Federated Space Systems Tradespace Exploration for Strategic Robustness

Jordan L. Stern* and Paul T. Grogan†
Stevens Institute of Technology, Hoboken, NJ, 07010

Motivated by the growth of the commercial space economy and renewed focus on the disaggregation of military space systems, this work develops a method for conceptual design of federated satellite systems as a collaborative system-of-systems (SoS). Objectives seek to improve the likelihood of successful SoS formation and pursue constituent system utility robustness. The proposed metaheuristic optimization tradespace exploration method accounts for technical and economic design variables and multi-decision maker strategy dynamics. Constituent system designs are ranked on their simulated net present value. A game-theoretic measure of risk dominance is used in concert with net present value to assess robustness and utility of candidate SoS designs. The method is validated with a notional application case that assesses potential collaboration between Earth observing and telecommunications systems. Results demonstrate a fundamental trade between system efficiency and robustness and highlight the importance of accounting for strategy dynamics when designing systems for collaboration.

Nomenclature

R	=	weighted-average log measure of risk dominance
ϕ	=	independent strategy
ψ	=	collaborative strategy
u_i	=	normalized deviation loss for player i
p_i	=	probability that player i selects strategy ψ
w_i	=	influence weight for player i
A	=	influence matrix
π_s	=	SATCOM system number of planes
N_s	=	SATCOM system satellites per plane
ϵ	=	SATCOM system user minimum elevation angle
C	=	number of user channels

*Captain, United States Air Force; Ph.D. Candidate, School of Systems and Enterprises, jstern2@stevens.edu.

†Assistant Professor, School of Systems and Enterprises, pgrogan@stevens.edu, Senior Member

p	=	per channel transmitter output power
R_s	=	slant range
G	=	gain
η	=	efficiency
A_θ	=	single satellite coverage area
$A_{\theta,eff}$	=	effective single satellite coverage area
S_{base}	=	SATCOM system subscriber base
K	=	maximum number of subscribers
b_1	=	subscriber growth model scaling factor
b_2	=	subscriber growth model inflection point
$m_{dry,s}$	=	SATCOM satellite dry mass
π_e	=	EO system number of planes
N_e	=	EO system satellites per plane
D	=	primary aperture diameter
a	=	altitude
γ	=	number of EO system ground stations
λ	=	information value decay rate
θ	=	imagery resolution
P	=	monthly revenue
ν_Λ	=	single attribute value of latency
ν_θ	=	single attribute value of resolution
$m_{dry,e}$	=	EO satellite dry mass

I. Introduction

THE history of distributed satellite systems is nearly as old as spaceflight itself [1]. While early satellite clusters and constellations focused on operating together to perform a single function, work within the last decade has investigated Federated Space Systems (FSS) [2, 3]. FSS are a collaborative type of system-of-systems (SoS), in which there is no central authority to enforce SoS level design goals and decisions [4]. Individual satellites or constellations within a federation have unique missions and may be operated by separate organizations. Yet, by leveraging one another's capabilities, they create new effects or improve the degree to which they perform core functions. As a SoS, FSS require application of an engineering methodology suited for their unique socio-technical challenges [5].

The potential benefits of FSS come with risks unique to collaborative systems. Coordination failure between

potential federation participants leads to two primary forms of consequences. The first consequence is non-recoverable investments made to enable the collaboration. In the majority of cases, these investments will be for information system interoperability [5, 6], though transmission of power and motive forces between spacecraft have been envisioned as well [7]. The second consequence is functional vulnerability stemming from efforts to reduce functional redundancy across the federation to maximize efficiency. These potential consequences highlight the trade between efficiency and robustness in engineered systems that is also found in biological systems [8]. Therefore, designing for utility robustness in the face of uncertain collaborative behavior from other system actors is the key challenge for FSS, as with other SoS. Additionally, uncertainties present in typical system development activities are only compounded by the interactions and interdependencies that exist in FSS.

Much of the research in SoS design has focused on balancing the independent interests of multiple stakeholders to achieve a compromise solution [9] or with models that aim to predict when successful collaboration will occur [10]. Some methods assume that global, SoS-level goals exist [11] or that there is unified managerial authority over each of the constituent systems [12]. Neither of these conditions are true of collaborative SoS, such as FSS [4]. Furthermore, none of these methods quantitatively measure the stability of a collaboration, indicate each system's robustness to coordination failure, or provide a way to assess designs and design combinations for their ability to improve either of the aforementioned attributes.

A recent body of research applies risk dominance measures from game theory [13], using the canonical stag hunt game as an analogy for SoS development [14]. Grogan and Valencia-Romero [14] close the aforementioned gaps in SoS research with quantitative methods for assessing strategy dynamics amongst collaborators, determining the relative robustness of design solutions to defection of each SoS participant, and designing systems to incentivize participation by independent system owners. However, no existing work transitions the theory of risk dominance to a tradespace exploration setting suitable for domain-specific conceptual design studies. This paper applies SoS multi-actor value models [14, 15] to a collaborative space systems tradespace exploration problem, developing a methodology that indicates which system designs are rational choices for implementation in a FSS. This work goes beyond previous SoS tradespace exploration efforts by considering the primary, unique difference between collaborative SoS design and traditional system design; the strategy dynamics induced by multiple decision makers with differing goals. While previous works have recognized the challenges created by multiple decision makers, none present a methodology to improve upside utility of every constituent system through collaboration *and* ensure that the strategy dynamics as a whole favor the selection of the payoff dominant collaborative strategy, creating the conditions in which the SoS can form. System designs which facilitate the attainment of these properties are *strategically robust*, having improved utility robustness to strategic variability and contributing to the stability of the efficient strategy.

The benefits of the method presented here are measured in two ways. First, it yields system designs that result in strategy dynamics which more strongly favor collaboration for a rational decision maker, and can be adapted to varying

risk postures through utility function updates. Second, the method yields designs that retain greater value or utility if the FSS fails. Therefore, they are utility robust to coordination failure.

The balance of this paper is organized as follows. Section II reviews a background of issues related to SoS development and fielding, with a special focus on challenges of multi-decision maker collaboration. Section III describes the tradespace exploration methodology, system models, and the baseline application case. Section IV presents a game-theoretic equilibrium selection measure as an evaluation metric in a tradespace exploration of the design spaces and re-evaluates the application case with the updated methodology and an extended design space. Finally, Section V discusses findings and Section VI concludes the paper.

II. Background

This section outlines a brief background of the unique challenges of FSS conceptual design, previous work targeted at these challenges, and an introduction to the tools used in this work to narrow existing methodological gaps.

A. Systems-of-Systems

Understanding the unique challenges of FSS requires a clear definition of their parent system type, SoS. Several papers propose definitions for SoS with agreement on a subset of the proposed SoS attributes. This section provides a brief overview of the existing work to establish the definition used throughout the remainder of this paper.

Maier [5] characterizes SoS with a two part definition: 1) a SoS's component systems must fulfill their own function or purpose and continue performing that function if separated from the SoS and 2) the component systems must be managed for their own purposes rather than the purposes of the SoS. Other works add to Maier's definition with geographic distribution, emergent behavior, and evolutionary development as additional defining features [16, 17]. These definitions implicitly assume there exists an upside for each constituent system to participate in the SoS and, correspondingly, downside risks must be weighed against the upside potential [5, 17]. This paper adopts Maier's definition, with the understanding that constituent system owners must expect to benefit from collaboration to pursue it.

Accommodating multiple system owners with independent objectives is the unique challenge of SoS engineering (SoSE). Several methods have been proposed to address this issue. DiMario et al. [11] propose a method to discover satisficing SoS solutions employing the Analytical Hierarchy Process (AHP) for group decision-making. They recognize that constituent system owners will only collaborate if it increases their expected utility. AHP requires weights and combinations of the objectives of each constituent system and any global SoS objectives. Others model SoS formation using a chemistry analogy in which systems are represented by elements which complete their valence shells by forming molecules [10]. Still others propose transfer contract mechanisms from corporate management to align the objectives of the constituent systems with global system goals [12]. While some of these works recognize that the constituent systems should benefit from participation in the SoS, none presents a methodology that considers how the unique SoS risks and

benefits will affect the independent decisions of each constituent system actor.

Design methods for SoS are fundamentally limited by the distributed authority among system actors. A SoS authority, to the extent it exists, has little control over shaping the objectives or decisions of constituent system actors. Corresponding SoS design methods therefore shift from identifying solutions to proposing solution processes that facilitate the discovery of desirable alternatives preferred by system actors and exhibiting properties preferred by SoS observers such as Pareto efficiency, fairness, and stability to deviations. In short, each constituent system actor is seeking to get the “best” possible system [18], and the task of SoSE is to provide a process which explores possible alternatives in pursuit of this goal, recognizing that the existence of the SoS depends on achieving it.

B. Tradespace Exploration

Tradespace exploration techniques have gained traction in recent years as design methods to support conceptual design [19, 20]. Traditional conceptual design methods focus on Analysis of Alternatives (AoA) that evaluate and compare a few designs with respect to system objectives [21]. Consequently, AoAs can provide poor coverage of a design space, increasing the probability that a sub-optimal design will be implemented [21]. On the other-hand, automated tradespace exploration, whether by enumeration or guided by an optimization routine, enables relatively rapid low to mid-fidelity evaluation of a large design space. The broad coverage by tradespace exploration helps locate promising areas for more detailed analyses and identifies trends and relationships amongst the design variables.

Multi-Attribute Tradespace Exploration (MATE) is a method developed to take the design attributes, attribute value ranges, single-attribute utility functions, and multi-attribute utility function for a system concept and output system utility and cost for each design in the specified design space. The exploration portion of MATE is generally achieved by enumeration of the possible designs in the space which achieves a complete mapping from the design attribute space to the utility-cost space, but can be time prohibitive for large design spaces or computationally expensive utility functions. Several researchers have addressed the issue of computation time by guiding the tradespace exploration process with an optimization routine, often using a metaheuristic such as simulated annealing [22] or a genetic algorithm [23]. While these metaheuristic driven techniques cannot guarantee optimality, they can be much faster than direct enumeration.

Noting a dearth of quantitative methods for conceptual SoS design, a body of research establishes MATE as a method for discovering SoS or multi-stakeholder system designs (note that multi-stakeholder systems need not be an SoS but the cited works share a continuity of methodology) that trade the objectives of the constituent systems to find workable solutions for all [9, 24, 25]. These methodologies assume overlap in objectives between systems and higher-level goals or a degree of unified managerial authority that allows implementation of combined utility measures. As noted earlier, these conditions are not applicable to collaborative SoS. Additionally, simply modifying MATE to evaluate utility independently for each system is inadequate because an optimistic upside benefit for each system alone is insufficient grounds for participation in a collaborative system. Utilization of expected utility for each system, which considers

downside risks of collaboration, would seem to be the answer; however, individual evaluation of expected utility does not account for the interactive dynamics created by multiple decision makers. Consequently, a new method is needed to determine rational courses of action in a multi-decision-maker scenario in which common goals cannot be assumed.

C. Game Theory for Collaborative System Design

Game theory studies strategic interactions between multiple stakeholders [26] and is well suited for application to the SoS design problem. Essential game theoretic features include a set of decision-making actors (players), a set of strategies that define a complete course of action, and outcomes (payoffs) resulting from combinations of strategies selected by each actor. As an interactive decision-making problem, the strategy selected by one actor is influenced by other actors and vice-versa. Solution strategies build on decision rules such as maximin or minimax and equilibrium conditions that identify stable strategy sets where no actor has incentive to change strategies.

Game theory has been applied to study collaboration between independent businesses [27], engineering design in competitive environments [28, 29], and to negotiate between subsystem designers and stakeholders in collaborative design of individual systems [30, 31]. Recent work applies a risk dominance measure from equilibrium selection literature to determine whether system design combinations produce dynamics that favor independent or collaborative strategies [13, 14]. Accordingly, these methods can evaluate designs with the goal of selecting those which are strategically robust. The concepts presented in Ref. [14] are explained in greater detail in Section IV, and form the foundation of the research in this paper.

One of the main drawbacks of game-theoretic analysis is a focus on strategic decision-making at the highest levels of abstraction. Analysis of strategy dynamics and equilibrium points only evaluate broad decisions such as whether to pursue collaborative or independent architectures, rather than more detailed decisions governing system design and implementation. The logical gap between strategic and non-strategic design decisions presents a barrier to adopting game-theoretic metrics to a tradespace exploration paradigm. The work presented here addresses this issue with a bi-level decision model. The lower-level design information determines each constituent's utility given a particular implementation and strategic context. The constituent system utilities under each strategic context are then used for game-theoretic analysis of the strategy dynamics; linking design decisions to their impacts at the strategy level.

D. Research Objectives

The broad objective of this work is to develop and evaluate a methodology for finding the “best” constituent systems for operation in FSS and other SoS. While “best” may seem ambiguous, it is analogous with value or utility maximization, the objective of all engineering and design. As previously noted, utility maximization under real-world conditions demands robustness to common perturbations. Coordination failure between constituents is a unique perturbation for SoS which means constituent actors must consider two new system characteristics. First, they must design their systems

to be robust to coordination failures to minimize the loss of utility if the SoS dissolves. Second, they must design their systems to increase the stability of the collaborative strategy for all constituent systems, reducing the likelihood of SoS dissolution. These tasks are related—a system actor who loses relatively little under coordination failure is more likely to choose the collaborative strategy than one who takes a great risk by collaborating.

Two components comprise this work’s methodology for finding utility maximizing systems in the context of FSS. The first component implements a game-theoretic equilibrium selection criterion within a simple FSS tradespace exploration process to determine if selected designs are robust to coordination failure and contribute to favorable strategy dynamics. The next component broadens the initial scope to include economic factors such as contract terms and financial resource exchanges that affect system actor payoffs to study how the proposed methodology can guide selection of economic variable values and how the broader scope impacts the utility and robustness of candidate designs.

III. Baseline Model

This section introduces a notional FSS application case, constituent system models, and results of a baseline tradespace exploration process typical of existing analysis methods. A later section compares the results obtained in this section with those obtained when SoS unique strategy dynamics are considered.

A. Application Case

Conceptual design of commercial communication (SATCOM) and earth observation (EO) satellite systems is used to illustrate the methodological concepts presented in this paper. Net present value (NPV), in dollars, measures attainment of individual objectives and is calculated from system cost and revenue time series, assuming a 10% discount rate. SATCOM system revenue depends on subscription users and EO system revenue depends on imagery resolution and its latency, measured as the time from request of an image of a specific location to the downlinking of that image.

Both systems can increase revenue by forming a FSS. EO latency decreases, increasing system revenue, by utilizing the SATCOM system to relay image data to the ground. SATCOM revenue increases by selling the data transport service to the EO system. Figure 1 graphically displays the two systems operating independently and as a FSS.

B. SATCOM System Model

The SATCOM system is modeled as a Low Earth Orbit (LEO) constellation with a primary mission to provide internet connectivity services. Table 1 lists variable tradespace parameters. For design space simplicity, all SATCOM systems use a polar orbit with a streets of coverage constellation design. Constellation design evaluation uses the specified number of planes (π_s), satellites per plane (N_s), and elevation angle (ϵ) to determine the lowest operating altitude allowing constant coverage. First, Eq. (1) calculates the minimum altitude, a_{min} , to achieve a minimal street of coverage, where R_E is the radius of the Earth. An optimizer varies the altitude to minimize the difference between the

Fig. 1 System operations diagrams.

combined longitudinal coverage of all the streets (measured in units of Earth central angle) and 2π radians. Altitudes below 400 km are not permitted; constellations that can maintain coverage below 400 km have greater overlap between antenna footprints. The altitude and minimum user elevation angle ϵ determine the maximum slant range (R_s) and coverage area (A_θ , deg^2) of each satellite.

$$a_{min} = \left[\frac{R_E \cdot \cos \epsilon}{\sin \frac{\pi}{2} - \epsilon - \frac{\pi}{N_s}} \right] - R_E \quad (1)$$

Table 1 SATCOM system tradespace

Variable	Symbol	Maximum	Minimum
Number of planes	π_s	60	4
Number of satellites per plane	N_s	80	8
Number of user channels	C	32	1
Per channel transmit power (W)	p	10	1
Minimum user elevation angle (deg)	ϵ	40	10
Modulation scheme		22 options	

The next step determines maximum data throughput for each satellite. Steerable and shapeable beams with 10% effective coverage are assumed for all designs, i.e. 10% of the satellite field-of-regard is covered by beams at maximum gain. Equation (2) calculates the area covered by each beam. Equation (3) calculates maximum transmit antenna gain (G , dBi) where η is transmit antenna efficiency [32].

$$A_{\theta,eff} = \frac{A_\theta \cdot 10\%}{C} \quad (2)$$

$$G = 10 \cdot \log \left(\frac{41,253}{A_{\theta,eff}} \right) + 10 \cdot \log(\eta) \quad (3)$$

The specified transmit power (p) and modulation scheme determine the maximum per channel data rate as the minimum of the power limited and bandwidth limited rates. Per-satellite data rate is simply the channel rate multiplied by the number of channels. See the Appendix for an example link budget. The number of user subscriptions, as the minimum of the supportable subscriptions (based on deployment) and the subscription base for the month of the revenue calculation, determines monthly revenue. The number of subscriptions supportable by the constellation uses the total constellation throughput, a 10 Mbps user data rate, and a conservative over subscription ratio of 5:1 [33]. A logistic curve [34, 35] using satellite internet market growth projections published in Ref. [36] caps the subscriber base, S_{base} . Eq. (4) implements the logistic curve, where K is the maximum number of subscriptions in millions, b_1 is the scaling factor, t is the time in months from the start of system development, and b_2 is the inflection point in months.

$$S_{base} = \left[\frac{K}{1 + e^{-b_1(t-b_2)}} \right] \quad (4)$$

The SATCOM system cost model uses parametric cost-estimating relationships (CERs) starting with the estimation of dry mass from transmit power in Eq. (5). The cost models assume the total communication payload transmit power, including gateway, user, and inter-satellite links (ISLs), is 200% of the user link transmit power with an additional 10% overhead for receivers and other payload electronics. The estimate of spacecraft dry mass divides the payload power by a 0.46 payload power fraction [32] and multiplies by a density factor 0.20 W/kg and a redundancy factor of 0.8 to account for the short, five year mission life [37].

$$m_{dry,s} = \left[\frac{p \cdot C \cdot 200\% \cdot 110\%}{\eta_{Tx} \cdot 0.46} \right] \cdot 0.20 \frac{\text{W}}{\text{kg}} \cdot 0.8 \quad (5)$$

The model uses communication satellite CERs published in Ref. [32], Table 11-5 to estimate spacecraft non-recurring engineering (NRE) and production costs. Production costs assume an 85% learning curve [38]. Estimates of total spacecraft mass assume an additional 27% propellant mass [32]. Launch costs assume direct insertion, mass-limited launches with at least one launch per plane, Atlas V 551 performance data [39], at \$62M per launch. A 1:10 gateway ground station to satellite ratio determines the number of ground stations required [40]. The model implements CERs published in Ref. [32] to estimate costs for ground station infrastructure, operations, launch and orbital operations, and program level costs. The NRE period is 24 months, followed by 12 months of production and launch preparation, with the first launch occurring 36 months from the start of the program. Subsequent launches occur monthly until the entire constellation is deployed. The model spreads costs uniformly by month over the phase in which they are incurred. The model incurs launch costs starting 24 months prior to each launch and groups production costs into lots by launch and

spreads them over a 12 month period, working backwards from the launch date. See the Appendix for a detailed cost model including the factors and CERs used.

C. EO System Model

The model represents the EO system as a low-Earth orbit (LEO) constellation with circular, polar orbits. Table 2 lists variable tradespace parameters. The model uses a fixed minimum elevation angle of 40° for imaging and 15° for communication with ground stations.

The model uses Orekit 10.0* and a Python wrapper† to measure latency for each architecture by propagating spacecraft orbits and performing spacecraft-to-target geometric calculations. 50 points distributed uniformly in longitude, with a triangular distribution between 89° North and South latitude, approximating a uniform global distribution, comprise the target set. All targets enter the imaging queue at the beginning of the simulation. The satellite with the minimum time to receive a target imaging command, collect the image, and downlink to a ground station is tasked with collection. The model selects the first γ ground stations from a list that prioritizes extreme latitudes for favorable access to all satellites in the system (see Appendix for all ground station locations). The time from simulation start to imagery downlink is logged as the latency. The simulation runs until the data for the last target is downlinked. Simulation replications consider five start times, each offset by six hours, to mitigate effects of initial conditions. The mean latency for all targets and all simulation trials represents the performance metric for a given architecture.

The model does not consider observation range or angle to improve execution speed and to enable a greedy algorithm to schedule imaging operations. The resulting metric captures best case latency, but not data quality. In a real-world application one would likely sacrifice a small amount of latency for better quality data. However, a more complex targeting valuation model would complicate interpretation of results with additional assumptions. Therefore, resolution is simply determined by the Rayleigh diffraction limit and small angle approximation for a nadir target.

Table 2 EO system tradespace

Variable	Symbol	Maximum	Minimum
Number of planes	π_e	4	1
Number of satellites per plane	N_e	4	1
Aperture diameter (cm)	D	100	10
Altitude (km)	a	800	400
Number of ground stations	γ	5	0

A two objective multiplicative value function [41] computes monthly revenue with a maximum revenue of \$200M in Eq. (6). An exponential single-attribute value function (SAVF) for latency represents the decay of information value

*Available from CS GROUP at <https://orekit.org>

†Available from CS Systèmes d'Information at <https://gitlab.orekit.org/orekit-labs/python-wrapper>

[42, 43] in Eq. (7). An aggressive decay rate (λ) of $1/30,000 \text{ s}^{-1}$ requires system mean latency significantly less than 24 hours for appreciable value generation. An exponential SAVF in Eq. (8) for resolution (θ) yields a value of 1 for resolutions better than 20 cm.

$$P_{EO} = \$200\text{M} \cdot \nu_{\Lambda} \cdot \nu_{\theta} \quad (6)$$

$$\nu_{\Lambda} = e^{-\Lambda \cdot \lambda} \quad (7)$$

$$\nu_{\theta} = 0.17 \cdot \theta^{-1.1} \quad (8)$$

The EO system cost estimation process mirrors that of the SATCOM system with a few differences. EO system dry mass is estimated from aperture diameter (D) in Eq. (9) using a parametric relationship from Ref. [37]. NRE and spacecraft production costs are estimated using reconnaissance satellite CERs from Ref. [32] Table 11-5. Lastly, the number of ground stations is an independent design variable, rather than a parameter determined by the number of satellites in the system.

$$m_{dry,e} = D \cdot 22.87 \frac{\text{kg}}{\text{cm}} \cdot 0.8 \quad (9)$$

D. Collaborative System Model

A collaborative system utilizes excess SATCOM system capacity to transport EO system commands and data, increasing the potential revenue streams for the SATCOM system and the value of the EO system data. The collaborative system model is implemented with updates to the EO latency model and revenue models, SATCOM revenue model, and both cost models.

The EO system latency model assumes imaging tasks are instantaneously transmitted to the EO system upon demand generation, and data is immediately available upon collection. Collaborative systems use the same targets and start times as the independent systems, but latency for each target is reduced to the time from simulation start to the first possible observation of the target. EO monthly revenue is reduced by \$10M to pay a data transport service fee. The collaborative EO system cost model increases system mass by a factor of 5% to account for inter-satellite link hardware, NRE cost increases by an additional 10% to account for software to enable open inter-satellite links and additional bus complexity from adding link hardware. Recurring costs increase as a result of the mass increase, plus an additional 5% complexity factor.

The SATCOM system starts collecting the data transport service fee after it deploys the minimum number of satellites

required to access any other satellite in LEO and one or more EO satellites are deployed. The baseline SATCOM system network is a lattice with phased arrays for steerable links that are orthogonal to the velocity vector. In implementation, a small area of each array would be used periodically as a low gain “listening” antenna to receive data transport requests from the EO system [44]. When a request is received and accepted, the array would focus a high gain beam at the EO satellite to receive the data [44]. Therefore, no additional hardware was necessary to enable interoperability. The only change to the SATCOM cost model was a 10% increase in NRE to account for the ad-hoc networking protocol implementation.

E. Baseline Tradespace Exploration

The baseline analysis executes tradespace exploration in two phases. The first phase uses a heuristic search technique, specifically a genetic algorithm, to find the value-maximizing independent systems. The second phase searches for collaborative solutions that maximize NPV under successful collaboration for each system actor (i.e., as a multi-attribute objective). A collaborative design resulting in NPV greater than the independent designs for all systems is a viable candidate FSS. Figure 2 depicts the tradespace exploration process.

Fig. 2 Tradespace exploration structural diagram.

Tradespace exploration uses the Distributed Evolutionary Algorithms in Python (DEAP) eaMuPlusLambda genetic algorithm (GA) implementation [45]. Each trial starts with a population of 200 designs and runs for 100 generations. The cross-over and mutation rates are set to 0.8 and 0.2 respectively. Initial trials use the tradespaces displayed in Table 1 and Table 2 to narrow the variable ranges, increasing the probability of finding the optimal designs in the subsequent trials. Two or three trials are conducted for each tradespace.

Table 3 displays the top five independent EO system designs. All designs are similar with two or three planes and

three or four satellites per plane. No advantage is gained by employing more than three ground stations. Designs 1 and 2 are identical aside from the employment of two additional ground stations for design 2, which reduce NPV. Design 1 is the single Pareto efficient design.

Table 3 Top five independent EO systems to maximize NPV

Design	π_e	N_e	D (cm)	a (km)	γ	NPV (\$M)
1	3	3	100	400	3	346.75
2	3	3	100	400	5	311.42
3	3	3	95	400	3	303.72
4	3	4	100	400	3	275.70
5	2	4	100	400	3	273.74

Table 4 shows the top five independent SATCOM system designs. As was the case with the EO system, the highest value SATCOM system designs are clustered around a narrow set of design variables. Most high-value SATCOM systems select low transmitter power and large constellations, likely due to several factors. Large constellations can maintain coverage at the minimum altitude, maximizing launch vehicle capability, and reducing free-space losses. Additionally, the NRE for a smaller satellite is lower and learning effects benefit large constellations much more than small ones. Therefore, a given power flux-density is more efficiently achieved with large numbers of relatively low-flying, low-power satellites than with small numbers of higher-flying, high-power satellites. The relationship between required power flux-density and satellite quantity also explains the preference for high minimum elevation angles, which require more satellites but reduce the maximum slant range and enable the use of higher gain antennas.

Table 4 Top five independent SATCOM systems to maximize NPV

Design	π_e	N_e	ϵ (°)	p (W)	C	Modulation Scheme	NPV (\$M)
1	41	80	40	1	32	8PSK, 2/3 Code Rate	9035.65
2	40	80	40	1	32	8PSK, 2/3 Code Rate	9034.57
3	42	80	40	1	32	8PSK, 2/3 Code Rate	9025.21
4	39	80	40	1	32	8PSK, 2/3 Code Rate	9021.90
5	38	80	40	1	32	8PSK, 2/3 Code Rate	9021.07

Amongst the EO systems designed for collaboration, the highest value designs in Table 5 favor large constellations with no ground stations. Collaboration increases maximum NPV by 103% over the highest NPV independent design. The complete elimination of ground stations is the most striking feature of the designs which maximize NPV under collaboration. Eliminating ground stations maximizes efficiency, but also creates functional fragility; a feature that is explored later.

Unlike the highest value collaborative EO systems, the SATCOM architectures in Table 6 are nearly unchanged aside

Table 5 Top five collaborative EO systems to maximize NPV

Design	π_e	N_e	D (cm)	a (km)	γ	NPV (\$M)
1	3	4	100	400	0	704.38
2	3	3	100	400	0	685.78
3	2	4	100	400	0	662.45
4	3	4	95	400	0	622.02
5	3	3	95	400	0	606.41

from the addition of interoperable ISLs. The highest value independent and collaborative systems are identical with respect to other architectural decisions. Successful collaboration increases NPV by a modest 3.3%. Analysis presented in subsequent sections shows that the relatively invariant SATCOM system architecture benefits collaboration because no modification is made to the core system design which may inhibit system performance if coordination fails.

Table 6 Top five collaborative SATCOM systems to maximize NPV

Design	π_s	N_s	ϵ (°)	p (W)	C	Modulation Scheme	NPV (\$M)
1	41	80	40	1	32	8PSK, 2/3 Code Rate	9332.78
2	40	80	40	1	32	8PSK, 2/3 Code Rate	9331.70
3	42	80	40	1	32	8PSK, 2/3 Code Rate	9322.34
4	39	80	40	1	32	8PSK, 2/3 Code Rate	9319.03
5	38	80	40	1	32	8PSK, 2/3 Code Rate	9318.20

Baseline analysis results show collaborative designs can achieve superior NPV than independent alternatives for both EO and SATCOM systems; however, the results critically assume successful FSS formation. The analysis does not consider sources of risk from coordination failures that diminish the desirability of collaborative solutions, exemplified in the potentially-fragile choice of eliminating dedicated EO ground stations. Furthermore, as a strategic decision, choosing to collaborate or remain independent is an interactive problem among the constituent system actors that cannot simply be addressed with probabilistic analysis alone. Analysis of strategy dynamics in the following section demonstrates that other factors should be considered in design selection.

IV. Collaborative System Design with Strategy Dynamics

This section explains and illustrates fundamental game theoretic principles of risk dominance and applies it to SoS conceptual design. Risk dominance is then computed for results presented in the last section. Finally, an updated tradespace exploration methodology is presented and applied to the FSS design case with the baseline design variables and an extended case with additional design space dimensions.

A. Risk Dominance in Bi-level Design Games

Previous sections cited *strategic robustness* as a desirable property of constituent systems of FSS. In the context of this paper, strategic robustness is a SoS property that enables a system designer or owner to pursue a collaborative strategy that increases payoff over an independent strategy without decreasing expected value when strategy dynamics are considered. The game-theoretic concept of risk dominance is used here to measure the strategic robustness of system designs and stability of the efficient strategy in a FSS context. This section introduces risk dominance and its application to engineering design.

Grogan and Valencia-Romero [14] develop a methodology to apply game-theoretic principles to engineering design. Their methodology uses the concept of risk-dominance from equilibrium selection literature to quantify the relationships between design decisions and strategic stability in a federated system. The weighted average log measure of risk dominance (R) converts payoffs from a multi-actor design game into a single number that indicates which strategy is risk dominant [13]. When comparing two or more SoS alternatives, the lowest R value most strongly favors collaboration.

The risk dominance concept is easily illustrated by application to the canonical stag hunt game [46] illustrated in Table 7 in normal form. It presents a coordination problem between two hunters who have the choice of pursuing hare (ϕ) or stag (ψ). If both hunters select the hare-hunting strategy, then each receives a moderate payoff (2 utils). If both hunters pursue a stag-hunting strategy, then they each improve their gains (5 utils) relative to the hare-hunting strategy. However, if one hunter chooses to cooperate and the other defects, then the cooperating hunter receives nothing (0 utils) from their unsuccessful hunt. Whereas, in this case, the non-cooperative, defecting hunter receives a greater reward (4 utils) from hunting hare due to reduced competition.

Table 7 Normal form representation of a stag hunt game

Actor 1	Actor 2	
	Hare (ϕ)	Stag (ψ)
Hare (ϕ)	$V_1^{\phi\phi} = 2$ $V_2^{\phi\phi} = 2$	$V_1^{\psi\phi} = 4$ $V_2^{\phi\psi} = 4$
Stag (ψ)	$V_1^{\psi\phi} = 0$ $V_1^{\psi\psi} = 5$	$V_2^{\psi\psi} = 5$ $V_2^{\phi\psi} = 0$

Choosing a strategy in the stag hunt game must consider interactive effects; specifically, the strategy chosen by the other hunter and the payoff for a given strategy combination as a function of the player's selected design. Both hare/hare and stag/stag outcomes are Nash equilibria in a stag hunt game. There is no reason to pursue stag if one's partner chooses hare and, alternatively, no reason to pursue hare if one's partner chooses stag. While both are "stable" solutions, the two equilibria produce very different outcomes. Similar to how payoff dominance identifies the alternative with higher payoffs under successful coordination, risk dominance identifies the alternative with higher (expected) payoffs

under a possible coordination failure.

To visually explain risk dominance, Fig. 3 (a) illustrates a hunter's expected payoff as a function of the probability that the other hunter chooses to hunt stag (i.e. collaborates). The intersection point (u_i) of the two expected value lines displays the threshold probability that player j collaborates (p_j) for which the efficient (expected value-maximizing) strategy shifts from hunting hare (ϕ) to hunting stag (ψ). Equation (10) computes u_i for a payoff function, V , where superscripts indicate players i and j hunt hare ($\phi\phi$), i hunts hare and j hunts stag ($\phi\psi$), i hunts stag and j hunts hare ($\psi\phi$), and both players hunt stag ($\psi\psi$). Due to symmetry, $u_1 = u_2 = 2/3$. Without additional information, i.e. under a 50/50 chance the other hunter chooses to hunt stag, a rational decision maker will choose to hunt hare which yields an expected payoff of $2 \cdot 0.5 + 4 \cdot (1 - 0.5) = 3.0$ which exceeds the stag payoff of $0 \cdot 0.5 + 5 \cdot (1 - 0.5) = 2.5$. This analysis shows why choosing the hare-hunting strategy is viable and, under specific conditions, even rational or normative, despite stag/stag being the payoff dominant equilibrium.

$$u_i = \frac{V_i^{\phi\phi} - V_i^{\psi\phi}}{(V_i^{\phi\phi} - V_i^{\psi\phi}) - (V_i^{\phi\psi} - V_i^{\psi\psi})} \quad (10)$$

To connect with engineering applications, a design layer is added by assuming payoffs associated with the strategic decisions in Table 8 are also affected by the hunting implement (design) selected by each of the actors. For example, a hunter who intends to hunt hare brings dogs, whereas a hunter who intends to hunt stag with a partner brings a spear.

Table 8 Stag hunt design-strategy payoffs

Design	Strategy Combination			
	Hare, Hare	Hare, Stag	Stag, Hare	Stag, Stag
Dogs	2	4	0	0
Spear	0	0	0	5
Bow	1	1	1.75	4.5

Adding a third design, bow, changes the strategy dynamics. Though the bow has a lower payoff than dogs if hunting hare and a lower payoff than spear for a successful stag hunt, it significantly reduces the downside risk of collaboration in the event of a failed stag hunt. A similar probabilistic analysis in Fig. 8, selecting the bow for a stag hunt, shows the collaborative strategy has higher expected payoff for probabilities of cooperation above $1/3$, graphically represented in Fig. 3 (b), increasing $E[V]_i$ at $p_j = 0.5$ from 3.0 to 3.125 despite the bow option being Pareto dominated in each fixed context. Cooperation is the rational strategy if both hunters use the bow and no other factors influence strategy selection.

The risk dominance metric R formalizes the concept of risk-informed strategy selection when there are more than two players or asymmetric payoffs. Several decades of research have demonstrated that the risk dominant strategy has the greatest basin of attraction; that is, it is selected in repeated games between multiple players, updating their strategies to maximize payoff in each round of play [47]. Carlsson and van Damme [48] also found that the risk dominant equilibrium

Fig. 3 Expected value of player strategies under uncertainty.

should be selected in single-shot games if players allow the possibility of a strictly dominant equilibrium (this requires that the players are not certain the game is a stag hunt, an entirely reasonable assumption for a real-world ‘game’ in which payoffs are uncertain). R is computed using Eq. (11) where w_i are influence weights based on an influence matrix A and $w_i = 0.5$ for two-player games (see Ref. [14] for a complete explanation of w_i and A). A positive R indicates the independent strategy (ϕ) is risk dominant while a negative R indicates the collaborative strategy (ψ) is risk dominant. More importantly, R provides a relative measure of collaborative stability that can be compared across scenarios.

$$R \equiv \sum_{i=1}^n w_i(A) \ln \frac{u_i}{1 - u_i} \quad (11)$$

The R value for the stag hunt scenario in Table 7 is 0.69 which is reduced to -0.69 after selecting the bow design alternative in Table 8. The bow design makes the payoff dominant strategy also risk dominant; in other words, the bow design under the collaborative strategy (ψ) is the rational choice in the absence of additional information about the likely actions of the other player. In the context of SoSE, R acts as a criterion for collective stability of individual objectives as a function of the selected system designs. Selecting a system design that reduces R more strongly supports collaboration either by increasing the upside potential of collaboration or by decreasing the downside risk of failed collaboration (as demonstrated with the bow design). However, as illustrated here, risk dominance may also decrease upside potential, demanding a multi-attribute evaluation process to balance the two desirable traits.

B. Baseline Analysis of Strategic Robustness

Returning to the independent and collaborative EO and SATCOM systems presented at the end of Sec. III, the systems designed for collaboration appear to have superior value. Naïve collaborative system design methodologies may stop once the value maximizing designs have been discovered, assuming that collaboration will likely be successful

because mutual benefit is maximized. However, simple mutual benefit is insufficient to determine the rational strategy. Table 9 shows the normal form game for the EO-SATCOM SoS with value-maximizing architectures selected for independent and collaborative strategies. Simulations of FSS coordination failure produce the off diagonal values. System cost, performance, and revenue determinations for all strategic outcomes follow the two-stage decision process in Fig. 4.

Table 9 Normal form representation of EO-SATCOM SoS strategies

EO	SATCOM	
	Independent	Collaborative
Independent	\$9035.61M	\$9024.36M
Collaborative	\$346.75M	\$9332.78M
	\$9035.61M	\$704.38M
	-\$689.11M

Fig. 4 Two-stage decision flow chart.

The payoffs in Table 9 show the SATCOM system losses are relatively small if collaboration fails, whereas the EO system losses significantly exceed upside potential. The normalized deviation losses, u_i , are 0.743 and 0.036 for the EO and SATCOM systems respectively. The difference in downside losses has two causes. First, the EO system costs to enable collaboration are much more significant than those of the SATCOM system. Second, maximization of the upside value of collaboration requires architectural changes that severely inhibit functionality in independent operations (the “best” collaborative EO design has no ground stations). The model implements a ground station leasing contingency plan using publicly available pricing[‡] for zero ground station cases under failed collaboration. While the leased ground station recovers some capability and avoids initial investment costs, operation costs are significantly higher relative to a dedicated installation and capability does not match that of the three ground stations implemented in the best independent design. These factors result in negative NPV for EO in the case of failed collaboration.

Considering the information in Table 9, it appears that the rational strategy for each system owner is different. However, mutual collaboration and mutual independence are both strict Nash equilibria. In other words, it would

[‡] Accessed 7 August 2020 at <https://aws.amazon.com/ground-station/pricing/>

be irrational for the SATCOM system to pursue a collaborative strategy if the EO system is certainly *not* going to collaborate or for the EO system to pursue an independent strategy if the SATCOM system certainly *is* going to collaborate. Unfortunately, the actions of other actors cannot be known with certainty. In the absence of any information about the likelihood of the other actors actions, it is difficult to readily identify the rational strategy.

This is where risk dominance is helpful. R provides a quantifiable measure, indicating the relative preference for strategy-design pairs, by taking into consideration the relative impacts of each actor on the other(s) as well as the expected values for each strategy. In this case, applying Eq. (11) shows R is -1.11 . Assuming no prior information about either actor's preference for a particular strategy, the rational strategy for *both* system actors is to collaborate. The relative losses of the SATCOM system are small, so they are likely to collaborate. Combined with the significant upside gains for the EO system, the overall strategy dynamics favor collaboration.

C. Tradespace Exploration with Risk Dominance

While the NPV maximizing designs produced by the baseline model produce favorable dynamics, guiding tradespace exploration with *a priori* knowledge of risk dominance can produce designs that more strongly favor collaboration by sacrificing some upside potential (efficiency) for reductions in downside loss (robustness). The results presented in this section are produced by an updated tradespace exploration methodology that adds simulation of systems under coordination failure to generate values to compute R . Implementation of R as a measure of the collective stability of individual objectives differentiates this work from previously proposed SoSE design methods. Figure 5 shows the modified structural diagram elements for the updated tradespace exploration methodology. The output is a Pareto efficient front in three dimensions: R and NPV for each of the two systems.

Fig. 5 Tradespace exploration with risk dominance structural diagram.

Table 10 shows the Pareto efficient designs. Figure 6 plots the expected value of each EO solution against the independent solution and Fig. 7 shows the EO NPV and R dimensions of the three-dimensional tradespace for all designs with defined R . Figure 6 clearly shows that design 3 from Table 10 sacrifices substantial upside potential relative to the other two Pareto efficient designs, but also has significantly reduced downside risk. Design 3 is similar to the optimal design for independent operations, giving it utility robustness when collaboration fails. Figure 7 shows that the viable EO system design space is fairly narrow and a subset of designs with positive NPV under the independent strategy. The narrow range of viable design variables indicates a stable region in the space which yields high-value designs for both strategies; in this case resulting in a number of designs which favor the collaborative strategy.

Table 10 Pareto efficient collaborative designs with risk dominance

EO Design	Planes	Satellites per plane	Aperture diameter (cm)	Altitude (km)	Ground stations	NPV_e (\$M)	NPV_s (\$M)	R	u_e
1	3	4	100	400	0	704.38	9332.78	-1.11	0.743
2	3	3	100	400	0	685.78	9332.78	-1.13	0.733
3*	3	3	100	400	3	486.35	9332.78	-1.17	0.717

*Same as the value-maximizing design for the independent strategy, with interoperable ISLs added.

All SATCOM designs were Table 6, design 1

Fig. 6 Expected value for Pareto efficient EO solutions with consideration of risk dominance.

The results show that the primary dilemma is for the EO system. The u_e values in Table 10 indicate the minimum probability of SATCOM collaboration for which the corresponding design yields higher expected value than the independent strategy. Note that all u_e exceed 0.5, yet the R values indicate that collaboration is dominant because it accounts for SATCOM's very low u_s value near 0.036, which strongly favors collaboration. However, u_e is a valuable metric because it can diagnose the ability of the two systems to successfully engage without requiring global payoff visibility, as R does.

EO design 1 yields the highest upside NPV. However, it is only preferred over the independent solution for probabilities

Fig. 7 Projected EO system tradespace under the collaborative strategy.

of SATCOM collaboration in the range $0.85 \leq p_{satcom} \leq 1$, while design 2 is preferred for $0.743 \leq p_{satcom} < 0.85$ and design 3 is preferred for $p_{satcom} < 0.743$. This information enables the EO system decision maker to select the design that maximizes expected value tailored to an estimated probability of successful collaboration.

While the difference between u_e values and corresponding preference ranges are relatively small, they would be enhanced with increased decision maker risk aversion, strengthening the favorability of the design with the lowest downside risk. Such risk aversion could be incorporated in the tradespace exploration activity with a risk-adjusted utility metric.

The most notable feature of this analysis is the clear trade between efficiency and robustness for the EO system. While design 1 yields high NPV under collaboration, the downside is significant when SATCOM pursues an independent strategy. Design 3 trades some upside for a substantial decrease in downside by reducing space segment investment costs and adding ground stations, mimicking the highest value independent design.

D. Extended Application Case: Effect of Economic Design Variables on Strategy Dynamics

Solutions to real-world engineering problems are intertwined with economic and mission factors that impact utility throughout the system's life-cycle. Therefore, this section provides expanded analysis of the original problem with added economic design variables. Adding economic design variables aims to understand how the proposed tradespace exploration methodology can facilitate evaluation of technical and non-technical variables and determine the usefulness of including economic variables in design space exploration.

It is reasonable to assume that contract terms between the system owners are part of the design space of a collaborative system and that the utility of a given technical implementation is a function of economic factors as well as system

performance. Furthermore, economic design should be assessed for impacts to strategy dynamics because efficiency alone does not create the conditions for collaboration. Conversely, simultaneous evaluation of technical and economic variables can identify designs with greater strategic robustness, producing more stable dynamics, including designs that would not be considered when assessing technical variables only.

The extended application case implements the monthly data transport service fee and a development cost-share as economic design variables. Fixed fee results in the preceding section indicate the downside risk of failed collaboration for SATCOM is low as compared to EO. A new cost-sharing agreement assigns up to 100% of EO's collaboration costs to SATCOM to balance the risk burden for each system. The monthly service fee can vary between \$1M and \$20M. The SATCOM owner does not recoup the cost-share if they break the contract to pursue an independent solution. EO reimburses SATCOM for the collaboration investment if EO defects. The variable fee and cost-share enable SATCOM to collect higher data transport service fees to recoup their investment from EO without jeopardizing the federation.

The economic arrangement reduces EO's downside risk and disincentivizes SATCOM's defection without incentivizing EO defection. Table 11 shows a normal form example representing a modification to the highest NPV collaborative design examined earlier with the data transport fee raised to \$16.2M and addition of 50% cost-share. Note that values are similar to Table 9 but with a transfer of \$192M to EO in the event that EO collaborates and SATCOM defects. While the game is no longer strictly a stag hunt, it is still a bipolar game where R identifies the risk dominant strategy. The upside payoffs are almost unchanged but the u_i values are substantially reduced and $R = -1.45$. The cost-share agreement increases SATCOM's commitment to the collaborative strategy (a fact that the EO system owner knows, even if SATCOM's actual payoffs are unknown), and the cost penalty imposed on SATCOM can be recovered by an increased data transport service fee, while still improving R .

Table 11 Example normal form game for cost-share contract

EO NPV (\$M)	SATCOM NPV (\$M)	
	Independent	Collaborative
	9035.61	9024.36
Independent	346.75	346.75
	8843.92	9332.27
Collaborative	-497.38	704.88

Addition of fee and cost-share variables produce many Pareto efficient designs for each technical implementation with desirable characteristics. Table 12 lists a selection of high performing collaborative system designs with added service fee and cost-share design variables in the tradespace exploration. Note that the design column has been changed from the numeric identifiers in the previous tables (with the exception of designs carried over from the preceding section, included for reference) to descriptive names for further discussion. In the context of design names, min Δ designs are

those which minimize the difference in upside of collaboration for both systems.

Table 12 Select Pareto efficient collaborative designs with fee and cost-share as design variables

Design	π_e	N_e	D (cm)	a (km)	γ	fee (\$M)	cost-share	NPV_e (\$M)	NPV_s (\$M)	R
1	3	4	100	400	0	10.00	0.00	704.38	9332.78	-1.11
2	3	3	100	400	0	10.00	0.00	685.78	9332.78	-1.13
3	3	3	100	400	3	10.00	0.00	486.35	9332.78	-1.17
min R	3	3	100	400	3	13.49	0.99	731.13	9087.99	-4.41
max NPV_e	3	4	100	400	0	6.76	0.51	1000.04	9037.11	-1.30
max NPV_s	3	4	100	400	0	19.74	0.01	406.28	9630.87	-0.56
max up, min R	3	4	100	400	0	17.56	0.99	852.44	9184.72	-1.80
max up, min Δ	3	4	100	400	0	19.91	0.72	673.25	9363.91	-1.57
3x4, 3 γ	3	4	100	400	3	17.56	0.99	660.86	9179.64	-2.65
2x4, min R	2	4	100	400	3	13.49	0.99	707.54	9098.41	-2.52
2x4, min Δ^*	2	4	100	400	4	14.42	0.82	534.40	9187.49	-1.75
2x3, min R^*	2	3	100	450	0	14.60	0.68	556.40	9260.86	-1.32
2x3, 1 γ^{**}	2	3	100	450	1	14.60	0.68	437.11	9259.36	-0.86

Note: All SATCOM designs were Table 6, design 1

*Not on Pareto front

**Not in the results produced by the GA, but a promising low cost solution.

Figure 8 displays designs from Table 12 as well as lines which represent the range of upside values for which R is defined for each technical implementation on the Pareto frontier. Three of the designs in Table 12 are not on the Pareto frontier, so their technical implementation value range lines are excluded. Two of these designs are apparent in the lower left quadrant of Fig. 8; the third is nearby and is located at (556.40, 9260.86). R values are expressed in the color map, with the scale maximum at 0. Points with $R > 0$ are colored the same as those with $R = 0$. Note that R decreases as EO NPV increases across technical implementations because of the low downside risk for SATCOM relative to EO.

Several designs which would not be otherwise feasible, such as the two plane, three satellite per plane EO designs, become feasible when economic variables are included in the tradespace exploration. Furthermore, the preference for lower-cost designs may be even greater for a risk averse decision maker because downside risk is limited to the investment cost, which is decreased.

Both the addition of economic variables and the application of risk dominance to assess the resulting designs create insights over analyses that lack one or both of these features. The first benefit from implementing economic design variables is an expanded Pareto front with new technical implementations, such as the two plane, four satellite per plane EO system design and the three plane, four satellite per plane, three ground station design that were not feasible under the fixed economic conditions presented above. Additionally, economic variables enable balancing of the upside and downsides between each actor such that those bearing the greatest risk (EO in this example) have the most to gain. This

Fig. 8 Pareto frontier, collaborative designs with fee and cost-share as design variables. Designs in Table 12 are represented by ‘+’ markers. Lines each represent the range of payoffs and R for a single technical implementation that appears on the Pareto frontier. Note that the maximum R value on any line is 2.6, but the color map maximum is set to 0 for clarity

influences the dynamics towards strongly favoring collaboration; as demonstrated by the min R design in Table 12, which is identical to design 3 apart from the economic variables. Lastly, the economic variables move the Pareto front such that design 3 is dominated by the max up, min δ design, yielding a superior option for both systems.

As previously mentioned, the addition of economic variables greatly expands the number of Pareto efficient designs. Discriminating between designs with similar technical implementations requires an additional measure. R quantifies the basin of attraction for each strategy as a function of the game payoffs, which, in this context are a function of technical and economic design. Therefore, R indicates which set of economic variables produce the greatest basin of attraction for the collaborative strategy. The four “max” designs in Table 12 illustrate this point well. All four technical implementations are identical. However, the first two divide the upside benefit of collaboration to maximize gains by one or the other systems, whereas the last divides the upside nearly equally between the two systems. The min Δ design favors collaboration the most strongly of the three, but still does not represent the optimal arrangement in terms of maximizing the basin of attraction for the SoS. The max up, min R design shifts a greater proportion of the payoff to the EO system, maximizing the favorability of collaboration for the most efficient technical implementation. While it is intuitive that the solutions that maximize the payoff for one system with minimal benefit for the other are not optimal, R quantifies this intuition and indicates which designs are “best” with respect to creating the conditions for the SoS to form and survive.

These results demonstrate the advantage of including economic design variables and applying the risk dominance criterion to their assessment. Using only the upside payoffs as design selection criteria creates a dilemma for each system owner between pursuing a solution that maximizes their own payoff and agreeing to a solution that is most attractive to the other system owners, thereby facilitating mutually beneficial coordination. R helps to solve this dilemma by providing an objective measure of the favorability of collaboration for a given set of designs as a consequence of balancing the risk and upside potential for each system actor.

V. Discussion

This work demonstrates the application of the game-theoretic equilibria selection criterion, risk-dominance (R), to satellite SoS tradespace exploration. Results show that multi-objective tradespace exploration combining traditional measures of utility with a measure of risk-dominance yields designs that are more robust to dissolution of the SoS. Furthermore, the results reinforce the idea that efficiency must be traded to gain robustness. In the case of the earth observation and satellite communications SoS studied here, that means reducing the cost of the Earth observation system space segment and increasing the number of ground-stations to ensure functionality in the absence of data transport services from the satellite communications system.

Adding economic variables to the tradespace, in the form of a data transport service fee and a cost-share contract, expands the number of feasible alternatives and the feasible regions of the technical design space. R is shown to be a valuable metric for discriminating between designs with common technical parameters and differing economic parameters. While negotiation based methods may produce satisfactory results, R quantifies the stability of the collaborative strategy given the system design utilities. This enables the identification of designs which most strongly support desirable strategy dynamics.

The high-performing designs for both systems, whether independent or as an FSS, are architecturally similar to systems currently in development or deployment [49, 50]. The EO systems are characterized by relatively large numbers of satellites and low altitudes when compared to legacy systems. The SATCOM architectures are comprised of satellites with many channels, low transmit power, narrow beams, and low operating altitude. This combination of features results in a large number of small satellites. The number of users and data rates held constant, large numbers of small satellites are superior to fewer large satellites because learning curve effects result in much lower production costs. It is reasonable to conclude that this finding holds true for other satellite systems, assuming that the mission's physics permit disaggregation.

Several problem specific modeling assumptions are made to accelerate the simulation efforts. For example, illumination conditions are not included in the models, a major consideration for imaging. Additionally, spacecraft and user demand models that enable simulation of data collection and transport would likely uncover orbital configurations, regions, and time periods, that are more or less conducive to interoperation between the EO and SATCOM systems.

Simulating these interactions between thousands of satellites would be computationally prohibitive. Therefore, this problem requires further consideration, and potential solutions need to be carefully weighed against the time it takes to generate results. While the specific results are contingent upon these and other modelling assumptions, the methodological contributions of the work are minimally impacted.

There are also assumptions that influenced results related to the core contributions of this work. The model assumes that each system is “locked-in” to the design choices that are made at the beginning of the program. This is not likely to be the case. Relaxing this assumption could make collaborative designs more favorable when there are design paths to solutions that are higher value under coordination failure. Most importantly, the conclusions reached in this work assume that risk dominance is an appropriate measure of strategic stability, and in turn, the strategic robustness of system designs. While work in other fields indicates that this is the case [51], additional research on the bi-level decision dynamics of SoS design problems is required to fully understand its normative application to design.

A priori consideration of significant sources uncertainty is required to generate the reliable utility measures on which the methodology depends. Future work will address this gap in the current methodology by implementing games of incomplete information [52] and other uncertainty modelling techniques; enabling computationally efficient, up-front risk modeling and methodological realism for cases where partner utility functions are uncertain.

VI. Conclusion

This work demonstrated a methodology for Federated Space System (FSS) tradespace exploration, implementing a risk dominant equilibrium selection method from game theory that yields system designs that are well-suited to collaboration. Robustness to common perturbations is essential to good design. FSS, like other system-of-systems (SoS) with distributed decision authority, are subject to a system actor withdrawing cooperation. Therefore, FSS engineers should design constituent systems to reduce strategic uncertainty and/or its impacts. The work assumes, *ceteris paribus*, that an equilibrium that is both risk and payoff dominant is the rational choice for all system actors; a property this work refers to as strategic stability. Constituent system designs determine the payoffs for each system actor under the possible strategic outcomes, and therefore strongly affect the stability of the FSS. The methodology can be implemented to assess factors affecting constituent system payoffs, yielding an objective measure of design quality as it relates to strategic robustness.

The methodology is implemented in the evaluation of a FSS comprised of an earth observation (EO) and a satellite communication (SATCOM) system in two cases. Results show that optimal EO and SATCOM systems are composed of many spacecraft in low orbits (relative to the nearest analogs from previous decades). While the details differ between the systems, the chief reasons for these two architectural characteristics are that many small spacecraft are less expensive than few large spacecraft due to learning during production, and shorter observation and communication ranges increase performance for a set platform design.

Minimization of the risk dominance measure in the tradespace exploration activity yields system designs exhibiting utility robustness, with significantly reduced utility losses when FSS formation fails. Constituent system designs achieved robustness by independent provisioning of some of the functionality provided by the FSS. These robustness enhancements diminish FSS efficiency, but increase the overall favorability of collaboration, thereby strengthening the FSS. Varying the economic parameters describing the interaction between systems in the FSS increases the range of possible technical implementations and improves collaborative dynamics. The risk dominance measure indicates which values of the economic variables most strongly promote collaborative dynamics; an insight unattainable when measuring only the utility of each system or the FSS.

Rigorous testing and redundant systems have long been mainstays of spacecraft design. Collaborative systems introduce a new source of uncertainty that is not easily addressed through testing and other traditional engineering processes. As FSS become a reality, system designers and decision makers will need to understand the interaction between system design decisions and the strategic decision of whether to collaborate or design a stand-alone system. Strategic decisions interact with technical designs, economic factors, and uncertainty to create complex decision spaces. System designers, managers, and owners must account for these interactions when considering decisions at all levels. This work has demonstrated how modelling system strategy decisions as games enables the use of the weighted average log measure of risk dominance, R , as a criterion in multi-system tradespace exploration activities, discovering designs that are robust to coordination failure and influence strategy dynamics to favor collaboration.

Appendix

Table 13 shows an example link budget. Note that transmitter power, coverage area, free space loss, required E_b/N_0 and spectral efficiency are influenced by design variables; additional parameters are in turn influenced by these.

Table 14 shows the factors and constants used for the cost estimate. Equation (12) determines space segment non-recurring (NRE) costs for SATCOM by multiplying single spacecraft dry mass by an NRE factor and the inflation from the base year of the factor to 2020.

$$\chi_{nre,s} = m_{dry,s} \cdot NRE_s \cdot (1 + i_{10}) \quad (12)$$

Equation (13) applies an additional factor when the collaborative strategy is selected.

$$\chi_{nre,s,\psi} = \chi_{nre,s} \cdot (1 + ISL_s) \quad (13)$$

Table 13 Example single channel link budget

Parameter	Value	Units
Downlink frequency (f)	11.7	GHz
Bandwidth	250	MHz
Tx power (p)	2.6	W
Coverage area	6683	deg. ²
Tx gain (G)	31.41	dBi
Tx line loss	-4.5 ^a	dB
EIRP	31.06	dBW
Free space loss	-169.4	dB
Atmospheric loss	-3.5 ^b	dB
Rx antenna diam.	0.7	m
User gain	36.07	dBi
Rx line loss	-2.0 ^a	dB
Rx carrier power	-107.75	dBW
System noise temp.	25.6 ^b	dB-K
Rx C/N ₀	95.25	dBW
Req. E _b /N ₀	5.49 ^a	dB
Spectral efficiency	3.0 ^a	-
Link margin	1.0	dB
Power limited rate	751.5	Mbps
Bandwidth limited rate	632.4	Mbps

^a parameter value from Ref. [32]

^b parameter value from Ref. [40]

Equation (14) calculates first unit production cost (T1).

$$\chi_{T1,s} = m_{dry,s} \cdot P_s \cdot (1 + i_{10}) \quad (14)$$

Equations (15)–(16) calculate EO system space segment NRE and first unit production costs respectively.

$$\chi_{nre,eo} = m_{dry,e} \cdot NRE_e \cdot (1 + i_{10}) \quad (15)$$

$$\chi_{T1,eo} = m_{dry,e} \cdot P_e \cdot (1 + i_{10}) \quad (16)$$

Equations (17)–(18) are applied to increase EO system mass and cost respectively when the collaborative strategy is selected.

$$m_{dry,e,\psi} = m_{dry,e} \cdot (1 + ISL_m) \quad (17)$$

$$\chi_{nre,eo,\psi} = m_{dry,e,\psi} \cdot NRE_e \cdot (1 + i_{10} + ISL_c) \quad (18)$$

Table 14 Cost estimating relationship factors and constants

Factor	Variable	Value	Units
Tx efficiency	η_{Tx}	0.17 ^a	-
Power-to-mass ratio	PMR	5.0	W/kg
2010 to 2020 inflation	i_{10}	0.1858 ^b	-
Annual inflation	i	0.0205 ^b	-
Payload power fraction	PPF	0.46 ^a	W/W
Learning curve	S	0.85 ^d	-
First ground station	GS_1	0.09 ^a	-
Subsequent ground station	GS_n	0.06 ^a	-
Systems engineering	SE	0.20 ^a	-
Program management	PM	0.15 ^a	-
Integration & test	$I\&T$	0.15 ^a	-
Launch & orbital operations support	$LOOS$	0.061 ^a	-
Other	$MISC$	0.16 ^a	-
Operations	OPS	0.05 ^a	-
Ground maintenance	MNT	0.135 ^a	-
Launch cost	L	62	\$M
Fuel fraction	FF	0.27 ^a	-
Redundancy reduction	RD	0.2 ^b	-
Open inter-satellite link complexity	ISL_c	0.1	-
Open inter-satellite link mass	ISL_m	0.05	-
SATCOM non-recurring engineering	NRE_s	0.429 ^a	\$M/kg dry mass
SATCOM recurring engineering	P_s	0.09 ^a	\$M/kg dry mass
EO non-recurring engineering	NRE_e	0.402 ^a	\$M/kg dry mass
EO recurring engineering	P_e	0.082 ^a	\$M/kg dry mass

^a from Ref. [32], ^b from Ref. [53], ^c from Ref. [37], ^d from Ref. [38]

^e accessed 10 May 2020 from <https://www.spacex.com/about/capabilities>

Equation (19) increases T1 costs from increased mass and complexity when the collaborative strategy is selected.

$$\chi_{T1, eo, \psi} = m_{dry, e, \psi} \cdot P_e \cdot (1 + i_{10} + ISL_c/2) \quad (19)$$

Equation (20) calculates the cost of each satellite with learning effects.

$$\chi_{unit}(n) = \chi_{T1} \cdot n^{(1+\ln S/\ln 2)} - \chi_{T1} \cdot (n-1)^{(1+\ln S/\ln 2)}, \quad n = 1, \dots, (N \cdot \pi) \quad (20)$$

Equation (21) calculates individual spacecraft wet mass for all systems.

$$m_{wet} = m_{dry} \cdot (1 + FF) \quad (21)$$

Equation (22) calculates maximum launch mass, m_l using a linear approximation of Atlas V 551 capability to a polar orbit [39], where a is altitude in km.

$$m_l = 15888 - 1.4856 \cdot a \quad (22)$$

Equation (23) determines the number of launches, n_l , as the ceiling of the total mass of all satellites in a plane divided by the launch vehicle capability to that orbit multiplied by the number of planes.

$$n_l = \left\lceil \frac{N \cdot m_{wet,i}}{m_l} \right\rceil \cdot \pi_i \quad (23)$$

Equation (24) calculates total launch cost as the number of launches multiplied by the single launch cost.

$$\chi_l = L \cdot n_l \quad (24)$$

Equation (25) calculates the number of satellites per launch to determine the number of production lots.

$$n_{sats} = \frac{N_i \cdot \pi_i}{n_l} \quad (25)$$

The number of ground stations is a design variable for the EO system. Equation (26) calculates the number of ground stations for the SATCOM system.

$$\gamma_s = \frac{N_s \cdot \pi_s}{10} \quad (26)$$

Equation (27) calculates the ground NRE costs estimated based on the spacecraft T1 and NRE costs, where χ_{nre} is space segment NRE cost for either system. Note that the independent spacecraft NRE costs are always used as the model assumes the ground system NRE would not increase substantially with the addition of open inter-satellite links to the space segment.

$$\chi_{nre,gnd} = (\chi_{nre} + \chi_{T1}) \cdot (GS_1 + GS_n \cdot \gamma_i) \quad (27)$$

Equation (28) calculates ground operations costs as the sum of space segment operations and ground system maintenance costs. The independent strategy space segment NRE costs are always used.

$$\chi_{ops} = \chi_{nre,gnd} \cdot MNT + (\chi_{T1} + \chi_{nre}) \cdot OPS \quad (28)$$

Equations (29)–(30) apply wrap factors to the space segment NRE and each production lot respectively, where χ_{lot} is the cost of each production lot determined by the number of satellites in each lot and the cost of each satellite with

learning effects applied as calculated in Eq. (20).

$$\chi_{nre} = \chi_{nre} \cdot (1 + SE + PM + I\&T + MISC) \quad (29)$$

$$\chi_{lot} = \chi_{lot} \cdot (1 + SE + PM + I\&T + MISC + LOOS) \quad (30)$$

Costs are finally spread uniformly over each system program phase as described in Sec. III.B and inflation, (*i*), applied proportionally to each element of the cost series.

Table 15 shows the location of each ground station used in the EO models. Ground stations are always selected in ascending index order starting with number 1. All ground stations locations are near existing Kongsberg Satellite Service[§] or Swedish Space Corporation[¶] locations.

Table 15 Ground station locations

Index	Latitude	Longitude
1	78.20	15.30
2	-72.00	2.50
3	-52.93	-70.85
4	67.88	21.07
5	68.40	-133.5

Funding Sources

This material is based upon work supported by the National Science Foundation under Grant No. 1943433. The view expressed in this paper are those of the authors and do not represent the policy of the U.S. Air Force, the U.S. Department of Defense, or the U.S. Government.

References

- [1] Selva, D., Golkar, A., Korobova, O., Lluch i Cruz, I., Collopy, P., and de Weck, O. L., “Distributed Earth Satellite Systems: What Is Needed to Move Forward?” *Journal of Aerospace Information Systems*, Vol. 14, No. 8, 2017, pp. 412–438. <https://doi.org/10.2514/1.I010497>.
- [2] Grogan, P. T., Golkar, A., Shirasaka, S., and de Weck, O. L., “Multi-stakeholder interactive simulation for federated satellite systems,” *2014 IEEE Aerospace Conference*, 2014, pp. 1–15. <https://doi.org/10.1109/AERO.2014.6836253>.
- [3] Akhtyamov, R., Vingerhoeds, R., and Golkar, A., “Identifying Retrofitting Opportunities for Federated Satellite Systems,” *Journal of Spacecraft and Rockets*, Vol. 56, No. 3, 2019, pp. 620–629. <https://doi.org/10.2514/1.A34196>.

[§] Accessed 11 May 2020 at <https://www.ksat.no/services/ground-station-services/>

[¶] Accessed 11 May 2020 at <https://www.sscspace.com/ssc-worldwide/ground-station-network/>

- [4] Office of the Under Secretary of Defense for Acquisition, Technology, and Logistics, *Systems Engineering Guide for Systems of Systems*, United States Department of Defense, 2008.
- [5] Maier, M. W., “Architecting principles for systems-of-systems,” *Systems Engineering*, Vol. 1, No. 4, 1998, pp. 267–284. [https://doi.org/10.1002/\(SICI\)1520-6858\(1998\)1:4<267::AID-SYS3>3.0.CO;2-D](https://doi.org/10.1002/(SICI)1520-6858(1998)1:4<267::AID-SYS3>3.0.CO;2-D).
- [6] Lluch, I., and Golkar, A., “Design Implications for Missions Participating in Federated Satellite Systems,” *Journal of Spacecraft and Rockets*, Vol. 52, No. 5, 2015, pp. 1361–1374. <https://doi.org/10.2514/1.A33172>.
- [7] Brown, O., and Eremenko, P., “The Value Proposition for Fractionated Space Architectures,” *Space 2006*, AIAA, 2006, pp. 1–22. <https://doi.org/10.2514/6.2006-7506>.
- [8] Doyle, J. C., and Csete, M., “Architecture, constraints, and behavior,” *Proceedings of the National Academy of Sciences of the United States of America*, Vol. 108, No. 3, 2011, pp. 15624–15630. <https://doi.org/10.1073/pnas.1103557108>.
- [9] Chattopadhyay, D., Ross, A., and Rhodes, D., “Demonstration of System of Systems Multi-Attribute Tradespace Exploration on a Multi-Concept Surveillance Architecture,” *7th Annual Conference on Systems Engineering Research*, 2010, pp. 1–12.
- [10] Baldwin, W. C., Ben-Zvi, T., and Sauser, B. J., “Formation of Collaborative System of Systems Through Belonging Choice Mechanisms,” *IEEE Transactions on Systems, Man, and Cybernetics - Part A: Systems and Humans*, Vol. 42, No. 4, 2012, pp. 793–801. <https://doi.org/10.1109/TSMCA.2011.2164522>.
- [11] DiMario, M. J., Boardman, J. T., and Sauser, B. J., “System of systems collaborative formation,” *IEEE Systems Journal*, Vol. 3, No. 3, 2009, pp. 360–368. <https://doi.org/10.1109/JSYST.2009.2029661>.
- [12] Fang, Z., Davendralingam, N., and DeLaurentis, D., “Multistakeholder Dynamic Optimization for Acknowledged System-of-Systems Architecture Selection,” *IEEE Systems Journal*, Vol. 12, No. 4, 2018, pp. 3565–3576. <https://doi.org/10.1109/JSYST.2018.2794325>.
- [13] Selten, R., “An axiomatic theory of a risk dominance measure for bipolar games with linear incentives,” *Games and Economic Behavior*, Vol. 8, 1995, pp. 213–263. [https://doi.org/10.1016/S0899-8256\(05\)80021-1](https://doi.org/10.1016/S0899-8256(05)80021-1).
- [14] Grogan, P. T., and Valencia-Romero, A., “Strategic risk dominance in collective systems design,” *Design Science*, Vol. 5, 2019, p. e24. <https://doi.org/10.1017/dsj.2019.23>.
- [15] Grogan, P. T., Ho, K., Golkar, A., and de Weck, O. L., “Multi-Actor Value Modeling for Federated Systems,” *IEEE Systems Journal*, Vol. 12, No. 2, 2018, pp. 1193–1202. <https://doi.org/10.1109/JSYST.2016.2626981>.
- [16] Sage, A. P., and Cuppan, C. D., “On the Systems Engineering and Management of Systems of Systems and Federations of Systems,” *Information, Knowledge, Systems Management*, Vol. 2, 2001, pp. 325–345.
- [17] Boardman, J., and Sauser, B., “System of Systems - the meaning of of,” *2006 IEEE/SMC International Conference on System of Systems Engineering*, 2006, pp. 118–123. <https://doi.org/10.1109/SYSESE.2006.1652284>.

- [18] Hazelrigg, G. A., and Saari, D. G., "Toward a Theory of Systems Engineering," *ASME 2020 International Design Engineering Technical Conferences and Computers and Information in Engineering Conference*, Vol. 8: 32nd International Conference on Design Theory and Methodology (DTM), 2020, pp. 1–10. <https://doi.org/10.1115/DETC2020-22004>.
- [19] Ross, A. M., Hastings, D. E., Warmkessel, J. M., and Diller, N. P., "Multi-Attribute Tradespace Exploration as Front End for Effective Space System Design," *Journal of Spacecraft and Rockets*, Vol. 41, 2004, pp. 20–28. <https://doi.org/10.2514/1.9204>.
- [20] Hastings, D. E., Tour, P. A. L., and Giri, D. K., "Architectural Concept of Disaggregation of Space Systems: Application to Weather Satellites," *Journal of Spacecraft and Rockets*, Vol. 56, No. 5, 2019, pp. 1492–1507. <https://doi.org/10.2514/1.A34353>.
- [21] Ross, A. M., and Hastings, D. E., "The Tradespace Exploration Paradigm," *15th Annual International Symposium of the International Council on Systems Engineering*, 2005, pp. 1706–1718. <https://doi.org/10.1002/j.2334-5837.2005.tb00783.x>.
- [22] Paek, S. W., Kim, S., and de Weck, O., "Optimization of Reconfigurable Satellite Constellations Using Simulated Annealing and Genetic Algorithm," *Sensors*, Vol. 19, No. 4, 2019, pp. 1–29. <https://doi.org/10.3390/s19040765>.
- [23] Colombi, J. M., Stern, J. L., Wachtel, S. T., Meyer, D. W., and Cobb, R. G., "Multi-Objective Parallel Optimization of Geosynchronous Space Situational Awareness Architectures," *Journal of Spacecraft and Rockets*, Vol. 55, No. 6, 2018, pp. 1453–1465. <https://doi.org/10.2514/1.A34043>.
- [24] Fitzgerald, M. E., and Ross, A. M., "Guiding Cooperative Stakeholders to Compromise Solutions Using an Interactive Tradespace Exploration Process," *2013 Conference on Systems Engineering Research*, *Procedia Computer Science*, Vol. 16, edited by C. J. Paredis, C. Bishop, and D. Bodner, 2013, pp. 343–352. <https://doi.org/10.1016/j.procs.2013.01.036>.
- [25] Ross, A., McManus, H., Rhodes, D., and Hastings, D., "Role for Interactive Tradespace Exploration in Multi-Stakeholder Negotiations," *AIAA Space Conference Exposition 2010*, 2010, pp. 1–17. <https://doi.org/10.2514/6.2010-8664>.
- [26] Myerson, R. B., *Game Theory: Analysis of Conflict*, Harvard University Press, 1991.
- [27] Parkhe, A., "Strategic Alliance Structuring: A Game Theoretic and Transaction Cost Examination of Interfirm Cooperation," *Academy of Management Journal*, Vol. 36, 1993, pp. 794–829. <https://doi.org/10.5465/256759>.
- [28] Briceño, S. I., "A Game-Based Decision Support Methodology for Competitive Systems Design," Ph.D. thesis, Georgia Institute of Technology, 2008.
- [29] Panchal, J. H., Sha, Z., and Kannan, K. N., "Understanding Design Decisions Under Competition Using Games With Information Acquisition and a Behavioral Experiment," *Journal of Mechanical Design*, Vol. 139, 2017, pp. 091402–1–12. <https://doi.org/10.1115/1.4037253>.
- [30] Franchi, L., "A Robust and Optimal Approach for Space Systems Conceptual Design," Ph.D. thesis, Politecnico di Torino, 2019.
- [31] Bhatia, G. V., Kannan, H., and Bloebaum, C. L., "A Game Theory approach to Bargaining over Attributes of Complex Systems in the Context of Value-Driven Design," *54th AIAA Aerospace Sciences Meeting*, 2016. <https://doi.org/10.2514/6.2016-0972>.

- [32] Wertz, J. R., Everett, D. F., and Puschell, J. J., *Space Mission Engineering: The New SMAD*, Microcosm Press, 2011.
- [33] Raju, A., Gonçalves, V., Lindmark, S., and Ballon, P., “Evaluating the Impacts of Oversubscription on Future Internet Business Models,” *Lecture Notes in Computer Science*, Vol. 7291, 2012, pp. 105–112. https://doi.org/10.1007/978-3-642-30039-4_13.
- [34] Jha, A., and Saha, D., “Forecasting and analysing the characteristics of 3G and 4G mobile broadband diffusion in India: A comparative evaluation of Bass, Norton-Bass, Gompertz, and logistic growth models,” *Technological Forecasting and Social Change*, Vol. 152, No. June 2018, 2020, p. 119885. <https://doi.org/10.1016/j.techfore.2019.119885>.
- [35] Andrés, L., Cuberes, D., Diouf, M., and Serebrisky, T., “The diffusion of the Internet: A cross-country analysis,” *Telecommunications Policy*, Vol. 34, No. 5-6, 2010, pp. 323–340. <https://doi.org/10.1016/j.telpol.2010.01.003>.
- [36] Jonas, A., Sinkevicius, A., and Flannery, S., “Space: Investment Implications of the Final Frontier,” Tech. rep., Morgan Stanley, November 2017.
- [37] Shao, A., Koltz, E. A., and Wertz, J. R., “Quantifying the cost reduction potential for earth observation satellites,” *AIAA SPACE 2014 Conference and Exposition*, 2014, pp. 1–11. https://doi.org/10.1007/978-3-319-34024-1_16.
- [38] Fox, B., Brancato, K., and Alkire, B., “Guidelines and Metrics for Assessing Space System Cost Estimates,” Tech. Rep. TR-418-AF, RAND Corporation, 2008.
- [39] United Launch Alliance, “Atlas V Launch Services User’s Guide, Revision 11,” Tech. rep., United Launch Alliance, March 2010.
- [40] del Portillo, I., Cameron, B. G., and Crawley, E. F., “A technical comparison of three low earth orbit satellite constellation systems to provide global broadband,” *Acta Astronautica*, Vol. 159, No. March, 2019, pp. 123–135. <https://doi.org/10.1016/j.actaastro.2019.03.040>.
- [41] Keeney, R. L., “Multiplicative Utility Functions,” *Operations Research*, Vol. 22, No. 1, 1974, pp. 22–34. <https://doi.org/10.1287/opre.22.1.22>.
- [42] Cormode, G., Shkapenyuk, V., Srivastava, D., and Xu, B., “Forward decay: A practical time decay model for streaming systems,” *2009 IEEE 25th International Conference on Data Engineering*, 2009, pp. 138–149. <https://doi.org/10.1109/ICDE.2009.65>.
- [43] Placide, M., and Lasheng, Y., “Information decay in building predictive models using temporal data,” *Proceedings of the 3rd International Symposium on Information Science and Engineering*, 2010, pp. 458–462. <https://doi.org/10.1109/ISISE.2010.108>.
- [44] Lluch, I., Grogan, P. T., Pica, U., and Golkar, A., “Simulating a proactive ad-hoc network protocol for Federated Satellite Systems,” *IEEE Aerospace Conference*, 2015, pp. 1–16. <https://doi.org/10.1109/AERO.2015.7118984>.
- [45] Fortin, F. A., De Rainville, F. M., Gardner, M. A., Parizeau, M., and Gagné, C., “DEAP: Evolutionary algorithms made easy,” *Journal of Machine Learning Research*, Vol. 13, 2012, pp. 2171–2175.
- [46] Rousseau, J.-J., *A Discourse on Inequality*, Penguin Classics, Penguin: London, 1984.

- [47] Kandori, M., Mailath, G. J., and Rob, R., “Learning, Mutation, and Long Run Equilibria in Games,” *Econometrica*, Vol. 61, No. 1, 1993, pp. 29–56. <https://doi.org/10.2307/2951777>.
- [48] Carlsson, H., and van Damme, E., “Global Games and Equilibrium Selection,” *Econometrica*, Vol. 61, No. 5, 1993, pp. 989–1018. <https://doi.org/10.2307/2951491>.
- [49] Scott, W. S., Anderson, N., and Rogers, A. Q., “Design Drivers for Viable Commercial Remote Sensing Space Architecture,” *34th Annual Small Satellite Conference*, 2020, pp. SSC20–I–05.
- [50] Space Exploration Holdings, LLC, “Application for Fixed Satellite Service,” File Number SAT-MOD-20200417-00037, Federal Communications Commission, 2020. URL https://licensing.fcc.gov/cgi-bin/ws.exe/prod/ib/forms/reports/swr031b.hts?q_set=V_SITE_ANTENNA_FREQ.file_numberC/File+Number/%3D/SATMOD2020041700037&prepare=&column=V_SITE_ANTENNA_FREQ.file_numberC/File+Number, accessed: 2020-11-16.
- [51] Roca, C. P., Cuesta, J. A., and Sánchez, A., “Evolutionary game theory: Temporal and spatial effects beyond replicator dynamics,” *Physics of Life Reviews*, Vol. 6, 2009, pp. 208–249. <https://doi.org/10.1016/j.plrev.2009.08.001>.
- [52] Harsanyi, J. C., “Games with Incomplete Information Played by “Bayesian” Players, I–III: Part I. The Basic Model,” *Management Science*, Vol. 50, No. 12_supplement, 2004, pp. 1804–1817. <https://doi.org/10.1287/mnsc.1040.0270>.
- [53] Office of the Under Secretary of Defense, “National Defense Budget Estimates for Fiscal Year 2020,” Green Book, United States Department of Defense, May 2019. URL https://comptroller.defense.gov/Portals/45/Documents/defbudget/fy2020/FY20_Green_Book.pdf.