities associated with system interdependencies can span the functional or physical spaces of the system of systems construct and is subject to uncertainty. The developed strategy supports acquisitions, both in the pre- and post- milestone B phases, and considers current initiatives such as open architecture (OA) and competitive contracting (e.g. Fixed Price Initiatives) in improving affordability and BBP objectives while considering evolving military requirements. Work in this research extends the robust portfolio approach to include a multi-period portfolio perspective.

The multi-period portfolio optimization approach draws upon a rich history of algorithmic development, as noted in operations research related literature (Powell (2011), Bertsimas (2008), Bertsekas (2005), (Fabozzi, 2007), (Tutuncu, 2007) . Its roots stem from sequential decision making areas known broadly as dynamic programming or stochastic programming and adapts control theory methodologies to the dynamic management of resources in the interest of maximizing (or minimizing) some given metric. Stochastic programming focuses on issues of uncertainty whereas dynamic programming relates to the optimality of making sequential decisions; however, there has been a large degree of overlap and exchange between the two areas. Algorithmic development in these areas have been applied to a range of real-world dynamic decision making problems that range from financial portfolio management to real-time control of vehicles.

The *robust multi-period portfolio framework* allows for mathematical rigor of algorithmic techniques (transparent to the end user/practitioner), to support SoS level acquisition decisions through identification of optimal 'portfolios' of systems to be acquired in pursuit of desired SoS capabilities. While the acquisition process spans operationally and managerially independent defense groups, the tools and frameworks envisioned to support these aspects aim to provide adequate trade-space exploration capabilities and extend the prior section's mechanism design based framework to include combinatorial effects of different systems that can be put together towards achieving a military capability. These explorations require a domain agnostic framework, and hence intuitively resonate with the idea of treating the collection of systems across domains as a 'portfolio' of systems in the SoS.

The concept naval warfare scenario in this section demonstrates the application of the multi-period portfolio framework in managing the sequential acquisitions needed to propagate required capabilities whilst minimizing operational and developmental risks. The method illustrates the identification of optimal evolution of interconnected systems that cohesively function in providing an overarching SoS wide capability. A robust optimization approach to the multi-period portfolio formulation addresses issues of data uncertainty.

Portfolio Systems Modelling

The acquisition (and removal) of systems in an evolving a system of systems inherently involves a timeline of sequentially executed decisions. Decisions made at each epoch affects the decision options of future states, thus affecting long-term performance and risks of the system of systems. The translation of these sequential decisions to the context of a multi-period investment model requires an adequate description of node (system) attributes; this ensures the selection of feasible portfolios that satisfy nodal requirements and minimize cascading risks. Figure 5 shows generic behaviors for considered systems in a system of systems portfolio.

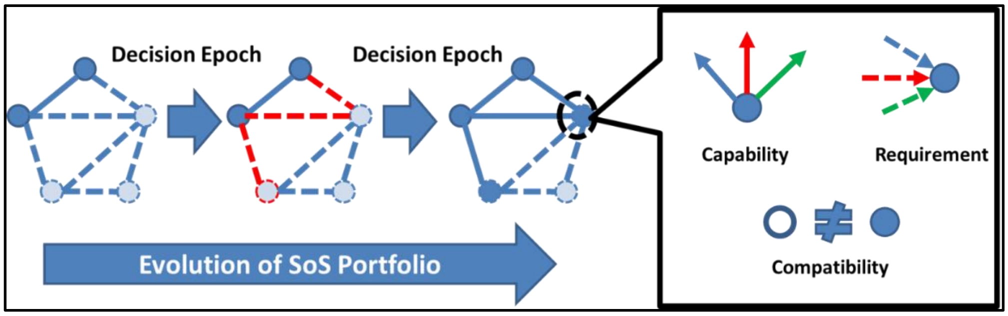

Figure 5. Archetypal node (system) behaviors

In Figure 5, the capabilities of an existing system of systems (initial blue nodes), have the potential to evolve, based on potential connections to yet-to-be acquired systems (dashed lines and nodes). At each decision epoch, the practitioner utilizes a decision-making framework (such as the multi-period portfolio framework) to evaluate the value and risks involved in the potential acquisitions of new systems (denoted by red dashed lines). The resulting new collection of systems that comprise the new SoS construct, now include the addition of the new systems.

A system of systems is treated as a set of generic discrete nodes with the following attributes:

- *Capability (Outputs):* Nodes have finite supply of capabilities that are limited by quantity (e.g. total power output of generator systems).
- *Requirements (Inputs):* Nodes have individual requirements. Requirements are fulfilled by receiving capabilities from other nodes that can fulfill said set of requirements (e.g. a high powered AMDS radar requirement of energy can be fulfilled by multiple generators)
- *Compatibility:* Nodes can only connect to other nodes based on a pre–established set of rule (e.g. AMDS radar can only accept power from high capacity nuclear reactor systems on specific ships).

Multi-Period Investment Portfolio Formulation

The problem statement for a multi-period investment portfolio is translated to the language of mathematical programming. The process begins with the definition of two main elements of a mathematical program, namely, the *objective function* and *constraints*. The objective function is a mathematical expression that is formulated to reflect a key performance metric of the system to be maximized (or minimized). Typical formulations of the objective function seek, for example, to minimize direct costs of operating a fleet of aircraft. For a system of systems, the objective function reflects a chosen measure of performance and/or associated costs. The second important aspect of a mathematical program is the formulation of the constraints.

The constraints reflect physical, resource and behavioral aspects of the systems as mathematical expressions. Our initial framework for a multi-period portfolio considers a long term horizon of acquisitions with discrete decision steps that denote periods of 'investment'; these investments involve the addition/removal of individual systems that comprise the overall system of systems network.

The following mathematical program describes a preliminary framework for the multi-period acquisition problem:

$$\max\left(\sum_{q}\left(\frac{S_{qc}-R_c}{R_c}\cdot w\cdot X^{B}_{q=T}\right)\right) \tag{12}$$

subject to:

$$X^{B}_{q,t} = X^{B}_{q,t-1} + U^{B}_{q,t} + V^{B}_{q,t} \tag{13}$$

$$C^{trans}_{t} = C^{B}_{q}U^{B}_{q,t} + C^{S}_{q}V^{S}_{q,t} \tag{14}$$

$$\sum_{t=0}^{T} C^{trans}_{t} \leq \text{Budget} \tag{15}$$

$$\sum_{q} S_{qtC}X^{B}_{q,t} \geq \sum_{q} S_{qtR}X^{B}_{q,t} \;\; \text{(Satisfy Requirements at each t)} \tag{16}$$

$$\left(X^{B}_{i,t} + .. + X^{B}_{n,t}\right)_{j,t} = M_{j,t} \;\;\; \text{j=1...k (Package System Compatibility)} \tag{17}$$

$$X^{B}_{q,t}, X^{B}_{q,t-1}, U^{B}_{q,t}, V^{B}_{q,t} \in [0,1] \qquad \text{t=0… T (time-steps)} \tag{18}$$

where:

w - weighting factor vector that weights the importance of constituent capabilities of index

R_c - baseline capability level for each of the capabilities that contribute to index

$C^{B}_{q,t}$ - cost of acquiring system (*q*) at time (*t*)

C^{S}_{t} - cost of retiring system (*q*) at time (*t*)

Equation (12) is the weighted objective function that seeks to maximize the end-developed system of system performance index. Here, the index is related to the final state of the portfolio (t=T) and is weighted according to the value that each capability (C) contributes to the index (however, this can naturally reflect maximization of each stage, if necessary). The index is normalized by referencing it to some chosen reference capability set (R_c). Equation (13) reflects the evolutionary nature of the portfolio of chosen systems (*q*) at time (*t*), represented by the decision vector $X_{q,t}^{B}$. Here, the decision vector is binary, to reflect discrete system choices; however, a more general setting can allow the variables to be continuous in nature.

The terms $U_{q,t}^{B}$ and $V_{q,t}^{B}$ reflect decisions to 'acquire' and 'remove/retire' individual systems respectively, in the portfolio of systems at each decision epoch of time (*t*). Equation (14) captures the 'transactional' costs at each stage; this means that decisions to acquire/remove systems translate to costs associated with each that are accrued at each time step. In acquisitions, the removal cost translates to a salvage/swap cost for changing out individual systems whereas the 'acquire' cost is simply the cost of purchasing and integrating a new system. Equation (15) ensures budgetary balance for total costs (transactional and acquisition) that occur.

Equation (16) ensures that the total 'capabilities' from systems acquired, satisfy the requirements that individual systems may have; for example, there must be adequate power generating systems selected to support selected communications systems that provide some system wide communications capability. Conditions for Equation (16) can be enforced at each time step (t) or at the final stage (t=T), depending on requirements at each time step. Equation (17) enforces compatibility constraints as binary conditions for a total of (*k*) set of rules; for example, the constraint that only one engine can be selected to generate power would translate to a constraint of $x_1 + x_2 = 1$ where (x_1,x_2) are binary variables. The rules can be applied across decision epochs, reflecting the need to have prior systems in existence, before particular upgrades can be implemented in future time steps. Equation (18) states that the decision variables are binary and that the time window consists of discrete steps from t=0 to a final time t=T. The problem formulation of Equations (12-18) constitutes a *binary integer program*, for which efficient methods of solution and commercial solvers are available.

Robust Multi-Period Investment Portfolio

The multi-period formulation of Equations (12-18) are deterministic and do not consider uncertainties in the data. Real world systems are inherently driven by uncertainty and thus challenge the optimality (and feasibility) of decisions made under deterministic assumptions. Research in mathematical programming has progressively focused more on the development of robust optimization methods to deal with manifestations of uncertainty. Robust optimization seeks to find solutions, to uncertain mathematical programming problems, that are less sensitive to parametric variations in the problem being solved. We consider uncertainties in the data for Equations (12-18), namely in the 'transaction costs' of Equations (14-15) that reflect system addition and removal costs. We also consider uncertainties in the capabilities of each system available.

The consideration of the uncertainty in the multi-period formulation requires the use of robust optimization methods for solution. There are a range of methods that can address the uncertain linear structure of the resulting optimization problem; however, we adopt the Bertsimas-Sim (correlated case) approach for our preliminary multi-period framework. The Bertsimas-Sim method (Bertsimas, 2004) is a robust optimization approach to solving linear optimization problems with uncertain data. The method allows for a flexible adjustment in the level of conservatism of the robust solutions (termed the *Price of Robustness*) in terms of probabilistic bounds of constraint violations.

We consider the following is a general uncertain linear program (LP):

$$\text{maximize} \qquad c^T x \tag{19}$$

subject to:

$$\mathrm{Ax} \leq \mathrm{b} \tag{20}$$

$$x \geq 0 \tag{21}$$

Where values a_{ij} of matrix A are uncertain and exist in the nominally symmetric bounds of [a_{ij}- $a_{ij,}$ a_{ij}+ a_{ij}]. The uncertainties are treated as *constraint-wise* uncertainties. In the correlated case, the uncertainties are modelled as the following equation:

$$\bar{a}_{ij} = a_{ij} + \sum_{k \in K_i} \bar{\eta}_{ik} g_{kj} \tag{22}$$

where $\bar{\eta}_{ik}$ are the independent and symmetric random variables [-1, 1], and there are *k* number of uncertain sources. The robust optimization problem to the correlated case can be written as the following linear optimization problem (Bertsimas, 2004):

$$\text{maximize} \qquad c^T x_j \tag{23}$$

subject to:

$$\sum_j \mathrm{A}_{ij} x_j + z_i \Gamma_i + \sum_{j \in J_i} p_{ij} \le b_i \tag{24}$$

$$z_i + p_{ij} \ge y_j \tag{25}$$

$$-y_j \le \sum_{j \in J_i} g_{kj} x_j \le y_j \tag{26}$$

$$l_j \le x_j \le y_j \tag{27}$$

$$p_{ij}, y_{ij}, z_{ij} \ge 0 \tag{28}$$

where p_{ij} $y_{ij,}$ z_{ij} are the dual variables associated with the dual problem of the nonlinear formulation of the Bertsimas-Sim method (See (Bertsimas, 2004) for full derivation), and J is the set of uncertain coefficients. The conservatism term, Γ_i, is adjusted to control probabilistic guarantees of constraint (i) violation. For example, changing Γ, for linear constraints that dictates power distribution flow over a network, controls the probability of net power being supplied at a prescribed level of cost. The constraint violation probability bounds for individual constraints can be approximated using the following De-Moivre approximation of the binomial distribution (Bertsimas, 2004):

$$B(n, \Gamma_i) \approx 1 - \Phi\left(\frac{\Gamma_i - 1}{\sqrt{n}}\right) \tag{29}$$

where n is the $|J_i|$ and Φ is the normal cumulative distribution function. The manipulation of Γ in controlling the probability of constraint violation, allows for an intuitive interpretation of the conservatism of solutions generated, and permits practitioners the means of assessing solution performances against associated risk in terms of individual constraint violations.

Robustification: Bertsimas-Sim (Correlated) Approach

The robust (correlated) implementation of the Bertsimas-Sim approach in Equations (22-28) is applied to the multi-period model of Equations (12-18). The following equations described the robustified budget constraints for the multi-period model, in particular context of budget feasibility, expressed earlier in Equation (15):

$$\underbrace{X^B_{q,t=T} + \sum_{t=0}^{T} C_q V^B_{q,t}}_{'c^T x_j'} + z\Gamma + \sum_{j \in J_i} p_j \leq \text{Budget} \quad (1)$$

$$z_i + p_j \geq y_j \quad (2)$$

$$-y_j \leq \sum_{j \in J_i} g_{kj} x_j \leq y_j \quad (3)$$

$$l_j \leq x_j \leq y_j \quad (4)$$

$$p_{ij}, y_{ij}, z_{ij} \geq 0 \quad (5)$$

where x_j is the concatenated decision vector $\{X^B_{q,t=T}\ V^B_{q,t=0,1,2}\}$ associated with all transactions (t=0,1, 2).

Interpretation of risk

The inclusion of correlation information reflects an important contribution where protection levels of each robust constraint, in the non-correlated case assumes the simultaneous worst-case scenarios at the uncertainty bounds – a condition that is highly improbable. The correlated case accounts for the simultaneous ‘movements’ in performance and/or risks across the capabilities of individual assets. Prior research has utilized a mixed integer semidefinite programming (MISDP) approach to dealing with uncertainties in the covariance matrix, a matrix that is associated with variances (risk) in system development time. However, there are very limited solvers that are able to solve MISDPs, which limits practical implementation, despite some of the computational advantages in dealing with uncertainty.

Concept Application: Naval Acquisition Scenario

The Naval Acquisition Scenario is based on the Littoral Combat Ship (The USA’s new Littoral Combat Ships, 2011) model. The LCS (Figure 6) is a naval combat vessel, developed by Lockheed Martin and General Dynamics, because of the Navy’s dual contracting efforts to reduce cost through competition. The design of these ships seeks to provide a more agile and cost effective solution to various near shore environment missions. These missions are executed through use of interchangeable ship packages that include Mine Warfare (MIW), Anti-Submarine Warfare (ASW) and Surface Warfare (SUW). The highly modular design of the platform, allows for a great degree of operational flexibility. The modularity also translates to the ability for *open architecture* and small business initiatives to be brought to bear in reducing program costs and improving competition. Work in this research assumes an LCS inspired scenario as representative ‘simple’ SoS model where the objective is to identify potential *sequence of investment decisions* and the corresponding end collection of systems that can best maximize core capabilities of the SoS mission (in this case, MIW,ASW, SUW).

Our simplified model consists of a hypothetical list of candidate systems, listed in Table 3, that are available to the Navy for acquisition. Although the number presented in the table are fictitious, the salient features of capability, requirements, cost and uncertainty are nevertheless represented. Each subset of systems (listed by categories of ASW, MCM, SUW, Seaframe, Comm), represents a subset collection of systems that are available in meeting the needs of each category. The (ASW, MCM, SUW) categories are the core LCS mission packages, ‘Seaframe’ reflects the ship seaframe support options and ‘Communications’ represents the support communications systems available for deployment. The first five columns show capabilities of each system, and their respective numerical valuations. Column 6 and 7 are the *Power* and *Communications* requirement needed for operation of the listed systems, in providing the capabilities listed. Also listed are the acquisition (buy) and retiring (sell/salvage) costs, along with the estimated uncertainty of each cost. We consider uncertainty in costs for this simplified problem; however, more general uncertainty in capabilities and/or requirements can be introduced in the same fashion.

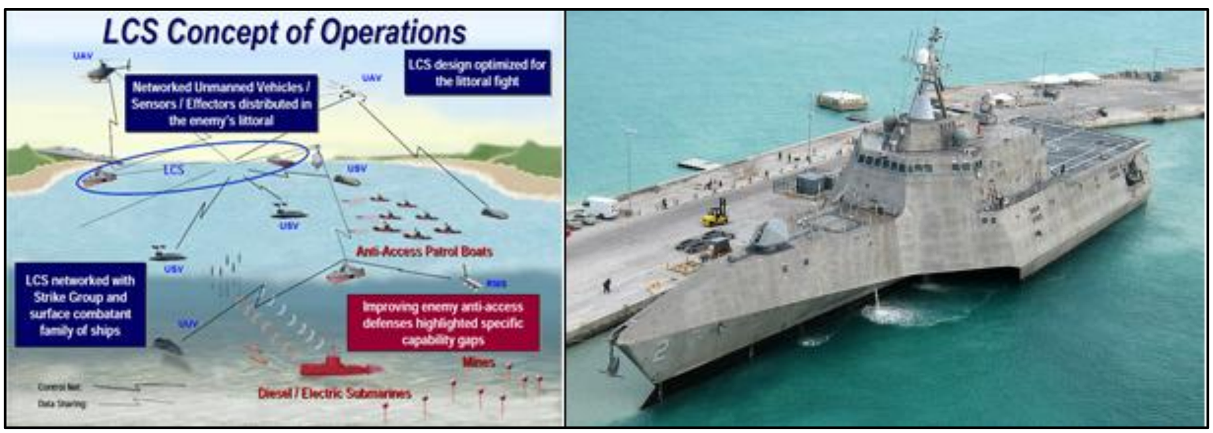

Figure 6. (L) concept of operations[1] (R) General Dynamics independence class LCS

Table 3. LCS Candidate system scenario

Category	System	Weapon Strike Range	Surface Detection Range	Anti Mine Detection Range	Comm Bandwith	Power Bandwith	Power Required	Comm Required	Acquisition Cost	Retiring Cost	Uncertainty Acquisition Cost	Uncertainty Retiring Cost
ASW	Variable Depth	0	50	0	0	0	95	100	1.00E+05	1.00E+05	9.84E+01	3.04E+01
	Multi Fcn Tow	0	40	0	0	0	90	120	2.00E+05	2.00E+05	1.74E+02	1.83E+02
	Lightweight tow	0	30	0	0	0	75	100	3.00E+05	3.00E+05	1.15E+02	2.37E+02
MCM	RAMCS II	0	0	10	0	0	70	120	1.00E+05	1.00E+05	7.80E+01	9.05E+00
	ALMDS (MH-60)	0	0	20	0	0	90	150	2.00E+05	2.00E+05	1.91E+01	1.33E+02
	New Prototype 1	0	0	30	0	0	100	170	3.00E+05	3.00E+05	2.58E+02	1.91E+02
SUW	N-LOS Missiles	25	0	0	0	0	0	250	1.00E+05	1.00E+05	3.49E+01	9.19E+01
	Griffin Missiles	3	0	0	0	0	0	100	2.00E+05	2.00E+05	1.69E+02	8.05E+01
	New Prototype 1	30	0	0	0	0	0	300	3.00E+05	3.00E+05	1.72E+02	2.91E+01
Seaframe	Package System 1	0	0	0	0	300	0	0	1.00E+05	1.00E+05	7.02E+01	4.72E+01
	Package System 2	0	0	0	0	450	0	0	2.00E+05	2.00E+05	1.54E+02	1.42E+02
	Package System 3	0	0	0	0	500	0	0	3.00E+05	3.00E+05	2.41E+02	2.60E+01
Comm.	Comm System 1	0	40	0	180	0	100	0	1.00E+05	1.00E+05	1.26E+01	3.59E+01
	Comm System 2	0	0	0	200	0	120	0	2.00E+05	2.00E+05	1.24E+02	9.83E+01
	Comm System 3	0	0	0	240	0	140	0	3.00E+05	3.00E+05	2.17E+02	7.00E+01
	Comm System 4	0	0	0	300	0	160	0	4.00E+05	4.00E+05	2.20E+02	3.98E+02
	Comm System 5	0	0	0	360	0	180	0	5.00E+05	5.00E+05	7.03E+01	4.15E+02
	Comm System 6	0	0	0	380	0	200	0	6.00E+05	6.00E+05	4.09E+02	4.62E+02

Naval Acquisition Scenario: Results

We formulate the problem statement for the above LCS inspired acquisition problem as a mathematical program that follows the robustified formulation of Equations (34-41). We then solve the resulting mathematical problem using varied values of the conservatism parameter, Γ_i, to reflect a range of dynamically evolving acquisitions, at each prescribed level of conservatism. Here, we assume conservatism in dealing with the costs uncertainties of acquisitions; each chosen value of Γ (here 3 values) in this context thus reflects the probability of budget overruns occurring due to the associated costs uncertainties in each stage of acquisition. We assume a 3 stage (t=0,1,2) acquisition process, where the systems listed in Table 3 can be acquired/retired at each stage, culminating to a final 'portfolio' of assets at the end of stage 3 (t=2). Acquisition/retirement of these systems is subject to a prescribed set of rules that govern their compatibility, and availabilities in time (systems only available at specific epochs) as reflected in Equation 40 of the problem formulation. Figure 7 below shows the SoS performance frontier tradeoff against degree of conservatism in the budget constraint.

[1] *Image from: Presentation slides by RDML Vic Guillory of OPNAV at Mine Warfare Association Conference (titled "Littoral Combat Ship", 08-May-07

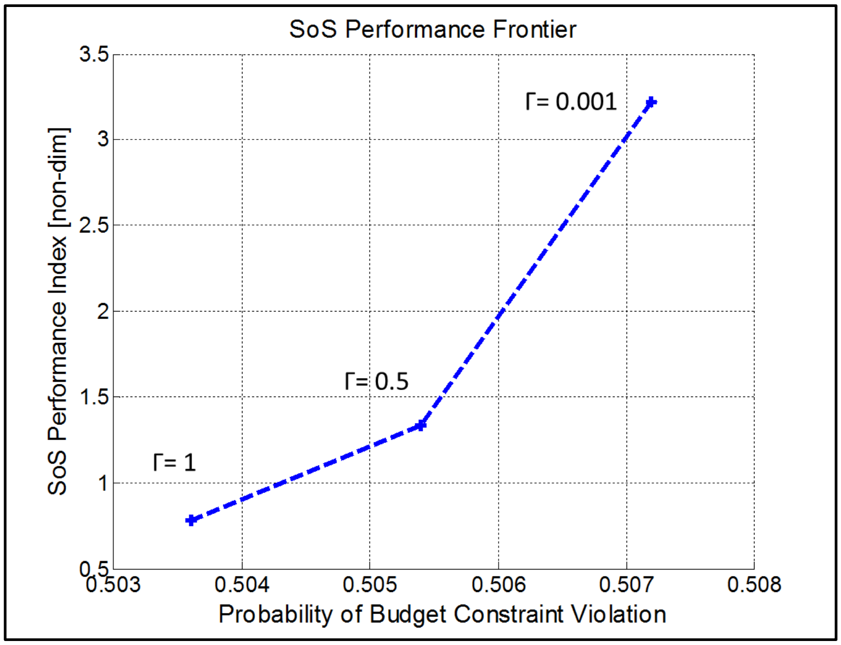

Figure 7. Performance index frontier

Figure 7 highlights 3 dynamic portfolios at conservatism level of Γ = 0.001, 0.5, 1 respectively; increasing values of Γ indicate a higher degree of conservatism. Each point corresponding to a particular chosen level of conservatism, reflect s a sequence of acquisition decisions that lead to the final portfolio performance index denoted on the graph. The sequence of acquisitions for each level of conservatism is shown in Table 4, where '1' denotes a decision to acquire a particular system at that time step, t. Figure 8 shows the normalized capability index for each subset of capabilities that comprise the index (in this case, *weapons strike range*, *surface detection range* and *anti-mine detection range*) of each of optimal points in Figure 7.

The results in Table 4 indicate evolving portfolio of systems where individual systems are acquired and retired throughout the decision epochs, preserving the satisfaction of requirements, towards maximizing the end goal of the overall SoS portfolio at time t=T. Retirements are denoted by the evolution from a previously selected state (e.g. x_{jt}=1 @t=2) to a state of (e.g. x_{jt}=0 @t=3). At a high level of conservatism (Γ=1.0), we observe the expected case of the portfolio being constant, where the initial investments are held over the entire decision horizon without any retirement or further acquisitions; this reflects the condition where risks associated with the buy/retire transactions are deemed to be too great, hence prompting the selection of a lower capability, but less financially risky acquisition strategy. At the low and mid-levels of conservatism, there is a possibility of sequential acquisitions, (subject to the availability and compatibility rules between systems), that can result in higher performing portfolios, but at higher prescribed level of acquisition risk.

The results of a Table 4 and Figure 8 provide practitioners a candid view of the ‘topology’ of acquisitions that can optimally be made over time, assuming a tolerance of risk (in this case budgetary risk). The risk uses correlated information on the costs and is quantified as the probability associated with the budget constraint violation. The analysis result presented can be useful to decision-makers in assessing the potential dynamic purchasing/retirement decisions that need to be made in view of quantifiable uncertainties. It also allows the decision-maker to assess the trade-offs between performance and risks in decisions at each epoch of the acquisition process, while bearing independencies and system compatibilities in mind. The mapping of the dynamic acquisition trade-space can also better inform independent acquisition groups, within a SoS, on the potential actions that various collaborative acquisition strategies can have on the overall scheme of development.

Table 4. Portfolio evolution at varying conservatism

System Description	System Package	Γ (Conservatism)								
		0.001			0.5			1		
		t=0	t=1	t=2	t=0	t=1	t=2	t=0	t=1	t=2
ASW	**Variable Depth**	0	0	0	0	0	1	0	0	0
	Multi Fcn Tow	0	0	0	0	0	0	0	0	0
	Lightweight tow	1	1	1	1	1	0	1	1	1
MCN	**RAMCS II**	0	0	0	1	0	0	0	0	0
	ALMDS (MH-60)	1	1	1	0	0	0	1	1	1
	New Prototype 1	0	0	0	0	1	1	0	0	0
SUW	**N-LOS Missiles**	0	1	1	0	0	0	0	0	0
	Griffin Missiles	1	0	0	1	1	1	1	1	1
	New Prototype 1	0	0	0	0	0	0	0	0	0
Seaframe	**Package System 1**	0	0	0	0	0	0	0	0	0
	Package System 2	1	1	1	1	1	1	1	1	1
	Package System 3	0	0	0	0	0	0	0	0	0
Communications	**Comm System 1**	1	1	1	1	1	1	1	1	1
	Comm System 2	1	0	0	1	1	1	1	1	1
	Comm System 3	0	0	0	0	0	0	0	0	0
	Comm System 4	0	0	0	0	0	0	0	0	0
	Comm System 5	0	1	1	0	0	0	0	0	0
	Comm System 6	0	0	0	0	0	0	0	0	0

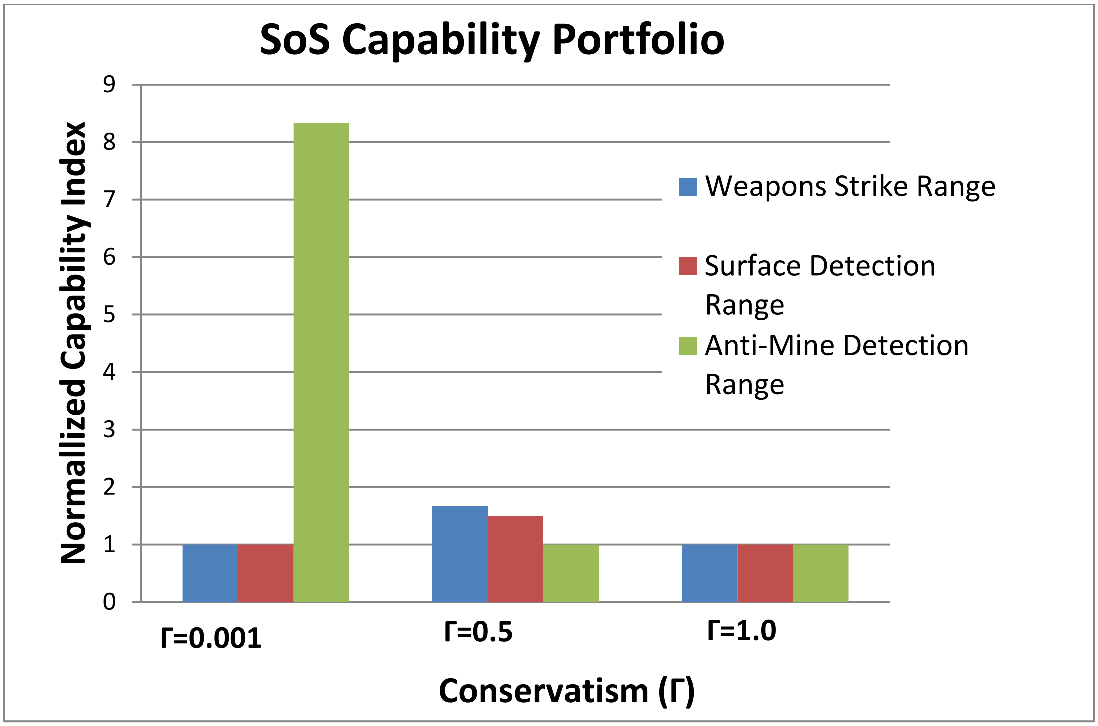

Figure 8. Normalized capability spread at varying conservatism

The analysis affords practitioners a candid view of the dynamic acquisition trade-space and allows for the selection of systems at the prescribed levels of accepted conservatism. In the larger context of acquisition affordability objectives, the algorithmic framework established here has direct bearing on BBP focus areas as listed below:

Table 5. BBP contributions

Better Buying Power Focus Area	Potential Contribution of Robust Multi-Period Portfolio Approach
Achieve Affordable Programs	• Robust decision-making in a multi-period setting enables mitigation of risks and planning of development steps
Control Lifecycle Costs	• Robust multi-period portfolio accounts for uncertainties in transactional costs at each stage of the decision horizon.
Incentivize Productivity and Innovation & Promote Effective Competition	• Metrics such as KVA and piece-wise linear modeling of incentivizations in a multi-period setting can provide robust management of investments for non-tangible investments and incentivizations • Enables effective management of larger set of acquisition possibilities (e.g. contributions from SBIRs, open architectures)

Method 3: Multi-Period Portfolio using Dynamic Programming Approaches

The work in Method 2 relates to dealing with multi-stage portfolio management problem in which a warfighter performance index for a large collection of systems or 'System of Systems (SoS)'. The method utilizes robust optimization techniques developed by Bertsimas (Bertsimas, 2004) to address correlated data uncertainties that may exist over the strategic horizon by treated all the potential decision variables over a . However, the implementation only considers static correlation over the entire strategic horizon – a notion that may be very difficult to accurately ascertain, and may not yield insights in tactical aspects in defense acquisition decision-making. At each decision epoch, the practitioner utilizes a decision-making framework to evaluate the value and risks involved in the potential acquisitions of new systems. Evaluation of such information can potentially come from prototyping/test and fielding results, or other such information seeking/risk reducing acquisition actions. The resulting new collection of systems that comprise the new portfolio, now include the addition of the new systems and identifies appropriate decision-paths that are necessary to achieve the target collection of systems. Research in this section explores the more explicit incorporation of tactical information at each update, to enable subsequent epoch decision-analysis using the portfolio-based framework.

Dynamic Investment Portfolio Formulation

The dynamic acquisition problem is expressed as a mathematical programming problem. The process begins with the definition of two main elements of a mathematical program, namely, the *objective function* and *constraints*. The objective function reflects key performance metrics of the system to be maximized (or minimized). For a system of systems, the objective function reflects a chosen measure of performance. The second important aspect of a mathematical program is the formulation of the constraints. The constraints reflect physical, resource and behavioral aspects of the systems as mathematical expressions. Our preliminary framework for a multi-period portfolio considers a long term horizon of acquisitions with discrete decision epochs that reflect investment decisions. These decisions can involve acquisition actions such as the addition/removal of individual systems towards achieving a desired capability.

The following mathematical program describes a preliminary framework towards the overall portfolio acquisition problem:

$$\max \left(\sum_q \left(\frac{S_{qc} - R_c}{R_c} \cdot w \cdot x_q^{t=T} \right) \right) \tag{35}$$

Subject to:

$$\sum_q S_{qc} x_q \geq \sum_q S_{qR} x_q \quad \text{(Satisfying each type (c) requirement)} \tag{36}$$

$$\left(x_i + .. + x_n \right)_j = M_j \quad \text{j=1...k (package system compatibility)} \tag{37}$$

$$\sum_{q=1}^{n} Cost_q x_q + Cost_{q \in TRL<8}^{\text{Research}} x_q \leq \text{Budget} \tag{38}$$

$$Mx_q - TRL_q x_q \leq 0 \tag{39}$$

$$TRL_q x_q - Mx_q \leq 0 \tag{40}$$

$$x_q \in [0,1], x_q^{TRL} \in [0,8] \tag{41}$$

$$TRL_{q \in TRL<8} \; Cost_{q \in TRL<8} \quad \text{(Uncertain)} \tag{42}$$

Equation (35) is the weighted objective function that seeks to maximize the end developed portfolio performance index. Here, the index is weighted according to the normalized value that each capability (C) contributes to the index. The normalization is performed with reference to some minimum acceptable performance value for each capability, Rc. Equation (36) ensures that the total ‘capabilities’ from selected systems are able to satisfy the requirements of connected systems that are in need of a particular capability. For example, there must be adequate communications bandwidth capability stemming from the selected communications assets, so as to enable performance of the weapons systems for the same naval asset. Equation (37) enforces compatibility constraints as binary conditions for a total of (*k*) set of rules; for example, the constraint that only one engine can be selected to generate power would translate to a constraint of $x_1 + x_2 = 1$ where (x_1, x_2) are binary variables. Equation (38) ensures that the costs of developing (in this case, the cost of promoting, via research, low Technology Readiness Level (TRL) technologies to an acceptable fielding level of TRL 8) and cost of acquisition are within a prescribed budget; this is in line with the notion of affordability where finite resources are considered. Equations 39 and 40 utilize a linear programming structure known as a Big-M approach to establish a logical expression; here the systems selected for the end deployment can only be of TRL level 8 and above. Equation 41 denotes the decision variable as being binary and the associated TRL number as being between 0 and 8.

Equations (35-42) constitute the overarching investment problem where the objective is to select and end portfolio that maximizes a warfighter portfolio performance index (objective function) while preserving budget and feasibility constraints on the readiness of technologies that need to enter to the final portfolio. The final acquisition costs of yet-to-be introduced systems below a TRL level 8 and the final TRL status (TRL_q) of researched systems are considered to be uncertain. These uncertainties intuitively have correlated properties as the development of technologies for interconnected systems, would likely benefit in some cooperative sense. We also assume that the TRLs and costs evolve as a product of research investment due to defense interests – this investment-guided evolution is in line with current practices of proof of concept and rapid prototyping of potential technologies and services at various TRL levels.

Dynamic Programming Overview

The investment portfolio problem of Eqs. (35-42) is reflective of the need to maximize the end portfolio capabilities of a collection of systems that are governed by behavioural rules of connectivity and influenced by data uncertainty. Our prior multi-period portfolio work has approached the problem within the context of a robust optimization problem that utilized innovations in robust (correlated data) linear programming techniques (Bertsimas 2004); the application of the method, however, is strategic in nature and depends on static correlations – a notion that may not hold true in dynamic defence acquisition environments. While the robust portfolio framework offers useful insights, there is nevertheless a need for a dynamic framework that can provide useful tactical timeline decision-making support, and, possess good long-term evolutionary performance.

Acquisition decisions in earlier epochs typically have a cascading implications on the performance and risks in subsequent decisions; this form of a problem has long been addressed under the premise of *dynamic programming*. Dynamic programming has evolved out of many areas of research, ranging from economics to modern control theory (Powell 2011). The general form of a dynamic programming problem can be written as the following:

$$V_t(S_t) = \max_{x_t} C_t\,(S_t, x_t) + V_{t+1}(S_{t+1}) \tag{43}$$

$$V_t(S_t) = \max_{t=0}\{\gamma^t C_t^{\pi}(S_t, x_t^{\pi}(S_t)\} \tag{44}$$

where $C_t()$ is the reward function of current time step

S_t is the current state

x_t is the action taken at time (T)

V_{t+1} is the value function of being in state S_{t+1}

Υ is a weighting constant, π is a set of all policies

Eq. (43) and Eq. (44) are the deterministic and stochastic representations of the Hamilton-Jacobi-Bellman (HJB) equations. Typically, these are solved using backward recursion, over all possible states and seek a sequence of decisions (x_t) that maximize (or minimize) an objective function. The value of the objective is dictated by being in particular states (S_t) (here, a state, in the context of our acquisition problem, may be the overarching military value of current holdings of systems and their potential connections to future systems). The traditional means of solving these equations backward in time can prove to be extremely expensive/difficult due to many reasons that include computational intractability (also known as the *curse of dimensionality*), absence of models for future states and dependency on data that does not yet exist. An alternative, and highly attractive practice in dealing with these kind of problems involves the use of Approximate Dynamic Programming (ADP) approach that essentially solve the problem in a *forward* dynamic programing approach (Powell, 2011) (Bertsekas, 2005). In the context of a defence acquisition scenario, this is highly intuitive given that the structure of testing, prototyping, simulation (etc.), presents new information in a forward sense, to help inform decision-makers in adjusting their portfolios of systems. Our research complements this *forward* view with our multi-period portfolio approach, using an ADP inspired methodology.

Dynamic Investment Portfolio using Approximate Dynamic Programming (ADP)

We formulate the investment portfolio problem (with uncertainty in TRL and cost) of Eqs. (35-40) as a forward dynamic programming problem where the objective is to sequentially update acquisition decisions as TRL and cost of potential, yet-to-be introduced system evolve over a discretized finite horizon. The resulting forward (approximate) dynamic programming problem is then stated as:

$$\max \ \mathrm{E}\left(\sum_q \left(\frac{S_{qc}-R_c}{R_c}\cdot w\cdot x_{q,t}^{TRL>8}\right)+\gamma\left(\frac{S_{qc}-R_c}{R_c}\cdot w\cdot x_{q,t}^{p}\right)\right) \quad (45)$$

Subject to:

$$\sum_q S_{qc}x_{q,t}^{p} \geq \sum_q S_{qR}x_{q,t}^{p} \quad \text{(Satisfying each type (c) requirement)} \quad (46)$$

$$\left(x_i^p+..+x_n^p\right)_j = M_j \quad \text{j=1...k (package system compatibility)} \quad (47)$$

$$\sum_{q=1}^{n} Cost_q x_{q,t}^{TRL>8} + Cost^{\mathrm{R}}_{q\in TRL<8} x_{q,t}^{R} \leq \mathrm{Budget}_t \quad (48)$$

$$\sum_{q=1}^{n} Cost_q x_{q,t}^{p} \leq \mathrm{Budget}_{t=T} \quad (49)$$

$$Mx_{q,t}^{TRL>8} - TRL_{q,t}x_{q,t}^{P} \leq 0 \quad (50)$$

$$TRL_{q,t}x_{q,t}^{P} - Mx_{q,t}^{TRL>8} \leq 0 \quad (51)$$

$$x_{q,t}^{R} = x_q^{P} - x_{q,t}^{TRL>8} \quad (52)$$

$$x_{q,t}^{TRL>8}, x_{q,t}^{p}, x_{q,t}^{R} \in [0,1], x_q^{TRL} \in [0,8] \quad (53)$$

where:

$x_{q,t}^{TRL>8}$:	Decision variable to acquire in system (q) at time (t)
$x_{q,t}^{p}$:	Total portfolio of systems (q) at time (t) based on current value of capabilities
$x_{q,t}^{R}$:	Decision variable to invest in research for systems below TRL 8 (q) at time (t)
ϒ:	discount term/belief term

Eq. (45) is the objective function that now seeks to balance the potential gains from investing in ready technologies at the current decision epoch, through investment decision variable ($x_{q,t}^{TRL>8}$), against the potential for future value in the overall portfolio of capabilities based on the decision variable (x_q^p); note that the contribution of the potential future value is dependent on the maturity of a TRL level to exceed level 8. Eq. (46) enforces that system requirements of the end potential portfolio of systems are satisfied by capabilities from other connected systems. Eq. (47) enforces compatibility constraints. Eq. (48) ensures that combined piece-wise acquisitions of costs at the current decision-epoch, and the cost of researching technologies below TRL 8. Eq. (49) enforces the long-term budget satisfaction of the projected portfolio of systems. Eqs. (50-51) ensure that only TRL>8 systems can be acquired at each decision-epoch. Eq. (52) establishes the relationship between decision-variables where decisions to research certain systems ($x_{q,t}^R$) and acquire mature ones ($x_{q,t}^{TRL>8}$) comprise the overall projected end portfolio of systems (x_q^P) at the final decision epoch. Equation (53) denotes the decision variable as being binary and the associated TRL number as being between 0 and 8.The optimization problem of Eqs. (45-53) constitute a Binary Integer Program (BIP) and was modeled using YALMIP (Lofberg, 2004) within the MATLAB environment (Mathworks, 2010), using the Gurobi Optimizer (Inc, 2004), solver option. The optimization problem of Eqs. (45-51) is solved recursively over each investment decision epoch. At the end of each epoch, TRLs (and cost) of yet-to-be introduced systems are evolved to a new estimate, based on the prior epoch's investment decision ($x_{q,t}^R$) in relevant technology.

Concept Application: Naval Acquisition Scenario

We apply our developed multi-stage portfolio framework for the case of a Naval Acquisition Scenario. The Naval Acquisition Scenario is based on the Littoral Combat Ship (LCS 2011) system model developed by Lockheed Martin and General Dynamics. The design of these ships allows for modular packages to be swapped for execution of a range of mission scenarios that include: Mine Counter Measure (MCM), Anti-Submarine Warfare (ASW) and Surface Warfare (SUW). Our simplified model consists of a hypothetical list of systems, listed in Table 6, that are available to the Navy for acquisition, and are presented with a corresponding Technology Readiness Levels (TRL). Although the number presented in the table are fictitious, the salient features of capability, requirements, cost and such, are represented. The (ASW, MCM, SUW, Unconventional Warfare) categories are the core mission packages, 'Communications' represents the support communications systems available for deployment. Power represents the power generation systems available for deployment and in support of other systems.

The first six columns show capabilities of each system, and their respective numerical valuations. Column 7 and 8 are the *Power* and *Communications* requirement needed for operation of the listed systems, in providing the respective capabilities in columns 1-6. Column 9 is the acquisition cost of the relevant system, assuming a TRL level of 8 or above; for systems less than this, the number is subject to uncertainty. Column 10 is the cost of research at each time period to promote a particular system's technology towards a TRL level 8 – this can be thought of as a development cost.

The recursive framework of the forward dynamic programming problem in Eqs. (43-50) is applied to the Naval Acquisition Scenario where the need is to evolve and acquire systems towards maximizing war fighter capabilities. The solution of the optimization at each decision epoch, assumes a value of 'belief' in the future states, as dictated by the discount term ϒ that takes a value between 0 and 1 and is assumed to be set by the practitioner. The result of the optimization problem, at each decision epoch, generates a list of systems acquired at the time step ($x_{q,t}^{TRL>8}$) which are then also included as existing systems in the subsequent epoch. Solution of the optimization problem also generates a list of systems to be researched as denoted by variable ($x_{q,t}^{R}$), that are then subject to a simulated dynamics of TRL evolution due to research investment; the evolution also generates a new cost of acquisition estimate for the researched systems as well.

Table 6. Naval Scenario candidate system specifications, cost and readiness level

System Module	Weapon Package	Weapon Strike Range (miles)	Surface Detection Range (miles)	Anti Mine Detection Range (miles)	Unconv Warfare Payload (kg)	Comm. Capacity (Mbps)	Power Capacity (kW)	Power Req. (kW)	Comm. Bandwidth Req. (Mbps)	Cost of Acquisition (USD)	Cost of Research (USD)	TRL
ASW	Variable Depth	0	30	0	0	0	0	50	75	80000	20000	8
	Multi Fcn Tow	0	40	0	0	0	0	100	125	90000	22500	6
	Lightweight tow	0	50	0	0	0	0	150	150	100000	25000	6
	ASW Prototype 1	0	60	0	0	0	0	175	150	120000	30000	7
	ASW Prototype 2	0	70	0	0	0	0	180	100	130000	32500	7
MCM	RAMCS II	0	0	30	0	0	0	100	75	80000	20000	8
	ALMDS (MH-60)	0	0	40	0	0	0	150	125	90000	22500	7
	MCM Prototype 1	0	0	50	0	0	0	200	150	100000	25000	7
	MCM Prototype 2	0	0	60	0	0	0	250	175	120000	30000	7
	MCM Prototype 3	0	0	70	0	0	0	270	185	140000	35000	7
SUW	N-LOS Missiles	3	0	0	0	0	0	150	100	80000	20000	8
	Griffin Missiles	25	0	0	0	0	0	200	200	90000	22500	7
	SUW Prototype 1	50	0	0	0	0	0	250	300	100000	25000	7
	SUW Prototype 2	60	0	0	0	0	0	200	120	120000	30000	6
	SUW Prototype 3	70	0	0	0	0	0	200	300	130000	32500	6
Unconventional Warfare	Package System 1	0	0	0	100	0	0	25	50	70000	17500	8
	Package System 2	0	0	0	150	0	0	50	150	80000	20000	8
	Package System 3	0	0	0	200	0	0	75	200	90000	22500	8
Comm. Package	Package System 1	0	0	0	0	300	0	50	0	80000	20000	8
	Package System 2	0	0	0	0	400	0	75	0	90000	22500	8
	Package System 3	0	0	0	0	450	0	100	0	100000	25000	6
	Package System 4	0	0	0	0	500	0	150	0	100000	25000	6
	Package System 5	0	0	0	0	550	0	200	0	110000	27500	6
Power Package	Package System 1	0	0	0	0	0	350	0	0	80000	20000	8
	Package System 2	0	0	0	0	0	450	0	0	90000	22500	8
	Package System 3	0	0	0	0	0	550	0	0	100000	25000	7
	Package System 4	0	0	0	0	0	650	0	0	110000	27500	7
	Package System 5	0	0	0	0	0	750	0	0	120000	30000	6

Results

The forward optimization scheme of Eqs. (43-50) is solved over six decision epochs, and using a choice of two levels of belief (how much to favour TRL>8 systems in each epoch over research investment) are captured in Table 7 and Table 8. Table 7 lists, for each degree of belief (Υ=1, 0.1), the acquisition of systems of TRL>8 at each decision epoch. A belief level of Υ =1 refers to a high preference policy on potentially investing in systems of higher value that may need research funding (TRL investment). A belief value of Υ =0.1 refers to the converse where the policy is to invest in assets that are more readily available at the immediate decision epoch. It is assumes that for each value of Υ used, we assume a constant value throughout the decision epochs. In realistic settings however, the values of Υ can be adapted at each decision epoch; this process can either be through the practitioner's insights or based on algorithmic rigor. Table 8 captures the research decisions (investment in system to potentially upgrade TRL) towards subsequent acquisition of the relevant system.

The results of Table 7 are intuitive; using a high preference value of Υ =1.0, we can observe that the recursive optimization scheme does not invest in immediate systems at the early stages, but rather in the best valued TRL systems that can potentially improve the overall portfolio index at later stages. The ‘exploration’ element of researching lower TRL technologies with potentially higher payoffs is seen in the decision to research such systems in Table 3. For example, at Υ =1.0, the decision to acquire an ASW system is left to the latter stage at the second decision epoch, after ASW Prototype 2 has been researched and reached a TRL of 8 for subsequent acquisition. At the lower level of preference, Υ =0.1, we observe that the policy favours the immediate acquisition of TRL>8 systems for short term gains. An acquisitions practitioner could conceivably use sequential results to select an appropriate policy of Υ, based on practitioner insights into the acquisition environment. Additionally, the optimization framework addresses the combinatorial aspects of the systems interconnectivities, accounts of acquisition sequencing and maximizes the potential utility of yet-to-be introduced systems by evaluating potential value to the overall architecture, based on investment research progress towards TRL 8 status.

Table 7. Decision Epochs Acquisitions ($x_{q,t}^{TRL>8}$)

		Decision Epochs (Acquisitions)											
	Gamma Value	1	0.1	1	0.1	1	0.1	1	0.1	1	0.1	1	0.1
	System												
ASW	Variable Depth	0	1	0	1	0	1	0	1	0	1	0	1
	Multi Fcn Tow	0	0	0	0	0	0	0	0	0	0	0	0
	Lightweight tow	0	0	0	0	0	0	0	0	0	0	0	0
	ASW Prototype 1	0	0	0	0	0	0	0	0	0	0	0	0
	ASW Prototype 2	0	0	1	0	1	0	1	0	1	0	1	0
MCM	RAMCS II	0	1	0	1	0	1	0	1	0	1	0	1
	ALMDS (MH-60)	0	0	0	0	0	0	0	0	0	0	0	0
	MCM Prototype 1	0	0	0	0	0	0	0	0	0	0	0	0
	MCM Prototype 2	0	0	0	0	0	0	0	0	0	0	0	0
	MCM Prototype 3	0	0	1	0	1	0	1	0	1	0	1	0
SUW	N-LOS Missiles	0	0	0	0	0	0	0	0	0	0	0	0
	Griffin Missiles	0	0	0	0	0	0	0	0	0	0	0	0
	SUW Prototype 1	0	0	0	0	0	0	0	0	0	0	0	0
	SUW Prototype 2	0	0	0	0	0	0	0	0	0	0	0	0
	SUW Prototype 3	0	0	0	0	0	0	0	1	1	1	1	1
nconventior	Package System 1	0	0	0	0	0	0	0	0	0	0	0	0
Warfare	Package System 2	0	0	0	0	0	0	0	0	0	0	0	0
	Package System 3	1	1	1	1	1	1	1	1	1	1	1	1
Comm.	Package System 1	0	0	0	0	0	0	0	0	0	1	0	1
Package	Package System 2	0	0	0	0	0	0	0	0	0	0	0	0
	Package System 3	0	0	0	0	0	0	0	0	0	0	0	0
	Package System 4	0	0	0	0	1	0	1	0	1	0	1	0
	Package System 5	0	0	0	0	1	0	1	0	1	0	1	0
Power	Package System 1	0	0	0	0	0	0	0	0	0	0	0	1
Package	Package System 2	0	0	0	0	0	0	0	0	0	1	0	1
	Package System 3	0	0	0	0	0	0	0	0	0	0	0	0
	Package System 4	0	0	0	0	1	0	1	0	1	0	0	0
	Package System 5	0	0	0	0	0	1	0	0	0	0	1	0

Table 8. Decision Epochs Research ($x_{q,t}^{R}$)

	Decision Epochs (Research TRL)											
Gamma Value	**1**	**0.1**	**1**	**0.1**	**1**	**0.1**	**1**	**0.1**	**1**	**0.1**	**1**	**0.1**
System												
Variable Depth	**0**	**0**	0	0	**0**	**0**	0	0	**0**	**0**	0	0
Multi Fcn Tow	**0**	**0**	0	0	**0**	**0**	0	0	**0**	**0**	0	0
Lightweight tow	**0**	**0**	0	0	**0**	**0**	0	0	**0**	**0**	0	0
ASW Prototype 1	**0**	**0**	0	0	**0**	**0**	0	0	**0**	**0**	0	0
ASW Prototype 2	**1**	**0**	0	0	**0**	**0**	0	0	**0**	**0**	0	0
RAMCS II	**0**	**0**	0	0	**0**	**0**	0	0	**0**	**0**	0	0
ALMDS (MH-60)	**0**	**0**	0	0	**0**	**0**	0	0	**0**	**0**	0	0
MCM Prototype 1	**0**	**0**	0	0	**0**	**0**	0	0	**0**	**0**	0	0
MCM Prototype 2	**0**	**0**	0	0	**0**	**0**	0	0	**0**	**0**	0	0
MCM Prototype 3	**1**	**0**	0	0	**0**	**0**	0	0	**0**	**0**	0	0
N-LOS Missiles	**0**	**0**	0	0	**0**	**0**	0	0	**0**	**0**	0	0
Griffin Missiles	**0**	**0**	0	0	**0**	**0**	0	0	**0**	**0**	0	0
SUW Prototype 1	**0**	**0**	0	0	**0**	**0**	0	0	**0**	**0**	0	0
SUW Prototype 2	**0**	**0**	0	0	**0**	**0**	0	0	**0**	**0**	0	0
SUW Prototype 3	**1**	**1**	1	1	**1**	**1**	1	0	**0**	**0**	0	0
Package System 1	**0**	**0**	0	0	**0**	**0**	0	0	**0**	**0**	0	0
Package System 2	**0**	**0**	0	0	**0**	**0**	0	0	**0**	**0**	0	0
Package System 3	**0**	**0**	0	0	**0**	**0**	0	0	**0**	**0**	0	0
Package System 1	**0**	**0**	0	0	**0**	**0**	0	1	**0**	**0**	0	0
Package System 2	**0**	**0**	0	0	**0**	**0**	0	1	**0**	**1**	0	1
Package System 3	**0**	**1**	0	0	**0**	**0**	0	0	**0**	**0**	0	0
Package System 4	**1**	**1**	1	1	**0**	**1**	0	0	**0**	**0**	0	0
Package System 5	**1**	**0**	1	1	**0**	**1**	0	0	**0**	**0**	0	0
Package System 1	**0**	**0**	0	0	**0**	**0**	0	1	**0**	**1**	0	0
Package System 2	**0**	**0**	0	0	**0**	**0**	0	1	**0**	**0**	1	0
Package System 3	**1**	**0**	1	1	**0**	**1**	0	0	**0**	**0**	0	0
Package System 4	**1**	**1**	1	0	**0**	**0**	0	0	**0**	**0**	0	0
Package System 5	**0**	**1**	0	1	**1**	**0**	1	0	**1**	**0**	0	0

Summary & Contributions of Research

The research performed in this report has explored three approaches to multi-staged decision-making for acquisition practitioners. Namely, these approaches are 1) policy construction for cost and schedule overruns using *mechanism design* 2) a strategic level *robust multi-period portfolio problem* and 3) a multi-period portfolio formulation that leverages d*ecision epoch updates for sequential decision-making.* The approaches leverage innovations in areas of system of systems engineering, financial engineering and operations research by providing defense acquisitions practitioners with quantitative frameworks that can alleviate some of the decision-making complexities associated with complex trade spaces.

Our mechanism design approach aims at using strategic level data and policy levers within the context of a mechanistic approach, where the underlying optimization problem allows for objective selection of qualitative policies towards potentially controlling cost and schedule growth in defense program management. Optimization methods from the mechanism framework are used to also construct a robust multi-period portfolio framework that allows practitioners to assess long term, multi-period decisions, and to generate long-term acquisition strategies in acquiring specific capabilities, while accounting for data uncertainties in the long term. Our third approach extends the long-term, strategic framework of the robust portfolio method to account for update effects where decisions at each epoch affects decisions at subsequent epochs; this is addressed in a dynamic programming centric framework of the third method. The research work has led to the following advancements in support of acquisition decisions:

1. Quantitative supportive frameworks that alleviate some of the decision-making difficulties associated with complex acquisition tradespaces. This enables the end practitioner to navigate decision-spaces with fewer dimensions, in their decision-making process.

2. Multi-staged decision support of sequentially interdependent decisions; our frameworks are amenable to addressing the inherent dependencies through physical, functional and temporal dimensions of the acquisition process.

3. The approaches account for the roles of data uncertainties in the formulation; this allows for the practitioner to utilize a priori knowledge in determining how much risk/uncertianty should strategies be protected against, using algorithmic innovations in the frameworks presented.

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