

# Federated Space Systems Tradespace Exploration for Strategic Robustness

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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. The proposed methodology reduces the threshold probability of partner collaboration for which SoS participation is economically rational by up to 18% for the most efficient designs compared to a typical conceptual design method, thereby increasing the likelihood of successful SoS formation. The results highlight the importance of accounting for strategy dynamics when designing systems for collaboration.

## Nomenclature

|         |   |                                                     |
|---------|---|-----------------------------------------------------|
| $R$     | = | weighted-average log measure of risk dominance      |
| $\phi$  | = | independent strategy                                |
| $\psi$  | = | collaborative strategy                              |
| $u_i$   | = | normalized deviation loss for player $i$            |
| $p_i$   | = | probability that player $i$ selects strategy $\psi$ |
| $w_i$   | = | influence weight for player $i$                     |
| $A$     | = | influence matrix                                    |
| $\pi_s$ | = | SATCOM system number of planes                      |

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|------------------|---|--------------------------------------------|
| $N_s$            | = | SATCOM system satellites per plane         |
| $\epsilon$       | = | SATCOM system user minimum elevation angle |
| $C$              | = | number of user channels                    |
| $p$              | = | per channel transmitter output power       |
| $R_s$            | = | slant range                                |
| $G$              | = | gain                                       |
| $\eta$           | = | efficiency                                 |
| $A_\theta$       | = | 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                  |
| $\pi_e$          | = | EO system number of planes                 |
| $N_e$            | = | EO system satellites per plane             |
| $D$              | = | primary aperture diameter                  |
| $a$              | = | altitude                                   |
| $\gamma$         | = | number of EO system ground stations        |
| $\lambda$        | = | information value decay rate               |
| $\theta$         | = | imagery resolution                         |
| $P$              | = | monthly revenue                            |
| $\nu_\Lambda$    | = | single attribute value of latency          |
| $\nu_\theta$     | = | single attribute value of resolution       |
| $m_{dry,e}$      | = | EO satellite dry mass                      |

## I. Introduction

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) [1, 2]. FSS are collaborative system-of-systems (SoS), with no central authority to enforce SoS level design goals and decisions [3]. 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 performance of core functions. As a SoS,

FSS require application of an engineering methodology suited for their unique socio-technical challenges [4].

The benefits of FSS come with risks of coordination failure unique to collaborative systems. Coordination failure 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 [4, 5], though transmission of power and motive forces between spacecraft have been envisioned as well [6]. 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 [7]. Therefore, designing for utility robustness in the face of uncertain collaborative behavior from other system actors is the key challenge for FSS.

Much of the research in SoS design has focused on balancing the independent interests of multiple stakeholders to achieve a compromise solution [8] or with models that aim to predict when successful collaboration will occur [9]. Some methods assume that SoS-level goals exist [10] or that there is unified managerial authority over each of the constituent systems [11]. Neither of these conditions are true of collaborative SoS, such as FSS [3]. 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 [12], using the canonical stag hunt game as an analogy for SoS development [13]. Grogan and Valencia-Romero [13] close the aforementioned gaps in SoS research with quantitative methods for assessing strategy dynamics amongst collaborators 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 [13, 14] 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 difference between collaborative SoS design and traditional system design; the strategy dynamics induced by multiple decision makers with differing goals. While previous works recognize 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.

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 are *strategically robust*, i.e., they retain greater value or utility under a FSS 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 [4] 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 [15, 16]. 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 [4, 16]. This paper adopts Maier's definition, with the understanding that constituent system owners must expect to benefit from collaboration to pursue it.

Several SoS engineering (SoSE) methods have been proposed to design systems to meet the objectives of independent system actors. DiMario et al. [10] 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 [9]. Still others propose transfer contract mechanisms from corporate management to align the objectives of the constituent systems with global system goals [11]. 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 [17], 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 [18, 19]. Traditional conceptual design methods focus on Analysis of Alternatives (AoA) that evaluate and compare a few designs with respect to system objectives [20]. Consequently, AoAs can provide poor coverage of a design space, increasing the probability that a sub-optimal design will be implemented [20]. 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 which helps to locate promising areas for more detailed analyses and identifies trends and relationships amongst the design variables.

Multi-Attribute Tradespace Exploration (MATE) takes as inputs the design attributes, attribute value ranges, single-attribute utility functions, and multi-attribute utility function for a system concept and outputs system utility and cost for each design in the specified design space. Designers generally perform the exploration portion of MATE enumerating possible designs in the space. Enumeration 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 addressed the issue of computation time by guiding the tradespace exploration process with an optimization routine, often using a metaheuristic such as simulated annealing [21] or a genetic algorithm [22]. Metaheuristic driven techniques cannot guarantee optimality, but are faster than direct enumeration.

A body of research establishes MATE as a method for discovering SoS or multi-stakeholder system designs that trade the objectives of the constituent systems to find workable solutions for all constituents [8, 23, 24]. These methodologies assume overlap in objectives between systems and higher-level goals or a degree of unified managerial authority—conditions that 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 is insufficient grounds for participation in a collaborative system. Evaluating 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 decision-makers [25] 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 [26], engineering design in competitive environments [27, 28], and to negotiate between subsystem designers and stakeholders in collaborative design of individual systems [29, 30]. 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 [12, 13]. Accordingly, these methods can evaluate designs with the goal of selecting those which are strategically robust. The concepts presented in Ref. [13] 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 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 objective of this work is to develop and evaluate a methodology to find the robust, utility maximizing constituent systems to operate in FSS and other SoS. 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.

The research methodology includes two components. The first component implements a game-theoretic equilibrium selection criterion within a simple FSS tradespace exploration process to determine if selected designs contribute to

favorable strategy dynamics. The second component includes 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

This work uses conceptual design of commercial communication (SATCOM) and earth observation (EO) satellite systems to illustrate the methodological concepts. 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 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. System actors maximize utility strictly by maximizing their revenue. No distinct FSS-level goals contribute to individual system utility. Similarly, system actors do not value each other's objectives (other than how they indirectly affect their own).

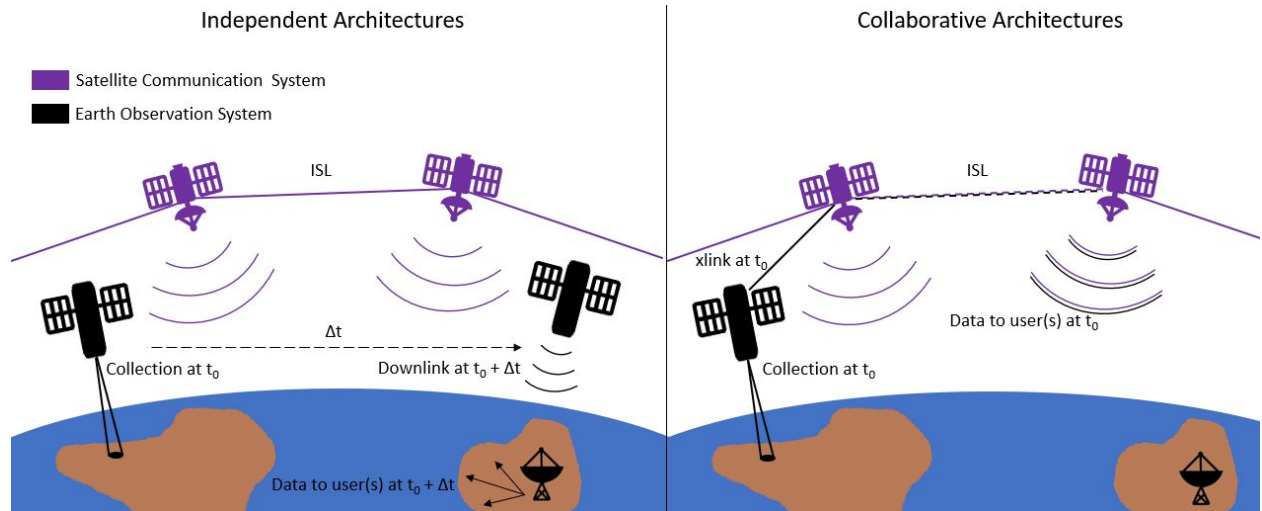


Fig. 1 System operations diagrams.

## 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 simplicity, all SATCOM systems use a polar orbit with a streets of coverage constellation design. First, Eq. (1) uses the specified number of planes ( $\pi_s$ ), satellites per plane ( $N_s$ ), and elevation angle ( $\epsilon$ ) to calculate 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 combined longitudinal coverage of all the streets (measured in units of Earth central angle) and  $2\pi$  radians. Altitudes below 400 km are not permitted because constellations that can maintain coverage below 400 km have greater overlap between antenna footprints. The altitude and minimum user elevation angle  $\epsilon$  determine the maximum slant range ( $R_s$ ) and coverage area ( $A_\theta$ ,  $\text{deg}^2$ ) 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                   | $\pi_s$    | 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) | $\epsilon$ | 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  $\eta$  is transmit antenna efficiency [31].

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

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

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 [32]. A logistic curve [33, 34] using satellite internet market growth projections published in Ref. [35] 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) by first estimating 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 [31] and multiplies by a density factor 0.20 kg/W and a redundancy factor of 0.8 to account for the short, five year mission life [36].

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

The model uses communication satellite CERs published in Ref. [31], Table 11-5 to estimate spacecraft non-recurring engineering (NRE) and production costs. Production costs assume an 85% learning curve [37]. Estimates of total spacecraft mass assume an additional 27% propellant mass [31]. Launch costs assume direct insertion, mass-limited launches with at least one launch per plane, Atlas V 551 performance data [38], at \$62M per launch. A 1:10 gateway ground station to satellite ratio determines the number of ground stations required [39]. The model implements CERs published in Ref. [31] 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 prior to the first launch. 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<sup>\*</sup> and a Python wrapper<sup>†</sup> 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  $\gamma$  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. 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               | $\pi_e$  | 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      | $\gamma$ | 5       | 0       |

A two objective multiplicative value function [40] 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 [41, 42] in Eq. (7). An aggressive decay rate ( $\lambda$ ) 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 ( $\theta$ ) yields a value of 1 for resolutions better than 20 cm.

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

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

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

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

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

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. [36]. NRE and spacecraft production costs are estimated using reconnaissance satellite CERs from Ref. [31] 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

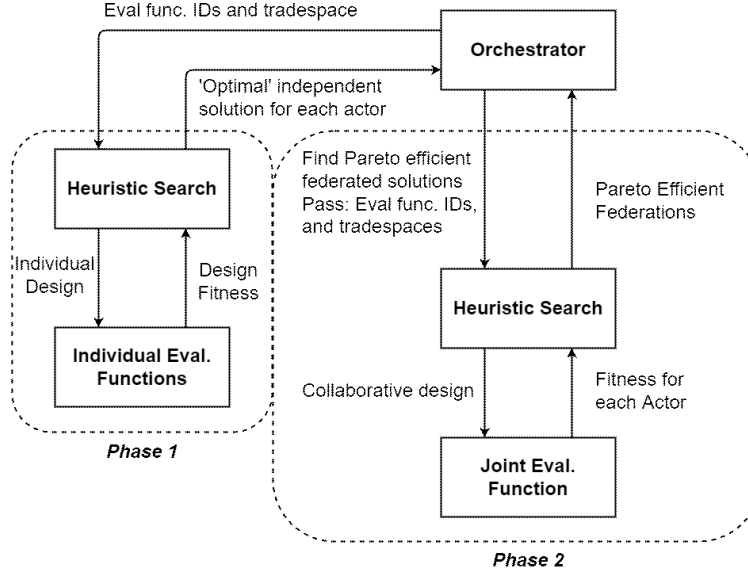
A collaborative system utilizes excess SATCOM system capacity to transport EO system commands and data, increasing the potential revenue streams for the SATCOM system and the value of the EO system data. The collaborative system model is implemented with updates to the EO latency model and revenue models, 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 and increases NRE cost 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 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 [43]. When a request is received and accepted, the array would focus a high gain beam at the EO satellite to receive the data [43]. 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 depicted in Fig. 2. The first phase uses 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.



**Fig. 2 Tradespace exploration structural diagram.**

Tradespace exploration uses the Distributed Evolutionary Algorithms in Python (DEAP) eaMuPlusLambda genetic algorithm (GA) implementation [44]. 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 economic 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.

All designs share similarities with existing or planned commercial imaging constellations. The 1m apertures yield nadir resolution of 22 cm at the 400 km operating altitude. Comparable systems, such as WorldView-3, obtain 30 cm nadir resolution at 600 km [45]. Constellation size is also similar to the planned, 10 satellite, Maxar constellation comprised of the four on-orbit systems and six WorldView Legion satellites scheduled for launch in 2022 [46, 47]. External validation of system latency using existing systems is more challenging. Imagery providers publish revisit rates, but do not disclose time from customer imaging requests to data delivery, which is the metric used here.

**Table 3 Top five independent EO systems to maximize NPV**

| Design | $\pi_e$ | $N_e$ | $D$ (cm) | $a$ (km) | $\gamma$ | 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, per channel power requirements grow exponentially with the bandwidth limited data rate. Lastly, 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.

Resulting architectures are similar to LEO mega-constellations that are in development or deployment. Design 1 is composed of 3,280 satellites, similar in number to Starlink (4,408) and Kuiper (3,236) [48]. The max throughput of a Design 1 satellite is 12.8 Gbps; again similar to estimated Starlink satellite performance (19.7 Gbps) [48]. Design 1's minimum elevation angle of 40° is similar to the almost identically-sized Kuiper constellations 35° minimum elevation angle [48]. The similarity of the results to contemporary LEO communication constellations provides external validation for the reasonableness of the trade space and the rigor of the evaluation procedures.

**Table 4 Top five independent SATCOM systems to maximize NPV**

| Design | $\pi_e$ | $N_e$ | $\epsilon$ (°) | $p$ (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.

**Table 5 Top five collaborative EO systems to maximize NPV**

| Design | $\pi_e$ | $N_e$ | $D$ (cm) | $a$ (km) | $\gamma$ | 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    |

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

**Table 6 Top five collaborative SATCOM systems to maximize NPV**

| Design | $\pi_s$ | $N_s$ | $\epsilon$ (°) | $p$ (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

This work uses the game-theoretic concept of risk dominance to measure the strategic stability of the efficient strategy as a function of the strategic robustness of the constituent system designs in a FSS context. This section introduces risk dominance and its application to engineering design.

Grogan and Valencia-Romero [13] 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 [12]. 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 [49] illustrated in Table 7 in normal form. It presents a coordination problem between two hunters who have the choice of pursuing hare ( $\phi$ ) or stag ( $\psi$ ). 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 ( $\phi$ )                              | Stag ( $\psi$ )                              |
| Hare ( $\phi$ ) | $V_1^{\phi\phi} = 2$<br>$V_2^{\phi\phi} = 2$ | $V_1^{\psi\phi} = 4$<br>$V_2^{\phi\psi} = 4$ |
| Stag ( $\psi$ ) | $V_1^{\psi\phi} = 0$<br>$V_1^{\psi\psi} = 5$ | $V_2^{\psi\psi} = 5$<br>$V_2^{\phi\psi} = 0$ |

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 ( $\phi$ ) to hunting stag ( $\psi$ ). 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 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.

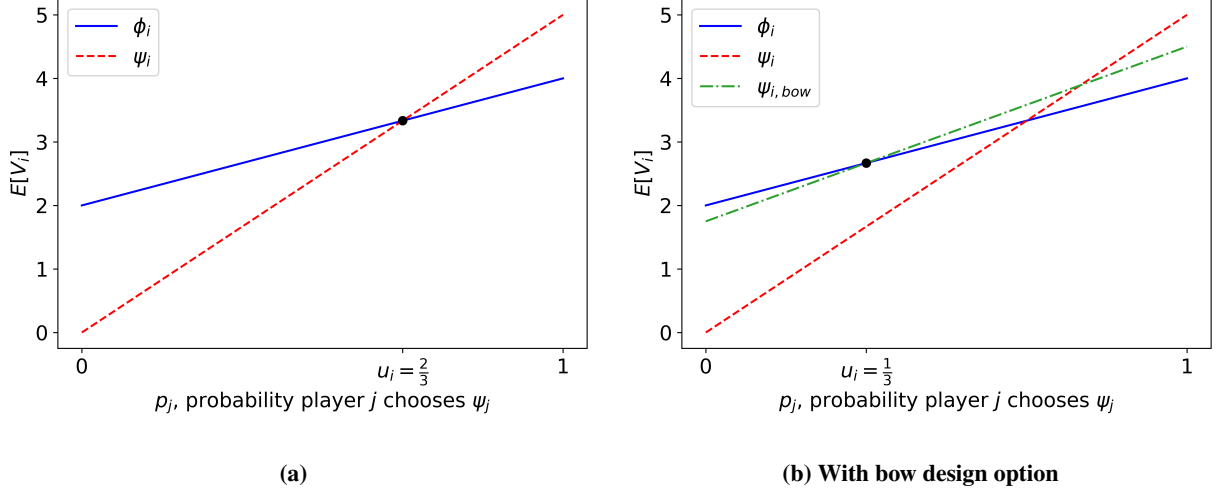
**Table 8 Stag hunt design-strategy payoffs**

| 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 [50]. Carlsson and van Damme [51] also found that the risk dominant equilibrium 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. [13] for a complete explanation of  $w_i$  and  $A$ ). A positive  $R$  indicates the





**Fig. 3 Expected value of player strategies under uncertainty.**

independent strategy ( $\phi$ ) is risk dominant while a negative  $R$  indicates the collaborative strategy ( $\psi$ ) 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 ( $\psi$ ) 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, mutually beneficial, designs have been discovered. However, simple mutual benefit is insufficient to determine if collaboration is rational. 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   | \$346.75M   | \$346.75M     |
| Collaborative | -\$689.11M  | \$704.38M     |

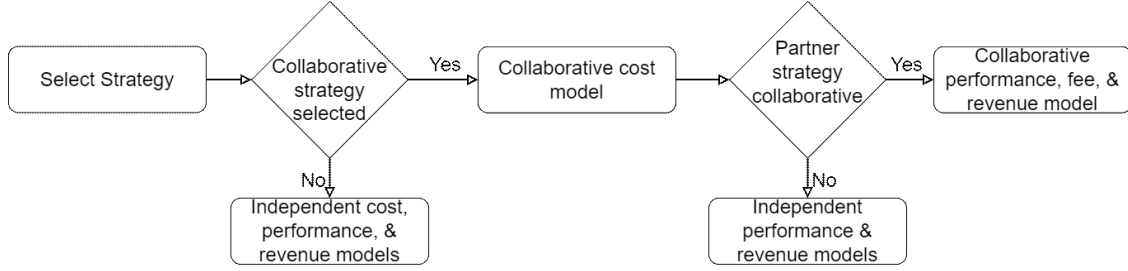
**Fig. 4 Two-stage decision flow chart.**

Table 9 shows that 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<sup>‡</sup> 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 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. In the absence of any information about the likelihood of the other actors actions, it is difficult to readily identify the rational strategy.

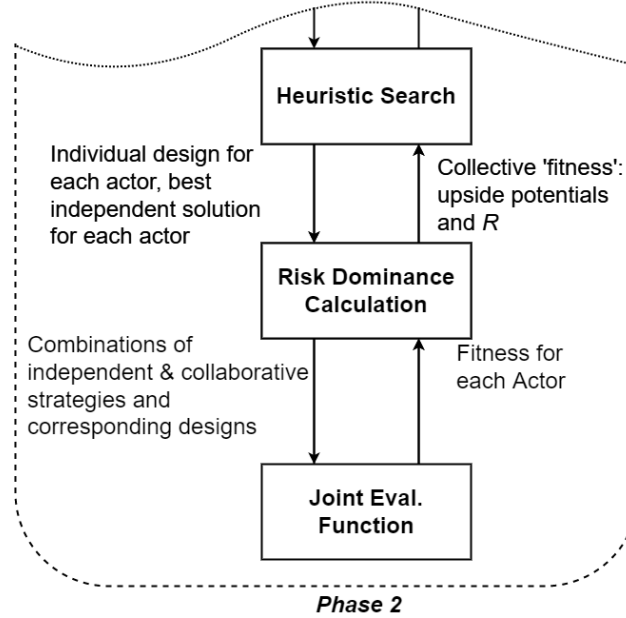
Applying Eq. (11) shows  $R$  is  $-1.11$ . Assuming no prior information about either actor’s preference for a particular strategy, the rational strategy for *both* system actors is to collaborate. The relative losses of the SATCOM system are

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

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 efficiency for increased 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.

However, design 3 also reduces the consequences of coordination failure through reduced space segment investment costs and increased functional redundancy in the form of three ground stations. Both modifications bring design 3 architecturally closer to the highest performing independent EO design.

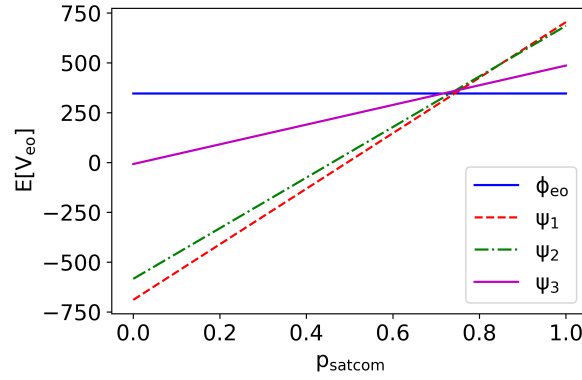
Figure 7 shows that the viable EO system design space is fairly narrow and a subset of designs with positive NPV under the independent strategy. The narrow range of viable design variables indicates a stable region in the space which yields high-value designs for both strategies; in this case resulting in a number of designs which favor the collaborative strategy.

**Table 10 Pareto efficient collaborative designs with risk dominance**

| EO Design | Planes | Satellites<br>per plane | Aperture<br>diameter (cm) | Altitude<br>(km) | Ground<br>stations | $NPV_e$<br>(\$M) | $NPV_s$<br>(\$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.

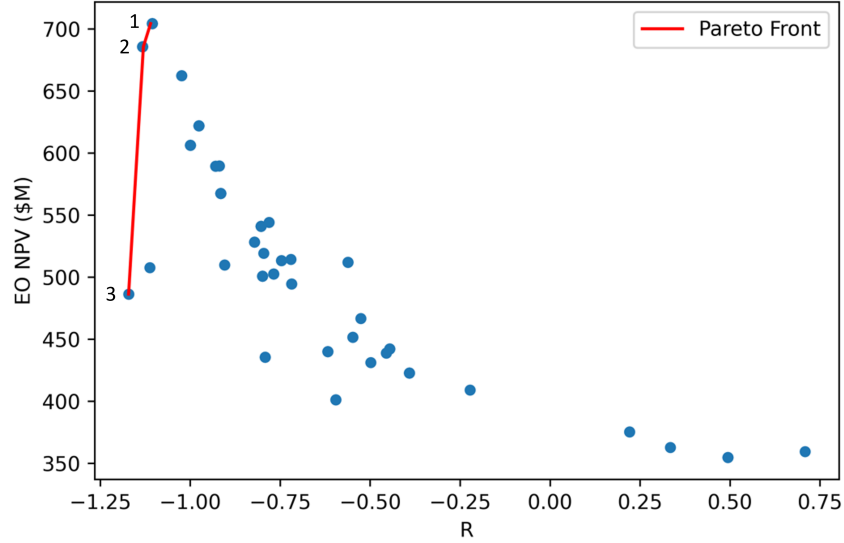
All SATCOM designs were Table 6, design 1



**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 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.



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

#### **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. Therefore, 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 incentiviz-

ing 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 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, 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 |
| Independent   | 346.75  | 9035.61          | 9024.36       |
|               |         | 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 is 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  $\Delta$  designs are those which minimize the difference in upside of collaboration for both systems.

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

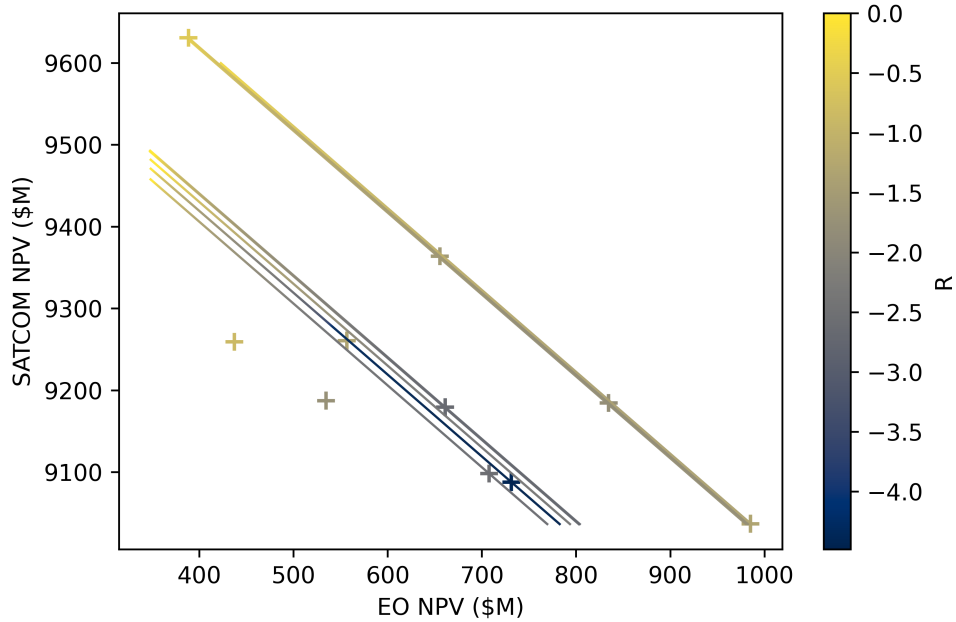
**Table 12** Select Pareto efficient collaborative designs with fee and cost-share as design variables

| Design               | $\pi_e$ | $N_e$ | $D$<br>(cm) | $a$<br>(km) | $\gamma$ | fee<br>(\$M) | cost-share | $NPV_e$<br>(\$M) | $NPV_s$<br>(\$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 $\Delta$ | 3       | 4     | 100         | 400         | 0        | 19.91        | 0.72       | 673.25           | 9363.91          | -1.57 |
| 3x4, 3 $\gamma$      | 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 $\Delta^*$  | 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 $\gamma^{**}$ | 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.



**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

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 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  $\delta$  design, yielding a superior option for both systems.

Discriminating between the Pareto efficient designs facilitated by the economic variables 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  $\Delta$  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 [47, 52, 53]. 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 and a given throughput is more efficiently achieved with many, low-flying satellites than with a smaller number of more powerful satellites. 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 some collaborative designs more favorable when there are real options for solutions that are higher value under coordination failure. Consequently, future work should include real options for implementing system modifications that increase robustness to coordination failures. The methodology presented in this paper could then be used to evaluate utility of the real options as well as their contribution to facilitating collaboration. Most importantly, the conclusions reached in this work assume that risk dominance is an appropriate measure of strategic stability. While work in other fields indicates that this is the case [54], 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 of 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 [55] 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 demonstrates a methodology for Federated Space System (FSS) tradespace exploration, implementing a risk dominance 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, shorter observation and communication ranges increase performance for a set platform design, and data rate is more efficiently increased by increasing the number of transmitters in the system than by increasing per transmitter power.

Minimization of the risk dominance measure in the tradespace exploration activity yields system designs exhibiting strategic 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 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. <sup>2</sup> |
| Tx gain ( $G$ )            | 31.41             | dBi               |
| Tx line loss               | -4.5 <sup>a</sup> | dB                |
| EIRP                       | 31.06             | dBW               |
| Free space loss            | -169.4            | dB                |
| Atmospheric loss           | -3.5 <sup>b</sup> | dB                |
| Rx antenna diam.           | 0.7               | m                 |
| User gain                  | 36.07             | dBi               |
| Rx line loss               | -2.0 <sup>a</sup> | dB                |
| Rx carrier power           | -107.75           | dBW               |
| System noise temp.         | 25.6 <sup>b</sup> | dB-K              |
| Rx $C/N_0$                 | 95.25             | dBW               |
| Req. $E_b/N_0$             | 5.49 <sup>a</sup> | dB                |
| Spectral efficiency        | 3.0 <sup>a</sup>  | -                 |
| Link margin                | 1.0               | dB                |
| Power limited rate         | 751.5             | Mbps              |
| Bandwidth limited rate     | 632.4             | Mbps              |

<sup>a</sup> parameter value from Ref. [31]

<sup>b</sup> parameter value from Ref. [39]

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

**Table 14 Cost estimating relationship factors and constants**

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

<sup>a</sup> from Ref. [31], <sup>b</sup> from Ref. [56], <sup>c</sup> from Ref. [36], <sup>d</sup> from Ref. [37]

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

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.

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

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.

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

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

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 [38], 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  $\chi_{nre}$  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  $\chi_{lot}$  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<sup>§</sup> or Swedish Space Corporation<sup>¶</sup> locations.

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

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

**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    |

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