



Game-theoretic Risk Assessment for Distributed Systems (GRADS)

Technical Report SERC-2019-TR-011

July 2, 2019

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Sponsor: Deputy Assistant Secretary of Defense for Systems Engineering

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The Systems Engineering Research Center (SERC) is a federally funded University Affiliated Research Center managed by Stevens Institute of Technology.

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EXECUTIVE SUMMARY

Distributed or collaborative system architectures present a fundamental strategic tradeoff in the design of engineering systems in large-scale domains such as defense and critical infrastructure. Effective collaboration among multiple design actors can lead to improved emergent capabilities and opportunities for cost sharing to field systems impossible to achieve through independent action. However, collaboration also requires a non-reversible commitment of effort that presents a fundamental source of uncertainty and can lead to coordination failures with significant cost penalties. Thus, interdependencies among design actors contributes both an upside potential and a downside risk associated with collaboration.

This project introduces a game-theoretic perspective to assess and evaluate the risk of collaboration in distributed architectures. Design actors are modeled as playing a binary coordination game with two alternatives: either to pursue an independent architecture or a collaborative architecture. Economic literature of equilibrium selection in game theory helps to measure the strategic dynamics present among design actors using a property called "risk dominance." Risk dominance, like payoff dominance for an alternative that is most preferred for all actors, is a desirable property that identifies favorable strategic dynamics and can help to guide architecture decisions under essential uncertainty in collaboration.

Starting from the foundational economic theory, this project proposes a new design method that uses risk dominance to assess the relative stability of collaborative architectures. The analysis is oriented towards conceptual design phases before significant cost commitments have been made and while the architecture is still fluid. A validation study using multi-agent simulation shows how the risk dominance metric helps to differentiate between dominant strategies (collaborate versus remain independent) under varying contextual conditions. Results show that each context is somewhat unique to interpret point values of risk dominance; however, generalizable patterns among relative values can guide strategic decision-making.

Finally, this project demonstrates how such a risk dominance measure can be applied to inform a realistic architecture decision using an example of a joint polar-orbiting satellite program similar to the National Polar-orbiting Environmental Operational Satellite System (NPOESS). NPOESS was envisioned to be a collaborative architecture between multiple government agencies to replace existing independent missions; however, it was ultimately canceled after more than a decade of turbulent history due to excessive cost overruns. Using a game-theoretic assessment method similar to that proposed in this project could help to evaluate the relative stability of a proposed joint architecture relative to other proposed joint architectures to help give collaborative projects the greatest opportunity for success.

INTRODUCTION

Interest in distributed system architectures presents an important tradeoff in conceptual design activities. Distributed systems may have superior performance compared to monolithic alternatives by increasing flexibility in phased deployment or operations (de Weck et al., 2004), robustness to individual component failures (Brown and Eremenko, 2006), and resource efficiency to match available resources to localized demands. However, distributed architectures also introduce new interdependencies between components, which can lead to poor performance if not understood or anticipated due to cascading failures and loss of critical functions. This paradoxical relationship has been described as "robust yet fragile" (Alderson and Doyle, 2010) as efforts to increase robustness through greater coupling expose innate fragility from corresponding internal interdependencies.

Interdependencies are not limited to physical or logical connections between components. Collaborative or federated systems pose engineering design problems where interacting design decision-makers pursue individual objectives. Each actor follows a strategic decision to either work independently or collaboratively. A collaborative strategy, analogous to a distributed architecture, pursues mutual benefits at the cost of additional interdependencies between actors. Misunderstanding or an inability to anticipate these interdependencies can yield similar "robust yet fragile" behavior, where the resulting joint pursuit may become inferior to an independent alternative. Acquisition programs leveraging significant inter-agency collaboration regularly have substantial overruns (National Research Council, 2010; National Research Council, 2011), illustrating the potential magnitude of this problem. This project proposes using game-theoretic concepts and assessment metrics to help understand the strategic dynamics underlying a collaborative system architecture and to identify, mitigate, or augment undesirable dynamics before significant resources have been invested.



Figure 1. Distributed system architectures are prone to "robust-yet-fragile" behavior.

The research objectives of this project are to:

1. Develop a body of knowledge and methodology for game-theoretic measures based on the equilibrium selection theory to assess risk dominance of collective design problems,
2. Demonstrate the proposed method on a representative case in the space domain, and
3. Validate results of the application case by selectively forming and dissolving joint programs to demonstrate the utility of such a metric in systems engineering problems.

From a theoretical perspective, this project investigates how applications of multi-actor value models and, specifically, the weighted average log measure (WALM) of risk dominance proposed by Selten (1995) contribute to a new design methodology to assess strategic dynamics in collaborative system design problems and evaluate stability of collective decisions. This thread

of research interprets and evaluates WALM's underlying assumptions and evaluates its applicability to inform design decision-making in joint engineering projects. As the WALM of risk dominance is defined in a highly simplified context of a single-shot decision, a validation study uses multi-agent simulation to understand the relationship between the numerical outputs and dominant strategies over longer evolutionary periods within an actor population.

From a more practical perspective, this project applies the WALM of risk dominance to an application case based on the National Polar-orbiting Operational Environment Satellite System (NPOESS) as a joint program between NASA, NOAA, and the DoD. This application case establishes a design scenario, formulates a multi-actor value model, identifies a proposed joint architecture, computes risk dominance measures, and validates the stability of resulting joint programs. This thread of research provides a concrete example to evaluate the usefulness of the proposed methodology to gain insight about whether the NPOESS architecture carried unfavorable or unstable risk dynamics susceptible to dissolution of the coalition of partners.

The overall proposed design methodology aims to transition fundamental theory from the field of economics and game theory closer to practice in systems engineering by representing and modeling value among multiple actors and computing metrics to assess the stability of strategic dynamics. It advances systems engineering methods, processes, and tools by evaluating anticipated outcomes of joint projects earlier in the conceptual design phase. The results of this work are expected to improve system architecting to identify favorable strategic dynamics and increase the stability of joint programs.

This project report proceeds as follows. First, a review of existing game-theoretic perspectives applied to systems engineering and design problems establishes key concepts of game theory and how they have been used in the past. Next, a discussion of equilibrium selection and risk dominance introduces the fundamental technical treatment to evaluate sources of collaborative risk in distributed architectures. A validation study illustrates how the risk dominance metric can be used to guide collaborative decisions by selectively forming and dissolving collaborative strategies among a network of simulated agents. An application case in the context of a joint polar-orbiting space system similar to NPOESS shows how to apply the risk dominance metric to assess the collective stability of a single point-proposed joint architecture. Finally, conclusions synthesize the key insights from this project and outline future work.

REVIEW OF GAME-THEORETIC PERSPECTIVES IN DESIGN

This project studies design of complex systems characterized by the presence of more than one actor exerting design authority over a set of interacting decisions. The concept of a multi-actor system is like that of systems-of-systems defined by the existence of operational and managerial independence (Maier, 1998) and demands new design methods to understand and evaluate complexity of collective decision-making activities. While there has been great progress on the use of economic theory to advance systems engineering and design, specifically on the use of decision and utility theory, these methods largely assume a single decision-maker. Multi-actor design problems pose both theoretical and practical problems to aggregate, negotiate, and allocate decisions across multiple decision-makers with unique and, often, contradictory objectives. Game theory represents the fundamental body of economic literature to represent interactive decision-making processes with more than one independent authority.

While there are some existing applications of game theory in engineering design, there is also significant criticism among the community (Reich, 2010). This section reviews existing literature on game-theoretic perspectives in engineering design and systems engineering to establish the foundation for this work.

BACKGROUND

Game theory has played a central role not only in mathematics but also in the social and the life sciences by providing an open-ended framework for studying the interplay between individual self-interest and cooperative effort in diverse settings (Erickson, 2015). Dominated by military-funded optimization and operations research prior to the 1960s, non-cooperative game theory has fueled interdisciplinary discussions regarding the nature of conflict in economic decisions (Nash, 1951; Harsanyi, 1967; Selten, 1975), evolution (Maynard Smith and Price, 1973; Dawkins, 1976), and, more recently, distributed systems (Halpern, 2003; Shoham, 2008). As an integrative discipline of and for decision-making, engineering systems design (ESD) has not been indifferent to the usefulness of game theory in the analysis of multi-actor and multi-criteria trade-offs; in fact, the intrusion of game theory as well as other approaches to understanding design as a centralized and distributed decision-making contributed to making the latter a science in its own right and span across many other disciplines, including engineering, architecture, and the cognitive, social and organizational sciences. Most notably, the past five decades of engineering literature have introduced applications of game theory to systems design ranging from the use of differential and continuous static games in the development of large-scale dynamical systems (Cruz et al., 1969) to the use of normal-form games to model organizational-level processes in collective systems design (Valencia-Romero and Grogan, 2018).

Although game theory is most commonly associated with the study of strategic interaction between rational actors, most game-theoretical applications in ESD have focused on the analysis of design problems with a single decision-making authority. Most contributions on this line of work use game theory to reformulate systems design optimization problems as games in which one of two design actors (often referred to as "nature") is indifferent about the outcome and

makes moves at random (McKinsey, 1952). Design decisions covered in these applications are mostly operational and relate to the system's functional properties and performance. Meanwhile, strategy design decisions are driven by long-term expectations on the system and have great impact on the system's ability to deliver in response to changes in context and the design actors' actions and needs. Not only does strategic decision-making in ESD require of methods like those of game theory to understand the effects of conflicting objectives on the system's performance, it also demands a more accurate representation of the design actors' preferences regarding the possible outcomes of the system design process.

This section provides background and discussion on the benefits and challenges of using non-cooperative game theory in the assessment of strategic decision-making processes in ESD. An extended use of game-theory to study strategy design decisions combined with the use of value-driven design methods to help abstract the design actors' preferences over different strategic settings can contribute to the design of systems subject to large environmental uncertainty and social complexity (e.g. systems-of-systems, federated systems). The next section summarizes some basic definitions in game theory, assumptions, and limitations. This is followed by a review of existing literature on the use of game theory in ESD, the role of value-driven design in representing the design actors' preferences, and the study of strategy design decisions. The section concludes with a discussion on the implications and opportunities of continued use of game-theoretical principles in ESD.

BASICS OF GAME THEORY

Game theory refers to the study of mathematical models of rational decision-making between several actors that interact strategically towards meeting their individual objectives. This strategic setting of collective action is referred to as *game*. All games under this mathematical framework have the next five basic elements in common (Watson, 2002):

- a set of *players*;
- a set of the players' possible *actions*;
- a description of the possible *outcomes* from players' actions;
- a description of the players' *preferences* over outcomes; and
- a description of the amount and type of *information* available to players.

In classical game theory, the players are assumed to be rational, utility-maximizing actors. Every possible combination of players' actions is linked to an outcome. The players' preference rankings over these outcomes are represented with numbers and commonly called *payoffs*. Finally, each player might have full, partial, and no access to information about the elements of the game (e.g. knowledge about the other players' preferences, information about previous events) which affects the way each player thinks about which actions to take.

REPRESENTING GAMES AND THE NOTION OF STRATEGY

Games in non-cooperative (general) settings are commonly represented in one of two ways: *extensive form* and *normal* (or *strategic*) *form* presented in Figure 2. Both represent the same

two-player game but emphasize different aspects. In this game, both players make their moves simultaneously and independently—player 1 chooses between alternatives A and B while player 2 chooses between alternatives C (or C') and D (or D')—, so neither one of them observes the other's choice. In such setting, the players cannot condition their actions on the actions of others and the game is said to have *imperfect information*. Removing the dotted line between player 2's nodes on Figure 2(a) would make the extensive form game sequential. Additionally, if random events happen out of the players' control (e.g. nature makes a move after any player moves), the game is said to have *incomplete information*.

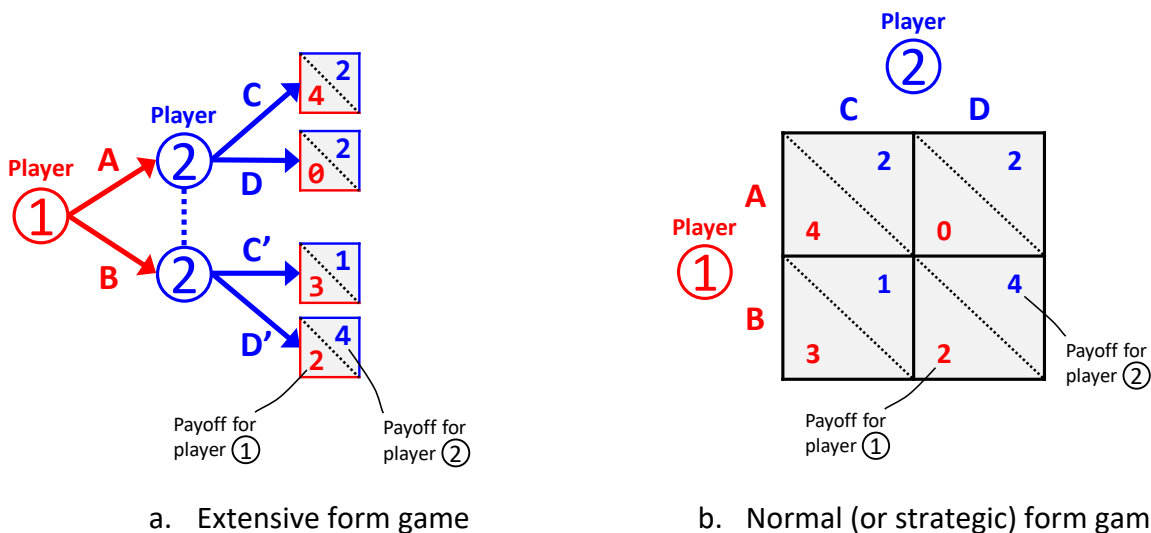


Figure 2. Common game representations for non-cooperative settings.

While a sequential game in extensive form tracks the actions for a player on each node or turn, a game in normal form focuses on providing each player with a full plan of action describing what each of them would do in any given situation. This full plan of action is known as *strategy*. The formal definition of strategy is "a complete contingent plan for a player in the game" (Watson, 2002). The notion of strategy encompasses the general principles that govern a player's choices and is the single most important concept in non-cooperative game theory (von Neumann and Morgenstern, 1944). The characteristics of the strategy space usually determine the type of game representation to use. For instance, if the number of strategies is finite, extensive and normal form games are appropriate. If the number of strategies is infinite, but the plan of action is constant, the game is classified as a *continuous static game* (Vincent and Grantham, 1981). Also, if the strategy space varies with time, the game is said to be differential (Issacs, 1965). Finally, a *mixed strategy* refers to the selection of one strategy according to a probability distribution while a *pure strategy* is a regular strategy that has been assigned all probability.

ASSUMPTIONS AND LIMITATIONS OF THE THEORY

The use of classical game theory to study decision-making processes with cognizant actors has three major limitations: 1) game theory, at its core, assumes that the actors are perfectly rational, 2) the scarcity of studies on games with asymmetric payoffs, and 3) the presence of focal points in experiments. Both aspects have been the most critical sources of controversy regarding the

applicability and usefulness of game theory to describe real-life situations (Schelling, 1959; Rubinstein, 1991; Erickson, 2015).

First, consider the assumption of perfect rationality. The issue on rationality in engineering systems design has been addressed previously with evidence regarding the situations in which the designers can converge to "optimal" outcomes (Hazelrigg, 1997; Franssen and Bucciarelli, 2004). From one perspective aligning with rational behaviors, normative methods guide decisions to (objectively) yield the best outcome, typically described as expected utility. From an alternative perspective, behavioral game theory attempts to describe actual behavior by accounting for bounds on rationality and limitations of human information (Camerer, 1997).

Second, consider asymmetric information games, referring to games with payoff asymmetry. In these games the actors' strategy sets (i.e. payoff structures) cannot be interchanged (e.g. the actors have different roles). The study of games with asymmetric information has mostly focused on degenerate versions of the social dilemmas (a.k.a. motive games) (King and Murnighan, 1988; de Jasay et al., 2004). It is common practice to "symmetrize" multi-actor conflicts at the expense of external validity to simplify the analysis of social phenomena.

Third, consider focal points (also known as Schelling points). The last drawback refers to the tendency of one actor toward "concerting his intentions or expectations with others if he knows that the others are trying to do the same", especially when the actors do not communicate or they do not know each other (Schelling, 1960). The presence of focal points affects the way players describe the strategies to themselves, a phenomenon called "labelling" (Sugden, 1995). Game theorists often replace generic strategy names like "top/bottom" and "left/right" with what labels they believe actors would use, like "opera/football" or "cooperate/defect." The former labels have widespread use in the study of the underlying dynamics behind cooperative and defective behavior.

APPLICATIONS OF GAME THEORY TO ENGINEERING SYSTEMS DESIGN

REPRESENTING GAMES IN ENGINEERING SYSTEMS DESIGN

Table 1 presents a list of game-theoretical approaches to decision-making in ESD found in the literature. In the context of ESD, the players are the design actors. A design actor might be an individual human decision-maker, a design organization, a machine agent, or indirect stakeholders whose strategic interests are unknown and would play the role of "nature". In most works, the strategy space is represented by continuous functions linked with functional attributes of the system thus informing decision-making at the operational level.

Table 1. Selected Game-Theoretic Models in Engineering Systems Design Literature

Reference	Game model	Players	Strategies	Objective	Solution concepts
Vincent, 1983	Continuous static game	n, objective functions	Infinite (continuous functional attributes)	Minimize cost associated to design parameters	Pareto efficiency Nash equilibria
Lewis and Mistree, 1997	Continuous static game	2, objective functions	Infinite (continuous functional attributes)	Minimize cost associated to design parameters	Pareto efficiency Nash equilibria Leader/follower
Hernández and Mistree, 2000	Extensive form game	2, product v. manufacturing teams	Infinite (continuous functional attributes)	Minimize cost associated to design parameters	Leader/follower
Arthanari, 2005	Zero-sum normal form game	2, designer v. nature	Tradeoff between intersected sets of continuous functional attributes	Maximize signal-to-noise ratio	Maximin strategy
Gurnani and Lewis, 2008	Repeated extensive form game	2	Infinite (normally-distributed around rational strategy sets)	Minimize cost associated to design parameters	Sub-game perfect Nash equilibria
Takai, 2010	Two-stage normal form game	2	Tradeoff between intersected sets of continuous functional attributes	Maximize system value	Nash equilibria
Ghotbi and Dhingra, 2012	Repeated extensive form game	2, objective functions	Infinite (continuous functional attributes)	Minimize manufacturing costs	Leader/follower
Gianetto and Heydari, 2015	Repeated normal form game	2, computational agents	Tradeoff between cooperative and defective strategies	Maximize system value	Evolutionarily stable strategy
Sha et al., 2015	Extensive form game	2, university students	Tradeoff between intersected sets of continuous functional attributes	Minimize cost associated to design parameters	Nash equilibria
Bhatia et al., 2016	Repeated extensive form game	2, company v. government	Tradeoff between intersected sets of continuous functional attributes	Maximize system value	Sub-game perfect Nash equilibria
Kang et al., 2016	Repeated extensive form game	2, market systems	Tradeoff between intersected sets of continuous functional attributes	Maximize overall profitability	Sub-game perfect Nash equilibria
Grogan et al., 2018	Normal form game	2, federated systems	Tradeoff between specific strategy design decisions	Maximize net present value	Pareto efficiency Risk dominant Nash equilibria
Valencia-Romero and Grogan, 2018	Normal form game	2,	Tradeoff between abstract strategy design decisions	Maximize system value	Nash equilibria

Design decisions are commonly approached in a normative fashion by evaluating them against idealistic scenarios of cooperative or non-cooperative equilibria, with the Nash equilibrium being the most used solution concept (Papageorgiou et al., 2016). In order to improve the outcomes predicted by the Nash equilibrium, some works have developed methods to allow design actors further explore the strategy space beyond rational reaction strategy sets.

Although the works in Table 1 are game-theoretical in nature, few provide details about the type of game representation used. There is a lack of studies in ESD that use game theory to study strategy design decisions. A recent work also uses game theory in combination with behavioral economics to study the underlying factors that impact on the actors' strategic behavior (Sha et al., 2015). Considering the need of verifiable theories regarding how independent interacting design actors make decisions, Sha et al.'s (2015) work highlight the great potential of using game theory in human-subject design experiments.

STUDYING STRATEGY DESIGN DECISIONS

Strategy design decisions in ESD can be approached in a normative fashion by comparing to idealistic scenarios of cooperative or non-cooperative equilibria, with the Nash equilibrium being the most used solution concept. Some the strategic elements in ESD include non-functional properties or "-ilities" (McManus et al., 2007), selection of processes and technologies, and system's mission. The biggest challenge in applying game theory in ESD is arguably mapping strategy design decisions to payoffs. More importantly, assessing whether the differences between the design actors' motivations represent a conflict worthy of game-theoretical analysis and how to represent these tradeoffs in terms of utility or value. Value-driven design (VDD) has often been cited as an alternative approach for constructing utility-based payoff functions in the context of ESD (Abbas and Cadenbach, 2018).

Value-driven design (VDD) refers to a collection of methods that capture the true needs and preferences of each actor involved in the development of a system into a scalar objective function or value model (Collopy and Hollingsworth, 2011). The use of value-driven methodologies proves most useful during conceptual design of large-scale systems when only the basic needs are known and the decision space can be explored at its widest extent (Papageorgiou et al., 2016). Value-driven design relies on the minimization of lower-level requirements and abstraction of upper-level needs applied to extensive attributes, such as weight, cost, or the so-called 'ilities'. In other words, VDD relaxes lower-level requirements to maximize the probability of meeting systems-level requirements that are directly linked to the stakeholders' needs (Collopy and Hollingsworth, 2011).

In a previous work, Grogan et al. (2016) apply VDD concepts to develop a multi-actor value model to study strategic decision-making processes in federated systems. In this work, the federated setting is represented in the form of a Stag Hunt game—a type of two-strategy coordination (bipolar) game—in which each actor chooses between a risk- and a payoff-dominant strict equilibrium. Federations realize of every type of collective effort at the technical, managerial, and executive levels (Sommerville, 2016). In these collective systems, actors switch between

collective strategies—from working independently to cooperating and forming a centralized system—to maximize rewards from individual and common objectives.

An extension to Grogan et al.'s work attempts to objectively assess the risk associated to selecting a particular design and strategy (Grogan et al., 2018). The approach, built upon Selten's (1995) theory of risk dominance in bipolar games, provides explicit assessment in net present value units on the upside potential versus downside risk tradeoff associated to the selection of each subsystem in a distributed satellite constellation. From a system-of-systems technical perspective (Maier, 1998), a monolithic constellation consisting of independent spacecrafts risk-dominates a distributed architecture of similar cost under uncertainty. On the other hand, a federated satellite system is more advantageous in terms of payoff if the proper functioning of the middleware communication packages is guaranteed (Grogan et al., 2018). Additionally, risk and payoff dominance between spacecraft constellation alternatives could be associated to how much autonomy the actors responsible for the operation of the subsystems have as well as their collective efforts: competition for service contracts, coordination of data exchange, and cooperation over shared resources.

DISCUSSION

It can be argued that the full potential of game theory to study strategic interaction has not been exploited in engineering systems design literature. Considering how relevant the concept of strategy has been in the evolution of game theory in the past half century from set of operations research methods to robust mathematical framework to study strategic behavior, it is unfortunate that the engineering systems design literature has not kept up with its most recent uses in the social and natural sciences.

There is great potential in using game theory to inform strategic decision-making processes in engineering systems design, both in prescriptive and descriptive fashion. As a prescriptive framework, game theory can be combined with value-driven design to help synthesize long-term design decisions into a finite sets of strategy profiles that can be assessed using existing solution concepts. On the other hand, game theory can be used as a tool to design human subject design experiments to help in the generation of theories of design decision-making in collective settings.

EQUILIBRIUM SELECTION AND RISK DOMINANCE

This section develops the theoretical contribution of this project by modeling joint engineering design problems as an economic coordination game using concepts from game theory. The essential strategic dynamics are best described as a stag hunt game with two Nash equilibria. Resulting analysis compares the relative preferences among the two Nash equilibria by comparing desirable properties of payoff and risk dominance.

Applied to engineering design or systems engineering problems, the formulation of a strategic design game enables analogous analysis techniques for strategic design games. In this context, the stag strategy is analogous to pursuing joint programs with high potential reward but also high risk while the hare strategy is analogous to pursuing independent programs at lower potential reward but also lower risk. Evaluating a measure of risk dominance and comparing across design alternatives can help select desirable joint architectures.

Portions of this section are drawn from material in the following publications:

Grogan, P.T. (2019). "Stag Hunt as an Analogy for Systems of Systems Engineering," *2019 Conference on Systems Engineering (CSER)*, April 3-4, Washington, D.C.

Grogan, P.T. and A. Valencia-Romero (n.d.). "Strategic Risk Dominance in Collective Systems Design," In revision for *Design Science*.

STAG HUNT GAME

The stag hunt game is a canonical coordination problem first posed by the philosopher Jean-Jacques Rousseau dating to the eighteenth century (Rousseau, 1984). It embodies essential dynamics in choosing between alternatives representing social coordination and defection. The stag hunt game remains an important analogy for framing and discussing the strategic dynamics of social contracts and collective decision-making (Skryms, 2001).

The classical description of a stag hunt focuses on two hunters' decisions determining an overall hunting strategy. There are two types prey available: hare and stag which form the basis of the strategy decision space $\mathcal{S} = \{\text{Hare}, \text{Stag}\}$. Hunting stag requires mutual coordination for a successful hunt after which the hunters divide and share the plentiful reward. However, if only one hunter pursues a stag, his or her hunt is not successful and yields no payoff. In contrast, hunting hare can be performed individually but yields a comparatively small payoff. Variations of the hare hunt either provide consistent or decreasing individual payoff for two versus one hare hunters (i.e. hunting hare may not benefit from coordination).

Table 2 expresses a stag hunt game in normal form for notional rewards modeled with a multi-actor value function $V^{s_1 s_2}: \mathcal{S}^2 \rightarrow \mathbb{R}^2$ that maps two strategy decisions to two real-valued payoffs. The rows represent alternative decisions for actor 1 and the columns represent alternative decisions for actor 2. The interior cells show the payoff values $(V_1^{s_1 s_2}, V_2^{s_1 s_2})$ received by each player under decision pair (s_1, s_2) . This example demonstrates the largest payoff (5) for both actors under the stag/stag scenario and a more modest payoff (2) for both actors under the

hare/hare scenario. The unsuccessful stag hunt yields the minimum payoff (0) and the individual hare hunt yields an intermediate payoff (4).

Table 2. Stag Hunt Game in Normal Form

Actor 1	Actor 2	
	Hare (<i>H</i>)	Stag (<i>S</i>)
Hare (<i>H</i>)	$V_1^{HH} = 2$ $V_2^{HH} = 2$	$V_1^{HS} = 4$ $V_2^{HS} = 0$
Stag (<i>S</i>)	$V_1^{SH} = 0$ $V_2^{SH} = 4$	$V_1^{SS} = 5$ $V_2^{SS} = 5$

The fundamental dilemma of a stag hunt game forces a choice between two alternatives that both provide desirable features. On one hand, the stag hunt presents the most desirable outcome but requires successful coordination. On the other hand, the hare hunt guarantees a minimal level of success, removing dependency on others' actions.

EQUILIBRIUM ANALYSIS AND SELECTION

Equilibrium analysis is the most common analysis technique in game theory. A Nash equilibrium represents a stable set of decisions (a pure equilibrium) or set of probability distributions (a mixed equilibrium) where neither actor has incentive to switch unilaterally to an alternative decision. A stag hunt game is characterized by the existence of two pure Nash equilibria. The first equilibrium in Table 2 is the (*H*, *H*) alternative—each actor stands to lose value (from 2 to 0) if they unilaterally deviate to the stag alternative. The second equilibrium in Table 2 is the (*S*, *S*) alternative—again, each actor stands to lose value (from 5 to 4) if they unilaterally deviate to the hare alternative.

Although both the hare (*H*, *H*) and stag (*S*, *S*) decision sets are considered stable from a Nash perspective, they do not represent equivalent outcomes. The stag result provides the highest payoff for each player and is described as the payoff-dominant equilibrium. The tradeoff, however, arises from the additional risk of potential losses under coordination failures. In contrast, the hare result provides a smaller but essentially risk-free minimum payoff. Thus, the fundamental challenge of a stag hunt game arises from how to choose between the two stable decision points.

Prior literature in game theory including Harsanyi and Selten (1988) and Selten (1995) study a specific class of problems where a risk dominance measure evaluates relative preference for more than one Nash equilibria. Specifically, Selten (1995) develops the weighted average log measure (WALM) of risk dominance as a scalar measure of normative strategy preference (i.e. what strategy *should* be selected to maximize expected value). Like payoff dominance, risk dominance is a desirable equilibrium quality that characterizes the risk posed by coordination failures from the perspective of rational actors seeking to maximize expected payoff. Although the general form applies to asymmetric stag hunts with two or more actors, it is most easily explained in the context of a two-actor symmetric game.

SIMPLE CASE: TWO SYMMETRIC PLAYERS

Continuing the example stag hunt game in Table 2, consider the graphical analysis in Figure 3 that inspects the expected value of each strategy as a function of the probability p that the opposing hunter chooses stag, ranging from 0 (guaranteed hare) to 1 (guaranteed stag). The two lines show the expected value of a one's own strategy: stag (solid, increasing from 0 to 5) and hare (dashed, increasing from 2 to 4) under uncertainty.

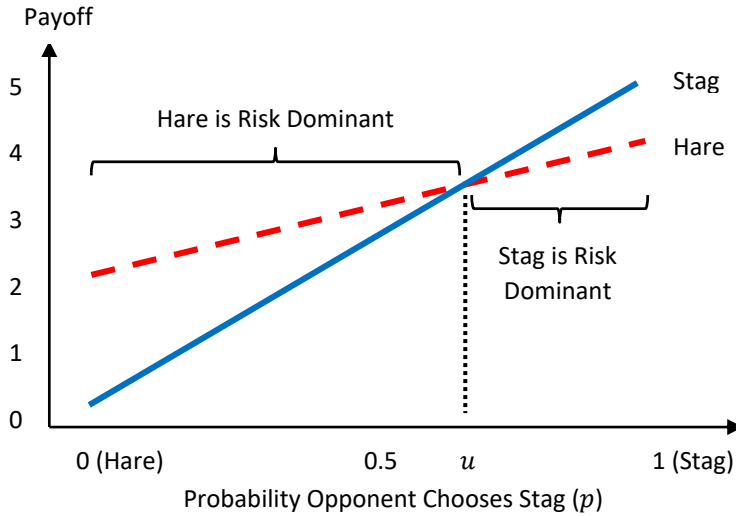


Figure 3. Stag hunt strategy selection using risk dominance.

Expected value maximizing (i.e. rational) actors prefer the hare strategy for low values of p and the stag strategy for high values of p . More specifically, the variable u , described in literature as the normalized deviation loss, marks the intersection between the two expected value lines and the crossover point between strategy preferences. The equation for u is a simple function of the four payoff values for symmetric two-player cases:

$$u = \frac{V^{HH} - V^{SH}}{(V^{HH} - V^{SH}) + (V^{SS} - V^{HS})}$$

which evaluates to $u = 2/3$ for the game in Table 2. This analysis result indicates that the expected value maximizing player should to hunt stag only if he or she believes a better than two-thirds chance the other player will also choose to hunt stag.

Variations on the stag hunt game produce different values of u with different thresholds to collaborative behavior. For example, consider the following alternative stag hunt games. Table 3 shows a case with a "trophy" stag which increases the upside payoff from 5 to 12, lowering the threshold for economic collaboration to $u = 0.2$. Table 4 shows a case with an "injury" incurred from a solitary stag hunt which decreases the downside payoff from 0 to -2, raising the threshold for economic collaboration to $u = 0.8$.

Table 3. Stag Hunt Game with $u=0.2$

Actor 1	Actor 2	
	Hare (H)	Stag (S)
Hare (H)	$V_1^{HH} = 2$ $V_2^{HH} = 2$	$V_1^{HS} = 4$ $V_2^{HS} = 0$
Stag (S)	$V_1^{SH} = 0$ $V_2^{SH} = 4$	$V_1^{SS} = 12$ $V_2^{SS} = 12$

Table 4. Stag Hunt Game with $u=0.8$

Actor 1	Actor 2	
	Hare (H)	Stag (S)
Hare (H)	$V_1^{HH} = 2$ $V_2^{HH} = 2$	$V_1^{HS} = 4$ $V_2^{HS} = -2$
Stag (S)	$V_1^{SH} = -2$ $V_2^{SH} = 4$	$V_1^{SS} = 5$ $V_2^{SS} = 5$

Lacking any subjective knowledge of the opponent's actions, a purely objective analysis assumes $p = 0.5$ such that $u < 0.5$ indicates a stag strategy is risk dominant while $u > 0.5$ indicates a hare strategy is risk dominant. Selten's proposed WALM of risk dominance (1995) applies a logit function in Figure 4 to transform u from the (0,1) scale to a real number:

$$R = \ln\left(\frac{u}{1-u}\right) = \ln\left(\frac{V^{HH} - V^{SH}}{V^{SS} - V^{HS}}\right).$$

Accordingly, a positive risk dominance measure $R > 0$ indicates the hare strategy is risk dominant and a negative risk dominance measure $R < 0$ indicates the stag strategy is risk dominant. More importantly, the magnitude of the risk dominance measure indicates the degree of dominance, useful for comparing alternatives if partial or subjective information about partners' likely decisions is available, as in most engineering design problems.

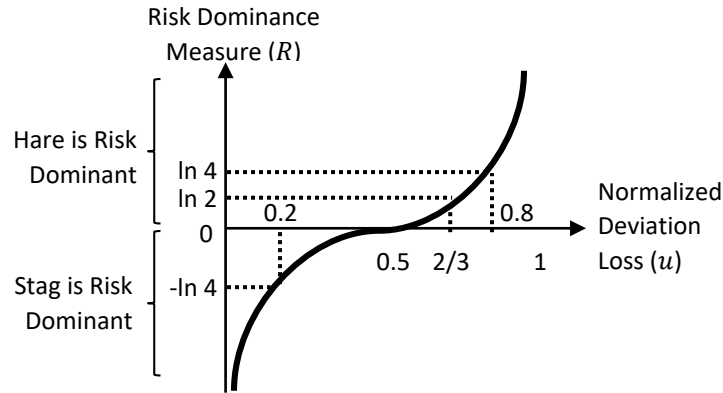


Figure 4. Risk dominance as a logit function of normalized deviation loss.

For example, the game in Table 2 yields $R = \ln 2 \approx 0.7$ which indicates the hare strategy is risk dominant. In contrast, the "trophy" scenario in Table 3 yields $R = \ln 0.25 \approx -1.39$ which indicates the stag strategy is risk dominant. Finally, the "injury" scenario in Table 4 yields $R = \ln 4 \approx 1.39$ which indicates the hare strategy is risk dominant and *more strongly so* than the original game. In the absence of any information about the other hunter's strategy, the sign of R recommends the expected value-maximizing action; however, in the presence of some subjective information, the magnitude of R determines relative risk dominance among two or more games.

GENERAL CASE: ASYMMETRIC PLAYERS

The more general case with $n \geq 2$ asymmetric actors computes risk dominance following a similar form but based on a weighted sum of contributions for each actor:

$$R = \sum_{i=1}^n w_i(A) \ln \left(\frac{u_i}{1 - u_i} \right)$$

where individual weighting factors w_i are a function of an $n \times n$ matrix $A = [a_{ij}]$ that measures influence among players. Some additional notation and derivation are required to explain this formulation in more detail.

The WALM of risk dominance is defined for bipolar games that have a strategy set of two alternatives $\mathcal{S}_i = \{\phi_i, \psi_i\}$ and two Nash equilibria defined by shared strategies among all players $\phi = (\phi_1, \dots, \phi_n)$ and $\psi = (\psi_1, \dots, \psi_n)$. Without loss of generality, assume that ψ is payoff dominant (i.e. corresponds to the stag hunt). Notation with negative subscripts on strategy sets denotes non-participation by certain actors, for example, $\phi_{-1} = (\psi_1, \phi_2, \dots, \phi_n)$ indicates player 1 chooses strategy ψ_1 but all others choose ϕ_i .

Normalized deviation losses u_i are expressed in terms of deviation losses L_i which provide a convenient notation that can be interpreted as the sensitivity to deviating away from a stable strategy set $\xi \in \{\phi, \psi\}$ through one's own actions. Deviation losses are defined up to a constant of proportionality as:

$$L_i(\xi) \propto V_i(\xi) - V_i(\xi_{-i}).$$

As the name suggests, normalized deviation losses *normalize* deviation losses to a unit scale:

$$u_i = \frac{L_i(\phi)}{L_i(\phi) + L_i(\psi)}.$$

The intuition behind normalized deviation losses is best explained through the incentive function D_i . The incentive function evaluates the relative benefit for player i to choose strategy ϕ_i over ψ_i as a function of the probability p that all other players choose the payoff dominant strategy ψ (i.e. the same concept as shown in Figure 3 but extended to any number of players). The incentive function can be expressed as a normalized difference in expected values and simplifies to a convenient form:

$$\begin{aligned} D_i(p) &= \frac{E[V_i|\phi_i] - E[V_i|\psi_i]}{L_i(\phi) + L_i(\psi)} = \frac{V_i(\phi) - V_i(\phi_{-i}) - [V_i(\phi) - V_i(\phi_{-i}) + V_i(\psi) - V_i(\psi_{-i})]p}{L_i(\phi) + L_i(\psi)} \\ &= \frac{L_i(\phi) - [L_i(\phi) + L_i(\psi)]p}{L_i(\phi) + L_i(\psi)} = u_i - p. \end{aligned}$$

Note that $D_i < 0$ for values of $p > u_i$ and $D_i > 0$ for values of $p < u_i$. As before, the normalized deviation loss u_i describes a threshold value of p where the two strategies ϕ_i and ψ_i both provide the same expected value.

The incentive function is more complicated when considering individual decision authority. For example, the expected value difference calculation for $n = 3$ players with individual probabilities of collaboration p_j and p_k for players j and k , respectively, expands to:

$$\begin{aligned}
E[V_i|\phi_i] - E[V_i|\psi_i] &= \begin{bmatrix} V_i(\phi)(1-p_j)(1-p_k) \\ +V_i(\phi_{-j})p_j(1-p_k) \\ +V_i(\phi_{-k})(1-p_j)p_k \\ +V_i(\psi_{-i})p_jp_k \end{bmatrix} - \begin{bmatrix} V_i(\phi_{-i})(1-p_j)(1-p_k) \\ +V_i(\phi_{-ij})p_j(1-p_k) \\ +V_i(\phi_{-ik})(1-p_j)p_k \\ +V_i(\psi)p_jp_k \end{bmatrix} \\
&= [V_i(\phi) - V_i(\phi_{-i})] - \begin{bmatrix} V_i(\phi) - V_i(\phi_{-i}) \\ +V_i(\phi_{-ij}) - V_i(\phi_{-j}) \end{bmatrix} p_j \\
&\quad - \begin{bmatrix} V_i(\phi) - V_i(\phi_{-i}) \\ +V_i(\phi_{ik}) - V_i(\phi_{-k}) \end{bmatrix} p_k - \begin{bmatrix} V_i(\psi) - V_i(\psi_{-i}) \\ -V_i(\phi) + V_i(\phi_{-i}) \\ +V_i(\phi_{-j}) - V_i(\phi_{-ij}) \\ +V_i(\phi_{-k}) - V_i(\phi_{-ik}) \end{bmatrix} p_jp_k.
\end{aligned}$$

Similar to the notation for deviation losses, a new quantity described as the pairwise deviation loss between players i and j provides a convenient notation to simplify the incentive function:

$$L_{ij}(\xi) \propto V_i(\xi_{-j}) - V_i(\xi_{-ij}).$$

Additionally, influence elements of the matrix $A = [a_{ij}]$ are defined in terms of the deviation losses and pairwise deviation losses:

$$a_{ij} = \frac{L_i(\phi) - L_{ij}(\phi)}{L_i(\phi) + L_i(\psi)}.$$

Using the above notation, the normalized incentive function simplifies to:

$$D_i(p_j, p_k) = \frac{E[V_i|\phi_i] - E[V_i|\psi_i]}{L_i(\phi) + L_i(\psi)} = u_i - a_{ij}p_j - a_{ik}p_k - (1 - a_{ij} - a_{ik})p_jp_k.$$

Selten (1995) only considers a class of bipolar problems with linear incentives such that $a_{ij} + a_{ik} = 1$. This simplifying assumption eliminates the interaction term between p_j and p_k , leading to the multivariate expression $D(p) = u - Ap$ valid for any number of players. Linear incentives eliminate third party effects so the effect of player j on i is not a function of player k . Although this is a strong assumption that restricts study of problems with returns to scale or network effects, an approximation to linear incentives will be introduced in the next section.

Finally, player weights w_i are implicitly defined through the properties:

$$w(A) = A^T w(A), \quad \sum_{i=1}^n w_i(A) = 1$$

which can be interpreted identifying the eigenvector (rescaled to unit norm) of A^T corresponding to the unit eigenvalue. Note that weights are equivalent to the stationary stochastic distribution for the Markov chain with state transition probabilities a_{ij} .

As introduced in the previous section, WALM of risk dominance was developed for a narrow class of problems with linear incentives to greatly simplify the resulting calculations. This is a problematic assumption for engineering design where the upside potential of a collaborative architecture often is affected by the number and particular set of participating players. Furthermore, the assumption of linear incentives is critical to yield a unit eigenvalue required for analysis of player weights. To overcome this limitation, this section introduces an approximation to linear incentives and a corresponding analysis technique to inspect errors resulting from the approximation.

Nonlinear incentives can only occur in games with $n \geq 3$ players. Figure 5, analogous to Figure 3 but for two probabilities rather than one, illustrates the expected value surface for player i 's two alternative strategies in games with linear and nonlinear incentives. Linear incentives produce planar value surfaces with a linear intersection region highlighted in black. Nonlinear incentives produce nonlinear value surface with a curved intersection region. This example illustrates a case where player i benefits more from collaboration of players j and k than the sum of their individual contributions.

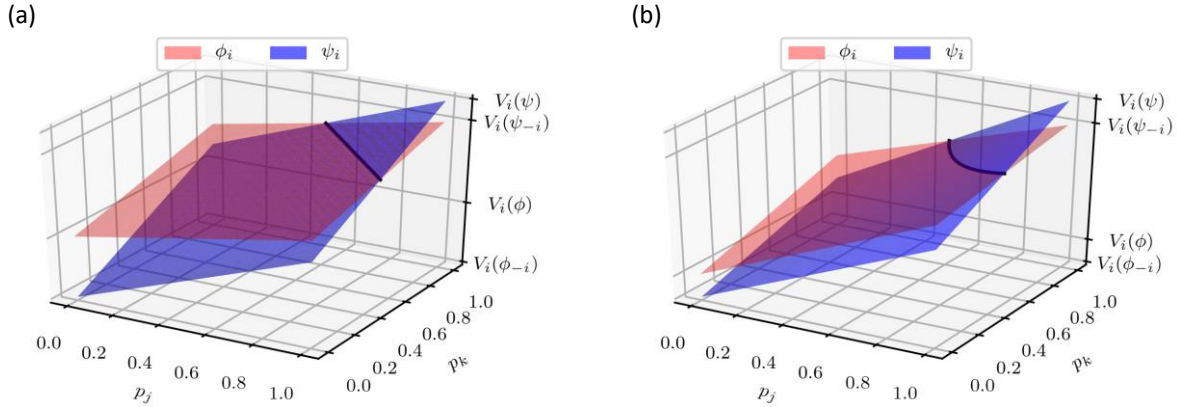


Figure 5. Value surfaces for $n=3$ player games with (a) linear and (b) nonlinear incentives.

The approximation to linear incentives fits new influence elements $\bar{a}_{ij}$ to the incentive function to eliminate interaction terms between players while preserving the interpretation of influence elements as a measure of sensitivity between players. For example, the approximate incentive function for games with $n = 3$ players can be expressed as:

$$D_i(p_j, p_k) = u_i - a_{ij}p_j - a_{ik}p_k - (1 - a_{ij} - a_{ik})p_jp_k \approx u_i - \bar{a}_{ij}p_j - \bar{a}_{ik}p_k.$$

Each approximate influence element is interpreted as the effect of player j 's probability of cooperation p_j on player i 's incentive function, i.e. $-\partial D_i / \partial p_j$, estimated using expectation with a uniform distribution for third party decisions $p_k \sim U(0,1)$. For the case with $n = 3$ players, the linearized influence element is:

$$\begin{aligned}\bar{a}_{ij} &= E \left[-\frac{\partial D_i}{\partial p_j} \right] = E[a_{ij} + (1 - a_{ij} - a_{ik})p_k] \\ &= a_{ij} + \int_0^1 (1 - a_{ij} - a_{ik})p_k dp_k = \frac{1}{2}(1 + a_{ij} - a_{ik})\end{aligned}$$

The more general case for games with n players requires some additional notation. Similar to the pairwise case, the set wise deviation loss between a player i and a set of players $\mathbf{k}$ provide a convenient notation to simplify expressions:

$$L_{i\mathbf{k}}(\xi) \propto V_i(\xi_{-\mathbf{k}}) - V_i(\xi_{-\mathbf{k}i}).$$

The resulting linearized influence elements are given by the expression:

$$\bar{a}_{ij} = \frac{1}{|\mathcal{K}_{ij}|} \sum_{\mathbf{k} \in \mathcal{K}_{ij}} \frac{L_{i\mathbf{k}}(\phi) + L_{i\mathbf{k}}(\psi)}{L_i(\phi) + L_i(\psi)}$$

where $\mathcal{K}_{ij} = \mathcal{P}(\{1, \dots, n\} \setminus \{i, j\})$ is the powerset (set of all subsets including the empty set) of all third parties with cardinality $|\mathcal{K}_{ij}| = 2^{n-2}$ given by the binomial theorem.

Inevitably, the linear approximation above introduces some error manifested as differences between the nonlinear incentive function and the approximate incentive function:

$$\delta_i(p_j, p_k) = D_i(p_j, p_k) - (u_i - \bar{a}_{ij}p_j - \bar{a}_{ik}p_k).$$

A corresponding error metric integrates the absolute difference in incentive function over the joint probability space. For example, in the case with $n = 3$ players the error metric has a closed form solution:

$$\begin{aligned}\varepsilon_i &= \int_0^1 \int_0^1 |\delta_i(p_j, p_k)| dp_j dp_k = |1 - a_{ij} - a_{ik}| \int_0^1 \int_0^1 \left| \frac{p_j}{2} + \frac{p_k}{2} + p_j p_k \right| dp_j dp_k \\ &= \frac{|1 - a_{ij} - a_{ik}|}{4}.\end{aligned}$$

Note that $D_i \in [u_i - 1, u_i]$ so ε_i can roughly be interpreted as percent error.

For example, consider a symmetric $n = 3$ player case with notational value function:

$$V_i(\xi) = \begin{cases} 0 & \text{if } \xi = \phi_{-i} \\ 2 & \text{if } \xi \in \{\psi_{-k}, \psi_{-j}\} \\ 3 & \text{if } \xi \in \{\phi, \phi_{-j}, \phi_{-k}, \psi_{-i}\} \\ 8 & \text{if } \xi = \psi \end{cases}.$$

This game has nonlinear incentives because the value of unanimous collaboration $[V_i(\psi) - V_i(\phi_{-i})] = 8$ exceeds the sum of partial collaboration $[V_i(\psi_{-j}) - V_i(\phi_{-i})] + [V_i(\psi_{-k}) - V_i(\phi_{-i})] = 4$. Risk dominance analysis of this game yields nonlinear influence elements $a_{ij} = 0.25$ and linear approximations $\bar{a}_{ij} = 0.5$. Figure 6 illustrates the incentive function $D_i(p_j, p_k)$, its linear approximation, and the error term $\delta_i(p_j, p_k)$ with overall mean error $\varepsilon = 0.125$. The

error is greatest in regions of the probability space with high probability that one player will choose the payoff dominant strategy but low probability the other player will choose the same.

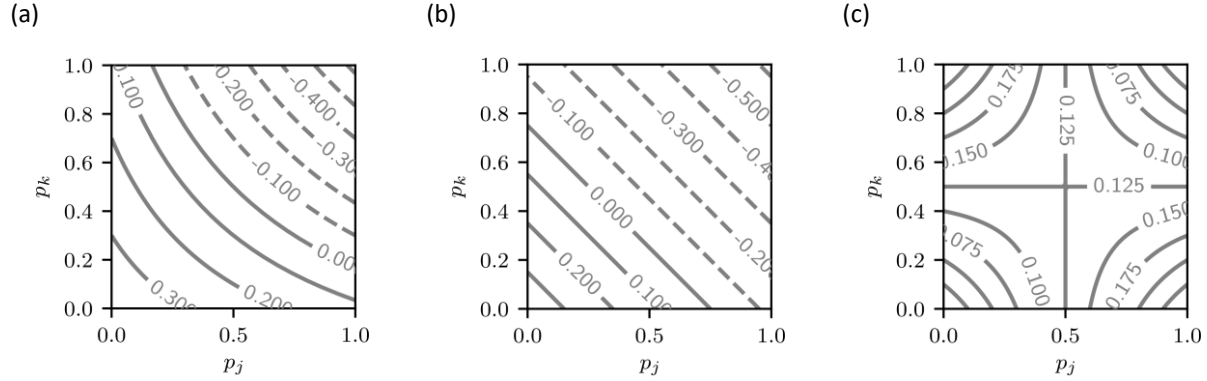


Figure 6. Incentive function for (a) nonlinear, (b) linearized cases and (c) difference.

STRATEGIC DESIGN GAMES

Game theory works at a high level of abstraction; however, a portion of engineering design deals with more concrete decisions that may not equate to strategies. A strategic design game models engineering design as a bi-level decision-making problem. Lower-level design optimization searches for value-maximizing designs from actor-specific design spaces $\mathcal{D}_i$. Upper-level strategy coordination selects value-maximizing strategies from actor-specific strategy spaces $\mathcal{S}_i$. The corresponding multi-actor value function:

$$V_i: \prod_{i=1}^n \mathcal{D}_i \times \mathcal{S}_i \rightarrow \mathbb{R}$$

maps the set of design and strategy decisions to a real number for each player.

For example, consider the stag hunt framed as a strategic design game with the typical strategy space $\mathcal{S}_i = \{\text{Hare}, \text{Stag}\}$. Lower-level design optimization resembles a second layer of decisions guiding the tools employed in the hunt such as $\mathcal{D}_i = \{\text{Atlatl}, \text{Bow}, \text{Club}, \text{Dog}\}$. Table 5 shows notional value function outputs $V_i^{s_i s_j}(d_i, d_j)$ for alternative designs in each strategic context.

Table 5. Value Function for a Stag Hunt Design Game

Design (d_i)	Strategic Context (s_i, s_j)			
	Hare, Hare	Hare, Stag	Stag, Hare	Stag, Stag
Atlatl	0	0	0	5
Bow	1	1	1.5	4.5
Club	1	1	0	2
Dog	2	4	0	0

Design optimization generally takes place within a fixed strategic context where actors identify designs that yield the best expected outcome. For the symmetric two actor case, the notation

$$d_i^{s_i} = \max_{d \in \mathcal{D}_i} V_i^{s_i s_i}(d, d)$$

identifies a context-specific payoff-maximizing design decision. For example, the design $d_i^H = \text{Dog}$ yields the highest value in the hare-hunting context but performs poorly in the stag-hunting context. Alternatively, the design $d_i^S = \text{Atlatl}$ yields the highest value in the joint stag-hunting context but performs poorly in all others. Selecting these two context-specific designs at the lower-level produces the original stag hunt game in Table 2 at the upper-level.

However, consider the alternative design $d_i = \text{Bow}$ in the stag-hunting context. While it does not provide as high of value in the stag-hunting context, it provides some insulation of potential losses for the solitary stag hunt. The resulting normal form in Table 6 provides more desirable strategic dynamics with a normalized deviation loss of $u = 0.5$ and WALM of risk dominance $R(\text{Bow}) = 0$, compared to $R(\text{Atlatl}) \approx 0.7$.

Table 6. Stag Hunt Design Game with $u=0.5$

Actor 1	Actor 2	
	Hare (H)	Stag (S)
Hare (H)	$V_1^{HH}(\text{Dog}, \text{Dog}) = 2$ $V_2^{HH}(\text{Dog}, \text{Dog}) = 2$	$V_1^{HS}(\text{Dog}, \text{Bow}) = 4$ $V_2^{HS}(\text{Dog}, \text{Bow}) = 1.5$
Stag (S)	$V_1^{SH}(\text{Bow}, \text{Dog}) = 1.5$ $V_2^{SH}(\text{Bow}, \text{Dog}) = 4$	$V_1^{SS}(\text{Bow}, \text{Bow}) = 4.5$ $V_2^{SS}(\text{Bow}, \text{Bow}) = 4.5$

Two other simplifying assumptions improve the presentation of strategic design games for engineering applications where the independent strategy more strictly corresponds to lack of influence on payoff values. First, the full multi-actor value function can be simplified to three cases (shown below for player 1; however, the similar principle applies for all others):

$$V_1^{s_1 s_2}(d_1, d_2) = \begin{cases} V_1^\phi(d_1) & \text{if } s_1 = \phi_1 \\ V_1^\psi(d_1) & \text{if } s_1 = \psi_1 \text{ and } s_2 = \phi_2 \\ V_1^\psi(d_1, d_2) & \text{if } s_1 = \psi_1 \text{ and } s_2 = \psi_2 \end{cases}$$

assuming (a) player 2's design and strategy decisions do not influence player 1's outcome if player 1 chooses the independent strategy ϕ_1 and (b) player 2's design decision does not influence player 1 if player 2 chooses the independent strategy ϕ_2 . Second, as a result of this independence, the optimal design under the independent context is given by d_i^ϕ such that the value function for the independent strategy can be simplified to $V_i^\phi(d_i^{\phi_i}) = \mathcal{V}_i^\phi$. Table 7 illustrates a strategic design game in normal form using simplified notation for $n = 2$ players.

Table 7. Stag Hunt as a Strategic Design Game

Actor 1	Actor 2	
	Independent (ϕ_2)	Collaborative (ψ_2)
Independent (ϕ_1)	$\mathcal{V}_1^\phi$ $\mathcal{V}_2^\phi$	$\mathcal{V}_1^\phi$ $\mathcal{V}_2^\psi(d_2)$
Collaborative (ψ_1)	$\mathcal{V}_1^\psi(d_1)$ $\mathcal{V}_2^\phi$	$\mathcal{V}_1^\psi(d_1, d_2)$ $\mathcal{V}_2^\psi(d_1, d_2)$

Finally, engineering design games must be checked if they exhibit the bipolar dynamic before proceeding with risk dominance analysis. Recall that the bipolar dynamic, a necessary condition for risk dominance analysis, requires the following two conditions:

1. (ϕ_1, ϕ_2) is a pure Nash equilibrium such that $\mathcal{V}_1^\phi \geq V_1^\psi(d_1)$ and $\mathcal{V}_2^\phi \geq V_2^\psi(d_2)$. In other words, the independent alternative should suffer a decrease in payoff if the opposing actor induces a coordination failure.
2. (ψ_1, ψ_2) is a pure Nash equilibrium such that $V_1^\psi(d_1, d_2) \geq V_1^\psi(d_1)$ and $V_2^\psi(d_1, d_2) \geq V_2^\psi(d_2)$. In other words, the collaborative alternative with mutual agreement should provide at least the same payoff as the same design under coordination failure.

The resulting risk dominance analysis for collaborative strategy ψ with design alternatives d_i for each actor i is calculated as:

$$R_\psi(d_1, \dots, d_n) = \sum_{i=1}^n w_i(A) \ln \left(\frac{\mathcal{V}_i^\phi - V_i(d_i)}{V_i^\psi(d_1, \dots, d_n) - \mathcal{V}_i^\phi} \right)$$

with influence elements:

$$a_{ij} = \frac{V_i^\psi(d_i, d_j) - V_i^\psi(d_i)}{V_i^\psi(d_1, \dots, d_n) - V_i^\psi(d_i)}$$

and linearized influence elements for the $n = 3$ case:

$$\bar{a}_{ij} = \frac{1}{2} \left(1 + \frac{V_i^\psi(d_i, d_j) - V_i^\psi(d_i, d_k)}{V_i^\psi(d_1, d_2, d_3) - V_i^\psi(d_i)} \right).$$

RISK DOMINANCE ANALYSIS SCRIPT

A Python script to perform the WALM of risk dominance analysis and generate relevant plots and visualizations following this analysis. Key functions include the following:

- Interface to specify a multi-actor value model (M) as the foundation for this work. It maps the design and strategy decisions by each of n actors to the values each realizes.
- Function to compile and format a strategic design game (G) for a set number of players n provided a multi-actor value model M .
- Function to visualize expected value surfaces for an actor in strategic design game G . Examples in Figure 7 show plots for games with two players (2D line plots with an indifference point) and three players (3D surface plots with an indifference curve).

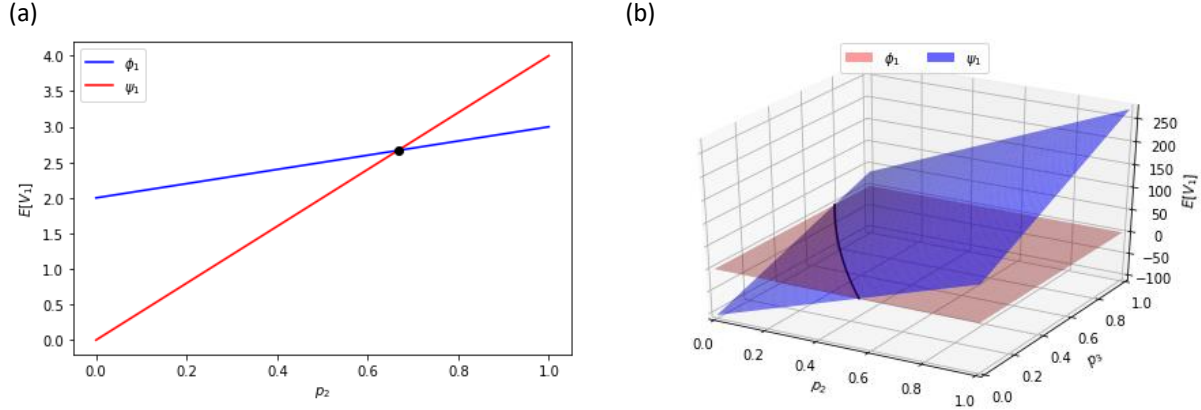


Figure 7. Example expected value surfaces for games with (a) $n=2$ and (b) $n=3$ players.

- Function to compute a biform (u, A) for strategic design game G either assuming linear incentives or applying the linear approximation developed in this project.
- Function to visualize incentive function contour plots for strategic design game G with either nonlinear or linearized incentives. The example in Figure 8 shows cases with (a) nonlinear incentives, (b) linearized incentives, and (c) difference between nonlinear and linearized incentive functions.

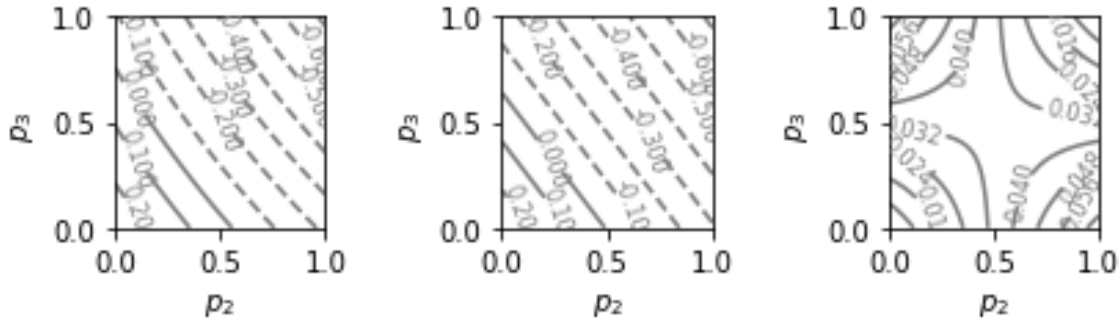


Figure 8. Example linearization error analysis for a game with nonlinear incentives.

- Function to compute an error metric (ϵ) for a strategic design game G with linearized incentives. The error metric is the integral of the difference between nonlinear and linearized incentive function values; however, there exists a closed form analytic solution for three-player games.
- Function to compute the weighted average log measure (WALM) of risk dominance (R) for a biform (u, A) .
- Example multi-actor value model and supporting analysis for a simple two-player symmetric Stag Hunt.
- Example multi-actor value models and supporting analysis for two three-player asymmetric scenarios developed for the *Orbital Federates* simulation context (see Grogan and Valencia-Romero, in revision for *Design Science*).

VALIDATION STUDY

This section develops a simulation platform to validate the WALM of risk dominance in a more abstract and generalizable case by modeling the effects of forming and dissolving joint programs under various strategy alternatives (namely, collaborate or remain independent). Following insights from the previous section, this section presents several variations of the design problem to illustrate the effect of the WALM including partial information about partner decisions in an evolutionary game model with imitation dynamics.

Rather than treating collaboration as a one-shot game, this research perspective treats it as a learned behavior subject to cultural norms. It is hypothesized that the WALM is useful to characterize the conditions in which collaboration is likely to emerge or dissolve. A Monte Carlo experiment using a bargaining-with-neighbors model built upon Skyrms (2004) and Kimbrough (2011) is used to determine the range of WALM that could predict general tendency toward selecting the payoff-dominant/socially efficient equilibrium in a symmetric Stag Hunt game.

STAG HUNT GAME WITH NORMALIZED PAYOFFS

The two-player normal form in Table 8 is a widely used representation of social dilemma games such as Prisoner's Dilemma, Harmony, Chicken, and the Stag Hunt. The payoffs corresponding to the diagonal strategy profiles (ϕ, ϕ) and (ψ, ψ) are normalized to a value of 0 and 1, respectively, for both players. (This is usually done by subtracting $V_i^{\phi\phi}$ to all payoffs in the original normal form and then dividing by the difference between $V_i^{\psi\psi}$ and $V_i^{\phi\phi}$). The off-diagonal payoffs are labeled S for sucker's payoff and T for temptation-to-defect. Any normal form represents a Stag Hunt game if and only if $V_i^{\psi\psi} > V_i^{\phi\psi} \geq V_i^{\phi\phi} > V_i^{\psi\phi}$ or, using normalized payoffs, $1 > T \geq 0 > S$ (Hauert, 2002). The lower the value of S , the greater the fear of failed cooperation towards the payoff-dominant equilibrium ("hunt stag"). On the other hand, the higher the value of T , the higher the incentive (or greed) to deviate from the socially efficient strategy profile (Macy & Flache, 2002).

Table 8. Normal Form Game with Normalized Payoffs

Actor 1	Actor 2	
	ϕ (Hunt hare)	ψ (Hunt stag)
ϕ (Hunt hare)	$V_1^{\phi\phi} = 0$ $V_2^{\phi\phi} = 0$	$V_1^{\phi\psi} = 0$ $V_2^{\phi\psi} = 0$
ψ (Hunt stag)	$V_1^{\psi\phi} = 0$ $V_2^{\psi\phi} = 0$	$V_1^{\psi\psi} = 0$ $V_2^{\psi\psi} = 0$

The WALM of risk dominance R for a two-player symmetric game with normalized payoffs is:

$$R = \frac{1}{2} \ln \frac{V_1^{\phi\phi} - V_1^{\psi\phi}}{V_1^{\psi\psi} - V_1^{\phi\psi}} + \frac{1}{2} \ln \frac{V_2^{\phi\phi} - V_2^{\psi\phi}}{V_2^{\psi\psi} - V_2^{\phi\psi}} = \ln \left(\frac{-S}{1-T} \right). \quad (1)$$

AGENT-BASED MODEL OF EVOLUTIONARY DYNAMICS

The agent-based model studies strategic interaction between a finite number of players under different conditions of information exchange. The model can be described in two parts: 1) definition of a network of information exchange and 2) definition of an evolutionary dynamic. In this work, five different network models with the same number of nodes ($N = 64$) are used and one bargaining dynamic of imitation between each agent (node in the network) and the agents adjacent to it.

NETWORKS OF INFORMATION EXCHANGE

The network models used in this validation case are:

Lattices:

1. Toroidal square lattice with von Neumann neighborhood
2. Toroidal square lattice with Moore neighborhood.

Random networks:

3. Random graph with no preferential attachment
4. Random graph with preferential attachment (also known as *rich-get-richer*)

Fully connected network: 5. complete graph.

The lattice used is a gridscape that wraps around on itself forming a torus shown in Figure 9. Each cell is adjacent to four other cells (one on each cardinal direction) for a von Neumann neighborhood. The Moore neighborhood extends the number of adjacent cells to eight by including the cells located on the intercardinal directions NW, NE, SW, and SE.

The random networks were generated using a modified version of the Barabási-Albert model with penalized preferential attachment (Barabási and Albert, 1999). This model consists of attaching node by node to the network in a way such that each new node will connect to m other nodes with a probability proportional to such nodes' degrees or popularity (Easley and Kleinberg, 2012). Depending on how much this preferential attachment mechanism is penalized, the growth of the network can go from mainly based on uniform random choices to follow a power law degree distribution (scale-free networks). In this implementation, $m = 1$, i.e. each new node is attached to only one other node in the network. (The same model is used to generate a complete graph by setting $m = N - 1 = 63$).

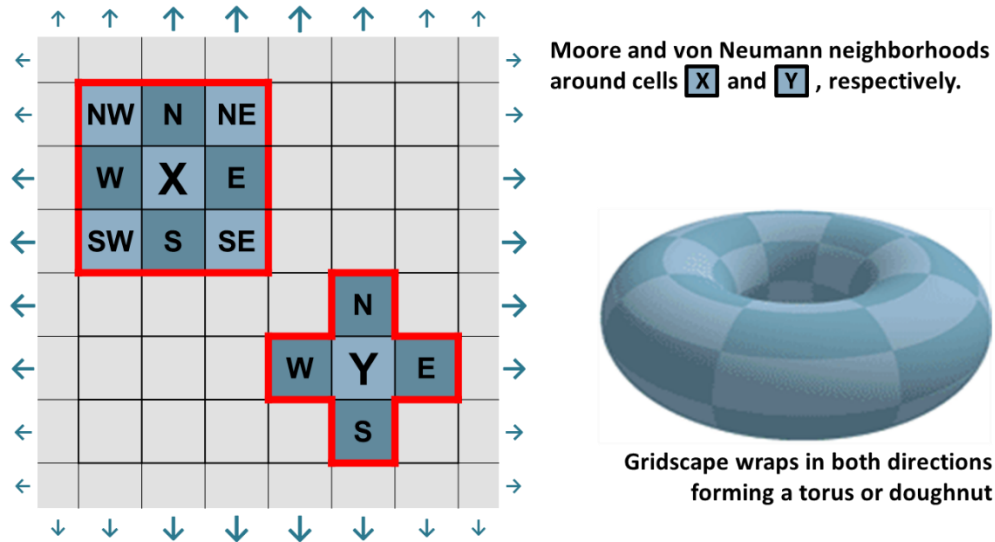
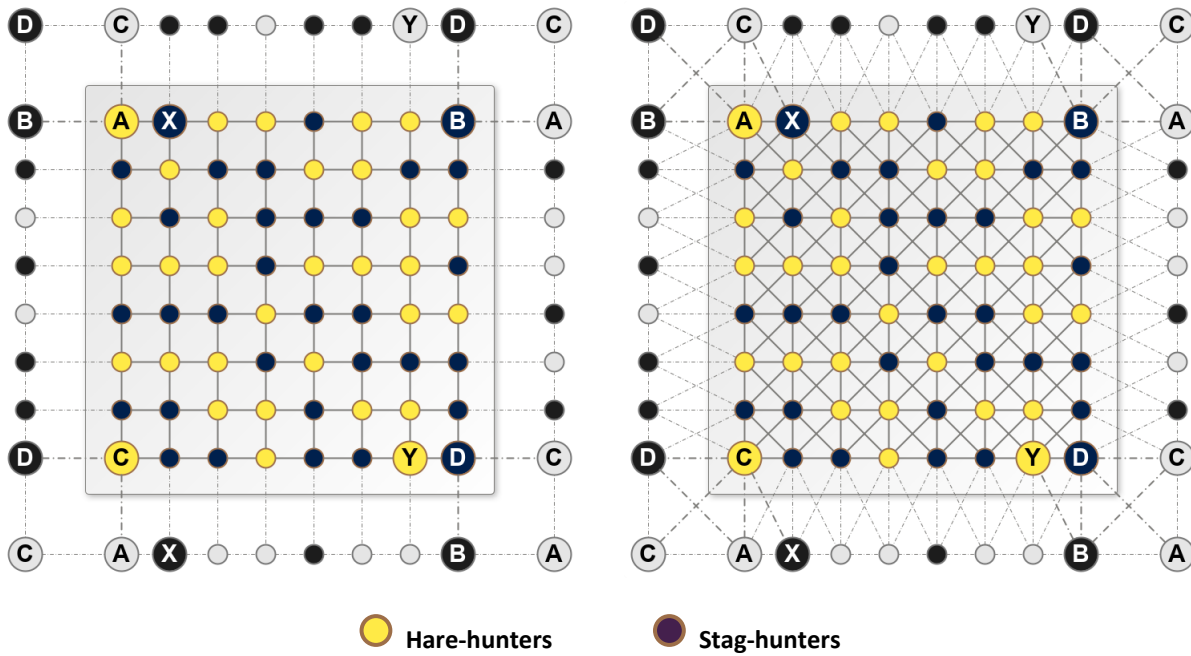


Figure 9. Toroidal square lattice.

After a network model has been set, each node is assigned an initial strategy, either "hunt hare" (●) or "hunt stag" (●) so the ratio of stag-hunters to hare-hunters is approximately 1:1. Figure 10 and Figure 11 show samples of toroidal square lattices and random networks, respectively, with $N = 64$ and same number of nodes per strategy.



b) von Neumann neighborhood

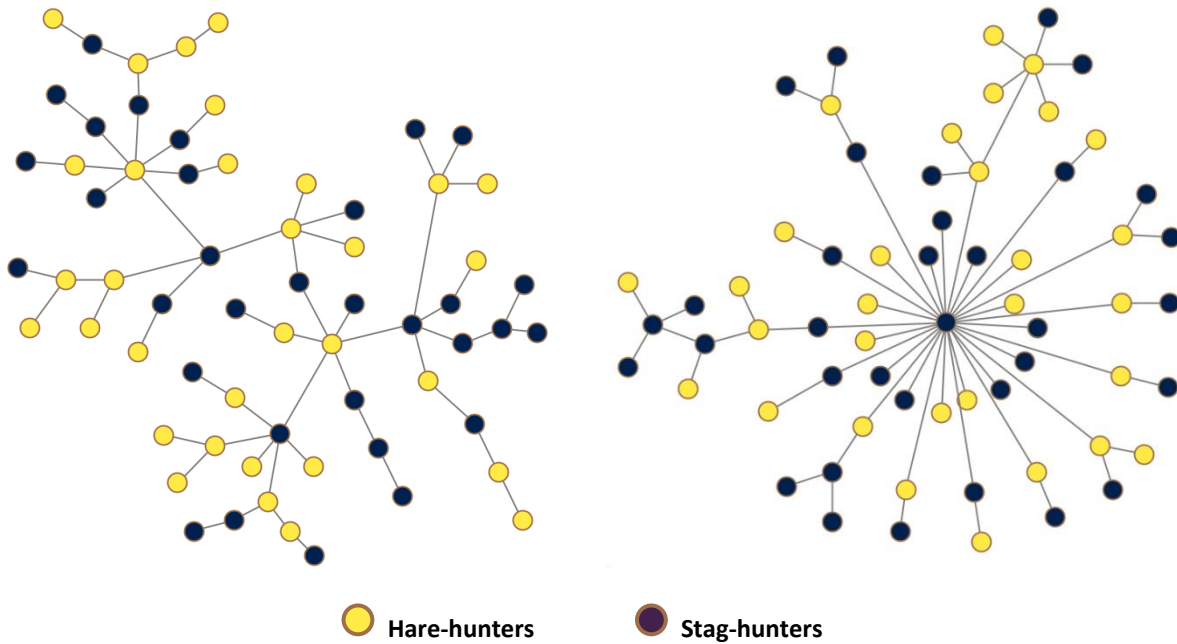
b) Moore neighborhood

Figure 10. Toroidal square lattices with a) von Neumann and b) Moore neighborhoods.

As the lattice wraps both horizontally and vertically, node **A** is adjacent to nodes **B** and **C** on the von Neumann model and to nodes **B**, **C** and **D** on the Moore model. Node **C** is adjacent to node **X** on the Moore model but not in the von Neumann model.

BARGAINING WITH NEIGHBORS: IMITATION DYNAMICS

Bargaining between agents in every round of the evolutionary game is done by imitation dynamics. Using the normal form game in Table 8, and after the values of S and T are set, each node plays a two-player game with each of its neighbor using an initial strategy assigned during the setup. The total payoff an agent gets at the end of each round is the sum of the payoffs earned at each two-player game. After each round, each agent imitates the strategy of the neighbor that earned the highest total payoff. If an agent's total payoff is higher than any of its neighbors, it will continue playing the same strategy in the next round. Convergence is reached if no agent updates its strategy after a round or if the percentage of stag-hunters is not altered.



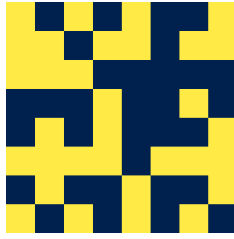
b) Random graph with no preferential attachment

b) Rich-get-richer graph

Figure 11. Random networks: a) no preferential attachment and b) preferential attachment.

The agent-based model of evolutionary dynamics was implemented on NetLogo 6.1.0 with $N = 64$ agents (Wilensky, 1999). The toroidal square lattice was implemented on a 8×8 gridscape with each node in the network represented as a 1×1 patch on NetLogo two-dimensional world interface. The Barabási-Albert model for generating random networks was adapted from Wilensky (2005) and modified to allow for different levels of preferential attachment.

Figure 12 shows sample results from the implementation of the model in NetLogo for the first 4 network structures listed. All samples come from the same evolutionary Stag Hunt game with $R = -1.012$ (i.e. “hunt stag” is the risk dominant strategy). A preliminary assessment of the significance of the WALM of risk dominance and the topology suggests that central nodes in *rich-get-richer* networks have a significant effect on what strategy dominates evolution.



generation = 0

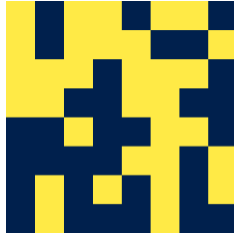


generation = 1



convergence at generation = 10

a) Network 1. Toroidal square lattice with von Neumann neighborhood



generation = 0

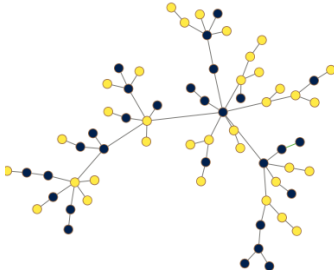


generation = 1

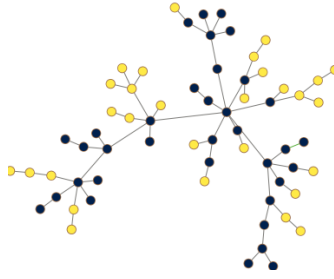


convergence at generation = 3

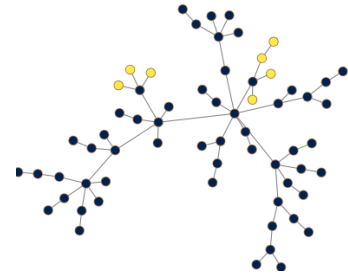
b) Network 2. Toroidal square lattice with von Neumann neighborhood



generation = 0

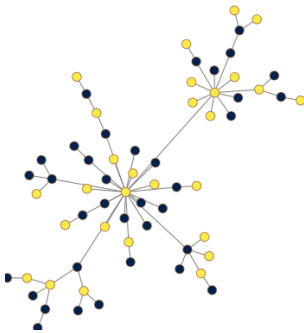


generation = 1

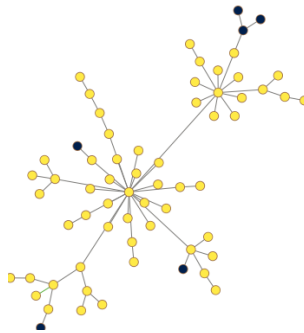


convergence at generation = 4

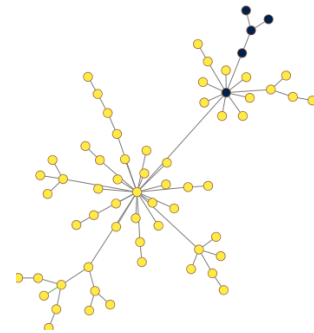
c) Network 3. Random graph with no preferential attachment



generation = 0



generation = 1



convergence at generation = 4

d) Network 4. Rich-get-richer graph

Figure 12. Sample results from evolutionary game with normalized payoffs.

Sample results include $N = 64$ agents with $S = -0.100$ and $T = 0.725$ ($R = -1.012$) using toroidal square lattices: a) with von Neumann neighborhood and b) with Moore neighborhood; and random graphs: c) with no preferential attachment and d) with preferential attachment or *rich-get-richer* behavior.

MONTE CARLO EXPERIMENT

The values of S and T are varied between $[-3, 0)$ and $(0, 1)$, respectively—within the Stag Hunt game region—and the values of R computed using Eq. (1). The model is run 1,000 times for each combination of S and T and network structure. Hare-hunters and stag-hunters are randomly distributed in the network in every run approximately equal number of initial agents of each type. Table 9 summarizes the degree distribution (i.e. number of neighbors per node) of each network. The toroidal square lattice and fully connected network structures are constant. The degree of the random networks is variable, ranging from $m = 1$ to around 7 and 17 for the random and preferentially attached graphs, respectively. Figure 13 shows S – T plots of the batch simulation results for average percentage of stag-hunters, its standard deviation, and the average number of runs/generations to convergence for each of the network structures assessed.

Table 9. Degree Distribution of Generated Networks

Network structure ($N = 64$)	Average Network Degree		
	min	mean	max
1. Toroidal square lattice with von Neumann neighborhood	4.00	4.00	4.00
2. Toroidal square lattice with Moore neighborhood	8.00	8.00	8.00
3. Random graph (no preferential attachment)	1.00	1.97	6.77
4. Rich-get-richer graph (preferential attachment)	1.00	1.97	16.87
5. Complete graph	63.00	63.00	63.00

FINDINGS

These results emphasize two key items. First, behaviors of simulated agents in the evolutionary game (stochastically stable strategies) with imitation dynamics are not precisely predicted by the sign of the WALM of risk dominance in network structural models where information exchange between agents is partial (namely, lattices and random graphs). Conversely, the sign of the WALM *does* predict strategy selection in the fully connected network model in a single round/generation. This makes sense because the WALM risk dominance sign prescribes the best strategy only in a single-shot game where each player does not have prior knowledge about the others' strategies, which is also a characteristic of the proposed model in its initial state. The evolutionary dynamics in this simulation provide a means for communication through repeated interactions and learned behaviors through the replicator dynamics mechanism, thus are probably more representative of real-world interactions and decisions.

While the sign of the WALM risk dominance score is not predictive of stochastically stable strategies, the relative score is predictive, subject to some interesting effects of S and T . Results in Figure 13 show low values of R result in stag-hunting populations and very high values of R result in hare-hunting populations. However, the delineation or threshold line between the two populations is not a linear a function of R , it is better described as a function of S and T as discussed above. This surprising result warrants additional investigation to identify if there is a feature about the gridscape, interaction mechanism, or evolutionary dynamics that give rise to this behavior.

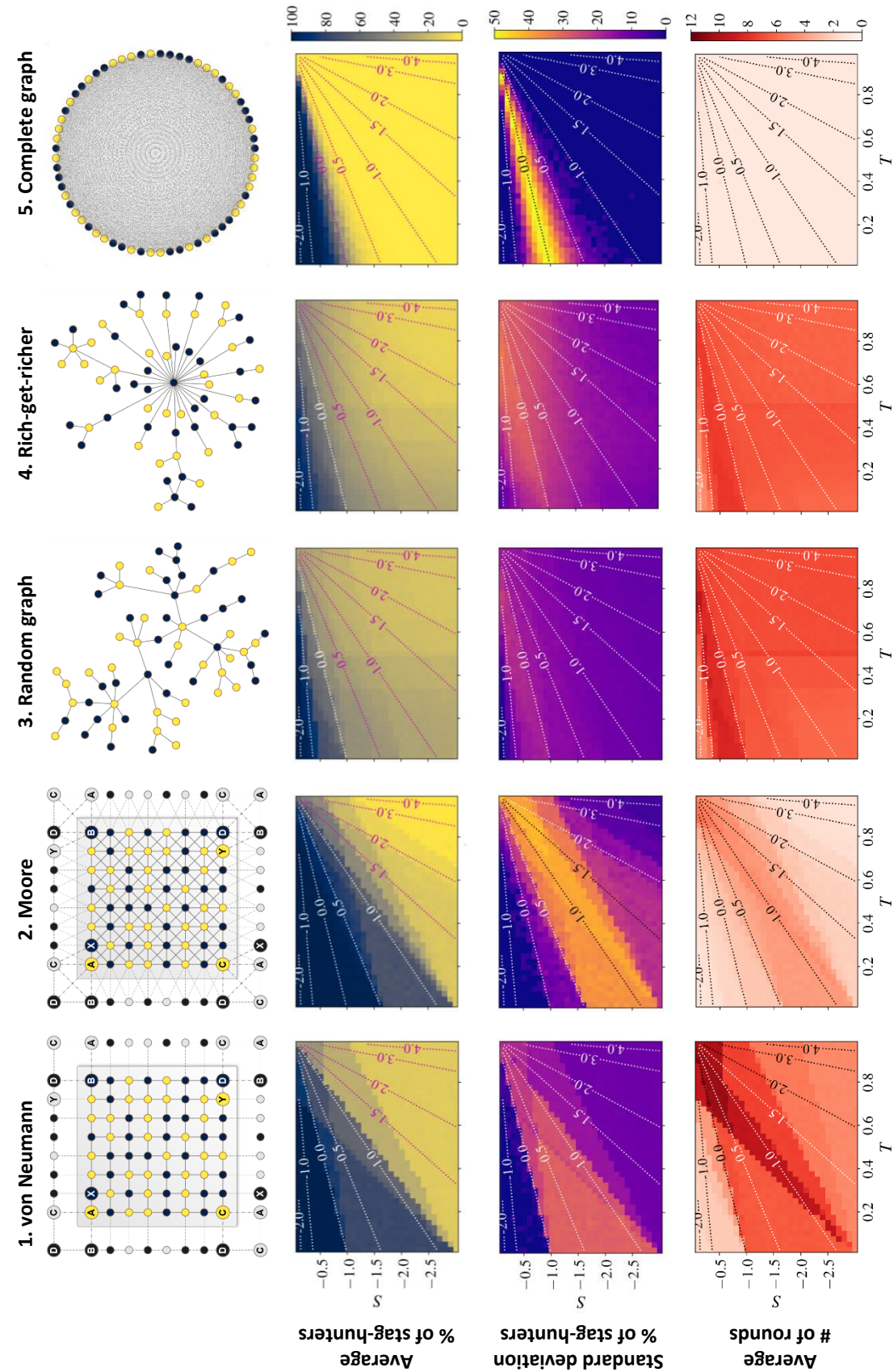


Figure 13. Results of multi-agent validation simulation.
Percentage of stag-hunters and number of generations to convergence for selected network structures and imitation dynamics (1,000 runs). Contour lines show values of R as a function of S and T .

APPLICATION CASE: JOINT POLAR-ORBITING SATELLITE PROGRAMS

This section introduces an application case to demonstrate risk dominance analysis as applied to a real-world decision to pursue a collaborative system architecture. The selected context builds on the National Polar-orbiting Operational Environmental Satellite System (NPOESS), a joint space program proposed to replace independent programs operated by the U.S. Department of Defense (DoD) and National Oceanic and Atmospheric Administration (NOAA). The NPOESS program was ultimately canceled after more than 15 years of development effort due to excessive cost overruns. Although the majority of existing academic literature attributes poor program performance to intense technical complexity; strategic dynamics may also play a role if agencies exhibit unbalanced objectives. This application case develops a multi-actor value model and a strategic design game around a decision similar to forming the NPOESS program to demonstrate how risk dominance can reveal underlying strategic dynamics.

BACKGROUND AND PROBLEM STATEMENT

The National Polar-orbiting Operational Environmental Satellite System (NPOESS) was a joint space program established by a presidential directive in May 1994 to field a single converged polar-orbiting satellite system (White House, 1994). It proposed to combine capabilities from three U.S. agencies:

1. *National Oceanic and Atmospheric Administration (NOAA)* operated the Polar-orbiting Operational Environmental Satellite (POES) program to collect atmospheric data for weather forecasting, climate research, and search-and-rescue assistance,
2. *U.S. Department of Defense (DoD)* operated the Defense Meteorological Satellite Program (DMSP) to collect visible and infrared data to support military operations, and
3. *National Aeronautics and Space Administration (NASA)* developed new instrument and spacecraft technologies as a part of its Earth Observing System (EOS).

Motivation for a merged NPOESS program aimed to replace existing POES and DMSP satellites with three polar-orbiting spacecraft, anticipated to save \$1.8 billion over the program lifecycle (Hinnant et al., 2001). As an initial mission to transfer functionality from EOS for NPOESS, the NPOESS Preparatory Project (NPP) aimed to demonstrate four new sensors including the Visible Infrared Imaging Radiometer Suite (VIIRS) (Murphy, 2006). However, NPP ultimately triggered three Nunn-McCurdy reviews due to excessive budget and schedule overruns (U.S. GAO, 2007). By February 2010 the White House announced the NPOESS program would be cancelled and separate satellite systems would be fielded for civilian and military programs.

Studies on interagency collaboration identify significant risks for joint programs, frequently leading to excessive cost and schedule growth (NRC, 2011). Other research hypothesizes joint programs exhibit high levels of technical complexity as a significant cost driver using the NPOESS program as a primary application case (Dwyer, 2015). Strategic tensions including actions to retain or regain autonomy may further drive cost growth (Dwyer et al., 2018). Existing approaches characterize risk as cost uncertainty; however, the design framework developed in

this project contributes a new game-theoretic approach based on risk dominance and stability of decisions under strategic dynamics among multiple design actors. Specifically, it hypothesizes the joint alternative *could* provide greater benefit to all parties; however, the potential losses attributed to risk of coordination failures influence decisions and lead to joint program coordination failures and ultimate selection of independent alternatives.

This application case investigates the strategic dynamics of the NPOESS design scenario using the concepts of risk dominance to understand how game-theoretic analysis can contribute to joint program architecture evaluation. This analysis does **not** aim to revisit or directly re-evaluate the 1994 decision to establish a joint program but instead considers a hypothetical parallel decision process influenced by the historical record. Some of the major deviations from the real NPOESS scenario are driven by architecture and technology evolution over the past 20 years, simplified models to evaluate architecture performance, and approximates of actor value preferences based on historical documentation.

DESIGN SCENARIOS

The design scenario considers a decision similar to that in 1994 to either pursue a joint polar-orbiting space system with cooperating agencies NOAA and DoD or continue independent programs. This scenario results in a strategic design game illustrated in Table 10.

Table 10. NPOESS Strategic Design Game

DoD	NOAA	
	Independent System	Joint System
Independent System	DMSP POES	DMSP NPOESS*
Joint System	DMSP* POES	NPOESS NPOESS

There are three alternative space system architectures to consider:

- **National Polar-orbiting Operational Environmental Satellite System (NPOESS)** - architecture envisioned for a successful collaborative system evaluated by both actors.
- **Defense Meteorological Satellite Program (DMSP)** - architecture for an independent system based on the prior DMSP program evaluated by a single actor.
- **Polar-orbiting Operational Environmental Satellites (POES)** - architecture for an independent system based on the prior POES program evaluated by a single actor.

Additionally, two adjusted architectures NPOESS* and DMSP* blend characteristics of joint and independent architectures. NPOESS* represents the same functional architecture as NPOESS but levies the full program cost on NOAA as a single partner. DMSP* represents the same functional architecture as DMSP but levies a partial program cost for NPOESS on DoD as expenditures towards a failed joint system. Note that the historical outcome (i.e. pursuing a joint program but dissolving it after more than a decade) is not represented by any of these scenarios. This analysis abstracts the decision to pursue a joint program to a single-shot game rather than the repeated

interactions that take place in real programs. The goal of analysis is to inform the desirability for a joint architecture in advance of committing significant resources.

Each of the five architectures above (DMSP, POES, NPOESS, DMSP*, and NPOESS*) is linked to a curated technical description to characterize satellite orbits, instruments, and ground networks. The resulting architectures merge historical data with synthetic information to harmonize systems designed and operated over more than two decades. The following sections discuss the historical perspectives for the constituent programs: DMSP, POES, and NPOESS.

DEFENSE METEOROLOGICAL SATELLITE PROGRAM (DMSP)

The Defense Meteorological Satellite Program (DMSP) was one of the first environmental satellite constellations and the DoD's satellite constellation in low earth orbit, originally intended for mission-critical military information. The program was developed to provide important weather information to American troops around the globe. Similar to POES, the civilian counterpart, DMSP was developed in the 1960s by the U.S. government. However, with a large budget allocated to the civilian POES, the DMSP was initially kept secret in fear that the U.S. government would not support two simultaneous weather-related space system projects and to protect new technology used in critical military missions.

DMSP's first successful launch was in 1962 and its last in 2014. The DMSP constellation was divided into Blocks with common busses. Blocks 1 through 5C spanned from 1962 to 1976 with 39 launches. Most of launches were short missions of less than two years or even as short as two or three months. Additionally, a significant fraction of launches ended in failures during orbit insertion, separation, or launch phases due to limitations in launch vehicle technology.

Block 5D is broken into three groups: group 1 from 1976 to 1980, group 2 from 1982 to 1997, and group 3 from 1999 to 2014. Group 3 is most parallel to that of POES with mostly successful satellite launches. Focusing on this group also allows for a concentration on the new line of DMSP instruments fully supported on missions F-16 to F-20. These instruments include:

- OLS: Operational Linescan System,
- SSMIS: Special sensor microwave imager/sounder,
- SSI/ES-3: Special sensor for ions, electrons, and scintillation,
- SSJ5: Special sensor for precipitating particles,
- SSM-Boom: Special sensor magnetometer - boom,
- SSULI: Special sensor ultraviolet limb imager,
- SSUSI: Special ultraviolet spectrographic imager, and
- SSF: Special sensor F.

The OLS instrument has flown on all missions in Block 5D1. It monitors clouds and cloud top temperatures using a low-resolution global and high-resolution regional imagery. Data products record a 3,000-kilometer swath width with satellite ephemeris, solar, and lunar information. Ground pixels measure 0.55 kilometers at high resolution and 2.7 kilometers at low resolution, approximately the mean of 25 high-resolution values (Data.gov, 2015).

The SSMIS instrument has flown on missions since Block 5D2 F-4 with versioning updates to F-16 where it is now most up to date. It provides atmospheric temperature and humidity profiles along with surface environmental parameters such as ocean wind speed and rain rates (Bommarito, 1993).

The SSI/ES instrument has flown on almost all missions in Block 5D with three version changes. It measures the environmental state in near-Earth space including thermal plasma, ionospheric electrons, and the electric potential between the plasma and the spacecraft (Rich, 1994).

The SSJ instrument has flown on all Block 5D missions with versions 3, 4, and 5. It includes a pair of nested electrostatic analyzers to measure auroral particles as a major source of ionospheric energy (Oberhardt et al. 1994).

SSM-Boom measures geomagnetic fluctuations associated with ionospheric currents at high latitudes and helps understand heating and dynamics of high-latitude ionosphere and atmosphere (Chatters and Medina, 2009).

SSULI is an imaging spectrometer that observes the earth's ionosphere and thermosphere. It measures vertical intensity profiles of airglow emissions in the extreme ultraviolet and far ultraviolet spectral range (Milazzo et al., 1998).

SSUSI is a spectrographic imaging and photometric system that measures ultraviolet emissions from the Earth's upper atmosphere related to high frequency communications and environmental hazards to astronauts on the International Space Station (JHU/APL, 2018).

SSF completed on-orbit testing and extensive calibration in 2004. It provides laser-threat warning for its host satellite to detect laser illumination, characterize wavelength and incident energy, and determine location of origin (Chatters and Medina, 2009).

Congress terminated the DMSP program in 2015, including the Block 5D-3/F20 satellite nearing the end of production, to move to a new satellite constellation program, the Weather System Follow-on (WSF). The WSF constellation will feature advanced instruments and will allow for the agency to move away from the long-running DMSP architecture while retaining focus on ocean surface vector winds, tropical cyclone intensity, and spaceborne energetic charged particles. The WSF plans to include three satellites; however, only two satellites will be placed into LEO. The third satellite, WSF-G, will be a repositioned NOAA GEO satellite.

Data in Table 11 characterizes constellation parameters for DMSP using information from the WMO OSCAR (2019). Note that all spacecraft fly in a sun-synchronous orbit at approximately 850 kilometers mean altitude. Two spacecraft are typically operational at a given time with early morning and morning equatorial crossing times (ECT).

Table 11. DMSP Block 5D-3 Constellation Parameters

Spacecraft	Launch Date	Instruments	Mass (kg)	Power (W)	Altitude (km)	Nominal ECT
F-15	12/12/1999	OLS, SSM/I, SSJ/4, SSI/ES-2, SSM-Boom, SSZ	1220	2200	850	AM
F-16	10/18/2003	OLS, SSMIS, SSI/ES-3, SSJ5, SSM-Boom, SSULI, SSUSI, SSF	1220	2200	848	AM
F-17	11/4/2006	OLS, SSMIS, SSI/ES-3, SSJ5, SSM-Boom, SSULI, SSUSI, SSF	1220	2200	848	Early AM
F-18	10/18/2009	OLS, SSMIS, SSI/ES-3, SSJ5, SSM-Boom, SSULI, SSUSI, SSF	1220	2200	850	AM
F-19	4/3/2014	OLS, SSMIS, SSI/ES-3, SSJ5, SSM-Boom, SSULI, SSUSI, SSF	1220	2200	850	AM

Table 12. DSMP Block 5D-3 Instrument Parameters

Instrument	Type	Mass (kg)	Power (W)	Channels	Swath (km)	Data Rate (Mbps)
OLS	Optical Imager	25	170	3	2960	0.26
SSMIS	Microwave Radiometer	96	135	24	1700	0.01
SSUSI	Space Spectrometer			n/a	n/a	
SSULI	Space Spectrometer			n/a	n/a	
SSI/ES-3	Radiowave Sensor			n/a	n/a	
SSM-Boom	Radiowave Sensor			n/a	n/a	
SSJ5	Particle Spectrometer			n/a	n/a	

POLAR-ORBITING OPERATIONAL ENVIRONMENTAL SATELLITES (POES)

The Polar Operational Environmental Satellites (POES) program was a weather satellite constellation developed and funded through the National Oceanic and Atmospheric Administration (NOAA) as a civilian weather analysis and forecasting satellite constellation. It started in 1960 with the launch of TIROS-1 (Television Infrared Observation Satellite) and continued through TIROS-10. Missions included operational durations less than two years and often ended in failure. Only TIROS-9 and 10 entered near-polar orbits. Closely related to TIROS, the Environmental Science Services Administration (ESSA) satellite program launched satellites between 1966 and 1969, providing service for a maximum of three years.

Starting in 1979, the POES satellites began a new naming convention starting with NOAA-6. This lasted until the program's integration into NPOESS after the launch of NOAA-19 in 2009. Satellites NOAA-8 through NOAA-19 can be divided into three groups: the ATN (Advanced TIROS-N) series of NOAA-8 E to NOAA-14 J; KLM (simply named for the alphabetic order of the satellites) series of NOAA-15 K, NOAA-16 L, NOAA-17 M, and the final two satellites NOAA-18 N and NOAA-19 N'. NOAA instruments also flew on EUMETSAT (Exploitation of Meteorological Satellites) METOP (Meteorological Satellites) missions A, B, and C, launching in 2006, 2012, and 2018 respectively.

The satellites from NOAA-15 through NOAA-19 are collectively described as the 5th generation series and provide a more direct comparison in terms of time and technology to the DMSP Block 5D group 3 satellites. These satellites generally contained the following instruments:

- AVHRR/3: Advanced very high resolution radiometer, version 3,
- ATOVS: Advanced TIROS operational vertical sounder, composed of:
 - HIRS/4: High resolution infrared radiation sounder, version 3,
 - AMSU-A/B: Microwave sounding unit A and/or B, and
 - MHS: Microwave humidity sounder,
- SEM-2: Space environment monitor,
- ARGOS (DCS-2): Argos advanced data collection system, and
- S&RSAT: Search & rescue satellite-aided tracking system.

The only exceptions are that the KLM series flew with HIRS/3 over the newer HIRS/4 and AMSU-B (microwave sounding unit B) over the newer MHS.

The AVHRR imager measures global cloud cover, sea surface temperature, ice, snow and vegetation (EUMETSAT, 2019). While it has six channels in the visible and infrared, only five channels are used in NOAA spacecraft. It uses a cross-track scanner with a 55-degree half-angle field of view to cover a swath width of approximately 1450 kilometers with a 1.1-kilometer ground resolution.

The HIRS/4 is an atmospheric sounding instrument that measures temperature profiles, moisture content, cloud height, and surface albedo (EUMETSAT, 2019). It includes 20 spectral bands in visible (1), shortwave infrared (7), and longwave infrared (12) channels with a 1.3 to 1.4-degree instantaneous field of view producing a ground resolution of about 20 kilometers.

AMSU-A is a microwave radiometer that measures scene radiance in 15 frequency channels between 23 to 90 GHz to measure atmospheric water except small ice particles (EUMETSAT, 2019). It provides a 50-degree field of view half angle and 2,074-kilometer swath width for 48-kilometer ground resolution. AMSU-B has five microwave channels including one at 89 GHz, one at 150 GHz, and three at 183 GHz (EUMETSAT, 2019). It measures the water vapor profile in the troposphere and lower stratosphere with a 17-kilometer ground resolution.

MHS is a microwave radiometer with five channels between 89 and 190 GHz (EUMETSAT, 2019). It measures low-altitude water vapor, clouds, and precipitation, surface temperature and emissivity, and water vapor profiles at higher altitudes. It has a 1920-kilometer swath width and a ground resolution of approximately 16 kilometers.

SEM-2 measures the intensity of charged particle radiation within the upper atmosphere (EUMETSAT, 2019). Charged particle radiation can disrupt radio communications, spacecraft operation, and threaten astronauts aboard the International Space Station.

A-DCS manages data uplink and downlink to and from the spacecraft. Additionally, it can locate objects on the Earth surface using Doppler shift calculations, useful for monitoring ocean buoys and wildlife with trackers (EUMETSAT, 2019). Finally, S&RSAT locates the source and relays distress signals using several emergency frequencies.

Data in Table 13 characterizes constellation parameters for NOAA POES using information from the WMO OSCAR (2019). Note that all spacecraft fly in a sun-synchronous orbit at approximately

830- or 870-kilometer mean altitude. Two or more spacecraft are operational at a given time with morning (AM) and afternoon (PM) equatorial crossing times (ECT).

Table 13. NOAA POES 5th Generation Constellation Parameters

Spacecraft	Launch Date	Instruments	Mass (kg)	Power (W)	Altitude (km)	Nominal ECT
NOAA 15	5/13/1998	AMSU-A, AMSU-B, AVHRR/3, HIRS/3, S&RSAR, DCS/2, SEM	2232	833	813	AM
NOAA 16	9/21/2000	AMSU-A, AMSU-B, AVHRR/3, HIRS/3, S&RSAR, SBUV/2, DCS/2, SEM	2232	833	849	PM
NOAA 17	6/24/2002	AMSU-A, AMSU-B, AVHRR/3, HIRS/3, S&RSAR, SBUV/2, DCS/2, SEM	2232	833	810	AM
NOAA 18	5/20/2005	AMSU, AVHRR/3, HIRS/4, MHS, S&RSAR, SBUV/2, DCS/2, SEM	2232	833	854	PM
NOAA 19	2/6/2009	A-DCS, AMSU, AVHRR/3, HIRS/4, MHS, S&RSAR, SBUV/2, SEM	2232	833	870	PM

Table 14. NOAA POES 5th Generation Instrument Parameters

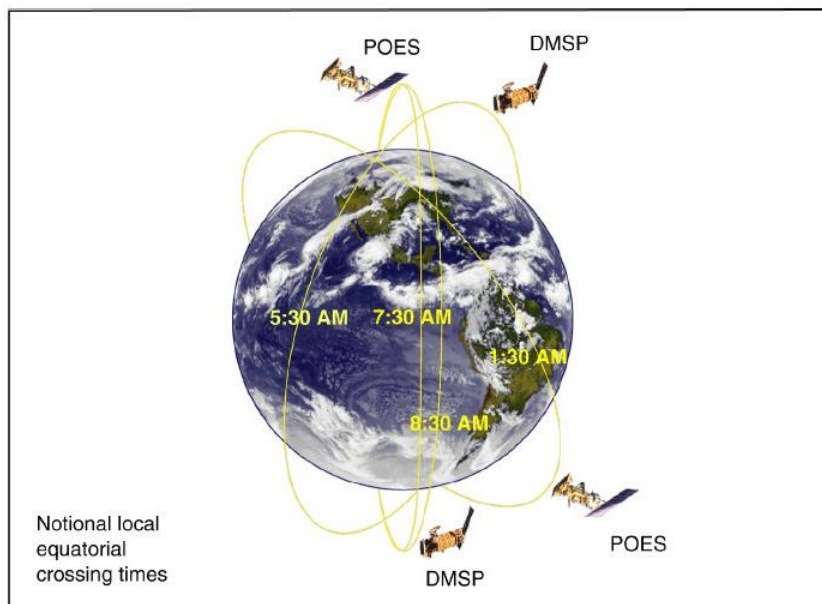
Instrument	Type	Mass (kg)	Power (W)	Channels	Swath (km)	Data Rate (Mbps)
A-DCS	Data Collection System	30	72	n/a	n/a	0.005
AMSU-A	Microwave Radiometer	104	99	15	2250	0.003
AVHRR/3	Optical Imager	33	27	6	2900	0.6
HIRS/4	Infrared Sounder	35	24	20	2200	0.003
MHS	Microwave Radiometer	63	93	5	2180	0.004
S&RSAT	Search and Rescue	52	86	n/a	n/a	0.002
SBUV/2	Shortwave Sounder	40	17	12	170	0.0003
SEM	Particle Spectrometer			n/a	n/a	

NATIONAL POLAR-ORBITING ENVIRONMENTAL SATELLITE SYSTEM (NPOESS)

The National Polar-orbiting Operational Environmental Satellite System (NPOESS) was a government space program established in 1994 and dissolved in 2010. It intended to produce a near-space environment monitoring satellite system to gather information about the Earth's weather, atmosphere, oceans, and land to combine two existing U.S. polar-orbiting satellite programs: DoD's DMSP and NOAA's POES. Additionally, NPOESS would integrate NASA's new Earth Observing System (EOS) instruments launched on two previous satellites—Terra and Aqua—to better analyze the atmosphere and oceans. Terra has five onboard sensors designed to monitor the Earth's environment and changes to climate. Aqua contains six sensors to study water in the Earth's atmosphere and surface.

Between 1972 and 1994, eight government studies evaluated the convergence of DoD and NOAA polar-orbiting programs but did not proceed due to unique agency missions and requirements (U.S. GAO, 1994). However, changing geopolitical environments after the end of the Cold War demanded a closer look at cost saving measures and a tri-agency team from the DoD, NOAA, and NASA developed a single integrated requirements document for a converged satellite system (U.S. GAO, 1994). A review led by Gore realized that there was significant overlap in the two satellite programs and called for an effort to reduce duplication of efforts and increase cost-

savings. In 1994, Clinton signed a Presidential Decision Directive and converged polar-orbiting satellites into one system (White House, 1994). The directive took notice of the three agencies operating polar-orbiting environmental systems in separate arms of the U.S. government. Furthermore, the program would produce three orbits in the joint venture, rather than an originally planned two civilian and two military satellites in Figure 14.



Source: NPOESS Integrated Program Office.

Figure 14. Geometric configuration of DMSP and NOAA POES polar satellites.

The initial NPOESS goal was to transition from two overlapping projects from different agencies to a five- or six-satellite joint-agency constellation. As the replacement and unifying system for previous programs, NPOESS required the collaboration of the DoD, NASA, and NOAA. An Integration Program Office (IPO) was established to coordinate the project. Each organization would be responsible for the design, planning, management, and funding of different portions of the project. In return, they would collaboratively save resources while still producing satellites equal to or greater than individually possible. In an effort to further collaboration both internally and internationally, the U.S. organizations were also encouraged to work with its European partners to try and include the METOP series of satellites. Similar to NASA's EOS, the METOP series was a part of the European Organization for the Exploitation of Meteorological Satellites (EUMETSAT) polar system for observations of the atmosphere, oceans, and continents. EUMETSAT uses METOP-A, METOP-B, and METOP-C to cover an orbital plane separate from that of the planned POES series of satellites.

The NPOESS mission initialized significant development effort for sensor research and creation supporting many environmental data records (EDRs) listed in Figure 15 (Haas and Swenson, 2001). In 1997, the NPOESS IPO awarded 18 contracts for sensor development for nine sensors. The IPO planned to have the contractors complete the initial phase of development in parallel for competition. These sensors include:

- Visible Infrared Imaging Radiometer Suite (VIIRS) contracted to Raytheon,

- Conical Microwave Imager/Sounder (CMIS) contracted to Ball Aerospace and Boeing,
- Cross-track Infrared Sounder (CrIS) contracted to ITT Corporation,
- Ozone Mapper/Profiler Suite (OMPS) contracted to Ball Aerospace, and
- Global Positioning System Occultation Sensor (GPSOS) contracted to Saab - Ericsson.

Atmospheric Vertical Moisture Profile	Cloud Top Pressure	Precipitable Water
Atmospheric Vertical Temp Profile	Cloud Top Temperature	Precipitation Type/Rate
Imagery	Downward Longwave Radiance (Sfc)	Pressure (Surface/Profile)
Sea Surface Temperature	Downward Shortwave Radiance(Sfc)	Sea Ice Characterization
Sea Surface Winds	Electric Fields	Sea Surface Height/Topography
Soil Moisture	Electron Density Profile	Snow Cover/Depth
Aerosol Optical Thickness	Energetic Ions	Solar Irradiance
Aerosol Particle Size	Geomagnetic Field	Supra-Thermal - Auroral Particles
Aerosol Refractive Index	Ice Surface Temperature	Surface Type
Albedo (Surface)	In-situ Plasma Fluctuations	Surface Wind Stress
Auroral Boundary	In-situ Plasma Temperature	Suspended Matter
Auroral Energy Deposition	Ionospheric Scintillation	Total Water Content
Auroral Imagery	Medium Energy Charged Particles	Vegetation Index
Cloud Base Height	Land Surface Temperature	
Cloud Cover/Layers	Net Heat Flux	
Cloud Effective Particle Size	Net Solar Radiation (TOA)	
Cloud Ice Water Path	Neutral Density Profile	
Cloud Liquid Water	Ocean Color/Chlorophyll	
Cloud Optical Thickness	Ocean Wave Characteristics	
Cloud Particle Size/Distribution	Outgoing Longwave Radiation (TOA)	
Cloud Top Height	Ozone - Total Column/Profile	

VIIRS	CMIS	CrIS/ATMS	OMPS	SES	GPSOS	ERBS	TSIS	ALT	CAPS
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Figure 15. NPOESS sensing capabilities by sensor.

VIIRS was the first instrument developed under the NPOESS mission in the new push for advanced environmental monitoring and weather prediction. It is an imaging radiometer with 22 bands over visual and thermal infrared wavelengths to monitor clouds, sea surface temperature, ocean color, polar wind, vegetation fraction, aerosol, fire, snow and ice, vegetation, and other phenomena.

CMIS is a passive microwave imager and sounder operating in the 6 to 250 GHz region. It provides global, all-weather measurements of atmospheric, land, and sea phenomena disseminated to military, civil, and international users throughout the world.

OMPS is a hyperspectral shortwave sounder that measures the global distribution of total atmospheric ozone column on a daily basis and the vertical distribution of ozone between 15 and 60 kilometers on a less frequent basis. A cross-track mapper operates between 200 and 380 nanometers with a 1 nanometer spectral resolution and a nadir ozone profiler operates between 250 and 210 nanometers.

NPOESS was more than just collaboration between multiple organizations—the contracted NPOESS instruments pushed technical boundaries and significantly increased the types of data and images that could be collected from satellites. Early development phases established the NPOESS Preparatory Project (NPP) to produce a new satellite that would serve as a bridge

between the existing satellites while demonstrating new instrument technology, instruments, and on-board satellite processing capabilities. However, many additional costs plagued NPOESS during instrument development. For example, the VIIRS instrument alone added over \$300 million in additional costs in one year related to testing incidents. Screw heads were sheared off and the entire instrument had to be disassembled, resulting in criticisms from Congress after the NOAA informed them of the incident.

Due to extreme cost overruns, NPOESS went through three Nunn-McCurdy reviews which are congressional hearings required when a project is 25% or more over budget. A Nunn-McCurdy review in 2006 restructured the NPOESS program by reducing key space segment capabilities (National Research Council, 2008; U.S. Committee on Science, 2006). NPOESS was reduced from six satellites in three orbits to four satellites in two orbits. Additionally, five climate sensors were completely removed from the scope and were only allowed to fly in orbit outside NPOESS. Four other instruments were reduced in their coverage or capability to reduce costs.

By 2008, the joint cost of NPOESS had grown to \$13.6 billion, with the Department of Defense asking for \$289.5 million for the following year, and NOAA asking for \$288 million. Finally, NPOESS was terminated in 2010 after a turbulent program history due to "conflicting perspectives and priorities among the three agencies who manage the program," resulting in a return to individual development for polar-orbiting satellite systems (White House, 2010). NOAA/NASA would operate a Joint Polar Satellite System (JPSS) consisting of JPSS-1 (now NOAA-20), launched in late 2017, and JPSS-2, planned for launch in 2022. The DoD initiated the Defense Weather Satellite System (DWSS) in 2010 but canceled it in 2012 and started awarding contracts in 2017 for the Weather System Follow-in (WSF).

After NPOESS, NASA and NOAA continued a joint program with NPP (now known as the Suomi National Polar-orbiting Partnership) and JPSS-1 launches. Despite development issues, VIIRS was ultimately launched on the Suomi NPP satellite in 2011. This weather satellite, operated by NOAA, contains four other instruments to capture images and data for major hurricanes, atmospheric aerosols, and large fires. Although the satellite is considered a success, it was launched almost two years after NPOESS was dissolved and is now a part of the NOAA/NASA Joint Polar Satellite System (JPSS). The joint project also plans to launch JPSS-2 through 4 and a solar irradiance satellite in the future.

Data in Table 15 and

Table 16 characterizes constellation and instrument parameters for NPOESS using information from the WMO OSCAR (2019).

Table 15. NPOESS Constellation Architecture Parameters

Spacecraft	Launch Date	Instruments	Mass (kg)	Power (W)	Altitude (km)	Nominal ECT
SNPP	10/27/2011	ATMS, CERES, CrIS, OMPS, VIIRS	2270	2285	833	PM
JPSS-1 (NOAA 20)	11/18/2017	ATMS, CrIS, OMPS, VIIRS, SEM, CERES	2540	1932	834	PM

Table 16. NPOESS Instrument Parameters

Instrument	Type	Mass (kg)	Power (W)	Channels	Swath (km)	Data Rate (Mbps)
VIIRS	Scanning Radiometer	275	200	22	3060	5.9
CERES	Radiometer	55	50	3	3000	0.01
ATMS	Microwave Radiometer	85	130	22	2200	0.02
OMPS	Shortwave Sounder	56	120	n/a	2800	0.4
CrIS	Infrared Sounder	165	123	3	2200	1.5

DESIGN SCENARIO ANALYSIS

Analysis of this design scenario considers five alternative architectures:

- **DMSP** is an independent architecture for the DoD
- **POES** is an independent architecture for NOAA
- **NPOESS** as a joint architecture for the DoD and NOAA
- **DMSP*** is equivalent to DMSP but with added cost from a failed joint architecture if DoD pursues a joint architecture but NOAA pursues an independent architecture.
- **NPOESS*** is equivalent to NPOESS but as an independent architecture if NOAA pursues a joint architecture but DoD pursues an independent architecture.

This section performs analysis to measure five relevant attributes for stakeholder preferences:

1. **Cost:** quantity of resources required to support an architecture's satellite.
2. **Observations:** types of phenomena that can be observed by an architecture.
3. **Coverage:** frequency of observation at terrestrial points or regions of interest.
4. **Downlink:** available downlink capacity (normalized to ground station access duration).
5. **Latency:** time delay between downlink opportunities.

Each architecture scores differently on these five attributes and the corresponding actors (DoD and NOAA) have differing preferences for each attribute. Table 17 summarizes analysis results.

Table 17. Design Scenario Analysis Results

Architecture	Cost (FY2019 \$M)	Observations (#)	Coverage (minutes)	Downlink (hours)	Latency (minutes)
DMSP	434	57	82.7	254.1	70.1
POES	412	63	120.4	110.6	84.3
NPOESS	1300	179	117.2	380.9	31.9
DMSP*	1950	57	82.7	254.1	70.1
NPOESS*	2600	123	117.2	380.9	31.9

COST ANALYSIS

Cost metrics were calculated by reviewing budget sheets from NOAA, NASA, and the DoD. Costs are estimates because: 1) some reference missions are on-going and costs will continue to rise, 2) cost has changed drastically over time with advances in technology, and 3) prior projects have been subject to major programmatic changes over time. However, with all of this in mind, budgets for each mission were gathered over the past few decades and the resulting cost was divided by the number of satellites launched during that time span to provide a fair estimate across the various missions.

DMSP budget figures were retrieved from 2003 to 2016 and combined with the F16, F17, F18, and F19 launch costs to create a mission cost figure. This figure was then divided by four, the number of launched satellites during the time figure, to create the cost metric.

POES budget figures were retrieved from 2005 to 2011 and combined with the NOAA 18 and NOAA 19 launch costs to create a mission cost figure. This figure was then divided by two, the number of launched satellites during the time figure, to create the cost metric.

NPOESS budget figures were retrieved from 2007 to 2011 and combined with the S-NPP launch cost to create a mission cost figure. This figure was then divided by one, the number of launched satellites during the time figure, to create the cost metric. The joint architecture assumes equal shares of the total program cost.

OBSERVATION ANALYSIS

Observation metrics were gathered from the WMO OSCAR (2019) database about each instrument aboard the standard satellite for each mission. POES and DMSP carried a similar instrument set while NPOESS developed new and expensive instruments. The total number of observations for all of the instruments is used for the metric regardless of the overall relevance, effectiveness, or importance of the observation variable to the mission.

DMSP observation figures for the mission were retrieved from the following instruments:

- OLS Operational Linescan System (12),
- SSMIS Special Sensor Microwave - Imager/Sounder (22),
- SESS/SSUSI Special Sensor Ultraviolet Spectrographic Imager (5),
- SESS/SSULI Special Sensor Ultraviolet Limb Imager (7),
- SESS/SSI/ES-3 Special Sensor Ionospheric Plasma Drift/Scintillation Monitor - 3 (5),
- SESS/SSM-Boom Special Sensor Magnetometer - Boom (3),
- SESS/SSJ5 Special Sensor Precipitating Electron and Ion Spectrometer (3).

Observation figures for the POES mission were retrieved from the following instruments:

- AMSU-A Advanced Microwave Sounding Unit - A (13),
- AMSU-B Advanced Microwave Sounding Unit - B (11),
- AVHRR/3 Advanced Very High Resolution Radiometer / 3 (25),
- HIRS/3 High-resolution Infra Red Sounder / 3 (13),

- S&RSAT Search & Rescue Satellite-Aided Tracking System (0),
- DCS/2 Data Collection System / 2 (also called "Argos-2") (0),
- SEM/MEPED SEM / Medium energy proton detector (2),
- SEM/TED SEM / Total Energy Detector (2).

Observation figures for the NPOESS mission were retrieved from the following instruments:

- ATMS Advanced Technology Microwave Sounder (14),
- CERES Clouds and the Earth's Radiant Energy System (2),
- CrIS Cross-track Infrared Sounder (35),
- OMPS-limb Ozone Mapping and Profile Suite (12),
- OMPS-nadir Ozone Mapping and Profiler Suite (19),
- VIIRS Visible/Infrared Imager Radiometer Suite (41).

COVERAGE ANALYSIS

Coverage was modeled using an STK simulation in which two of the satellites from each mission were placed in orbit and simulated for one month. The coverage metric is calculated as the average time duration between sequential access periods across a list of points of interest. Points of interest for civilian missions are within the continental United States while points of interest for military missions are countries of high military deployment.

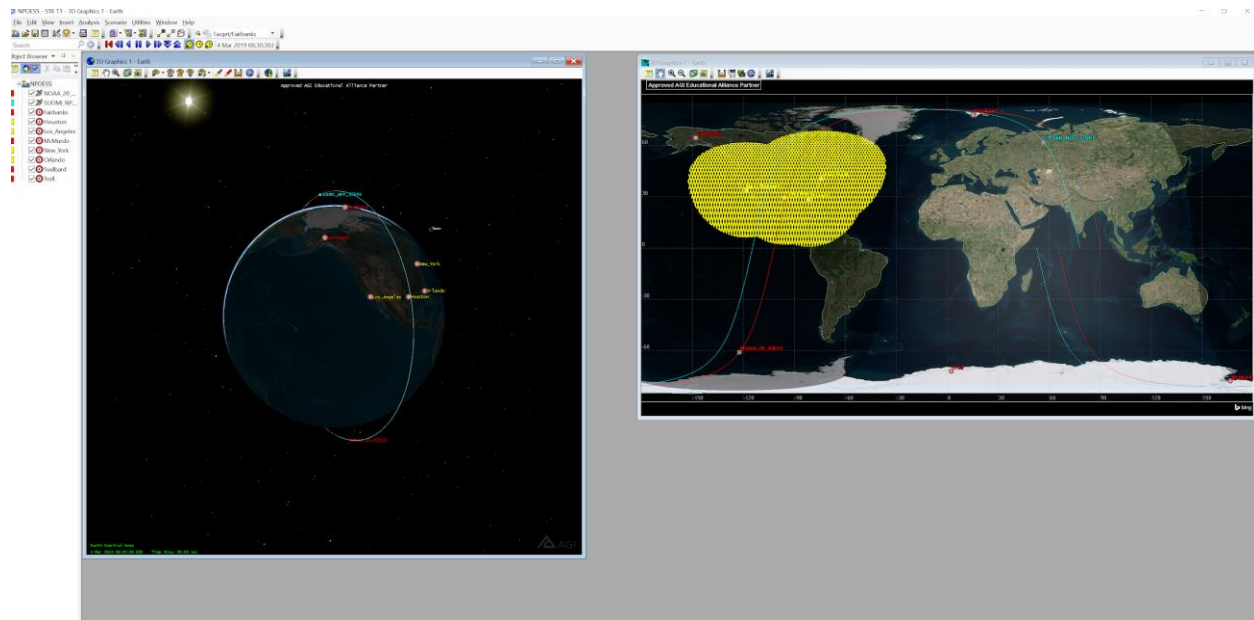


Figure 16. Example coverage simulation screenshot for NOAA POES mission.

DMSP coverage metrics mission were retrieved using high deployment countries (Japan, Hawaii, Germany, Alaska) in Table 19 and DMSP-F15 and DMSP-F16 with orbital elements in Table 18. At the time of these satellites being in orbit, they were in similar orbits following one another.

POES coverage metrics were retrieved using major cities (Orlando, New York, Los Angeles, Houston) in Table 19 and NOAA-16 and NOAA-17 in Table 18. At the time of these satellites being in orbit, they were in similar orbits following one another.

NPOESS coverage metrics retrieved using major cities (Orlando, New York, Los Angeles, Houston) in Table 19 and NOAA-20 and S-NPP in Table 18. At the time of these satellites being in orbit, they were in similar orbits following one another.

Table 18. Satellite Orbital Elements for Simulation Analysis

Satellite	Epoch	Eccentricity	Semimajor Axis (km)	Inclination (deg)	RAAN (deg)	Argument of Periapsis (deg)	Mean Anomaly (deg)
DMSP F-15	Sun, 12 Dec 1999 18:43:39 GMT	0.0005612	7223.46	98.8975	39.8677	333.8133	26.2786
DMSP F-16	Sat, 18 Oct 2003 17:22:39 GMT	0.0005981	7227.02	98.9284	325.346	270.3288	89.7198
NOAA-16	Sun, 11 May 2003 15:25:55 GMT	0.0011573	7231.35	98.9129	79.3798	75.6485	284.5968
NOAA-17	Sun, 11 May 2003 12:47:38 GMT	0.0012748	7187.80	98.7445	202.2552	117.6698	242.5775
NOAA-20	Sun, 03 Mar 2019 14:27:21 GMT	0.0000791	7205.02	98.7528	2.4235	102.4924	257.6341
S-NPP	Sat, 02 Mar 2019 21:00:25 GMT	0.0001233	7204.95	98.727	1.5739	111.5593	316.7742

Table 19. Points of Interest for Simulation Analysis

Point of Interest	Type	Latitude (deg)	Longitude (deg)
Japan	Military	36.704421256002355	137.47975753390352
Hawaii	Military	19.598830424167467	-155.51741066550923
Germany	Military	51.540646163878492	10.143047414118339
Alaska	Military	61.303475579948397	-151.69868226565984
Orlando	Civilian	28.538335499999999	-81.379236500000005
New York	Civilian	40.714269100000003	-74.005972900000003
Los Angeles	Civilian	34.052234200000001	-118.243684900000002
Houston	Civilian	29.763283600000005	-95.363271499999996

DOWNLINK AND LATENCY ANALYSES

The downlink and latency analyses are mostly a test of the constellation's ground network. The downlink metric is calculated by the total amount of time in contact with a ground station. The latency metric is calculated by the average amount of time between sequential downlink opportunities. The NPOESS ground networks utilize high inclination ground stations, making the downlink capability very high. Analysis does not evaluate whether the ground network is capable of offloading the entire payload captured between downlink availabilities.

DMSP downlink and latency metrics were retrieved using the ground network of Fairbanks, Hawaii, New Hampshire, and Thule in Table 20 and DMSP-F15 and DMSP F-16 in Table 18.

POES downlink and latency metrics were retrieved using the ground network of Fairbanks and Wallops in Table 20 and NOAA-16 and NOAA-17 in Table 18.

NPOESS downlink and latency metrics were retrieved using the ground network of Fairbanks, McMurdo, Svalbard, and Troll in Table 20 and NOAA-20 and S-NPP in Table 18.

Table 20. Ground Stations for Simulation Analysis

Ground Station	Latitude (deg)	Longitude (deg)
Fairbanks	64.858879089355483	-147.85411071777344
Hawaii	21.571903228759766	-158.26675415039063
New Hampshire	42.945590972900391	-71.629142761230469
Thule	76.515830993652344	-68.599998474121094
McMurdo	-77.846389770507827	166.66833496093750
Svalbard	78.229721069335938	15.407777786254881
Troll	-72.016670227050781	253.33330631256104

ACTOR PREFERENCES AND VALUE ANALYSIS

This section goes into depth on the information, research, and reasoning behind the assumed stakeholder preferences to value each architecture. Based on previous decisions, architectures, and public statements, a partial utility will be derived per actor per architecture.

DoD VALUE PREFERENCES

The DoD's main objective for satellite operations is to provide operational capabilities for the U.S. military. These provisions include, but are not limited to, communications, global positioning, reconnaissance, and meteorological information. DMSP only provided for one of these categories, but this section considers all preferences for related missions. The DoD currently operates a large network of satellites, most notably: Global Positioning System (GPS), DMSP, Defense Satellite Communications System (DSCS), National Reconnaissance Office (NRO) satellites, and Wideband Global SATCOM (WGS).

Coverage and Latency

The DoD operates troop deployments globally. Additionally, these troop deployments can be fixed at a base or mobile via land, air, sea, and even drone such that weather and communications data must be global. Even if current troop deployments are not fully global, the operational readiness still requires that global coverage is achieved.

Unlike NOAA, the DoD is unlikely to cooperate with international agencies. This reasoning is from the nature of military operations, as well as the DoD's history. First, the DoD seldom relies on another nation for military operations to guard against fallout of an international relationship or

foreign leadership. Secondly, the DoD has historically operated satellite missions independently, most likely due to the same reasoning as well as secrecy.

For these reasons, the Department of Defense is completely interested in global coverage and would have a hard time settling for anything less. Gaps in global coverage could lead to the compromise of the entire dataset. For similar reasons, the DoD is very interested in providing results to troop operations in a timely fashion.

Downlink and Observations

Downlink and observation metrics are connected through the reasoning that having more instruments yields more observational capacity, and more capacity requires more downlink time. All current meteorological satellites require raw data downlink to ground stations to post-process information.

The DoD has operated many communications and reconnaissance satellites but none of which help to determine observational capacity. Prior to NPOESS, DMSP had a similar range of observations to that of POES. During NPOESS, the number of instruments and observations was planned to be about three times more numerous. After NPOESS, the DoD's contract for WSF-M was very specific and narrow in its instrument and observational capacity. Additionally, to replace the NPOESS program, the Department of Defense planned on taking on an old GOES geostationary satellite to supplement (Keller, 2018). This leads to the assumption that the DoD is content without the cutting-edge advancement in observations and instruments that NOAA requires for research and is just requiring that basic meteorological forecasting be done.

Cost

The DoD budget is nearly 200 times larger than that of NOAA at \$720 billion (U.S. DoD, 2019). However, stemming from the conclusion that DoD satellites contain less advanced instruments of that of NOAA, its meteorological satellites have been on par or lower cost than that of NOAA. Additionally, after cost overruns broke up the NPOESS collaboration, the DoD went after cost saving measures of using a previously used GOES satellite, and a relatively low budget contract for WSF-M. For the reason of a comparatively large budget, the assumption is that the DoD has the ability to pay for high cost satellites such as Advanced Extremely High Frequency (AEHF) and GPS-III but would much prefer a less expensive alternative for meteorological applications.

NOAA VALUE PREFERENCES

NOAA is an agency of the American government that focuses on the environment both within the U.S. and globally. The agency is publicly funded through the Department of Commerce, fundamentally signaling its purpose to ensure and protect the U.S. economy. More specifically, the agency aims to warn about catastrophic weather events, atmospheric/oceanic changes, and changes in coastal resources. NOAA's core roles conduct scientific research on the environment, providing forecasting research products to the public and managing environmental resources and ecosystems as a result of these forecasts.

NOAA's positions on the following architecture selections was derived from previous, current, and future satellite missions, as well as their goals and international collaboration. NOAA currently operates the following satellites: NOAA-15, NOAA-18, NOAA-19, GOES 13, GOES 14, GOES 15, Jason-2 and DSCOVR.

Coverage and Latency

NOAA operates sun-synchronous, geostationary, and deep space satellites. Low-earth and deep-space orbiting satellites yield global coverage by nature of their orbits, not necessarily from of agency preference. Geostationary satellite constellations are better suited for specific coverages per country; however, NOAA operates GOES geostationary satellites to cover about half of the world.

NOAA leverages international cooperation to affordably monitor the entire earth and create a more complete understanding through partner data. Additionally, due to the nature of environmental and atmospheric conditions, global coverage is needed to forecast and research effectively. For these reasons, NOAA is interested in global coverage, but relies on other agencies, both foreign and domestic, if the opportunity is present. NOAA receives substantial value from satellite missions with national coverage; however, global coverage is needed to provide a full scope of environmental phenomena.

On the topic of revisit rate as it related to coverage, NOAA can handle some delay in atmospheric and oceanic data updates, as the phenomena tend to develop at a much slower rate than low Earth orbit satellite periods (even hurricanes). NOAA's research and forecasting is time sensitive in some immediate weather events, but on the whole, the data is not time sensitive compared to the speed of atmospheric and oceanic events.

Downlink and Observations

NOAA satellites have traditionally hosted a wide range of instruments, both complex and on the cutting edge. For example, GOES-17 carries ten instruments and NPOESS planned on having close to 150 observational records. Even JASON, a smaller satellite compared to JPSS and NPOESS, carries seven instruments (WMO, 2019). Finally, the assumption that NOAA requires advanced instruments and observational capacity is valid because NOAA's research portfolio over the past few decades requires creation of new instruments that did not previously exist.

Cost

The assumption is that NOAA does not have the ability to pay for high cost satellites over the long run because of a significantly lower budget than the DoD and that incredible cost overruns in NPOESS led to its dissolution. However, despite such a smaller budget, NOAA maintains high-cost satellite projects like JPSS and GOES by completing newer satellites using heritage instruments from previous versions (Leone, 2015).

PARTIAL UTILITY FUNCTIONS AND RELATIVE WEIGHTS

Figure 17 through Figure 21 show the partial utility functions for each of the five attributes based on DoD and NOAA preferences described above.

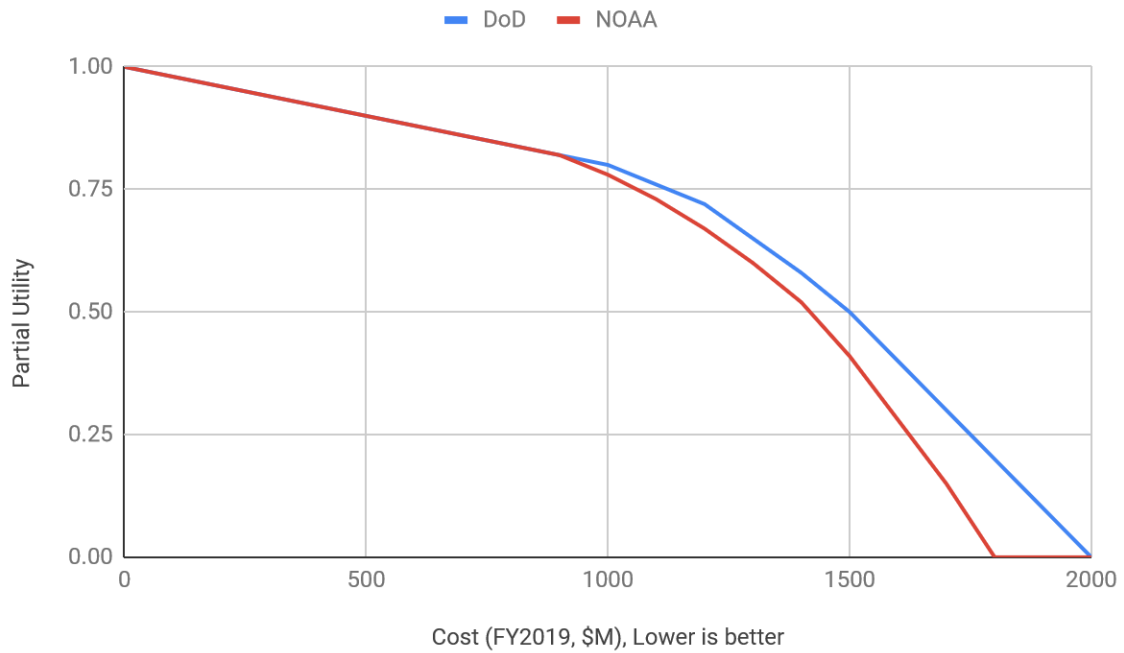


Figure 17. Partial utility functions for cost.

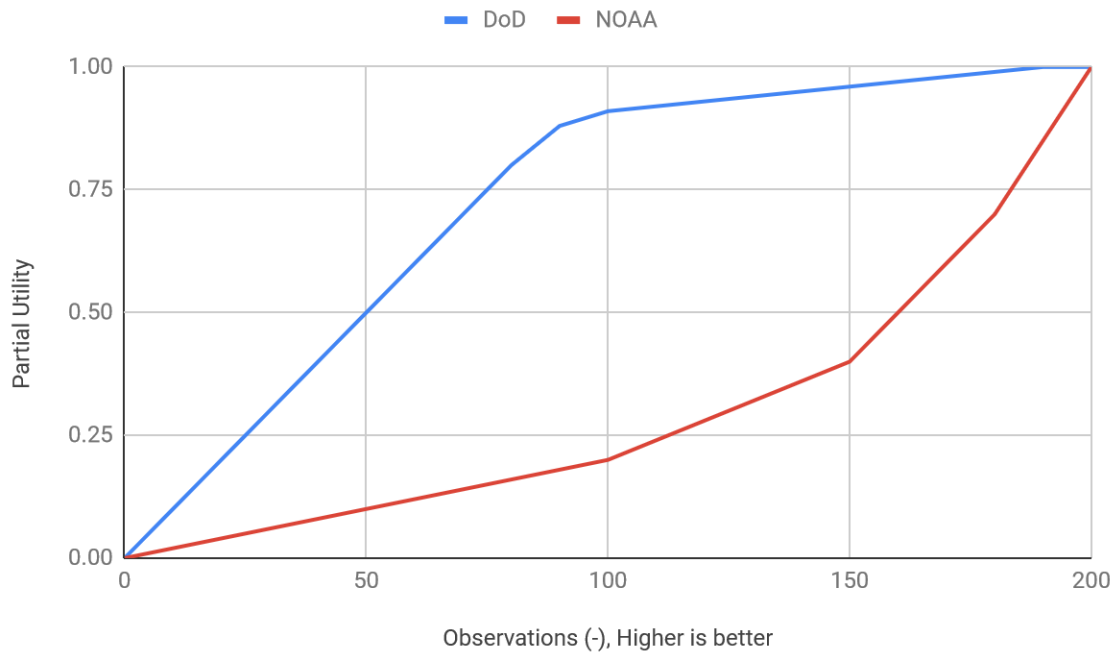


Figure 18. Partial utility functions for observations.

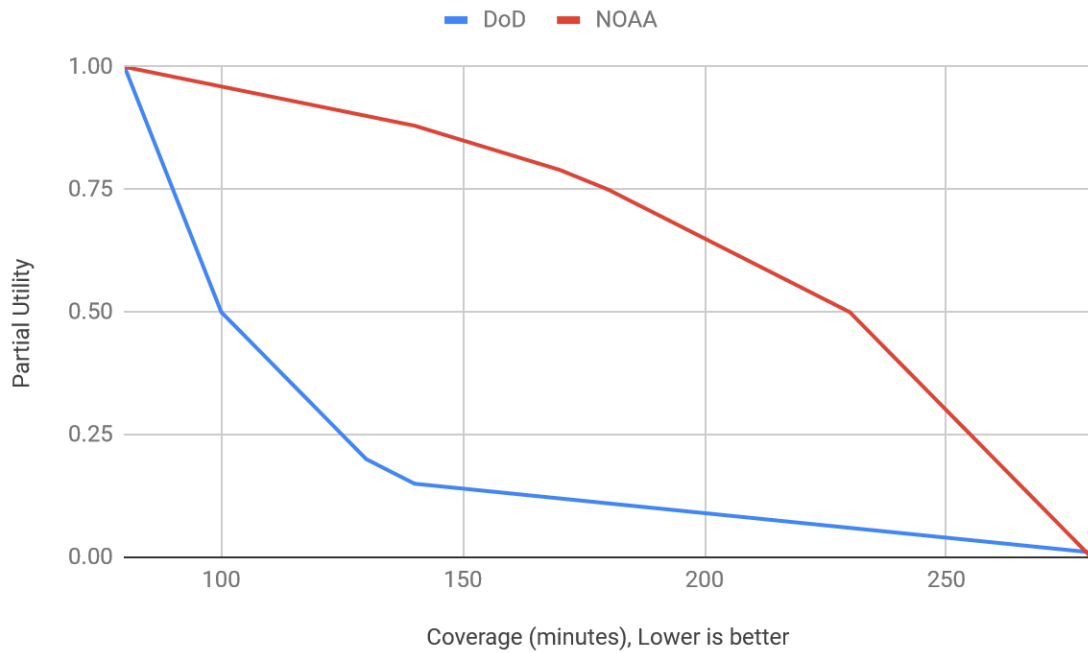


Figure 19. Partial utility functions for coverage.

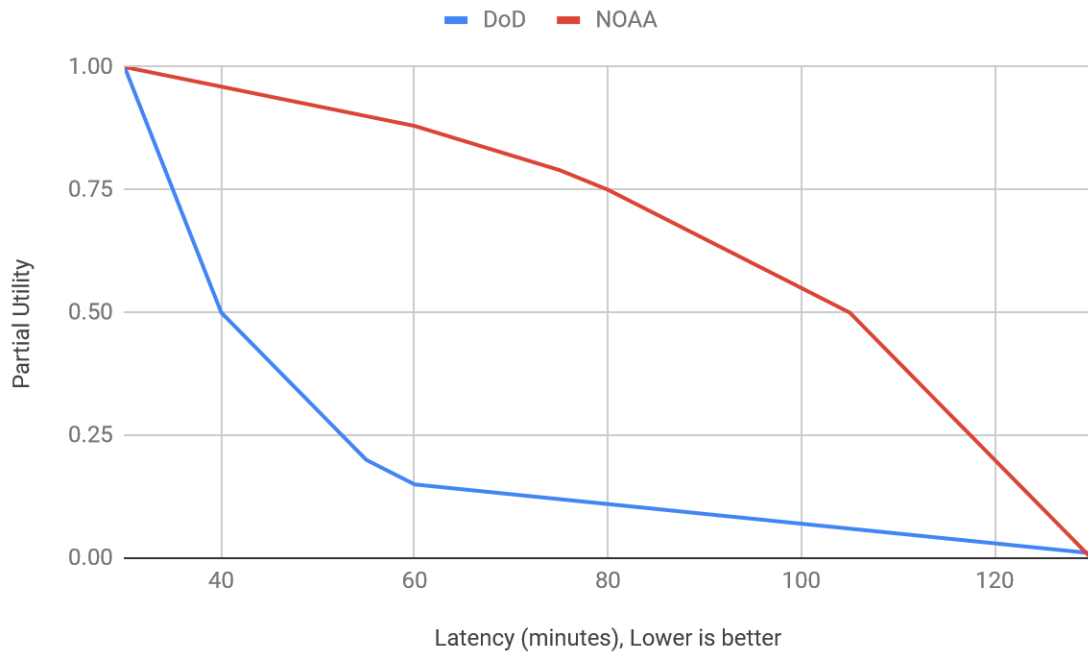


Figure 20. Partial utility functions for latency.

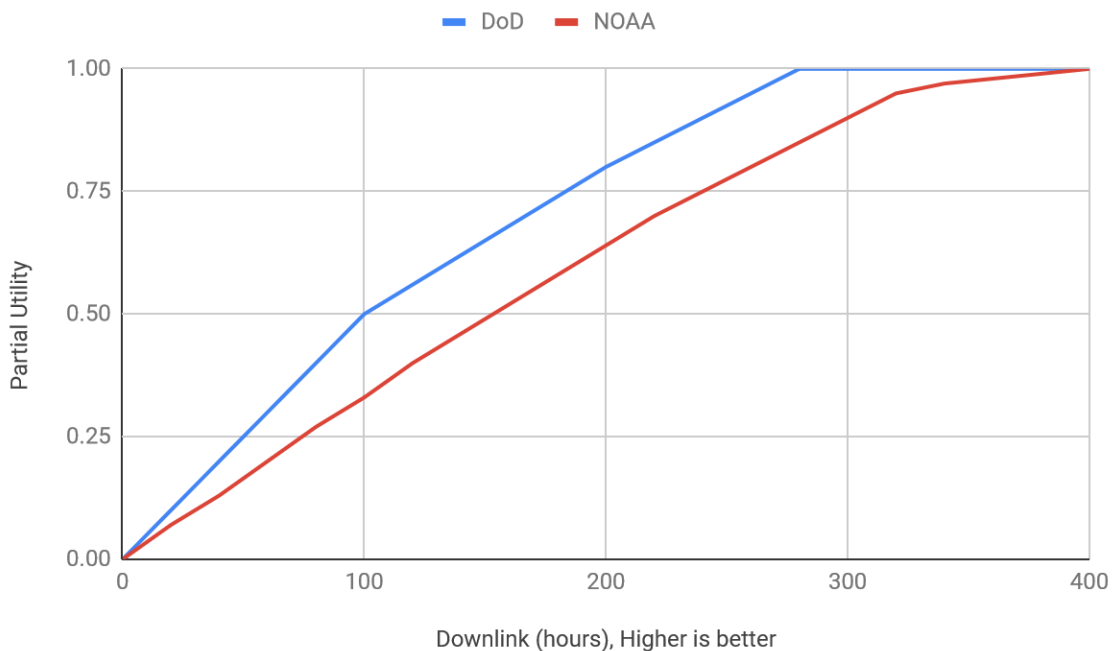


Figure 21. Partial utility functions for downlink.

Table 21 lists relative attribute weights for DoD and NOAA. The DoD has shown that cost was of large importance for their missions by dropping out of the NPOESS mission and initiating WSF proposals. NOAA on the other hand, ended up keeping a relatively similar cost profile into JPSS. For the reasons explained above, NOAA is extremely interested in pursuing new instruments and observations at cost. This is shown through NOAA's continuation of NPOESS development with the launch of S-NPP and the creation of JPSS. Coverage was set high for both NOAA and DoD as global coverage is important for both mission architecture goals. However, the DoD was set higher because they have shown that they are less likely to work with global partners. DoD was given very high weights for latency as their missions are more time sensitive to that of NOAA. Downlink was left to the remaining weights for both DoD and NOAA.

Table 21. Relative Attribute Weights for DoD and NOAA

Weight	Cost	Observations	Coverage	Downlink	Latency
DoD	0.25	0.05	0.30	0.10	0.30
NOAA	0.20	0.45	0.20	0.10	0.05

VALUE ANALYSIS

Using the partial utility functions and relative weights described above, Table 22 shows results of the value analysis to evaluate DoD preferences for alternative architectures and Table 23 shows equivalent results for NOAA.

Table 22. DoD Value Analysis Results

Architecture	Cost (0.25)	Observations (0.05)	Coverage (0.30)	Downlink (0.10)	Latency (0.30)	Total Value
DMSP	0.92	0.50	1.00	0.90	0.13	0.68
NPOESS	0.65	0.98	0.30	0.98	1.00	0.72
DMSP*	0.10	0.50	1.00	0.90	0.13	0.43

Table 23. NOAA Value Analysis Results

Architecture	Cost (0.20)	Observations (0.45)	Coverage (0.20)	Downlink (0.10)	Latency (0.05)	Total Value
POES	0.92	0.12	0.92	0.33	0.70	0.49
NPOESS	0.60	0.98	0.92	0.98	1.00	0.72
NPOESS*	0.00	0.28	0.92	0.98	1.00	0.46

Analysis reflects the expected ordering of preferences, namely the joint architecture NPOESS (as planned) contributes the highest level of value, reflecting potential for mutual benefits for a combined system with cost sharing. Next, the independent architectures DMSP and POES provide intermediate levels of value reflecting the nominal mission at a significantly lower budget level. Finally, the coordination failure cases DMSP* and NPOESS* provide the lowest level of value, largely driven by significant cost commitments required of a single actor. The major difference between DoD and NOAA is that NPOESS presents a significant improvement over POES for NOAA driven by significantly larger observation set and robust ground network while only a more modest improvement over DMSP for DoD.

It should be noted that value analysis is highly subjective and variations on the selected performance attributes, metric calculation, simulation assumptions, partial utility functions, or weighting factors may be adjusted with closer feedback from corresponding agencies. These additional considerations would fine-tune the model but would not be expected to significantly change the rank ordering of preference for the alternative scenarios. As a prospective analysis similar to before the 1994 decision point, this work also does not consider the large technical risk present in a large joint architecture such as NPOESS which led to significant cost overruns.

ANALYSIS OF RISK DOMINANCE

Risk dominance analysis can provide insights about the strategic dynamics between DoD and NOAA within the design scenario. Table 24 formats the value analysis results as a strategic design game. This game exhibits the bipolar strategy dynamic with two Nash equilibria represented by the (DMSP, POES) and (NPOESS, NPOESS) strategy sets and is suitable for risk dominance analysis. It can be classified as an asymmetric two-player game because the scenario-specific payoff values differ between DoD and NOAA.

Table 24. NPOESS Strategic Design Game with Values

DoD	NOAA	
	Independent System	Joint System
Independent System	DMSP: 0.68 POES: 0.49	DMSP: 0.68 NPOESS*: 0.46
Joint System	DMSP*: 0.43 POES: 0.49	NPOESS: 0.72 NPOESS: 0.72

The normalized deviation loss from the perspective of DoD and NOAA is calculated as:

$$u_{DoD} = \frac{V_{DoD}^{DMSP} - V_{DoD}^{DMSP*}}{(V_{DoD}^{DMSP} - V_{DoD}^{DMSP*}) + (V_{DoD}^{NPOESS} - V_{DoD}^{DMSP})} = \frac{0.68 - 0.43}{(0.68 - 0.43) + (0.72 - 0.68)} = 0.86$$

$$u_{NOAA} = \frac{V_{NOAA}^{POES} - V_{NOAA}^{NPOESS*}}{(V_{NOAA}^{POES} - V_{NOAA}^{NPOESS*}) + (V_{NOAA}^{NPOESS} - V_{NOAA}^{POES})} = \frac{0.49 - 0.46}{(0.49 - 0.46) + (0.72 - 0.49)} = 0.12$$

This result shows that DoD is incentivized to collaborate with the joint NPOESS architecture if they assess a greater than 86% chance that the venture will be successful. NOAA is incentivized to collaborate if they assess a greater than 12% chance that the venture will be successful, a much lower threshold value explained by their larger potential gains from the more capable NPOESS architecture.

The WALM of risk dominance measure takes the equally weighted sum of the logit function of normalized deviation loss for two-player games. The resulting metric is given by:

$$R = \frac{1}{2} \ln \left(\frac{u_{DoD}}{1 - u_{DoD}} \right) + \frac{1}{2} \ln \left(\frac{u_{NOAA}}{1 - u_{NOAA}} \right) = \frac{1}{2} \ln \left(\frac{0.86}{0.24} \right) + \frac{1}{2} \ln \left(\frac{0.12}{0.88} \right) = -0.07$$

Indicating that the joint architecture alternative is (slightly) risk dominant in this scenario. In other words, if neither DoD nor NOAA had any information about each other's actions, the joint architecture provides slightly higher expected value. In reality, the DoD and NOAA have potential to communicate and build trust for mutual participation in a joint architecture such that the nominal threshold for pursuing a collaborative architecture includes partial information. Thus, this analysis result primarily serves as a reference value on which to evaluate alternative joint architectures. For example, an alternative NPOESS architecture similar to later revisions after Nunn-McCurdy reviews may seek to reduce the WALM of risk dominance further to strengthen the incentives of DoD and NOAA to pursue the joint architecture.

COMPARISON WITH VALIDATION RESULTS

Outcomes from the application case can be compared to simulated results from the validation case for a broader appreciation of the WALM of risk dominance metric value $R = -0.07$. This value falls on the boundary between both strategies being risk dominant, indicating that rational actors in a highly simplified setting of a single-shot game with no information about their partner's action would not have a strong preference between the two strategies. However, if both actors had the perspective of DoD, the resulting WALM of risk dominance measure would

jump to $R = 1.84$, indicating the independent architecture is risk dominant and if both actors had the perspective of NOAA, the resulting WALM of risk dominance measure would fall to $R = -1.98$, indicating the collaborative architecture is risk dominant.

Table 25 overlays the three WALM of risk dominance results on top of the $S - T$ plane for evolutionary games with different strategic contexts denoted by the agent network connectivity. For example, the fully connected graph shows $R = -0.07$ lies precisely on the threshold between collaborative and independent dominant strategies; DoD is clearly within the independent architecture-dominant region and NOAA is within the collaborative architecture-dominant region. Alternatively, both the von Neumann and Moore lattice neighborhoods which both have a less connected network (i.e. more isolated agents), $R = -0.07$ falls within the collaborative architecture-dominant region. In other words, in settings where agents have a stronger opportunity to learn about and react to their neighbors' strategies, agents are more tolerant of collaborative architectures exhibiting higher levels of collaborative risk.

SUMMARY

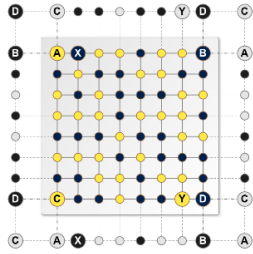
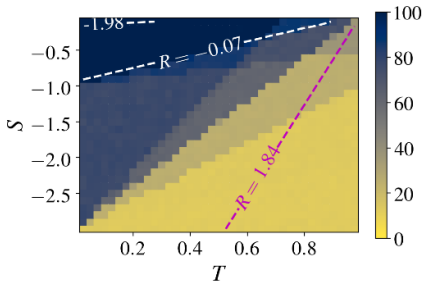
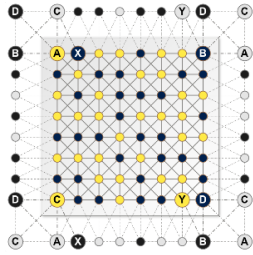
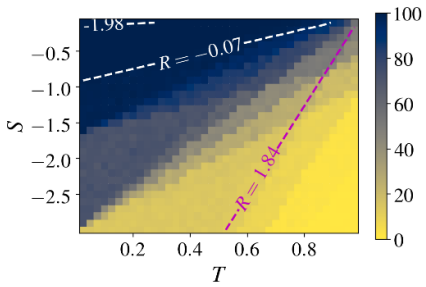
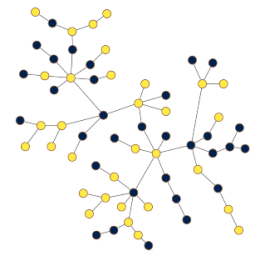
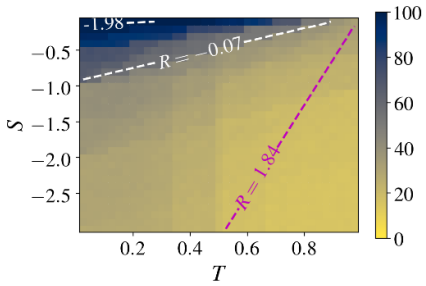
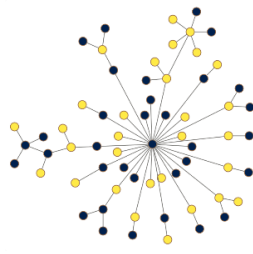
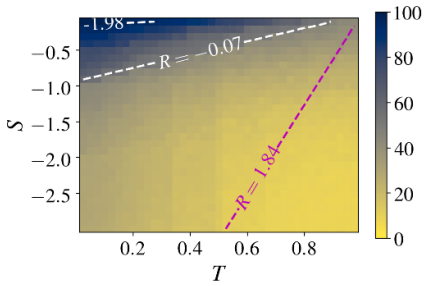
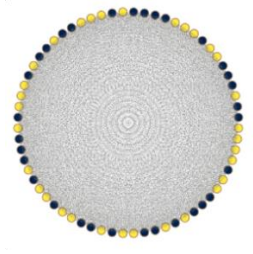
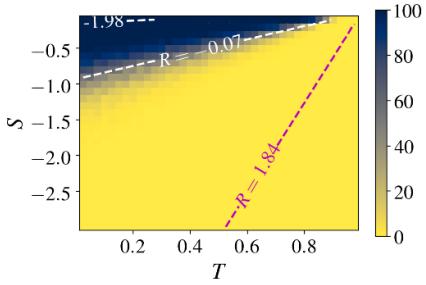
This application case discusses a real-world space system architecting problem that struggled with the decision to either pursue a joint architecture (NPOESS) requiring mutual collaboration of the DoD, NOAA, and NASA as three government agencies or pursue an independent alternative similar to programs of record (DMSP and POES). Motivation for the joint architecture relies on cost sharing and expanded capabilities beyond what is possible alone; however, potential risk of coordination failures imposes a significant risk on agency budgets.

Risk dominance analysis modeled the problem as a two-player asymmetric strategic design game with DoD and NOAA/NASA as primary design actors. Design scenarios representing the alternative architectures (NPOESS, DMSP, and POES) along with coordination failure conditions (DMSP* and NPOESS*) are based on historical program records but tailored to present a consistent design problem similar to the establishment of NPOESS in 1994. Technical models and simulations calculated performance attributes of interest related to the comparative capabilities of the alternative architectures and a value analysis using a weighted multi-attribute utility formulation estimated preferences from each design actor.

Results of the risk dominance analysis show that the two actors perceive the NPOESS scenario from different lenses. DoD views it as an opportunity to marginally improve performance over the baseline program of record while NOAA views it as an opportunity to significantly improve performance over the baseline program of record. While the large upside potential viewed by NOAA acts as a stabilizing factor on NPOESS, the comparatively high downside risk from the DoD acts as a destabilizing factor which may have contributed to its ultimate dissolution.

Table 25. Application Case Results in Context of Validation

Plots denote where application case WALM results fall on the S - T plane for percentage of stag-hunters.

Network model ($N = 64$)	Average network degree			S - T vs. average % of stag-hunters after convergence and R contour lines
	min	mean	max	
 1. von Neumann neighborhood	4.00	4.00	4.00	
 2. Moore neighborhood	8.00	8.00	8.00	
 3. Random graph	1.00	1.97	6.77	
 4. Rich-get-richer	1.00	1.97	16.87	
 5. Complete graph	63.00	63.00	63.00	

CONCLUSION AND FUTURE WORK

This project represents the first effort to model strategic dynamics in collaborative systems using the concept of risk dominance from equilibrium selection theory. Results presented in this report identify the underlying theory from the seminal works from Harsanyi and Selten and explain how to apply it within a bi-level model of engineering design with lower-level design optimization and upper-level strategy selection. The weighted average log measure (WALM) of risk dominance provides a simple metric that explains relative strategic behaviors relative to a strategic context, as demonstrated in the validation section. Furthermore, the application case shows how to translate theoretical concepts to an applied context using the example case of the National Polar-orbiting Environmental Satellite System (NPOESS). Results show that the two actors carry different perspectives on the value proposition of NPOESS and alternative architectures may have been able to stabilize the strategic dynamics further.

This research report, however, does not address several important issues that should be investigated in further research. Foremost, the current treatment of strategic interactions is characterized as "non-cooperative" where each design actor has no information about others' strategy selections. Although results of risk dominance analysis can still be interpreted from a relative perspective, this assumption limits evaluation of point-design collaborative system architectures. It is also very a conservative assumption because partnering agencies work closely with each other to understand sources of value and likely decisions to continuously update an internal measure of probability for successful collaboration. Future work should investigate applications of Bayesian game theory, a topic also pioneered by Harsanyi, to account for partial information available from each of the design actors. Revised analysis would be able to provide more contextual analysis specific to a point in time and set of design actors.

Second, this project focused primarily on evaluating point architectures, rather than using the WALM of risk dominance metric to guide tradespace exploration. This limitation was purposefully selected to limit the scope of this work and should be broadened in future work. The risk dominance metric can be applied in two ways during tradespace exploration: either to evaluate alternative designs for collaborative architectures or alternative collaborative arrangements to maximize risk dominance (i.e. minimize the risk metric). The former concept operates like traditional tradespace exploration with an additional strategic performance attribute associated with each architecture. The latter concept builds on concepts from mechanism design to effectively design the strategic game the actors play.

Finally, additional work can revise and refine the application case which was purposefully limited in scope and detail due to available time and effort. As discussed, the real-world NPOESS case was tremendously complex, both technically and politically, and the analysis results presented in this project are only a shadow of the real architecting problem. Analysis results are highly dependent on specific assumptions about initial conditions, technical performance, and value models associated with each design actor. Future work may consider an interactive multi-stakeholder modeling and design environment to engage with real stakeholders and elicit value functions representative of underlying objectives.

PROJECT TIMELINE & TRANSITION PLAN

The long-term transition goal for this research is to develop a prescriptive analysis methodology and associated quantitative metric to support system-of-system architecture selection in conceptual design phases. This approach would help systems engineers to detect architectures with unfavorable strategic dynamics as early as possible to either avoid or mitigate the source of strategic instability. To achieve this long-term transition goal, the research contributes three types of artifacts to support knowledge transfer to external sponsors:

1. Foundational theory and intuitive explanations disseminated in scholarly papers,
2. Standalone scripts and software tools to demonstrate and facilitate calculations, and
3. Application case narratives demonstrating the use of the proposed methodology and resulting insights in the context of simplified and realistic design scenarios.

This research is of interest to two communities—the U.S. Department of Defense and the civilian NASA Earth Science Technical Office—both engaged with distributed or decentralized architecture strategies for future space systems. In the military context, the cooperating organizations include military branches and allied nations. In the civilian context, the cooperating organizations include commercial firms and international space agency partners. A future phase of this research seeks to support an active project in either the U.S. DoD or NASA ESTO that is considering a joint or distributed architecture.

Table 26. GRADS Project Timeline

Year	Focus	Key Deliverables
Pre- 2018	• Perform initial feasibility study of game-theoretic measures for asymmetric games with more than two players	• Technical report disseminated under RT-180 New Project Incubator
2019	• Refine of systems engineering and design methodology to evaluate point design concepts using game-theoretic measures • Demonstrate game-theoretic measures in application case based on National Polar-orbiting Operational Environmental Satellite System (NPOESS)	• Scholarly paper(s) introducing overall design methodology and documenting results of validation case study • Supporting computational scripts to calculate and visualize game-theoretic metrics
2020	• Extend systems engineering and design methodology using game-theoretic measures to evaluate design trade spaces • Demonstrate use of game-theoretic measures in extended application case based on distributed or federated space systems	• Scholarly paper(s) discussing overall design methodology and documenting results of validation case study
2021-23	• Transition design methodology to practice by working in concert with a prospective development or acquisition project	• Technical reports and/or scholarly papers discussing application of design methodology to prospective projects

Table 27. GRADS Project Transition Action Plan

#	Transition Action	Principles Implemented
1	Project selected in competitive process for RT-180 New Project Incubator to perform an initial feasibility study and reduce risk for a dedicated research task.	• Engage Community • Plan Early
2	Intermediate results presented at SERC Advisory Board Meeting, SERC Incubator Day, and SERC Sponsored Research Review to receive feedback.	• Engage Community • Pilot Continuously
3	Targeted application case scenario leverages an existing case study analyzed within the Department of Defense and NASA Earth Sciences Division.	• Engage Community • Support Centrally
4	Research deliverables include scholarly papers and computational artifacts to help transition fundamental knowledge to academic and practitioner audience.	• Engage Community • Productize

Table 28. GRADS Project Transition Characteristics

Characteristic	Evidence
Readiness (relevance, practicality)	• Distributed or federated systems are a topic of active discussion across multiple levels of the federal government but not well-characterized by existing design methods and tools. • Formulation of a game-theoretic metric enables a rapid assessment of strategic dynamics to inform decision-making in proposed joint or collaborative projects.
Progress (approval, adoption)	• One journal publication in review. • Initial engagement with the NASA Earth Sciences Division to synergize research topics.

APPENDIX A: LIST OF PUBLICATIONS AND INVITED TALKS

- Grogan, P.T. (2018). "Game-theoretic Risk Assessment for Distributed Systems (GRADS)," Presentation at *SERC Sponsor Research Review*, November 8, Washington, D.C.
- Grogan, P.T. (2019). "Stag Hunt as an Analogy for Systems of Systems Engineering," *2019 Conference on Systems Engineering (CSER)*, April 3-4, Washington, D.C.
- Lee, H. and P.T. Grogan (2019). "Measuring Strategic Risk Dominance Using the Multi-Actor Value Model: A Study of the National Polar-orbiting Operational Environmental Satellite System" *AIAA SciTech Forum 2019*, January 7-11, San Diego, CA.
- Grogan, P.T. and A. Valencia-Romero (n.d.). "Strategic Risk Dominance in Collective Systems Design," In revision for *Design Science*.
- Valencia-Romero, A., J. Thekinen, and P. T. Grogan (n.d.). "On the Use of Game Theory in Engineering Systems Design," In preparation.
- Valencia-Romero, A. and P. T. Grogan (n.d.). "Evaluation of Collective Equilibrium Selection and Risk Dominance with Evolutionary Dynamics," In preparation.

APPENDIX B: REFERENCES CITED

- Abbas, A. E. and A. H. Cadenbach (2018). "On the Use of Utility Theory in Engineering Design." *IEEE Systems Journal*, 12(2):1129-1138. doi: 10.1109/JSYST.2016.2602562
- Anderson, D.L. and J.C. Doyle (2010). "Contrasting Views of Complexity and Their Implications for Network-centric Infrastructures." *IEEE Transactions on Systems, Man, and Cybernetics - Part A: Systems and Humans*, 40(4):839-852. doi: 10.1109/TSMCA.2010.2048027
- Arthanari, T. S. (2005). "A Game Theory Application in Robust Design." *Quality Engineering*, 17(2):291-300. doi: 10.1081/QEN-200056498
- Barabási, A. L., & Albert, R. (1999). "Emergence of Scaling in Random Networks. *Science*, 286(5439):509-512. doi: 10.1126/science.286.5439.509
- Bhatia, G. V., H. Kannan, and C. L. Bloebaum (2016). "A Game Theory Approach to Bargaining over Attributes of Complex Systems in the Context of Value-driven Design." In *Proceedings of the 54th AIAA Aerospace Sciences Meeting*, American Institute of Aeronautics and Astronautics. doi: 10.2514/6.2016-0972
- Bommarito, J. J. (1993). "DMSP Special Sensor Microwave Imager Sounder (SSMIS)," *Proceedings of Microwave Instrumentation for Remote Sensing of the Earth*, August 19, Orlando, FL, USA. doi: 10.1117/12.152601
- Brown, O. and P. Eremenko (2006). "The Value Proposition for Fractionated Space Architectures." *AIAA Space 2006*, September 19-21, San Jose, CA, USA. doi: 10.2514/6.2006-7506
- Camerer, C. F. (1997). "Progress in Behavioral Game Theory." *Journal of Economic Perspectives*, 11(4):167-188. doi: 10.1257/jep.11.4.167
- Chatters E. P. and G. Medina (2009). "Weather/Environmental Satellites," Chapter 15 in *AU Space Primer*, September. Online: <http://space.au.af.mil/au-18-2009/>
- Collopy, P. D. and P. M. Hollingsworth (2011). "Value-driven Design." *Journal of Aircraft*, 48(3):749-759. doi: 10.2514/1.C000311
- Cruz, J. B., C. I. Chen, G. Dans, J. Davis, J. E. Heller, R. Hecht, M. Jamshidi, P. Kokotovic, J. Medanic, and W. R. Perkins, M. Rice, and G. Singh (1969). "Control Systems." In *Coordinated Science Laboratory's Progress Report for September 1968 through June 1969*, Chapter 13, pp. 270-291. Research Publications from the University of Illinois at Urbana-Champaign.
- Data.gov, (2015). "DMSP OLD - Operational Linescan System," Online: <https://catalog.data.gov/dataset/dmsp-ols-operational-linescan-system>
- Dawkins, R. (1976). *The Selfish Gene*. Oxford University Press.

- Dwyer, M.M. (2015). *The Cost of Jointness: Insights from Environmental Monitoring Systems in Low Earth Orbit*, Ph.D. Dissertation, Engineering Systems Division, Massachusetts Institute of Technology.
- Dwyer, M., Z. Szajnarfarber, B. Cameron, and E. Crawley (2018). "A Model for Understanding and Managing Cost Growth on Joint Programs." *Acta Astronautica*, 152:59-70. doi: 10.1016/j.actaastro.2018.07.004
- Easley, D., & Kleinberg, J. (2012). *Networks, Crowds, and Markets: Reasoning about a Highly Connected World*. Cambridge University Press, Cambridge, UK.
- Erickson, P. (2015). *The World the Game Theorists Made*. University of Chicago Press.
- European Organization for the Exploitation of Meteorological Satellites (2019). "METOP Design." Online: <https://www.eumetsat.int/website/home/Satellites/CurrentSatellites/Metop/MetopDesign/index.html>
- Franssen, M. and L. L. Bucciarelli (2004). "On Rationality in Engineering Design." *Journal of Mechanical Design*, 126(6):945-949. doi: 10.1115/1.1803850
- Ghotbi, E. and A. K. Dhingra (2012). "A Bilevel Game Theoretic Approach to Optimum Design of Flywheels." *Engineering Optimization*, 44(11):1337-1350. doi: 10.1080/0305215X.2011.637557
- Gianetto, D. A. and B. Heydari (2015). "Catalysts of cooperation in system of systems: the role of diversity and network structure." *IEEE Systems Journal*, 9(1):303-311. doi: 10.1109/JSYST.2013.2284959
- Grogan, P. T. and A. Bayrak (2018). "Operational and Strategic Decisions in Engineering Design Games." In *Proceedings of the ASME 2018 International Design Engineering Technical Conferences and Computers and Information in Engineering Conference*, Québec City, QC, Canada. doi: 10.1115/DETC2018-85317
- Grogan, P. T., K. Ho, A. Golkar, and O. L. de Weck (2016). "Bounding the Value of Collaboration in Federated Systems." In *Proceedings of the 2016 Annual IEEE Systems Conference*, Orlando, FL, USA. doi: 10.1109/SYSCON.2016.7490657
- Grogan, P. T., K. Ho, A. Golkar, and O. L. de Weck (2018). Multi-actor Value Modeling for Federated Systems. *IEEE Systems Journal*, 12(2):1193-1202. doi: 10.1109/JSYST.2016.2626981
- Gurnani, A. and K. Lewis (2008). "Collaborative, Decentralized Engineering Design at the Edge of Rationality." *Journal of Mechanical Design*, 130(12):121101. doi: 10.1115/1.2988479
- Haas, J. M. and H. Swenson (2001). "NPOESS Instruments: The Future of METSAT Observations," In *11th Conference on Satellite Meteorology and Oceanography*, Madison, WI.

- Halpern, J. Y. (2003). "A Computer Scientist Looks at Game Theory." *Games and Economic Behavior*, 45(1):114-131. doi: 10.1016/S0899-8256(02)00529-8
- Harsanyi, J. C. (1967). "Games with Incomplete Information Played by Bayesian Players, Part I. The Basic Model." *Management Science*, 14(3):159-182. doi: 10.1287/mnsc.14.3.159
- Harsanyi, J. C. and R. Selten (1988). *A General Theory of Equilibrium Selection in Games*. MIT Press, Cambridge, MA, USA.
- Hauert, C. (2002). Effects of space in 2×2 games. *International Journal of Bifurcation and Chaos*, 12(7):1531-1548. doi: 10.1142/S0218127402005273
- Hazelrigg, G. A. (1997). "On Irrationality in Engineering Design." *Journal of Mechanical Design*, 119(2):194-196. doi: 10.1115/1.2826235
- Hernández, G. and F. Mistree (2000). "Integrating Product Design and Manufacturing: A Game Theoretic Approach." *Engineering Optimization*, 32(6):749-775. doi: 10.1080/03052150008941320
- Hinnant, F.G., H. Swenson, and J.M. Haas (2001), "The NPOESS (National Polar-orbiting Operational Environmental Satellite System): A Program Overview and Status Update," *Proceedings of the IEEE 2001 International Geoscience and Remote Sensing Symposium*, July 9-13, Sydney, Australia. doi: 10.1109/IGARSS.2001.976113
- Issacs, R. 1965. *Differential Games*. New York, NY, United States: Wiley.
- de Jasay, A., W. Güth, H. Kliemt, and A. Ockenfels (2004). "Take or Leave? Distribution in Asymmetric One-Off Conflict." *Kyklos*, 57(2):217-235. doi: 10.1111/j.0023-5962.2004.00251.x
- Johns Hopkins University Applied Physics Laboratory (2018). "SSUSI: Special Sensor Ultraviolet Spectrographic Imager." Online: <https://ssusi.jhuapl.edu/>
- Kang, N., Y. Ren, F. M. Feinberg, and P. Y. Papalambros (2016). "Public Investment and Electric Vehicle Design: A Model-based Market Analysis Framework with Application to a USA-China Comparison Study." *Design Science*, 2(6):1-42. doi: 10.1017/dsj.2016.7
- Keller, J. (2018). "Ball Aerospace wins half-billion-dollar contract to build first WSF-M microwave imaging weather satellite," *Military & Aerospace Electronics*, November 12. Online: <https://www.militaryaerospace.com/unmanned/article/16726604/ball-aerospace-wins-halfbilliondollar-contract-to-build-first-wsfm-microwave-imaging-weather-satellite>
- Kimbrough, S. O. (2011). *Agents, Games, and Evolution: Strategies at Work and Play*. CRC Press, Boca Raton, FL.
- King, T. R. and J. K. Murnighan (1988). "Stability and outcome tradeoffs in asymmetric dilemmas: Conditions promoting the discovery of alternating solutions." In R. Tietz, W. Albers, and R. Selten (Eds), *Bounded Rational Behavior in Experimental Games and Markets*, pp. 85-94. Springer-Verlag.

- Leone, D. (2015). "Launch of GOES-R Satellite Delayed Six Months," *Space News*, October 19. Online: <https://spacenews.com/launch-of-goes-r-satellite-delayed-six-months/>
- Lewis, K. and F. Mistree (1997). "Modeling Interactions in Multidisciplinary Design: A Game Theoretic Approach." *AIAA Journal*, 35(8):1387-1392. doi: 10.2514/2.248
- Macy, M. W. and Flache, A. (2002). Learning Dynamics in Social Dilemmas. *Proceedings of the National Academy of Sciences*, 99(suppl 3):7229-7236. doi: 10.1073/pnas.092080099
- Maier, M. W. (1998). "Architecting Principles for Systems-of-systems." *Systems Engineering*, 1(4):267-284. doi: 10.1002/(SICI)1520-6858(1998)1:4<267::AID-SYS3>3.0.CO;2-D
- Maschler, M., E. Solan, and S. Zamir (2013) *Game Theory*. Cambridge, MA, United States: Cambridge University Press.
- Maynard Smith, J. and G. R. Price (1973). "The Logic of Animal Conflict." *Nature*, 246(5427):15. doi: 10.1038/246015a0
- McKinsey, J. C. C. (1952). "Applications to Statistical Inference." In *Introduction to the Theory of Games*, Ch. 13. The RAND Corporation.
- McManus, H., M. Richards, A. Ross, and D. Hastings (2007). "A Framework for Incorporating "ilities" in Tradespace Studies." In *Proceedings of the AIAA SPACE 2007 Conference & Exposition*, Long Beach, CA, United States. doi: 10.2514/6.2007-6100
- Milazzo, A.-C., S. E. Thonnard, and C. Lam (1998). "Performance measurements and results of the SSULI (Special Sensor Ultraviolet Limb Imager) stacked-grid collimator," *Proceedings of X-Ray and Ultraviolet Spectroscopy and Polarimetry II*, December 17. doi: 10.1117/12.333615
- Murphy, R.E. (2006). "The NPOESS Preparatory Project," Chapter 10 in *Earth Science Satellite Remote Sensing*. J.J. Qu, W. Gao, M. Kafatos, R.E. Murphy, V.V. Salomonson (Eds). Springer, pp. 182-198.
- Nash, J. (1951). "Non-cooperative Games." *Annals of Mathematics*, 54(2):286-295. doi: 10.2307/1969529
- National Research Council (2008). "Implications of the NPOESS Nunn-McCurdy Certification and the Descoping of GOES-R," *Options to Ensure the Climate Record from the NPOESS and GOES-R Spacecraft: A Workshop Report*. National Academies Press, Washington, DC. doi:10.17226/12033.
- National Research Council (2010). *Controlling Cost Growth of NASA Earth and Space Science Missions*. National Academies Press, Washington, DC.
- National Research Council (2011). *Assessment of Impediments to Interagency Collaboration on Space and Earth Science Missions*. National Academies Press, Washington, DC.
- von Neumann, J., and O. Morgenstern (1944). *Theory of Games and Economic Behavior*. Princeton, NJ, United States: Princeton University press.

- Oberhardt, M. R., D. A. Hardy, W. E. Slutter, J. O. McGarity, D. J. Sperry, A. W. Everest, A. C. Huber, J. A. Pantazis and M. P. Gough (1994). "The shuttle potential and return electron experiment (SPREE)," *Il Nuovo Cimento*, 17(1):67-83. doi: 10.1007/BF02506681
- Papageorgiou, E., M. H. Eres, and J. Scanlan (2016). "Value Modelling for Multistakeholder and Multi-objective Optimisation in Engineering Design." *Journal of Engineering Design*, 27(10):697-724. doi: 10.1080/09544828.2016.1214693
- Reich, Y. (2010). "My Method is Better!" *Research in Engineering Design*, 21(3):137-142.
- Rich, F.J. (1994). "Users Guide for the Topside Ionospheric Plasma Monitor (SSIES, SSIES-2, and SSIES-3) on Spacecraft of the Defense Meteorological Satellite Program (DMSP) Volume I: Technical Description," Tech. Rep. PL-TR-94-2187, Phillips Laboratory, Hanscom AFB, MA.
- Rousseau, J.-J. (1984). *A Discourse on Inequality*. Penguin, London, UK.
- Rubinstein, A. (1991). "Comments on the Interpretation of Game Theory." *Econometrica: Journal of the Econometric Society*, 59(4):909-924. doi: 10.2307/2938166
- Schelling, T. C. (1959). "For the Abandonment of Symmetry in Game Theory." *The Review of Economics and Statistics*, 41(3):213-224. doi: 10.2307/1927448
- Selten, R. (1975). "Reexamination of the Perfectness Concept for Equilibrium Points in Extensive Games." *International Journal of Game Theory*, 4(1):25-55. doi: 10.1007/BF01766400
- Selten, R. (1995). "An Axiomatic Theory of a Risk Dominance Measure for Bipolar Games with Linear Incentives." *Games and Economic Behavior*, 8(1):213-263. doi: 10.1016/S0899-8256(05)80021-1
- Selva, D., A. Golkar, O. Korobova, I. L. I. Cruz, P. Collopy, and O. L. de Weck (2017). "Distributed Earth satellite systems: What is needed to move forward?" *Journal of Aerospace Information Systems*, 14(8):412-438. doi: 10.2514/1.1010497
- Sha, Z., K. N. Kannan, and J. H. Panchal (2015). "Behavioral Experimentation and Game Theory in Engineering Systems Design." *Journal of Mechanical Design*, 137(5):051405. doi: 10.1115/1.4029767
- Shoham, Y. (2008). "Computer Science and Game Theory." *Communications of the ACM*, 51(8):74-79. doi: 10.1145/1378704.1378721
- Skryms, B. (2001). "The Stag Hunt Game." *Proceedings and Addresses of the American Philosophical Association*, 75(2):31-41.
- Skryms, B. (2004). *The Stag Hunt and the Evolution of Social Structure*. Cambridge University Press, Cambridge, UK.
- Sommerville, I. (2016). "Systems of Systems." In *Software Engineering*, Tenth Edition, Ch. 20. Pearson Education.

- Sugden, R. (1995). "A Theory of Focal Points." *The Economic Journal*, 105(430):533-550. doi: 10.2307/2235016
- Takai, S. (2010). "A Game-theoretic Model of Collaboration in Engineering Design." *Journal of Mechanical Design*, 132(5):051005. doi: 10.1115/1.4001205
- United States Committee on Science (2006). "The Future of NPOESS: Results of the Nunn-McCurdy Review of NOAA's Weather Satellite Program," Hearing Before the Committee on Science, House of Representatives, Serial No. 109-53, Government Publishing Office, pp. 1-90. Online: <https://www.gpo.gov/fdsys/pkg/CHRG-109hhrg27970/pdf/CHRG-109hhrg27970.pdf>
- United States Department of Defense (2019). "DOD Releases Fiscal Year 2020 Budget Proposal," Press Release NR-049-19, March 12. Online: <https://dod.defense.gov/News/News-Releases/News-Release-View/Article/1782623/dod-releases-fiscal-year-2020-budget-proposal/>
- United States General Accounting Office (1994). "National Space Issues: Observations on Defense Space Programs and Activities." Tech. Rep. GAO/NSAID-94-253. August 16.
- United States Government Accountability Office (2007). "Polar-orbiting Operational Environmental Satellites: Restructuring is Under Way, but Challenges and Risks Remain," Tech. Rep. GAO-07-910T. June 7.
- Valencia-Romero, A. and P. T. Grogan (2018). "Toward a Model-Based Experimental Approach to Assessing Collective Systems Design." In *Proceedings of the ASME 2018 International Design Engineering Technical Conferences and Computers and Information in Engineering Conference*, Québec City, QC, Canada. doi: 10.1115/DETC2018-85786
- Vincent, T. L. and W. J. Grantham (1981). *Optimality in Parametric Systems*. New York, NY, United States: Wiley.
- Watson, J. (2002). *Strategy: An Introduction to Game Theory*. New York, NY, United States: WW Norton & Co.
- de Weck, O.L., R. de Neufville, and M. Chaize (2004). "Staged Deployment of Communications Satellite Constellations in Low Earth Orbit." *Journal of Aerospace Computing, Information, and Communication*, 1(3):119-136.
- White House of the United States of America (1994). "Convergence of U.S. Polar-orbiting Operational Environmental Satellite Systems: NSTC-2," May 5. Online: <https://clintonwhitehouse3.archives.gov/WH/EOP/OSTP/NSTC/html/pdd2.html>
- White House of the United State of America (2010). "Restructuring the National Polar-orbiting Operational Environmental Satellite System," February 1. Online: https://obamawhitehouse.archives.gov/sites/default/files/npoess_decision_fact_sheet_2-1-10.pdf

World Meteorological Organization (2019). " Observing Systems Capability Analysis and Review Tool (OSCAR)." Online: <https://www.wmo-sat.info/oscar/>