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Metrics for Evaluating Survivability in Dynamic Multi-Attribute Tradespace Exploration

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Survivability engineering is critical for minimizing the impact of disturbances to the operation of space systems. To improve the evaluation of survivability during conceptual design, metrics are proposed for the assessment of survivability as a dynamic, continuous, and path-dependent system property. Two of these metrics, time-weighted average utility loss and threshold availability, are then incorporated into a tradespace study on the survivability of future space tug vehicles to orbital debris. A value-based design approach, dynamic multi-attribute tradespace exploration, is taken to evaluate survivability based on the relationship between stochastic space tug utility trajectories and changing stakeholder expectations across nominal and disturbed environmental states. Results of the tradespace study show that moderate levels of bumper shielding and access to an on-orbit servicing infrastructure benefit space tugs with large exposed cross-sectional areas, whereas active collision avoidance only delivers value to extremely-risk-averse decision-makers. Time-weighted average utility loss and threshold availability are found to be discriminating metrics for navigating survivability tradespaces of thousands of design alternatives.

Nomenclature

A_T	=	threshold availability, %
CS	=	campaign-level survivability
P_H	=	probability of hit (susceptibility)
P_K	=	probability of kill
$P_{K\|E}$	=	probability of kill for multiple-shot engagement
$P_{K\|H}$	=	probability of kill given a hit (vulnerability)
$P_{K\|SS}$	=	probability of kill from a single shot
P_S	=	probability of survival
$P_{S\|E}$	=	probability of survival for multiple-shot engagement
TAT	=	time above critical value threshold, years
T_{dl}	=	time of design life, years
T_r	=	permitted recovery time, years
$U(t)$	=	utility delivery over time, multi-attribute utility trajectory
$U(\underline{x})$	=	multi-attribute utility function over attributes $\underline{x}$ at a point in time
U_e	=	emergency utility threshold (zero by definition), utilities are dimensionless
$\bar{U}_L$	=	time-weighted average utility loss from design utility, U_o
U_n	=	utility delivery during normal conditions
$\bar{U}_t$	=	time-weighted average utility
U_x	=	required utility threshold
$U^i(x^i)$	=	single-attribute utility function over attribute x^i
$V(t)$	=	value delivery over time
V_e	=	emergency value threshold
V_x	=	required value threshold
ΔV	=	change in velocity, m/s

I. Introduction

SURVIVABILITY is the ability of a system to minimize the impact of a finite-duration environmental disturbance on value delivery [1]. Given the growth of military and commercial dependency on space systems [2,3], identified vulnerabilities in current systems [4], the proliferation of threats [5,6], and the weakening of the sanctuary view in military space policy [7,8], survivability is an increasingly important consideration during the design of space systems [9]. Counterintuitively, the risk-averse nature of the space industry, which manifested in the common satellite design elements of redundancy, proven technology, and long design lives [10], exacerbates space architecture fragility [11] by increasing the magnitude of potential downside losses and by reducing the speed at which space capabilities might be reconstituted. Although survivability is an emergent system property that arises from interactions among components and between space systems and their environments, conventional approaches to survivability engineering are often reductionist in nature (i.e., focused only on selected properties of subsystems or modules in isolation). Furthermore, existing survivability engineering methodologies are normally based on specific operating scenarios and presupposed disturbances rather than a general theory with indeterminate threats. As a result, current methods neither accommodate dynamic threat environments nor facilitate stakeholder communication for trading among system life-cycle cost, performance, and survivability [12].

To address these limitations, a set of metrics is introduced for the evaluation of satellite survivability in tradespace studies during conceptual design. The metrics are based on a characterization of survivability as the ability of a system to meet required levels of value delivery during nominal and perturbed environmental conditions. To demonstrate the survivability metrics, the survivability of a low-Earth-orbit (LEO) satellite to orbital debris is evaluated for systems incorporating various combinations of susceptibility reduction, vulnerability reduction, and resilience enhancement features. In particular, integrated cost, performance, and survivability trades are performed for an orbital transfer space tug vehicle operating in LEO for 10 years. Building on previous work [13], the impact of bumper shielding [14], collision avoidance [15], and on-orbit servicing [10] strategies on space tug encounters with orbital debris is examined.

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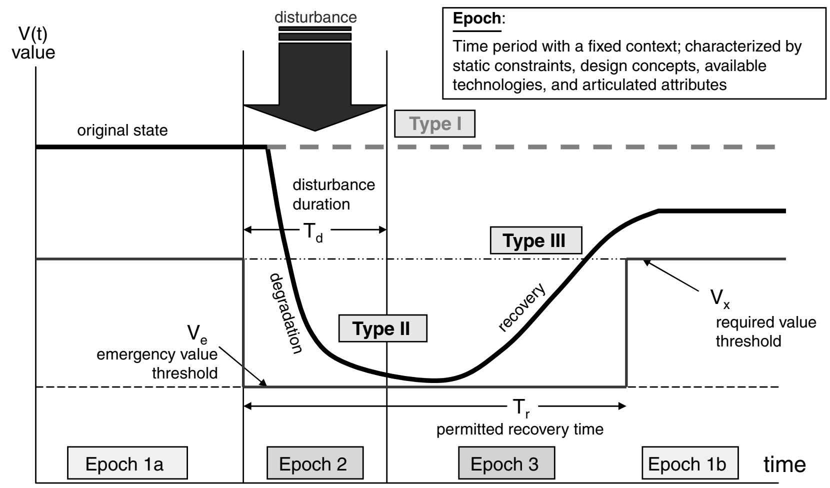


Fig. 1 Three types of survivability.

The modeling approach for applying the survivability metrics consists of four general phases: 1) static multi-attribute tradespace exploration (MATE) [16], 2) epoch-era analysis [17], 3) stochastic simulation of space tug operation, and 4) Monte Carlo analysis. First, a legacy MATE study on space tug vehicles [18] is extended in which decision-maker preferences (i.e., attributes) are quantified and aggregated using multi-attribute utility theory [19], and then candidate satellite designs are assessed in terms of cost and utility using parametric computer models and simulations. Second, epoch-era analysis is performed in which satellite lifetimes (i.e., eras) are modeled as sets of discrete time periods with fixed contexts and needs (i.e., epochs). Potential system eras for the candidate space tug designs are constructed by stringing together both baseline (i.e., ambient environment) and disturbance epochs (i.e., debris conjunction events). Third, a stochastic simulation of space tug operations is performed in which debris impacts are modeled as forced transitions of space tugs in the tradespace to lower utility designs (or end-of-life states). Each run of the simulation produces a utility trajectory (i.e., a plot of multi-attribute utility over time) for a candidate space tug in the tradespace. Fourth, a Monte Carlo analysis is performed across the stochastic path-dependent utility trajectories, and the survivability metrics are applied.

The paper consists of five sections. Following this introduction, a value-centric definition of survivability is described and illustrated in Sec. II. This definition provides a foundation against which the construct validity of survivability metrics may be examined in Sec. III. In Sec. IV, the survivability metrics are applied to a space tug tradespace study. The modeling methodologies and simulation architecture are discussed in detail and several tradespace plots using the metrics are shown. Local response surfaces are also drawn to illustrate the impact of the survivability features in each region of the tradespace. Implications of the results are discussed in Sec. V, and general conclusions are drawn in Sec. VI. Development of the dynamic survivability assessment methodology and its associated metrics are illustrative of the challenges and opportunities for better incorporating survivability as a decision metric in tradespaces during conceptual design.

II. Definition of Survivability

Survivability may be defined in physical terms as "the capability of a system to avoid or withstand hostile natural and manmade environments without suffering abortive impairment of its ability to accomplish its designated mission" [20]. Survivability may also be defined, more generally, as *the ability of a system to minimize the impact of a finite-duration environmental disturbance on value delivery.* Value is a subjective measure of benefit from a bundle of consequences that is specified by a stakeholder [21]. A value-centric conceptualization of survivability is desirable during the conceptual design of systems because it provides a fundamental metric for relating system properties to desired stakeholder outcomes. Taking the value-centric perspective during conceptual design empowers decision-makers to rigorously evaluate and compare different system concepts in the technical domain (e.g., geosynchronous satellite vis-à-vis low-Earth-orbit satellite constellation for a communications mission) using a unifying set of attributes in the value domain (e.g., signal isolation, information rate, information integrity, and data availability) [22]. The ability to consider multiple system concepts using a unifying set of attributes is particularly useful for survivability when original value-delivery mechanisms may be blocked by a disturbance.

In addition to conceptualizing survivability as a value-centric property, it is also important to recognize the inherently dynamic nature of survivability. Survivability emerges from the interaction of a system with its environment *over time*. Depending on stakeholder needs, satellite survivability requirements may allow limited periods during which the system operates in a degraded state, unavailable state, or safe mode [23]. Recognizing survivability as a dynamic system property informs three general survivability design strategies over the life cycle of a disturbance. Type I survivability, susceptibility reduction, is the reduction of the likelihood or magnitude of a disturbance. Type II survivability, vulnerability reduction, is the minimization of the disturbance-induced losses on value delivery. (Systems that are type-II-survivable may exhibit graceful degradation in which at least minimal functionality is maintained in the event of disturbance-induced losses. The reduced magnitude and rate of value losses in systems that degrade gracefully is in contrast to fragile systems in which small disturbances may cause total system failure.) Type III survivability, resilience enhancement, is the maximization of the recovery of value delivery within a permitted recovery time.

Figure 1 provides a notional illustration of type I, type II, and type III survivability in terms of value delivery over time [$V(t)$]. Time is discretized across four epochs, periods of a fixed context, and static stakeholder needs.[¶] Following successful value delivery during baseline environmental conditions and stakeholder expectations (epoch 1a), the system experiences a finite disturbance that degrades performance. Value-delivery expectations on the system may be lower during the disturbance (epoch 2) and in the time period immediately following (epoch 3) before returning to baseline expectations (epoch 1b). Type I survivability, depicted as a dashed horizontal line, is achieved if the disturbance fails to reduce $V(t)$ below

[¶]Equivalent to short-run analysis in economics, a given epoch defines a scenario in which constraints, design concepts, available technology, and articulated attributes remain fixed [17]. Given the focus on survivability in this paper, the only changes across epoch boundaries are finite-duration disturbance events in the environment (i.e., debris impacts) and changing stakeholder expectations (i.e., short-term relaxation of stakeholder expectations during disturbance and recovery epochs).

the required value threshold V_x over all of the epochs. To determine whether the system is type-II- or type-III-survivable, two additional factors must be defined: the minimum acceptable value to be delivered during and immediately after the disturbance (V_e) and the permitted recovery time elapsed past the onset of the disturbance (T_r). In Fig. 1, the solid line depicts a system achieving type II survivability by maintaining $V(t)$ at a level above V_e during epoch 2 and epoch 3. The solid line also depicts a type-III-survivable system as $V(t)$ recovers to a level above V_x within T_r.

For taxonomic precision, it is helpful to discuss the similarities and differences that survivability has with a closely related system property: robustness. Both survivability and robustness are measures of the ability of systems to reduce the sensitivity of their outputs to changes in the environment. However, although similar, survivability and robustness are distinct. Whereas designing for robustness focuses on accommodating permanent changes in context (e.g., continuous noise factors), design for survivability focuses on the mitigating finite changes in context (e.g., impulse event). Therefore, survivability can be considered a special case of robustness with a finite condition on disturbance duration [1].

III. Quantification of Survivability

A. Existing Survivability Metrics

Although a diverse array of survivability metrics exists (e.g., range of environments within which an entity remains operational; disturbance threshold above which an entity will cease to function; degree to which performance remains following a disturbance; and time required to restore health following a compromising disturbance) [1], survivability is traditionally incorporated in aerospace design as a binary metric using probabilistic risk assessment. As articulated in Ball's foundational work on combat aircraft survivability [24], the probability of surviving a one-on-one engagement, P_S, is the complement of the probability of hit P_H (susceptibility) times the probability of kill given a hit, $P_{K|H}$ (vulnerability):

$$P_S = 1 - P_K = 1 - P_H \cdot P_{K/H} \tag{1}$$

(The susceptibility portion of the calculation, P_H, can be further decomposed into a five-step event tree or kill chain. For example, at the engagement level, five probability assignments are used to assess system susceptibility: P[weapon is active], P[sensor detects], P[fire control solution is obtained], P[weapon intercepts], and P[weapon hits].)

To reduce the complexity associated with dependent-shot-outcome probabilities, independent shot outcomes are assumed for computing survivability to multiple-shot engagements, $P_{S|E}$ [24]. For example, when the individual shots P_K are identical and equal to a single-shot probability of kill ($P_{K|\mathrm{SS}}$) for all N shots, $P_{S|E}$ is

$$P_{S|E} = 1 - P_{K|E} = (1 - P_{K|\mathrm{SS}})^N \tag{2}$$

This logic is extended for computing campaign-level survivability CS, assuming a campaign of N missions with a constant mission survivability rate:

$$\mathrm{CS} = (P_S)^N = (1 - P_K)^N \tag{3}$$

Although these metrics for assessing single-shot, engagement, and campaign-level survivability provide an elegant mathematical framework for structuring and analyzing the survivability of a system throughout its operational life, challenges remain for the survivability analyst. For example, the reliance on probabilistic risk assessment and its underlying assumptions (e.g., probability distributions are known and disturbance events are independent) is problematic given the complex nature of satellite systems and the known dependencies in a disturbance encounter. For example, the susceptibility of a satellite is not conserved as a constant probability across disturbance encounters if its maneuverability and defensive countermeasures have been reduced by a previous encounter.

Another challenge associated with current survivability metrics is their binary nature. The ability of space systems to gracefully degrade to reduced levels of capability is frequently cited as an enabler of survivability [25–27]. However, a binary P_S value applied across systems during conceptual design does not internalize the magnitude or rate of system degradation: a capability which may be useful for distinguishing between systems that fail precipitously and systems that can achieve partially functional states. Additionally, for systems that are not safety-critical (e.g., autonomous science missions), the impact of critical failures varies by when the failure occurs. To address the limitations of binary risk metrics, recent work [28,29] has extended traditional risk assessment techniques by introducing the concept of expected productivity. Expected productivity provides an aggregate measure of mission risk by quantifying mission performance based on the expected value of productivity (e.g., number of images of star systems for observatories and number of rocks tested for sampling roving missions). Although valuable for providing a continuous (nonbinary) measure of the magnitude of risk, defining an aggregate productivity metric may be difficult or impossible for systems intended to accomplish multiple independent missions. The applicability of expected productivity may also be limited for nonscientific missions. In particular, the mission tasks of service-oriented space systems (e.g., military satellites) may not necessarily be specified a priori, and critical survivability requirements may dictate the preservation of a minimal level of functionality over the entire mission duration.

The metrics discussed previously generally view disturbances as sequences of short-duration variations in the operating environment. Another body of literature has framed this problem from a dynamic perspective focusing on both sustained variations in the environment and temporary shocks [30,31]. The shock-based reliability literature provides a time-dependent characterization of the system state. However, the application of these shock models is focused on the part and component levels rather than a system-level unit of analysis.

Other existing quantifications of survivability and related terms include the reliability function and inherent availability [32]. However, these provide only a binary characterization of system health and are of questionable construct validity for survivability. Both reliability and availability are concerned with the ability of a system to perform its function under prescribed environmental conditions, whereas survivability is concerned with the state of a system that emerges based upon the interaction of that system with external disturbances.

A general challenge for survivability metrics related to the architectural tradespace is how to conduct integrated tradeoffs regarding the varying cost, mission utility, availability, and survivability of alternative system designs. Because these characteristics are interdependent (as survivability design features and operational tactics may lower mission utility and increase cost), pursuing the highest survivability for a given design alternative does not necessarily maximize that system's mission effectiveness. For example, in the lead-up to World War II (WWII), 900 lb of armor were added around the cockpit and fuel tanks of the Brewster F2A Buffalo fighter. Although these modifications were based on combat data from the European theater, the higher wing loading decreased F2A's service ceiling, maneuverability, and maximum speed, turning a marginally acceptable fighter into an unacceptable one [24].

B. Proposed Survivability Metrics

Although existing survivability approaches have a remarkable legacy for improving the survivability of individual systems (e.g., significantly enhanced combat aircraft survivability improvements from WWII to the present day), evaluation of survivability at higher levels in the system architecture (e.g., constellation and space mission area) is both desirable and required, given the increasing interdependencies among systems in networked environments. Based on the precepts discussed in the preceding section, three desirable criteria for evaluating survivability are 1) *value-based*, to allow comparisons across technically diverse system concepts, 2) *dynamic*, to allow assessment (and enhancement) of survivability across the life cycle of a disturbance, and 3) *continuous* (rather than a discrete binary characterization) to enable distinction between systems that gracefully degrade and those that fail immediately following a disturbance. In addition, it is also desirable to have survivability metrics that are intuitive as decision metrics and that do not require assumptions to be made regarding the independence of disturbance events. Guided by the definition of survivability in Sec. II and driven by the three desirable criteria, this section proposes two metrics for the assessment of survivability in tradespace studies during conceptual design: 1) time-weighted average utility/utility loss and 2) threshold availability.

1. Time-Weighted Average Utility/Utility Loss

The development of metrics with construct validity for survivability as defined previously requires evaluating a system's ability to *minimize value losses* and to *meet critical value thresholds* before, during, and after environmental disturbances. There are many ways to operationalize value, and one approach is to use utility functions. In this article, a Keeney–Raiffa multi-attribute utility function is used [19], but the approach is not dependent on this formalization.** The multi-attribute utility function $U(\underline{x})$ is an aggregation of von Neumann–Morgenstern single-attribute utility functions $U^i(x^i)$, which reflect preferences over multiple single attributes x^i [33]. Given that attributes are varying over time, one can define $U(\underline{x}(t))$ or, in shorthand, $U(t)$. Using this characterization of a system's utility delivery over the design life T_{dl}, the time-weighted average utility may be defined:

$$\overline{U}_t = \frac{1}{T_{\mathrm{dl}}} \cdot \int U(t)\mathrm{d}t \tag{4}$$

In addition, time-weighted average utility loss may be defined to assess the difference between the beginning-of-life design utility U_o and the time-weighted average utility achieved by a system across operational environments:

$$\bar{U}_L = U_o - \bar{U}_t \tag{5}$$

Although time-weighted average utility loss is useful for evaluating the impact of various survivability features on a single system, it is less useful for comparisons across systems, because U_o is not conserved across designs (i.e., a constant utility loss applied across designs in the tradespace will have varying implications for survivability). For example, overdesigned systems may have design utilities much greater than the utility threshold required in nominal conditions, $U_o \gg U_x$, whereas U_o may approach U_x in systems with small performance margins. Therefore, to appreciate the survivability implications of a system's ability both to incorporate margin in value delivery and to minimize losses in value, it is necessary to evaluate time-weighted average utility loss relative to U_o.

2. Threshold Availability

As the expected (average) temporal utility experienced, time-weighted average utility assesses a system's life-cycle performance over nominal and disturbed environments. However, although this enables continuous evaluations to be made across systems regarding the ability to minimize utility loss, it is a measure of central tendency that does not internalize ability to meet critical utility thresholds. Two threshold levels are identified on the emergency utility scale $U(t)$. U_e is the minimally acceptable level in an emergency epoch and is therefore always zero. U_x is the level of utility provided by a design that achieves zero utility on the nominal scale when measured on the emergency scale.††

To evaluate the ability of a system to meet these critical utility thresholds, threshold availability A_T is proposed as a survivability metric. A_T is defined as the time that $U(t)$ is above operable (required or emergency) utility thresholds to the total design life:

$$A_T = \frac{\mathrm{TAT}}{T_{\mathrm{dl}}} \tag{6}$$

Although structured similarly to the traditional metric of inherent availability [32], A_T is unique in that the critical utility threshold varies across nominal, disturbance, and recovery epochs. Performance losses, such as degradation or finite outage of capability, may be allowable in disturbance environments [i.e., U_x and U_e both correspond to the minimally acceptable level of utility delivery, $U(\underline{x}) = 0$, during their respective epochs].

One implication of value thresholds changing as a function of disturbance encounters is that the definition and scale of a utility axis will vary across epochs and are therefore not consistent across the system life cycle. This presents a challenge of how to present life-cycle utility data if the utility axis is a moving target. If one assumes that the attribute set and weightings composing the utility function are constant throughout the mission, then one can define a utility function $U(\underline{x})$ that reflects preference ordering across the normal, disturbance, and recovery epochs. $U(\underline{x})$ is constructed by increasing the acceptability range of the single-attribute utility functions $U^i(x^i)$. First, the single- and multi-attribute utility functions during normal operating conditions, $U_n(\underline{x})$, are elicited from the decision-maker. Second, the single- and multi-attribute utility functions during emergency conditions, $U(\underline{x})$, are elicited. Third, as described previously, U_x and U_e are set to reflect the minimally acceptable level of utility during the nominal and disturbed periods, respectively (Fig. 2). Given that $U(\underline{x})$ reflects decision-maker preference orderings across all epochs and provides a consistent scale, the time-weighted average utility is computed using the emergency $U(\underline{x})$. This approach assumes that decision-makers are willing to accept lower levels of performance during an emergency but will raise expectations back to nominal levels following an emergency.

Both proposed metrics are closely related to existing metrics in the literature. Threshold availability is essentially a modification of inherent availability that allows for a variable threshold of stakeholder expectations. Time-weighted average utility is analogous to the quality-adjusted life year (QALY). Often used in the medical community for patients evaluating treatment options, QALY is a multi-attribute quantity that varies as a function of time. QALYs scale the length of each year of remaining life by the quality of life expected in that year. The scaled years are then added to form QALYs. Thus, many years of low quality are equivalent to fewer years of high quality [34].

IV. Application of Survivability Metrics

Having discussed existing and proposed metrics for evaluating survivability during conceptual design, an extended example is now presented to demonstrate the survivability metrics in a tradespace study. The system evaluated is a space tug, for which an existing, well-understood, tradespace model is available [18]. The survivability is defined in terms of sustained tug performance in an orbit threatened by debris. Building on previous work that investigated the passive survivability benefits provided by bumper shielding [13], the survivability model presented here adds the active survivability strategies of collision avoidance and on-orbit servicing to the tradespace. Following an overview of the modeling methodologies employed, this section summarizes the software architecture of the space tug model and then applies various survivability metrics to a set of tradespaces. The purpose of the section is to demonstrate both the

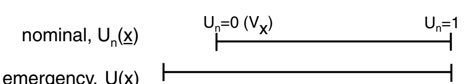


Fig. 2 Setting required and emergency utility thresholds.

**For systems that have multiple attributes, computing a single scalar value function that fully reflects decision-maker preferences can be difficult. As a proxy for $V(t)$, the multi-attribute utility function $U(t)$, as defined in [19], can be used to reflect the preference ordering of $V(t)$, if not the magnitude of that preference.

††Although the definitions of the critical utility thresholds are complex, they are carefully chosen to reflect the preferences regarding design acceptability as elicited from the multi-attribute utility interview process.

amenability of the metrics as decision criteria and how to incorporate the metrics into traditional cost-utility tradespaces.

A. Modeling Methodology: Multi-Attribute Tradespace Exploration

MATE is a conceptual design methodology that applies decision theory to model- and simulation-based designs. Decoupling the design from the need through tradespace exploration, MATE is both a solution-generating and a decision-making framework. Figure 3 summarizes the MATE process. At a high level, implementing the MATE approach to system design involves three activities. First, the preferences of a decision-maker (i.e., architecture evaluation criteria) are defined and specified with attributes (i.e., decision-maker-perceived metrics that measure how well decision-maker-defined objectives are met). These attributes are aggregated using multi-attribute utility theory to arrive at an aggregate utility function (a dimensionless metric of user satisfaction ranging from 0, minimally acceptable, to 1, highest of expectations). Second, the attributes are inspected, and various design variables (i.e., designer-controlled quantitative parameters that reflect aspects of a concept, which taken together as a set uniquely define a system architecture) are proposed. Each possible combination of design variables constitutes a unique design vector, and the set of all possible design vectors constitutes the design space. Third, a system model is developed to assess the cost and utility of the candidate architectures. In a static-MATE analysis, a limited number of Pareto-efficient designs may then be selected for more rigorous analysis [13]. In a MATE analysis incorporating survivability considerations, a simulation is developed to model system state transitions (e.g., forced transitions to lower utility states during disturbance events and transitions to higher utility states during recovery).

B. Design Problem: Space Tug Survivability to Orbital Debris

A space tug is a vehicle designed to rendezvous and to dock with a space object; to make an assessment of its current position, orientation, and operational status; and either to stabilize the object in its current orbit or to move the object to a new location with subsequent release [35]. A sample schematic of a space tug is provided in Fig. 4.

A baseline MATE study explored the tradespace for a general-purpose servicing vehicle [18]. Three attributes formed an additive multi-attribute utility function: total ΔV capability, capability of the grappling system, and response time (with attribute weights of 0.6, 0.3, and 0.1, respectively). To provide these attributes, three design variables were considered in subsequent modeling activities: manipulator mass, propulsion type, and fuel load. A full-factorial cost-utility tradespace was enumerated (featuring 128 designs) by inputting each possible combination of design variables into 1) a parametric cost estimation model and 2) a physics-based performance model. Building on both the baseline architecture trade study and a previous survivability study that investigated only passive bumper shielding [13], the dynamic MATE model presented in this

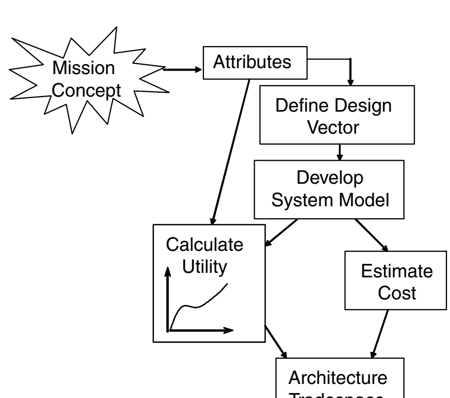


Fig. 3 Multi-attribute tradespace exploration.

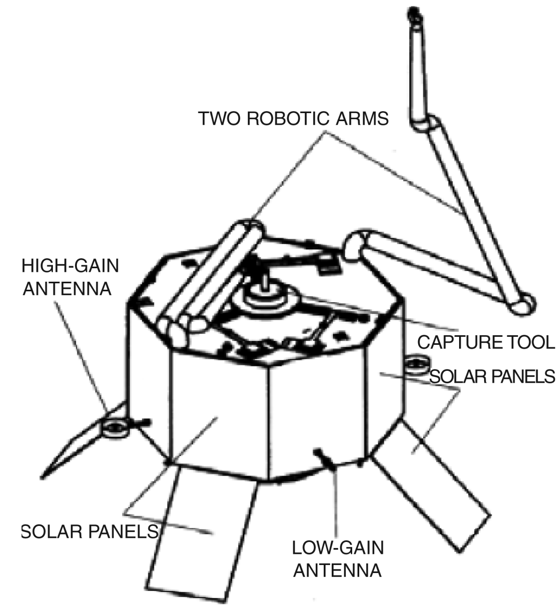


Fig. 4 Sample space tug configuration [40].

section incorporates passive and active survivability strategies into the tradespace.

Although the baseline MATE study focused on trades among the efficiency and response time of the propulsion system, grappling capability, and cost, the addition of survivability features to the design space introduces new trades between cost, design utility (i.e., utility achieved under nominal conditions at beginning-of-life), and survivability. Figure 5 depicts the six design variables used to specify a given design vector (i.e., design alternative), including three variables for survivability features. Each of the three variables is intended to drive a particular type of survivability. For type I survivability, susceptibility reduction is achieved through active collision avoidance of cataloged debris objects. Susceptibility is also reduced by selecting design vectors of small spacecraft (which will have smaller exposed cross-sectional areas to the debris flux). For type II survivability, vulnerability is reduced by selecting higher levels of bumper shielding. In addition, vulnerability may also be reduced by selecting space tugs of higher capability, potentially providing margin to degradation losses. For type III survivability, resilience may be enhanced by paying an upfront insurance fee for on-orbit servicing and repair in the event of noncatastrophic debris impacts.

Figure 6 provides a high-level perspective of how the space tug survivability model is implemented over seven general steps. First, 2560 space tugs designs are defined through a full-factorial sampling of the six enumerated design variables.

Second, the legacy space tug model and stakeholder multi-attribute utility function are used to assess the life-cycle cost and design utility of each design vector. After imposing dry mass and cost penalties for the shielding (variable mass penalty as specified by design variable), servicing ($100 million insurance fee and 50 kg docking ring [36]), and warning service for active collision avoidance (assumed fee of 5% of baseline space tug cost), the legacy model calculates the life-cycle cost and design utility of the expanded design vector.

Third, conjunction events (defined here as the passage of debris object greater than 1 mm in diameter within 25 m of the satellite) are generated according to a Poisson process in which the arrival rate is determined by the debris flux. Assuming that the space tugs are launched in 2009 into an 800 km circular orbit at 42.6 deg inclination (a relatively populated region of LEO), the orbital debris flux is extracted from NASA's ORDEM2000 model[‡‡] [8]. Flux is assumed isotropic and constant over the 10-year operational life.

[‡‡]Data available online at http://orbitaldebris.jsc.nasa.gov/model/engrmodel.html [retrieved 8 June 2009].

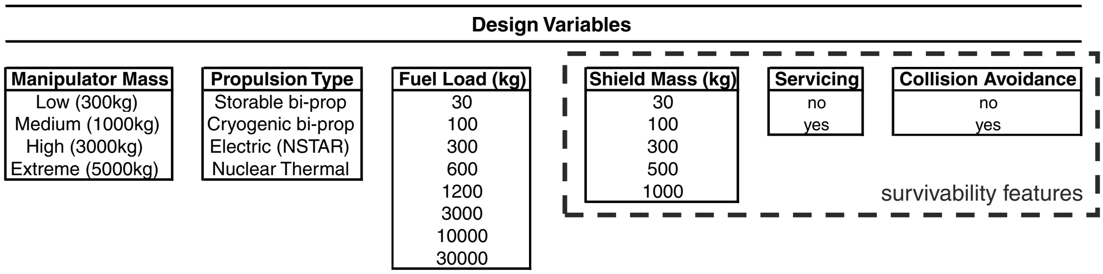


Fig. 5 Space tug design options ($n = 2560$).

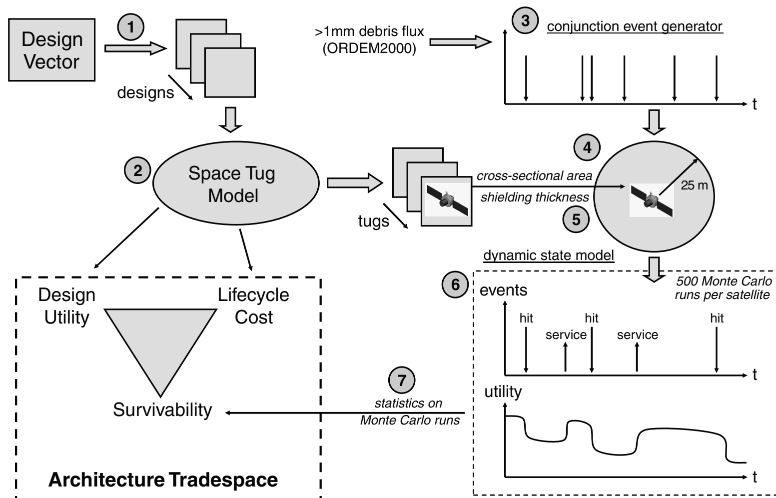


Fig. 6 Model overview.

Fourth, given a conjunction event, the baseline susceptibility of each satellite to a debris hit is computed as the ratio of the satellite cross-sectional area to the cross-sectional area of the conjunction sphere. Figure 7 shows a histogram of the probability of a hit given a conjunction event for all candidate space tug designs.

Fifth, given a hit, the probability of an encounter with one of three possible sizes of debris is computed: 1) a small debris impact, 2) a medium debris impact, or 3) a large debris impact. Table 1 enumerates the impact outcomes as reported in [37] as well as the modeling assumptions made regarding the degradation of a space tug design for a given size of impact. The modeling of damage due to impact is a complex subject depending on both the debris and the spacecraft being impacted [38]. As this is a conceptual design study with limited characterizations of the debris and spacecraft, the damage assumptions are coarse. The energies involved in large debris impacts (greater than 10 cm) are so great that it is unlikely that any spacecraft would survive [37]. Conversely, when encountering debris smaller

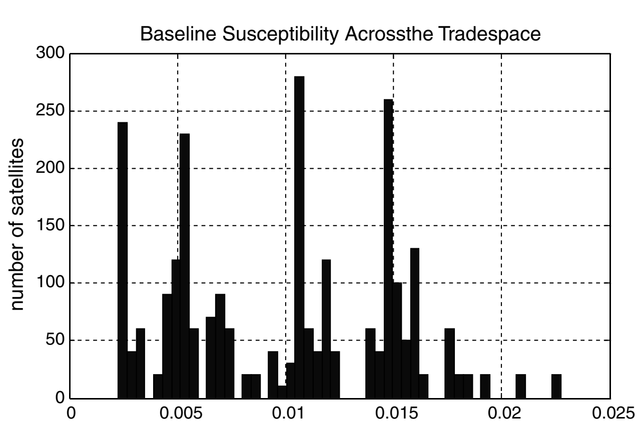


Fig. 7 Conjunction outcomes.

than 1 mm, spacecraft without dedicated shielding experience limited degradation. For modeling simplicity, these micro impacts are not considered. The effect of medium impacts will depend on which part of the spacecraft is hit. Regardless of where the impact occurs, some spacecraft capability will be lost. Because spacecraft behavior is modeled in terms of capability, the effect of impact is represented as a reduction in space tug capability level.

Although the probability of conjunctions with micro and large debris objects are constant across space tug designs, the probability of small and medium hits varies relative to the maximum-debris-size impact that can be sustained by the bumper shielding of a given space tug without deflection, rupture, or spalling. (The size of objects large enough to penetrate the bumper shield varies based upon the thickness of the shield, which in turn depends on the shield mass and satellite body area. Using an empirically derived bumper shield model [14], empirically derived relationships for relating debris diameter to debris mass [39], and assuming the approximate average orbital relative velocity in ORDEM2000 of 7 km/s, the maximum debris diameter for a small hit is computed.) Table 1 illustrates this variable threshold as x cm, meaning that an impact by a debris particle less than x cm will not penetrate the shield. However, assuming that the shield covers the leading edge ± 45 deg and surfaces 90 deg to the ram direction, there is an approximately 10% chance that impact occurs on an unshielded portion of the spacecraft [14]. Therefore, hits by small debris are assumed to penetrate the spacecraft 10% of the time, reducing the space tug capability level. Finally, given the three critical debris diameter thresholds of 1 mm, x cm, and 10 cm for each satellite, and using the spatial density of debris of those diameters in ORDEM2000 (Fig. 8), the cumulative probability that the intercepting particle of debris falls into each of the debris size bins is computed.

Because the outcome of a conjunction event is probabilistic and path-dependent in nature, a Monte Carlo analysis is performed around the sixth step. The 10-year operational life of each space tug is simulated 500 times to generate a diverse range of possible utility trajectories. Although ΔV expenditures from normal mission

Table 1 Impact outcomes

	Debris diameter			
	Micro (<1 mm)	Small (>1 mm, <x cm)	Medium (>x cm, <10 cm)	Large (>10 cm)
Impact outcome	Degradation	Damage	Severe damage	Satellite loss
Modeling assumption (7 km/s)	No impact	10% chance of loss in capability level	Loss in capability level	End-of-life/collision avoidance with 99% success

operations slowly degrade capability (at a rate of 1/15 of the ΔV budget per year), the most significant drivers of utility change are debris impact events and servicing. For each conjunction in a given run of the simulation, the probability of an encounter with a given type of debris is used to probabilistically insert disturbance epochs of small, medium, and large debris encounters. The implications of a given encounter may be uneventful, noncatastrophic (utility degradation), or catastrophic ($U = 0$ for the remainder of the 10-year period). In the event of an encounter with a large debris object, space tugs that did not invest in collision avoidance are catastrophically impacted, whereas those tugs investing in avoidance are able to maneuver away from these cataloged objects with 99% success [15]. In the event of a medium encounter, the debris object is too small to track (and hence avoid) but too large to completely shield. Space tug degradation from this penetrating impact is modeled as a forced transition in the tradespace network whereby the grappling capability design variable of the space tug is reduced by one discrete level. For example, if a space tug with low grappling capability ($U_i = .3$) is subjected to a noncatastrophic hit, grappling capability drops to none ($U_i = .0$), a minimalistic operational state in which no utility is derived from grappling. For those design vectors including a servicing option, an on-orbit repair is attempted following a noncatastrophic hit. Successful servicing missions restore grappling capability to the original (baseline) level in the design vector. (A given servicing mission is assumed to have a 70% success rate. Response times are lognormally distributed with a mean of six months and a standard deviation of a year.) In the event of an encounter with a small debris object, any debris hitting the bumper shield is stopped. However, as bumper shielding does not completely cover the satellite (as it is concentrated around the most susceptible and vulnerable regions), a 10% probability of noncatastrophic impact is assumed.

Having sampled 500 utility trajectories over the distribution of possible impact and recovery sequences for each of the 2560 space tug designs, summary statistics are collected in the seventh and final step of the model to measure central tendency of life-cycle survivability. These statistics include the existing and proposed metrics of survivability discussed in Sec. III.

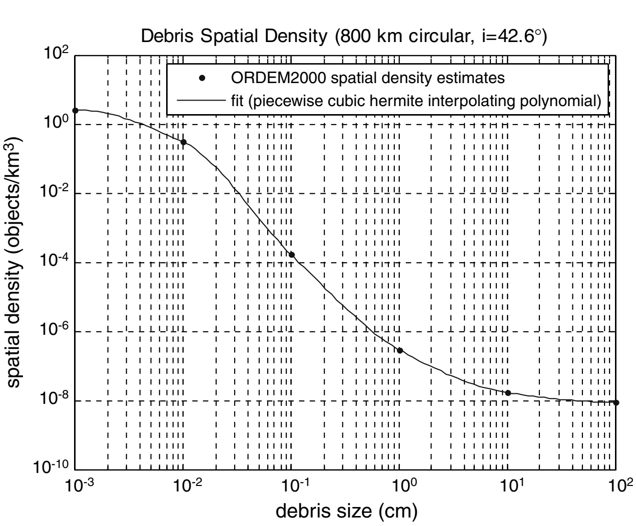


Fig. 8 Spatial density of debris.

C. Results

This section presents the results of the dynamic MATE analysis. After showing the impact of the survivability features on the baseline tradespace, results from the dynamic state characterization of space tug designs are shown. These results include sample utility trajectories, application of the survivability metrics within the baseline tradespace, and the introduction of a new survivability tradespace that allows integrated trades to be made among cost, performance, and survivability. The section concludes with a response surface analysis of each survivability feature, investigating the impact of shielding, collision avoidance, and servicing on each space tug design.

As discussed in [18], the original space tug analysis showed an interesting tradeoff among cost, grappling capability, and responsiveness. Several different classes of vehicles occupied the Pareto front, including small chemically fueled vehicles for low ΔV maneuver, servicing, and inspection; small electric vehicles that could apply considerable ΔV, although slowly; and large, expensive vehicles that could apply large ΔV quickly but only at high launch costs (for chemical fuel) or high development cost and risk (for nuclear-thermal vehicles).

The current analysis adds 20 possible combinations of survivability features for each of the design alternatives in the baseline set of 128 design vectors. Figure 9 depicts the new space tug tradespace of 2560 design alternatives. The horizontal axis is cost in millions of dollars (including recurring development and launch costs) and the vertical axis is multi-attribute utility, which is a function of ΔV capability, grappling system capability, and response time [18]. Each point is a design vector: a unique combination of the six design variables (Fig. 5). The Pareto-efficient region of the tradespace (in which utility is highest for a given expenditure) is located in the top-left region in the plot.

During normal operating conditions, space tug value is affected negatively by the addition of survivability features that only add cost and reduce ΔV capability. This effect is uneven, with smaller, less expensive vehicles being affected the most. Families of vehicles differentiated only by survivability features are visible as clusters. On the far left of the figure, many clusters run to the right (added costs) and also sharply down (decreased utility), indicating that adding survivability moderately increases cost but strongly degrades utility. Other families of vehicles (e.g., those near the center) show cost increases but without strong impact on utility. Finally, a few families (mostly near the top of the chart) show only cost increases because these electric propulsion vehicles actually have excess ΔV capacity (i.e., exceeding upper range of ΔV utility curve), and so the added weight of the shielding and docking interface (for servicing) does not decrease utility.

The baseline cost-utility tradespace is valuable to decision-makers during front-end design, as it enables cost-benefit analysis across thousands of concepts (avoiding the limits of local point solutions) and, most fundamentally, maps the decision-maker preference structure onto the design space. However, the tradespace dimensions are of limited applicability to a survivability analysis of a space tug. The survivability design variables are shown to only add cost and/or reduce utility in this representation, meaning that every perturbation off of one of the baseline 128 designs (i.e., full-factorial of first three design variables in Fig. 5) is dominated. Given that survivability features may add value to the space tug in the presence of disturbances (and given the problems associated with incorporating "ilities" such as survivability as an attribute within multi-attribute utility functions [13]), additional axes for survivability metrics must

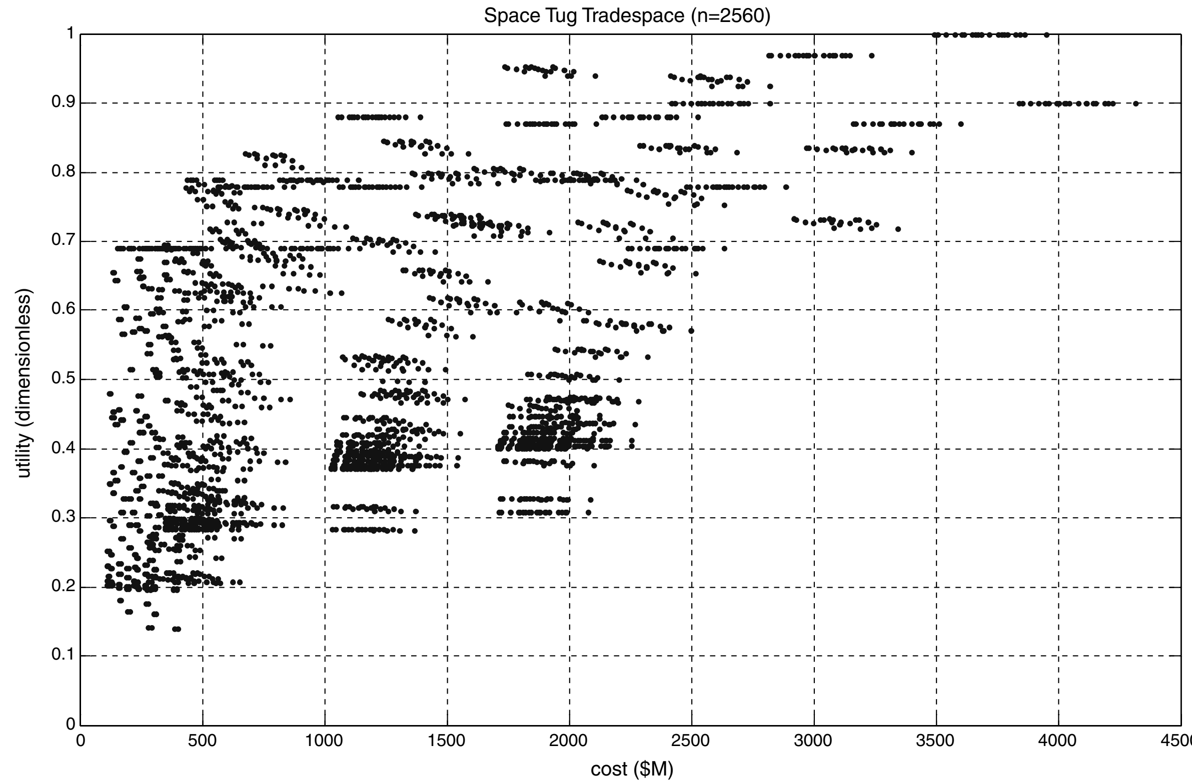


Fig. 9 Baseline tradespace.

be added to the tradespace for a decision-maker to have an integrated perspective of cost, performance, and survivability.

As discussed in Sec. II, survivability is an emergent system property which may be defined as the ability of a system to maintain value delivery within stakeholder-defined thresholds over the life cycle of a disturbance. The dynamic space tug model operationalizes this definition by simulating utility trajectories of alternative designs in the presence of orbital debris events. Figure 10 presents a sample utility trajectory output from the model, illustrating $V(t)$ (i.e., dynamic multi-attribute utility) over a possible 10-year operational life. Following normal degradation during the first 18 months of operation (modeled as nominal ΔV expenditures), two noncatastrophic debris impacts occur in quick succession during the latter part of the second year. Because of the reduction in expectations from

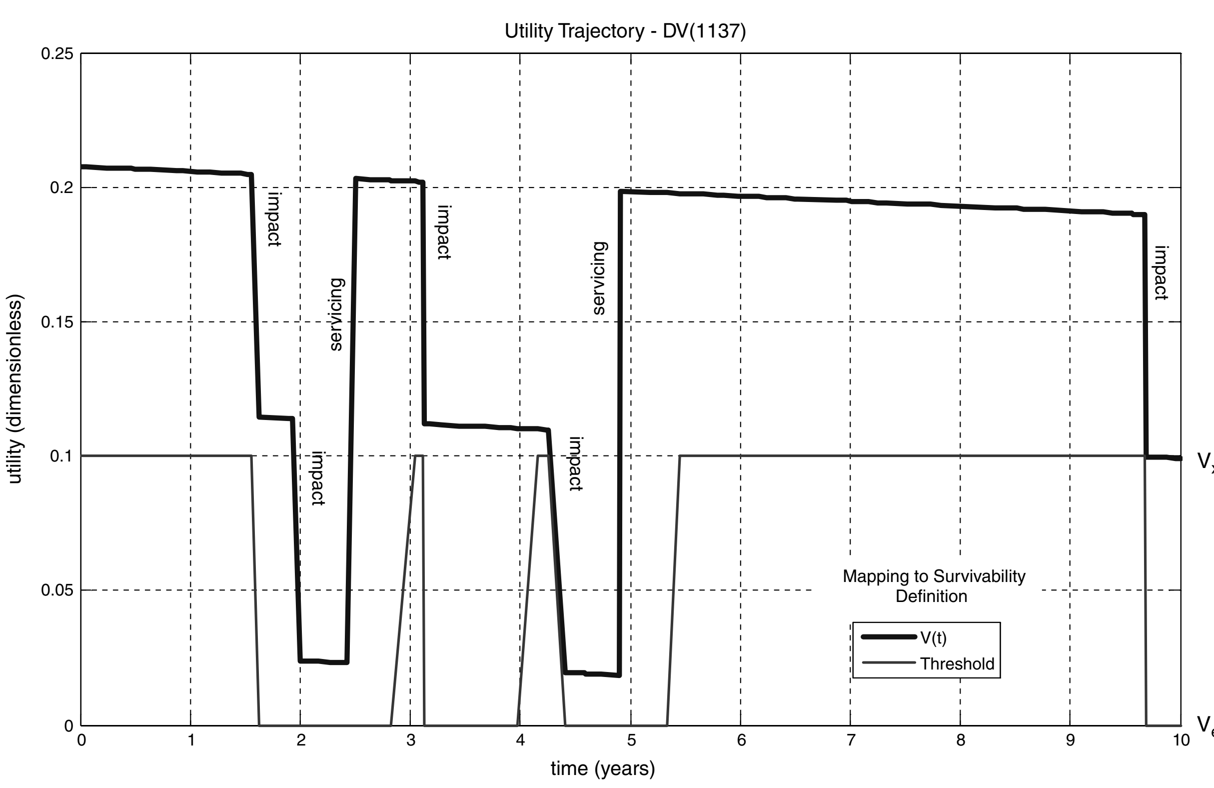
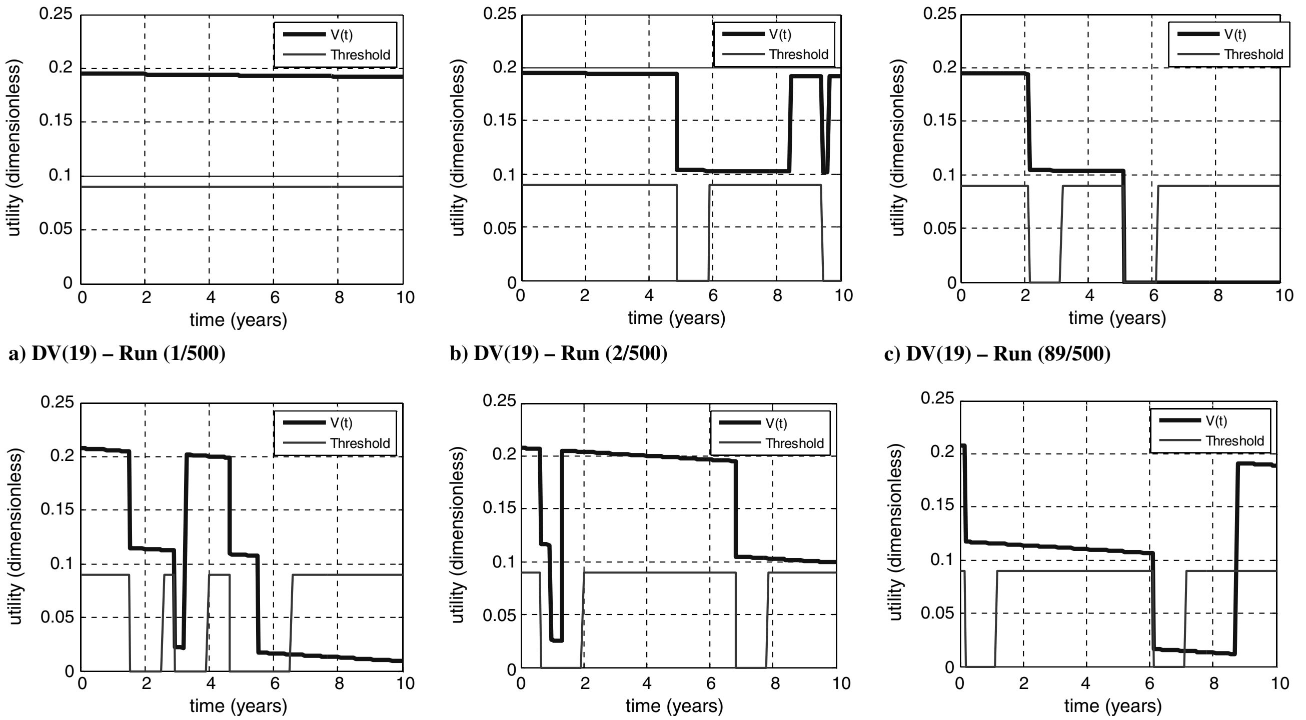


Fig. 10 Sample utility trajectory.



a) DV(19) – Run (1/500) **b) DV(19) – Run (2/500)** **c) DV(19) – Run (89/500)**

d) DV(1137) – Run (3/500) **e) DV(1137) – Run (20/500)** **f) DV(1137) – Run (426/500)**

Fig. 11 Sample utility trajectory outputs from design vectors 19 and 1137.

V_x to V_e for a year following the first impact (and renewed following the second impact), $V(t)$ does not pass below the value threshold. The first debris impact prompts a request for servicing that is successfully filled during the second year. A similar sequence of events (consecutive debris hits followed by successful servicing) occurs between the third and fifth years. In both cases, large quantities of utility are lost, whereas critical value thresholds are met.

Figure 11 depicts six more sample utility trajectories. The top row illustrates the outcomes from three Monte Carlo runs of design vector 19, DV(19), and the lower row illustrates three runs of DV (1137). Figure 11a depicts the most common utility trajectory output from the model: slight utility degradation over time without any debris impacts. Although Fig. 11b shows DV(19) receiving (and recovering from) two noncatastrophic debris impacts, Fig. 11c shows the mission ending prematurely at year five from a catastrophic impact. Similar erratic utility trajectories are observed across the lower row. Interestingly, whereas both runs 3 (Fig. 11d) and 426 (Fig. 11f) of DV(1137) reveal an active space tug at end-of-life, both

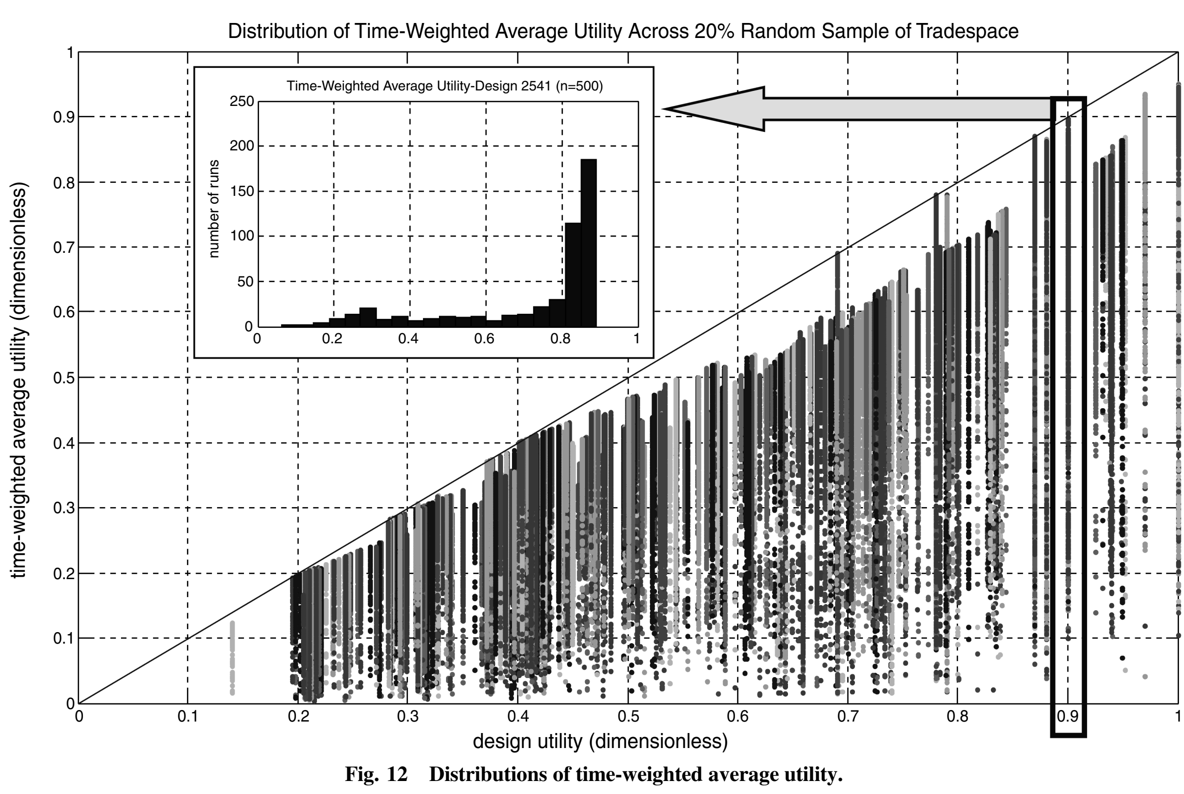


Fig. 12 Distributions of time-weighted average utility.

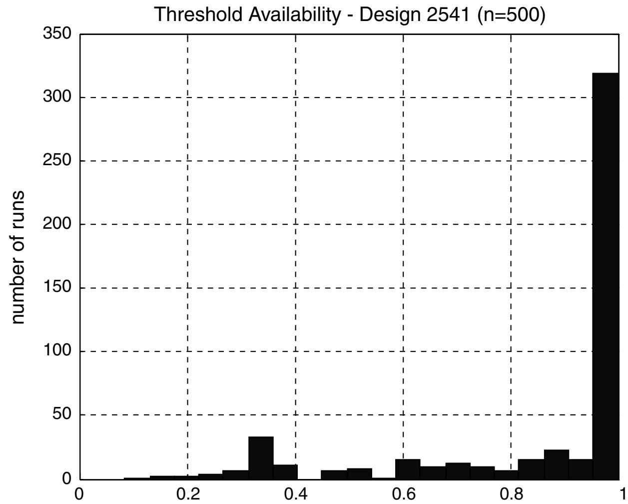


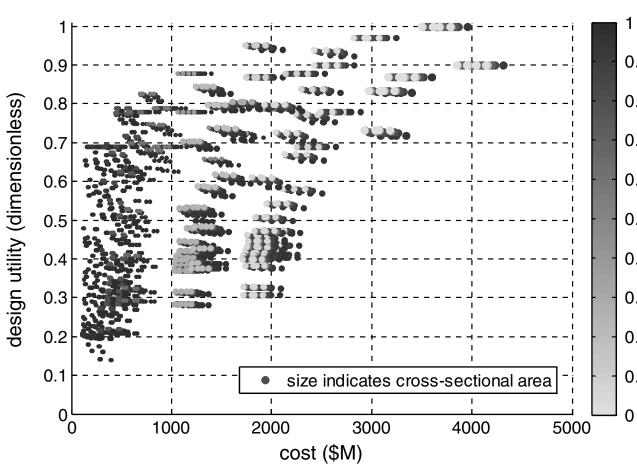
Fig. 13 Sample distribution of threshold availability.

spend at least a year below V_x due to failed and delayed servicing operations, respectively.

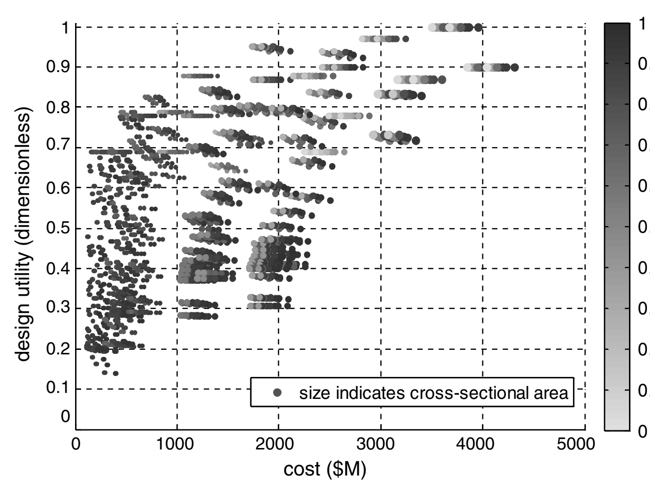
As survivability is a stochastic path-dependent property, the outcome of any particular run for a given design vector is not necessarily representative or meaningful from a decision-making perspective. Rather, each utility trajectory constitutes one data sample from a continuous distribution of potential system life cycles. Furthermore, there is a need to distinguish across collections of utility trajectories of different design vectors (e.g., illustrated by rows in Fig. 11). However, observing all 128,000 utility trajectories (500 runs of each of the 2560 design vectors) is not practical from a decision-making perspective. Therefore, the survivability metrics introduced in Sec. III (*time-weighted average utility/utility loss* and *threshold availability*) are applied as aggregate measures for each set of space tug utility trajectories.

Figure 12 depicts the distributions of time-weighted average utility achieved by 20% of the design vectors over 500 Monte Carlo runs. (A random sample of 20% was selected to aid in information visualization.) Each column of identically shaded points represents the distribution of time-weighted average utility for a single space tug design vector. To organize the data, the columns are ordered along the horizontal axis in terms of design utility: the deterministic beginning-of-life utility U_o achieved by a space tug before stochastic losses accrue from normal degradation and orbital debris. The design utility here is equivalent to the utility axis in the baseline tradespace (Fig. 9). A 45 deg line is also drawn to show the maximum time-weighted average utility value achievable.

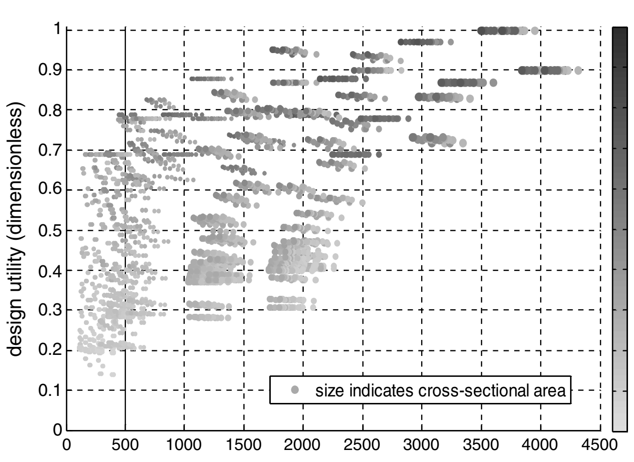
The results are illuminating, showing a consistent pattern of highly skewed distributions toward design utility. The histogram of DV(2541) in Fig. 12 is displayed as a representative distribution of the highly skewed behavior of time-weighted average utility across simulation runs. One interesting trend observed is the general regression of maximum time-weighted average utility values from U_o for space tugs as design utility increases. This is due to both the increased susceptibility of larger (and generally higher-utility) space tug vehicles to orbital debris and to the lower ΔV margins of the more massive space tug vehicles. (Given the full-factorial enumeration of



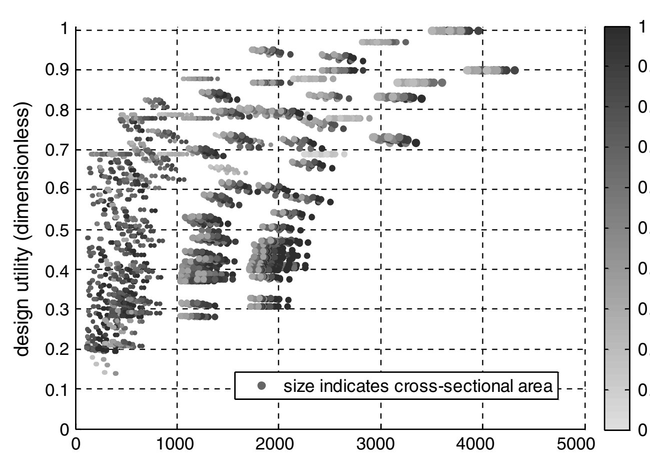
a) P[no penetration]



b) P[U(t=10)>0]



c) Time-weighted average utility - 5th percentile



d) Threshold availability - 5th percentile

Fig. 14 Application of survivability metrics to baseline tradespace.

design vectors, tradespace artifacts, such as the paring of low fuel mass with high-capability tugs, may result.) An additional behavior across the distributions is the presence of maximum time-weighted average utility outliers (in which no losses or degradation are observed vis-à-vis the design utility line) beginning around design utility values of 0.7. These outliers are attributed to simulation runs of high-capability electric propulsion space tug designs that were set with excessive ΔV margins and that did not suffer from orbital debris impacts.

The highly skewed, long-tailed nature of the distributions of time-weighted average utility across simulation runs was also observed for the distributions of threshold availability. Figure 13 shows the output from DV(2541) utility trajectories as a sample distribution.

Having generated a data set of utility trajectories and having applied two new measures of life-cycle survivability, we next compare the new metrics to existing survivability metrics and integrate the survivability metrics with measures of cost and design utility.

Figure 14 presents four separate survivability tradespaces, each incorporating one of four different survivability metrics to the baseline cost-utility tradespace in Fig. 9. The top two tradespaces apply existing static conceptualizations of survivability, and the bottom two tradespaces apply the proposed dynamic measures of survivability. Each survivability metric is depicted in shade (i.e., darker means more survivable). In addition, to indicate the varying susceptibility of small and large space tugs to orbital debris, the size of each point in the tradespaces is correlated with exposed cross-sectional area.

The results across the four tradespaces vary tremendously, indicating the importance of understanding and selecting the correct metric or metrics for evaluating system survivability (i.e., depending on the metric chosen, very different conclusions may be drawn). Figure 14a, P[no penetration], shades each space tug design by the probability of no debris penetration over the 10-year operational life. In this representation, lower-cost designs achieve a high degree of survivability due to their low susceptibility, whereas the survivability of high-cost designs fluctuates as a function of shielding and collision avoidance. (Resilience enhancement strategies, such as servicing, are exogenous to this survivability metric.) Figure 14b, $P[U(t = 10) > 0]$, is shaded by the probability of a nonzero utility (i.e., operational) space tug at end-of-life. Here, the high survivability of lower-cost designs is again observed. The survivability of high-cost designs varies considerably as a function of all three survivability features.

Figure 14c, time-weighted average utility–5th percentile, shades each point by the level of time-weighted average utility achieved by 95% of the simulation runs of that design vector. For example, a value of 0.53 for time-weighted average utility–5th percentile means that 95% of the simulation runs of that design vector achieved a time-weighted average utility of at least 0.53. (Rather than use a potentially misleading measure of central tendency such as average for the highly skewed distributions, aggregate simulation results for time-weighted average utility and threshold availability are reported as percentiles.) The results here are naturally correlated with design utility. Many designs deemed survivable by this metric are found in the interior of the traditional cost-utility Pareto front. Interestingly, clusters of space tugs (varying only by survivability design variables) are observed in which there is a nonmonotonic relationship between adding levels of survivability features (indicated by rising costs) and time-weighted average utility. Figure 14d, threshold availability–5th percentile, shades each point by the proportion of time over the 10-year operational life spent above the critical value threshold. (As illustrated in Fig. 11 and discussed in Sec. II, this threshold varies depending on environmental context.) In contrast to time-weighted average utility, threshold availability generally rises as survivability

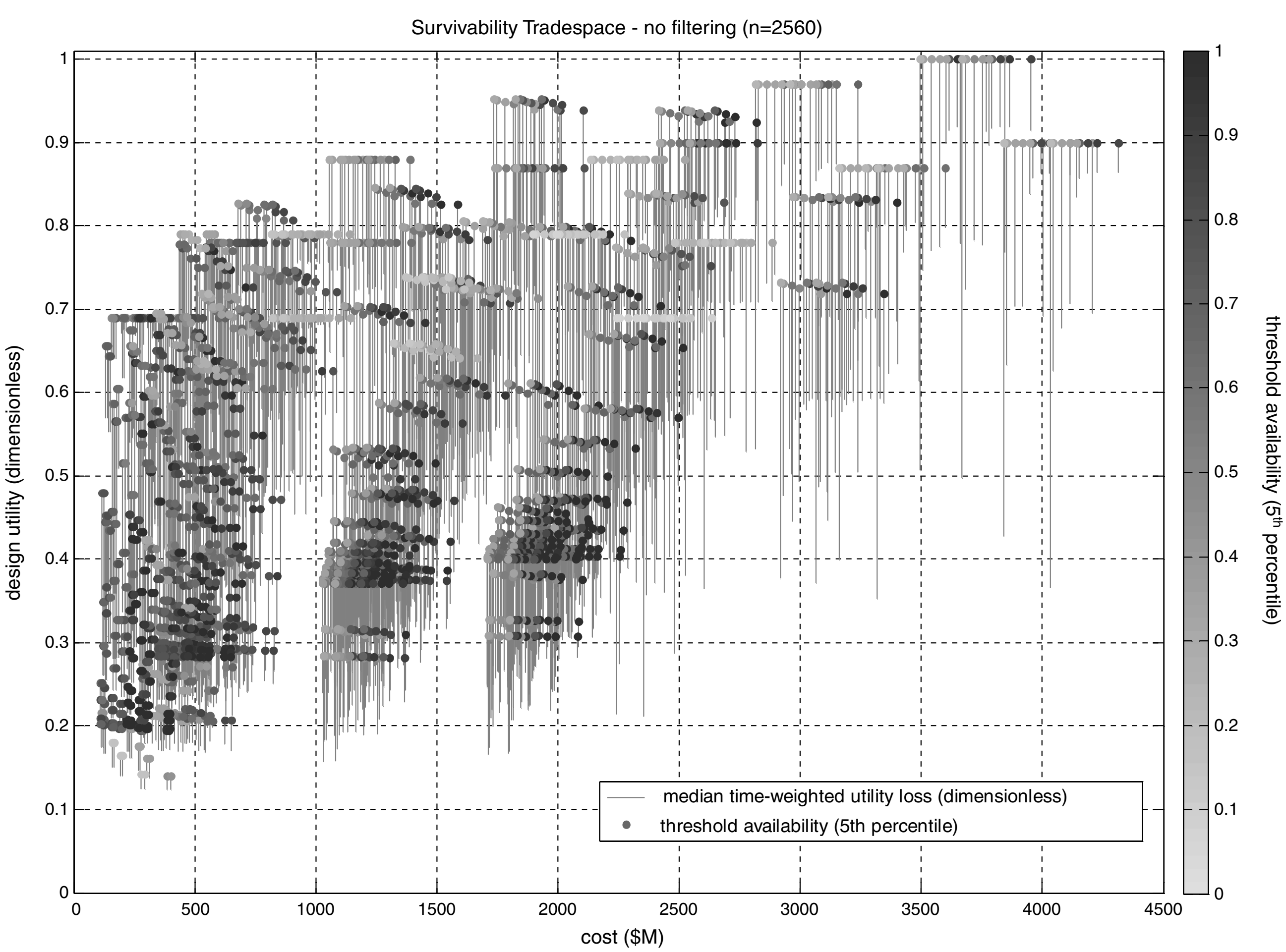


Fig. 15 Survivability tear tradespace.

features are added to each space tug. Threshold availability also appears to be sensitive to space tug size, as smaller, less-susceptible designs achieve higher availability than their larger counterparts. Exceptions to these trends are also observed, including the low-availability of the extremely-low-cost designs due to their tight performance margins.

The four tradespaces shown in Fig. 14 present four conflicting (yet interdependent) perspectives regarding the survivability of the 2560 candidate space tug designs. Each tradespace presents useful information to the decision-maker. However, there is a need to aggregate the information to allow integrated tradeoffs among other decision metrics for cost, performance, schedule, and risk. Although the upper two tradespaces communicate the relative survivability of designs based on binary calculations of survivability, the two lower tradespaces are based upon the definition of survivability as a continuous, stochastic, and path-dependent property that is assessed over the entire operational life. Therefore, to incorporate all of the information contained in the utility trajectories (rather than small samples of the data such as the utility state at end-of-life), the next two tradespaces focus on applying the new survivability metrics.

To address the need for trading life-cycle cost, performance, and survivability of design alternatives, Fig. 15 introduces a survivability tear (drop) tradespace representation. The purpose of the survivability tear tradespace is to integrate deterministic cost and design utility data with the distributions of time-weighted average utility and threshold availability. Preserving the cost and design utility axes of the baseline tradespace, the new survivability metrics are integrated using shade (threshold availability–5th percentile) and a line drawn to the median time-weighted average utility. By definition (see Sec. III.B), the length of this line is the median time-weighted utility loss across the 500 utility trajectories for each space tug design. Rather than the 95th percentile, the median is selected for summarizing the distribution of time-weighted utility loss for two reasons: 1) easing visualization for this particular data set by shortening the length of utility loss tails (from 95th to 50th percentile) and 2) recognition that decision-makers are likely to be more risk-averse regarding threshold availability (a construct for measuring assured access to some level of minimum capability) than time-weighted average utility (a construct for assessing degree of degradation).

Some interesting trends can be observed in Fig. 15, such as the poor performance of very-low-cost and very expensive designs in terms of threshold availability (due to low-performance margins and high-susceptibility, respectively). Irregular reductions in utility loss can be observed as survivability features are added to clusters of baseline space tug designs. Smaller utility losses appear to occur in the lower-cost (smaller), lower-susceptibility region of the tradespace. Unfortunately, one consequence of tagging each of the 2560 design alternatives with four data attributes is that Fig. 15 becomes very concentrated and difficult to interpret.

Figure 16 reduces the concentration of Fig. 15 by filtering the 2560 designs for Pareto optimality over the four decision metrics: cost, design utility, median time-weighted utility loss, and threshold availability. When considering the tradespace in four dimensions, the surface of Pareto-efficient designs contains three individual Pareto sets (as determined by a projection onto the cost-utility, cost-availability, and cost-utility loss planes) as well as other points that would not project onto any of these two-dimensional surfaces. These other points exist at the tradeoffs among design utility, threshold availability, and time-weighted utility loss for the decision-maker and represent compromise value solutions.

Counterintuitively, as decision metric axes are added to filter for Pareto-efficiency, more designs will remain after filtering in the survivability tear tradespace. This is because as each axis is added, a new two-dimensional Pareto front is created with a new set of projected compromise solutions. For example, a cost-utility filter

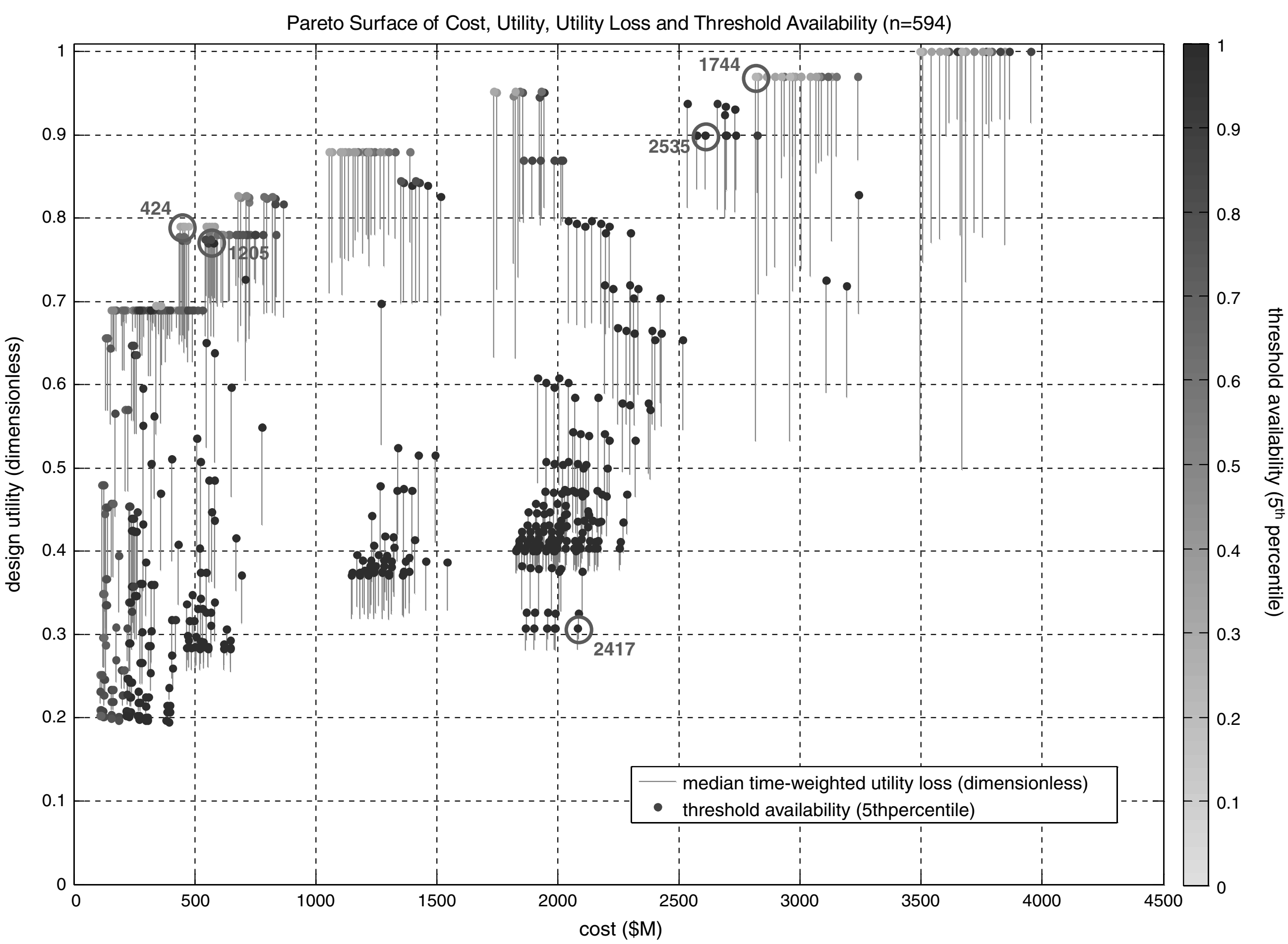


Fig. 16 Filtered Pareto surface of survivability tear tradespace.

Table 2 Characteristics of circled design vectors in Fig. 16

	Design vector ID				
	424	1205	1744	2535	2417
Manipulator capability	Low	Medium	High	Extreme	Extreme
Propulsion system	Nuclear	Electric	Nuclear	Electric	Electric
Propellant mass, kg	3000	1200	30,000	10,000	30
Shield mass, kg	30	100	30	500	1000
Avoidance	Passive	Active	Passive	Passive	Active
Serviceable	No	Yes	No	Yes	Yes
Cost ($ million)	439.1	577.6	2815	2607	2079
Design utility	0.79	0.77	0.97	0.90	0.31
Median utility loss	0.13	0.11	0.43	0.06	0.02
Threshold availability (5%)	0.32	1.0	0.24	1.0	1.0

applied to Fig. 15 leads to 111 Pareto-efficient designs, whereas a cost-utility-utility loss filter leads to 279 Pareto-efficient designs. As a fourth metric is added for filtering (as in Fig. 16), 594 designs are deemed Pareto-efficient. This growth of Pareto-efficient designs as decision metrics are added is analogous to the multistakeholder problem in utility theory [19].

One implication of filtering over the four decision metrics is that several interior designs become Pareto-efficient based upon their superior performance in terms of survivability. Rather than only allowing the selection of designs dominant in terms of cost and utility at beginning-of-life, the filtered survivability tear tradespace presents alternative designs that may offer superior performance over a life cycle of disturbances.

Having filtered the tradespace, it is now possible to conduct trades among designs along the four-dimensional Pareto surface. For example, Table 2 lists the design variable settings and performance parameters for five design vectors circled in Fig. 16. In the $400–600 million range, the nuclear DV(424) is optimized in terms of cost and design utility, whereas the electric DV(1205) is slightly dominated in terms of cost and design utility but with a 68% improvement in 5th-percentile threshold availability. As an example in the $2.5–3 billion range, DV(1744) is similar to DV(2535) in cost and design utility but requires a tremendous sacrifice in survivability (i.e., 0.43 rather than 0.06 median utility loss and a 0.76 difference in threshold availability). As an extreme case of high survivability, the characteristics of DV(2417) are also shown.

The results in Fig. 16 and Table 2 demonstrate two key benefits of the survivability tear tradespace analysis screening and down-selecting among thousands of design alternatives with survivability as an explicit decision criterion. Interestingly, most of the designs in the cost-utility Pareto front have much lower threshold availability (and considerably higher utility loss) than interior designs, whereas several of the highly survivable space tugs are only slightly dominated in terms of cost and design utility.

Having introduced a survivability tear tradespace for enabling integrated trades to be made across alternative concepts in terms of cost, performance, and survivability, the impact of each of the three survivability design variables on the survivability of each of the 128 baseline designs (i.e., full factorial of first three nonsurvivability design variables in Fig. 5) is now examined. This analysis may be used for maximizing the survivability of an individual satellite (if a baseline design concept has already been selected) as well as for investigating the overall sensitivity of the satellite tradespace to various survivability enhancement features.

Figure 17 plots survivability response surfaces for each of the baseline designs. Each design point is located in terms of cost and average time-weighted average utility[§§] and shaded by 5th percentile threshold availability. Linked clusters (labeled 1 through 128) indicate a common baseline space tug of fixed manipulator mass, propulsion type, and fuel load. The impact of survivability features is evaluated by finding the lowest-cost inverted triangle in each cluster to identify the baseline space tug design (which incorporates only 30 kg of shielding and no avoidance or servicing). Then the response surfaces for shielding, servicing, and avoidance may be identified by examining the solid, dark dashed, and light dashed lines, respectively. Designs incorporating no servicing are represented with three-sided shapes (i.e., as triangles for designs with avoidance and as inverted triangles for designs with no avoidance), and designs that do incorporate servicing are represented as four-sided shapes (i.e., as squares for designs with avoidance and as diamonds for designs with no avoidance).

Interesting trends may be identified in the (relatively) sparse high-cost region of Fig. 17. For example, increasing the shielding appears to increase threshold availability as shielding mass is increased, whereas average utility benefits only from the initial increases in shield mass. Avoidance appears to have no statistically significant impact across the 500 runs (as availability is constant and average utility fluctuates slightly up or down). Servicing has a very positive impact on both survivability metrics in this region of the tradespace. Unfortunately, it is hard to extract survivability response surface trends across this display of the entire tradespace given the density of clusters in lower-cost regions.

To compare survivability response surfaces in different regions of the tradespace, Fig. 18 magnifies five low-cost designs and one high-cost design from Fig. 17. Although the width and height of each magnification is conserved to enable comparison, the cost and average utility axes are necessarily different. At this higher resolution, the impact of shielding, avoidance, and servicing on both individual tug designs and different regions of the tradespace can be better observed. Table 3 shows the baseline design variable settings for each of the design vectors displayed in Fig. 18.

The impact of shielding on average utility and threshold availability is very different across these regions of the tradespace. For baseline design number 5, BD(5), shielding has a negative impact on both cost and average utility while providing no appreciable gains in threshold availability. This is also true of BD(27). The shielding impact on BD(5) and BD(27) stands in stark contrast to BD(120), in which the first two increases in shielding mass result in large increases in average utility and threshold availability at only marginal increases in cost. However, after the first two increases in shielding mass in BD(120), survivability benefits diminish, whereas dry mass penalties accumulate. BD(29) and BD(62) represent intermediate cases in which the first increase in shielding mass (from 30 to 100 kg) yields slight improvements in average utility and threshold availability before negative returns occur at 300 kg of shielding.

Avoidance does not have much of an impact on survivability in either region of the tradespace. The only general trend observed is the assumed 5% cost penalty associated with incorporating active collision avoidance. Indeed, some designs even occasionally show *losses* in average utility for incorporating active collision avoidance (despite the fact that, as modeled, avoidance can only improve utility trajectories). The limited impact of avoidance is due to the fact that detectable debris encounters (assumed to be greater than 10 cm in diameter) are extremely rare events. Therefore, the avoidance response surface is horizontal to account for the cost penalty, and slight vertical fluctuations may be attributed to random variation over the 500 Monte Carlo trials.

[§§]Time-weighted average utility is the average across a single trajectory, and average time-weighted average utility is the average of this value across the set of 500 Monte Carlo trials.

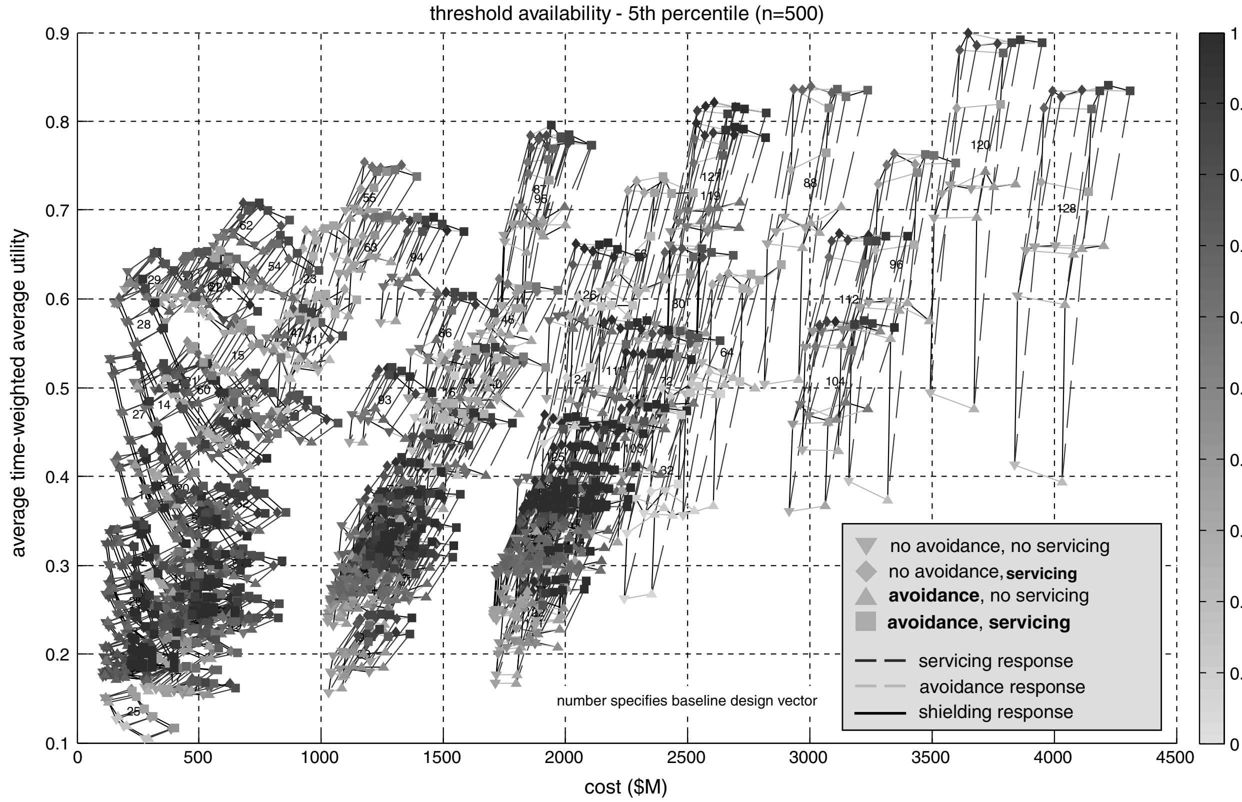


Fig. 17 Survivability response surfaces: 128 baseline designs.

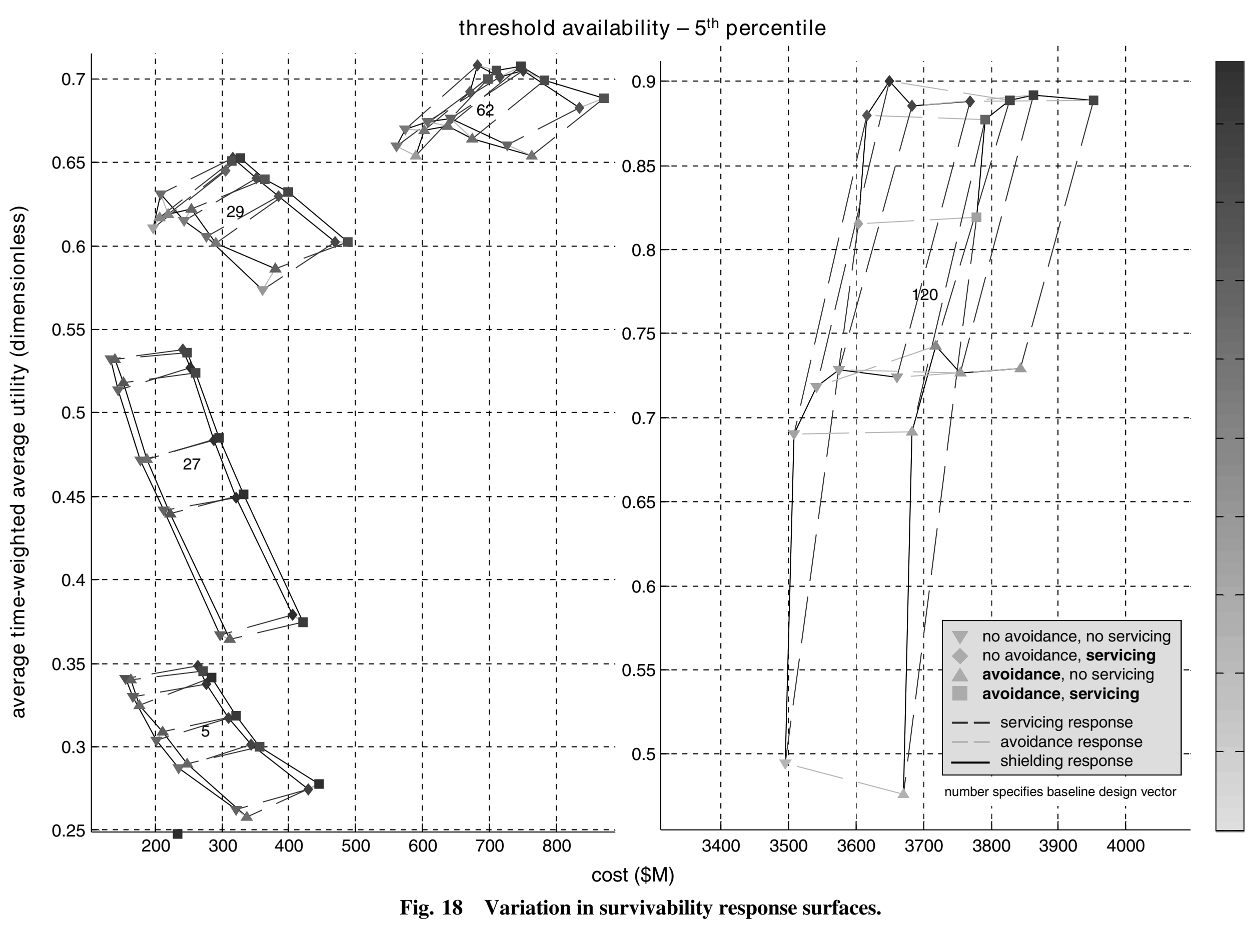


Fig. 18 Variation in survivability response surfaces.

Table 3 Characteristics of baseline design vectors in Fig. 18

	Baseline design vector ID				
	5	27	29	62	120
Manipulator capability	Low	Low	Low	Medium	Extreme
Propulsion system	Biprop	Electric	Electric	Electric	Nuclear
Propellant mass, kg	1200	300	1200	3000	30,000

Unlike shielding and avoidance, servicing has a positive impact on average utility and threshold availability across the tradespace. The impact is not uniform, however, as BD(120) (with its larger exposed cross-sectional area) is more susceptible to debris impacts. This space tug is much more likely to experience multiple noncatastrophic debris impacts over its operational life and therefore benefit substantially from servicing (increasing average utility approximately 25%). Servicing has a smaller positive impact on the lower-end designs, particularly in terms of threshold availability.

V. Discussion

The process of developing survivability metrics and applying them within the dynamic survivability model yielded several insights for the space tug tradespace. In terms of space tug survivability, one interesting result is the criticality of the inherent survivability derived from the baseline design vector (before incorporating survivability design variables). For example, selecting baseline tugs with smaller cross-sectional areas has a much greater impact on susceptibility reduction than active collision avoidance. Similarly, increasing grappling capability margin has a greater impact on reducing vulnerability than bumper shielding. Another modeling insight is the extreme sensitivity of the results to the damage model for small- and medium-sized impacts (for which limited empirical data exist). Of all the results, Fig. 16 is the most interesting from a decision-making perspective, as it reveals that the cost-utility Pareto-optimal designs exhibit poor survivability, whereas many highly survivable designs are only slightly dominated in terms of cost and utility.

The space tug example indicates that the metrics of time-weighted average utility/utility loss and threshold availability can be applied prescriptively to the evaluation of the survivability of alternative satellite designs. The metrics are unique but interdependent. Specifically, high average utility implies high threshold availability (although high threshold availability does not imply high average utility). Taken together, the metrics serve as powerful discriminators of survivability performance.

VI. Conclusions

The growth of dependency on space systems, their identified vulnerabilities, the proliferation of threats to satellites, and the weakening of the sanctuary view in military space policy underscore the criticality of survivability as a measure of spacecraft effectiveness. Existing metrics for evaluating system survivability during conceptual design traditionally involve binary characterizations of system state and assume independence among disturbance events to abstract away the complexities associated with path-dependent calculations of survivability. The metrics of time-weighted average utility loss and threshold availability can be used to better evaluate system survivability during conceptual design. These metrics assess both the ability of systems to minimize value losses to stakeholders and to meet critical value thresholds before, during, and after environmental disturbances. Time-weighted average utility loss and threshold availability empower system analysts to conduct comparisons across technically diverse system concepts, track survivability as a path-dependent dynamic system property, and distinguish between systems that gracefully degrade and those that fail immediately following a disturbance. When the survivability metrics are applied within multi-attribute tradespace exploration, tradeoffs among programmatic cost, mission performance, and life-cycle survivability are made explicit and readily communicated to decision-makers.

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