Flexibility "of" Versus "in" Systems: A Complementary Strategy for Designing Fleet-Based Systems for Uncertainty

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Complex systems must sustain value over extended lifetimes, often in the face of significant uncertainty. Flexibility "in" systems have been shown to be highly valuable for large monolithic systems (LMS). However, other research highlighted that the value of flexibility "in" is highly contingent on delays in implementation. These limitations become more important when applied to other classes of complex systems, including fleet-based systems (FBS). To overcome these challenges, this paper introduces a complementary approach to flexible design, termed flexibility "of," and applies it to a case study of a fleet of military vehicles (an FBS). Unlike LMS, FBS are composed of multiple identical units that collectively deliver value. While each unit is itself a complex system (e.g., a tank or aircraft), the collective nature of the operations provides additional paths to flexibility: in addition to implementing flexibility at the vehicle level, flexibility can be applied to the management of the fleet. Flexibility "of" involves procuring a mixed capability fleet upfront and then actively managing which subsets of that fleet are deployed to meet emerging needs. Our results demonstrate the potential value for an of strategy and provide guidance for when different flexibility strategies should be adopted alone or in combination. [DOI: 10.1115/1.4053157]

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1 Introduction

Flexible design is a well-established approach to mitigate an uncertain future in the lifespan of complex systems [1,2]. One increasingly popular method for implementing flexibility is to design the ability to change "in" systems. This strategy of flexibility "in" involves building an "option" to change into the physical design of the system. That option can be "called" (i.e., the system is changed) only if needed [3,4]. The flexibility "in" approach was developed by scholars focused on a particular class of complex systems, which we will refer to as large monolithic systems (LMS). Primarily infrastructure systems, with high capital expenditures (CapEx) and long planned lifetimes, include airports, real estate projects, railways, highways, power plants, and bridges [5].

Following multiple successful applications of the concept, designers from other domains have attempted to apply it more broadly [6,7]. However, recent work has identified potential limitations to designing "in" options, including implementation delays and physical limitations to option design [7–9]. We contend that the relative importance of these benefits and limitations depends on characteristics of the system of interest. What works for LMS systems might not apply directly to other classes of complex systems. Moreover, many of these sources of delays may be unavoidable, for example, typical budget cycles extend over a year or more [7]. Therefore, as this framework is applied to a broader range of systems, it is important to first investigate if the design of flexibility "in" systems should be the preferred approach or if there are other ways to enable flexibility in other classes of complex systems.

To that end, this paper proposes a complementary approach to flexibility which we demonstrate is particularly valuable in another class of complex systems. We define fleet-based systems (FBS) as systems composed of a large number of similar units, where the units themselves are complex systems. Viewed at the unit level, FBS and LMS share many common features in that they are expensive and must sustain value over a long life. However, unlike LMS, FBS possess an important design lever at the fleet level. FBS flexibility can be implemented within each unit (the traditional flexibility "in" approach), but it can also be implemented "of" the fleet. Since individual units can be changed and/or replaced over the life of the fleet, a flexibility "of" approach can be managed such that different mixes are allocated to different needs, achieving fleet-level flexibility without exercising any options within a particular system. FBS are found in a wide array of defense and commercial applications, including airlines, city utility vehicles, military vehicles, ships aircraft, and many others. The "in" and "of" approach are not mutually exclusive; in fact, within an "of" framework, some particular units within the fleet can adopt an "in" strategy.

In order to establish the value of a flexibility "of" approach and to understand when and under what conditions an "of" approach should be considered within a flexible design strategy, we developed a simulation-based case study of a fleet of autonomous light combat vehicles deployed by the Army. The simulation is inspired by the historical example of the high mobility multipurpose wheeled vehicle (HMMWV) during the Iraq War beginning in 2003. In that context, the implementation of flexibility "in" involved designing armor kits that could be bolted on to existing HMMWVs in theater. The Army aimed to add nearly 14,000 armor kits onto the existing fleet of unarmored vehicles. While the option to add armor to each vehicle was relatively simple (bolt-on armor to the frame), there were significant logistical challenges associated with implementing the change across the fleet. It took more than two years from the identification of the new threat of improvised explosive devices to the time when soldiers received the added protection provided by the installed kits. These delays likely resulted in the additional injuries, equipment loss, or, most tragically, the additional loss of life during the

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associated delay [10–12]. In the same context, if the Army had instead adopted a flexibility "of" approach, the initial 140,000 vehicle fleet would have been purchased as a mixture of unarmored and armored vehicles. Then, as the threat environment changed around the world, different vehicle mixes could be deployed or re-allocated to different theaters based on their needs. For example, new units would be deployed to Iraq with armored vehicles without extra delay. While the upfront cost may be higher, the reduction in avoidable losses can balance the overall value. It is that tradeoff that this paper explores.

After synthesizing the theoretical basis for this work, we conduct two separate but related modeling case studies to understand the relative strengths and weaknesses of flexibility "in" and "of" for different kinds of complex systems. The first analysis focuses on a simulated case study inspired by the HMMWV context, wherein we compare the flexibility "in" approach to the counterfactual of the planned flexibility "of" a mixed initial fleet that is deferentially allocated based on need. After establishing the significant benefit of an "of" approach in this specific context, the second analysis aims to generalize the insights to a broader class of system. To that end, the test cases are modified to remove case-specific assumptions and the analysis examines the performance of alternative flexibility strategies across a range of system effectiveness levels, costs to enable flexibility, and fleet utilization rates. Again, flexibility "of" performs well under a wide range of conditions, leading to the recommendation that this new flexible design approach receives greater attention in the literature and practitioner toolkit.

2 Related Work

This section builds the theoretical basis for the contributions the paper aims to make. It begins with a general discussion of the impact of uncertainty on complex systems and two common approaches to mitigate this uncertainty, robust, and flexible design. Next, it discusses the intellectual history of the concept of flexibility "in" systems. This provides the context in which the strategy was developed and the types of projects on which it is commonly employed. We then examine the challenges of building flexibility "in" a system. Next, we relate flexibility "in" the system to the broader concept of change, including across a fleet. Finally, the literature gap this paper addresses is described.

2.1 Mitigating the Impacts of Operational Uncertainty. Uncertainty has long been recognized as a challenge facing the design of complex systems. To mitigate these associated challenges, a series of "-ilities," such as flexibility, adaptability, versatility, evolvability, and robustness, have been studied and characterized [1,13–16]. While there is debate on the specific definitions of each, collectively they support two overarching approaches to mitigating uncertainty: (1) designing a system to be capable of changing in the face of uncertainty or (2) designing a system such that it is insensitive to a changing environment [1,2,16]. In this paper, we will refer to the former approach as flexibility and latter as robustness.

In robust design, designers typically aim to forecast the anticipated operating range of a system and design sufficient operating margin into the system to accommodate future scenarios [1,2]. On the other hand, flexible design looks to enable the system to change as the conditions in which the system operates change. Flexibility "in" systems, in the form of a real option, is a popular approach to enable system change. In this approach, an "option" to change, if and only if needed, is incorporated into the physical design of the system. This differs from another type of real option, described as a real option "on" where focus is on valuation of managerial decision making, where the physical design of the system is considered a black box [3].

The benefits of flexibility "in" the system are two-fold. First, it often allows for a lower initial CapEx, as the change is only paid for when "called" thereby mitigating downside risks associated with over-capacitation. Second, it improves performance over the systems lifespan by allowing for the operator to exploit upside potential if demand is higher than anticipated [4]. Flexibility "in" systems have demonstrated effectiveness in a wide range of projects, with a majority of these systems being LMS. [3–5,17,18,20–23]. While focused on LMS, these methods have been applied to other types of complex system [6,7,24]. So far, the value of flexibility—implemented as real options "in"—has only been compared to a robust alternative.

2.2 Evolution of Flexible Design Strategies. Strategies for designing value-sustaining complex systems have evolved significantly over the years. Traditionally, discounted cash flow methods were used to assess the value of alternative LMS. However, in the late 1970s, researchers realized that this approach was not adequately accounting for uncertainty in the future operating environment nor opportunities to mitigate it through design choices. First mentioned in 1977, real options as a design strategy and evaluation framework were developed in the 1980s as a bridge between strategic planning and finance in order to better value these large-scale investments. Extending from the financial options literature, the term "real" denotes that these investments are made in tangible assets, as opposed to financial instruments [5,25,26]. The types of options include the option to defer; staged investment; the option to alter operating scale; the option to abandon; and the option to switch [27].

With recognition that additional leverage could be found within the design of the complex system, a categorization of real options "in" and "on" was formulated in the early 2000s. Real options "in" systems incorporate flexibility "in" the design of the system itself and not just the management of the projects development. This allows for the system to change later on in its operating life, if the operating context does. Early examples of the benefits of real options "in" studies are bridge, communication satellite constellation, and parking garage expansion projects [3,17,28,29]. Increasingly popular in the infrastructure context, Martins et al. performed an in depth literature review of 73 studies in infrastructure from 2003 to 2014. Categories of projects include highways, airports, power plants, real estate development, water supply systems, hospitals, and other LMS projects [5].

As interest in flexibility "in" has grown, it has been applied to other types of non-LMS systems. These include studies of unmanned aerial vehicles, naval vessels, electric vehicles, and military ground systems. Although several of the systems could be considered FBS, per our above definition, the focus has been on designing options "in" each unit (i.e., each individual vehicle) [6,7,24,30], without considering fleet-level design options, which we elaborate here as flexibility "of."

2.3 Challenges Implementing Options "in" Systems. Despite the promise of value gained through flexibility "in" systems, another stream of literature has begun to articulate the challenges that arise during implementation [4,7,9]. So far, the potential scope of those challenges has been characterized [7] and general suggestions on strategies for screening for better options have been proposed [4]. However, it is unclear if these implementation challenges can be mitigated or if a new approach is needed in cases where they dominate. Here, we focus on two critical implementation challenges: (1) identifying affordable "options" that significantly improve performance and (2) unavoidable delays that limit the timeliness of "calling" the options.

In terms of identifying a suitable "option," Cardin proposes a five-step process to enable flexibility "in" [9]. Once the baseline design is selected (step 1) as a starting point to anchor design efforts and key operational uncertainties are identified (step 2), then the identification and selection of a flexibility strategy are performed (steps 3 and 4). These steps are all tied together by the process management phase (step 5) which considers the processes needed to design and implement the flexibility. A two-step approach is often required to select the proper enabler. The development of options can exponentially expand the design space and designers must be able to first screen though a large set with lower fidelity models in order to identify the most promising candidates for more intensive, complex modeling to determine a final design [4,9]. Long standing systems engineering principles such as modularity and tools such as design structure matrices are suggested to identify and develop enablers which allows the system to change [1,31,32]. While these approaches have been well studied, they also recognize the challenge associated with incorporating change into the physical design of systems. For example, it is often infeasible for tightly integrated systems to build in an option to change without significant overhead.

In terms of "calling" the option, there is a need to determine when an option should be called and then apply the resources to that decision. Recent work considering option implementation has focused on the identification and application of stochastically optimal decision rules to ensure decision makers understand when and how to call an option. An additional benefit of this approach is that it mitigates variance associated with calling the option, ensuring better implementation [23,33–35]. However, knowing the optimal timing of when to call only addresses a part of the issue. In most real situations, the decision and ability to provide resources and upgrade the system are separated by rigid bureaucratic and logistical processes [7,9,36]. Many considerations of implementation are outside of the normal considerations of the designers, but strongly impact value nonetheless. They include organizational, financial, regulatory constraints, and other social factors [4].

The HMMWV provides a good example of the challenges associated with both the design of flexibility and the implementation. Not all desired change can be implemented as part of flexible design. For the design of the HMMWV, a full underbody armor option was never developed, as the change could not be easily implemented in a field environment for two reasons. First, it is difficult, without the proper equipment to add heavy armor underneath the HMMWV. Second, they were unable to fully modularize the armor as it interacts with other mechanical systems, which require higher levels of service than are available at the field level. As far as implementation, the bolt-on armor was a simple addition, but organizational and supply chain issues led to a significant delays in implementation. In many cases, cheap and easy to implement change may be difficult to operationalize, if not impossible [8].

2.4 Basis for Considering Flexibility "of" the System. Since many of the implementation barriers discussed above are unavoidable in many practical settings, we wanted to explore other approaches to flexible design that did not involve (only) physical changes to a deployed system. Finding none in the context of flexible design, we looked more broadly for the inspiration. Here, we articulate the intellectual foundations that we adapted to formulate the flexibility "of" strategy proposed here.

First we found an implicit consideration of re-configuring existing resources within discussions of measuring changeability (a concept closely related to flexibility). Ross et al. [13] identify the change paths that a system can take within a tradespace, represented as a network of system parameters. Changeability of a system is measured by the filtered outdegree, which is determined by identifying the number of paths under an acceptable cost of change threshold identified by decision makers [37]. Through the case studies employed, this view inherently expands consideration of the "system" to also consider operational changes in combination with physical design changes [38,39]. For instance, some of the change paths identified in a case study of commercial offshore ships were enabled by flexibility designed "into" the ship, allowing for post deployment change, but others considered operations performed by the ship, without physical changes to the ship after deployment [39]. Although this paper does not discuss any approach what we are calling flexibility "of," the latter type opens the potential to achieve the desired outcome of sustained value despite context change through a fleet-level change to the system. We elaborate on that idea with the notion of flexibility "of" as a strategy.

Second, the operations management literature has explored a related idea conceptualized as the "fleet management problem." Here, the stock of mixed resources is fixed and the design problem is about how best to match these resources to needs (often at different locations). This problem has been studied in multiple contexts, including humanitarian logistics [40]. While the focus has primarily been on resourcing, scheduling, and facility location problems, there has been little, but increasing focus on fleet management [41]. These problems primarily focus on fleet sizing decisions and fleet optimization problems, as fleet management problems are significant cost to humanitarian organizations [40,42–45]. These problems are also common commercial applications, such as airline fleet sizing and routing optimization problems [46,47]. While these concepts do not make any explicit consideration of their relevance to flexible design, the underlying theory provides a basis for defining the strategy we will refer to as flexibility "of" the fleet.

2.5 Literature Gap and Focal Concept. Operational uncertainty has been established as a significant challenge in the design of any complex system. Much of the design literature has focused on two methods to mitigate these challenges, design systems to be flexible, and change in response to a changing environment, or design systems to be robust and not need to change despite the changing environment. Recognizing the limits of the latter, flexibility "in" the system is an established approach that has been demonstrated to be highly valuable for certain classes of complex systems: LMS. While this strategy has subsequently been applied more broadly, there are indications that it might not be the preferred flexibility strategy for all complex system types. Specifically, FBS may be particularly susceptible to implementation challenges which limit the value of a flexibility "in" approach.

To that end, building on related ideas from the measurement of changeability and the theory underlying solutions to the fleet management problem, we propose an alternative approach which we term flexibility "of" the fleet. While flexibility "in" the system focuses on the design of change within the system, and options "on" are managerial options without consideration of the physical design of the system, we propose a different approach, which we called flexibility "of" the fleet, which aims to leverage both the physical design(s) of a system and its fleet behavior through operational deployment and reallocation rules.

To clarify the distinction between the flexibility strategies, we will explore in the remainder of the paper; Table 1 provides a visual comparison to highlight the key concepts. Consider a scenario where the Army procures a fleet of ten vehicles which will be deployed as needed to meet the specific demand across three potential (future and uncertain) mission types (MTs). Consistent with military planning, this scenario assumes that after the procurement of the fleet, demand is identified for three MTs, a high, medium, and low threat scenario. The high threat mission requires three vehicles, the medium threat requires three vehicles, and the low threat requires two vehicles. Armor is preferred for the high and medium threat mission. There is no requirement for armor in the low threat mission.

When flexibility "on" is implemented, the focus is on investment valuation and not the design of the system. Leverage is gained through the investment strategy. In this instance, the option is to alter the scale of the fleet. Once the preferred system alternative is selected (robust), a smaller investment can be made up front (five vehicles), with an option to purchase more later, if needed as shown in Table 1. In this case, when three MTs arise at the same time, three of the five vehicles are deployed to the high threat mission and the remaining two are deployed to the medium threat mission. The option for the additional three vehicles is called and they arrive once purchased and produced, likely with a significant

Table 1 Flexibility type comparison

Flexibility Type	Fleet Design by Vehicle Type	High Threat Mission (D=3)	Medium Threat Mission (D=3)	Low Threat Mission (D=2)	Unallocated Vehicles
"On"	■■■■■	■■■	■■□	□□	
"In"	◇◇◇◇◇ ◇◇◇◇◇	◆◆◆	◆◆◆	◇◇	◇◇
"Of"	■■■■■ ○○○○○	■■■	■■○	○○	○○

■ Armored ◇ Add-On Armor (Enabled) ○ Unarmored
□ Armored (Called Flexibility "on") ◆ Add-On Armor (Implemented)

delay. One potential benefit is that there is no over-investment in vehicles. In the subsequent analysis, we do not consider a flexibility "on" approach as the delays associated with the production of new vehicles are not feasible to meet mission requirements.

For flexibility "in", the design lever is to incorporate the ability to change the physical design of the system. In this case, 10 vehicles are initially purchased, each with the ability to change, labeled as add-on armor (enabled) in Table 1. When vehicles deploy to the high and medium threat missions, the option is called and the armor is added, labeled as add-on armor (implemented). For the low threat mission, the armor is not needed, and therefore not called. Additionally, two unallocated vehicles are not needed in this scenario. This approach has the benefit of delaying the costs of the add-on armor until it is needed and only adding it to the subset of vehicles that need it. However, there is potential for delays in implementation of change in this case if not properly planned.

Flexibility "of" the fleet differs from the two other flexibility strategies as it considers two design levers. The first lever is the physical design of the system and potential variations of this design (including potentially a flexibility "in" strategy at the vehicle level). The second lever is the design (and re-design) of the subset of the fleet that is deployed to each new mission. In this case, a mixed fleet of five armored and five unarmored vehicles is purchased initially. Then each of the three deployments draw from that pool of mixed fleet vehicles. Three armored vehicles are deployed to the high threat mission and the remaining two are deployed to the medium threat theater, supplemented by an unarmored vehicle. The unarmored variant is the preferred vehicle type for the low threat mission and two vehicles deploy there with two remaining unallocated. Even in this extremely high demand scenario, all but one of deployed vehicles matches the preferred armor, but the Army only needed to purchase half of the expensive armored vehicles upfront. Additionally, this approach mitigates the challenges associated with the design and implementation of flexibility "in" the system and ensures demand is met in a timely manner, albeit without the desired system in all cases.

3 Model Development

In order to compare the effectiveness of alternative flexibility strategies, a previously published Monte Carlo simulation [7] is evolved to suit the present purpose. The original simulation focuses on a vehicle design scenario motivated by the HMMWV example discussed above. While the original simulation examined the impact of implementation delays on vehicle flexibility strategies, the new simulation assesses the performance of alternative flexibility strategies at the fleet level. Consider the scenario where the Army is developing a fleet of 1000 new light unmanned armored vehicles (LUMAVs). They are considering five alternative fleet designs. The first four involve homogeneous fleets of (a) lightly armored vehicles (the baseline), (b) low cost, low protection option to add-on to each baseline vehicle, (c) high cost, high protection option to add-on to each baseline vehicle, and (d) a robust heavily armored vehicle. The last fleet alternative is a mixture of (a) and (d), lightly armored and heavily armored vehicles, that can be re-allocated based on changing needs. Only a subset of the 1000 vehicle fleet is needed in theater at any given time, consistent with historical military operations. The alternative vehicles vary in both their distribution of costs and level of protection, and the fleet level strategies offer alternative operational choices. In all cases, fleet performance is measured as the lowest total expected net present cost (TENPC) over the expected lifecycle of the fleet (11 years). Consistent with the previous simulation, the Army anticipates two critical operational uncertainties, the duration and intensity of combat deployments. In addition to operational uncertainties, implementation uncertainties, in the form of generic time delays, representing budgetary or supply chain challenges, are considered.

This study consists of two related but separate modeling studies, both of which build on the original model. The first study analyzes the LUMAV fleet and assesses alternative flexibility strategies in that context; adopting most of the original model parameters. The second study generalizes the model to consider the tradeoffs among flexibility strategies more generally. To clarify the technical basis for the analysis, this section provides a brief overview of the *original model*, documents the modifications necessary to conduct the *fleet-level model* analysis and then highlights the parameter changes made to create a *generalized model* scenario.

3.1 Overview of the Original Model. The original model was developed with a focus on vehicle-level choices. The simulation flow follows a typical deployment cycle, illustrated in the top portion of Fig. 1. A separate simulation is run for each vehicle type. At each time-step, a MT is randomly drawn based on three potential types. Once the MT is determined, the deployment schedule is randomly selected. The deployment scenario selected also defines the enemy effectiveness and initial number of attacks per vehicle values. These values allow for a probability of a vehicle being destroyed in a given month to be calculated. If lost, a new vehicle is purchased to replace the lost vehicle. Across all scenarios we assume that lost vehicles are replaced with robust vehicles, which are already in production during a time of war. Here, we provide a brief summary of the key model parameters, but additional details can be found in Ref. [7].

3.1.1 Vehicle Alternatives. The original model included four alternative vehicles, comparing two flexible options to two

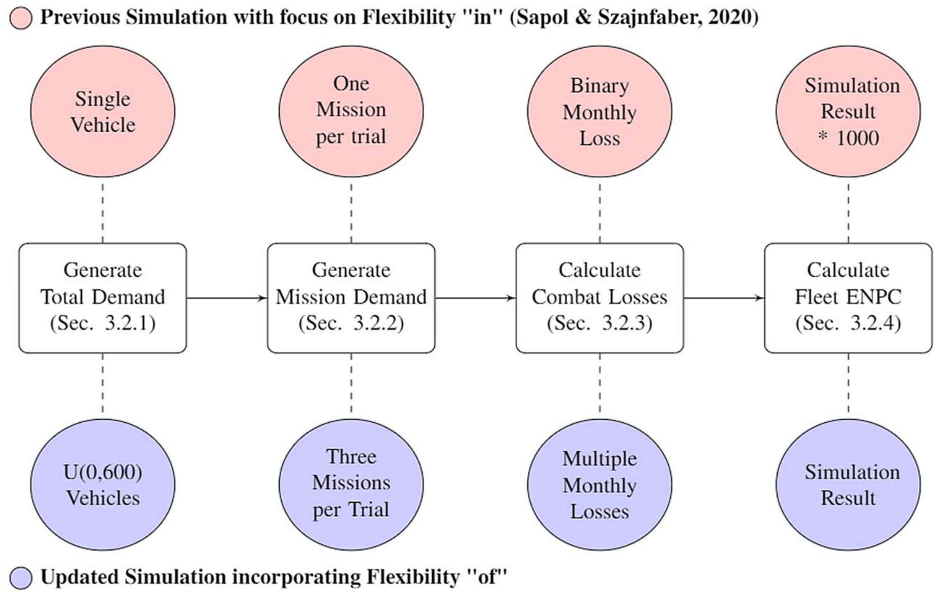

Fig. 1 Simulation overview and comparison

inflexible alternatives which are not impacted by implementation delays. In this study, we consider the same vehicle alternatives, which are the basis for our five fleet alternatives. The first four fleet alternatives are homogeneous fleets corresponding to the four vehicle types, and the last is a fleet that mixes the two inflexible options to consider flexibility "of" the fleet.

The vehicles considered are all modifications of the LUMAV, an unmanned derivative of the Stryker combat vehicle. The baseline variant is moderately armored, providing more protection than light skinned vehicles, such as an unarmored HMMWV, but less armor than a heavily armored vehicle, such as a tank. The primary benefits of this vehicle are that they are fast, maneuverable, and easy to transport. The LUMAV is vulnerable to a direct hit from anti-armor weapons and roadside bombs. In this scenario, decision makers desire to select the fleet design which minimizes the cost of 1000 vehicles over an 11 year time horizon (one-year fielding + ten-year operational).

Costs in this analysis include the purchase price, any costs to call options, and any replacement costs due to combat losses. We will assume that the difference in any other operational costs, such as fuel, is negligible and therefore will not be considered as part of this analysis. Additionally, we assume this vehicle will remain unmanned and therefore, human life is not put at risk. This modeling assumption is made for two reasons. First, it retains the focus on the system under development, eliminating the requirement to delve into the complex decision making required when determining acceptable risks associated with the loss of life. Second, it is consistent with current military research and development projects [48].

This original study assumed all design decisions have been made except for the type of armor to select; whichever armor is chosen will be applied to all vehicles in the fleet. An overview of the alternatives is described below and in Table 2. In the new study, we also consider the decision of how many of each type of vehicle to buy.

(a) *Baseline vehicle*: The baseline vehicle is approximately \$4M per unit, which is roughly the unit price on a Stryker vehicle [49]. This Stryker has been in service since the early 2000s and therefore, the baseline system is a relatively established system [50].
(b) *Simple add-on armor*: This option allows steel cage armor to the vehicle later if needed. This vehicle marginally improves survivability by 10% over the baseline and costs approximately \$50K per vehicle. If incorporated as an option, it costs \$10K to build in the flexibility (connections to attach the cages) and \$40K to call the option. This is an existing armor option for the Stryker and can be implemented with little technical risk.
(c) *Advanced add-on armor*: This is a more advanced add-on armor option. This option provides active protection which detects and intercepts some incoming anti-armor rounds. This armor improves survivability by 35% over the baseline and costs \$500K per vehicle. If incorporated as an option, it costs \$250K to build in the flexibility (connections, wiring, and software upgrades) and \$250K to call the option. This is an existing armor option for the Stryker and can be implemented with little technical risk.
(d) *Robust heavy armor*: The best performing alternative provides a suite of extra protection and can only be installed during production. With upgraded armor and sensors, this alternative provides the most effectiveness, increasing survivability by 70% over the baseline and increases costs by \$1M

Table 2 Armor type overview

Armor type	Improvement over standard	Baseline cost (\$K)	Option design cost (\$K)	Option call cost (\$K)	Total option cost (\$K)	Total cost (\$K)
Baseline	–	\$4000	–	–	–	\$4000
Simple add-on	10%	\$4000	\$10	\$40	\$50	\$4050
Advanced add-on	35%	\$4000	\$250	\$250	\$500	\$4500
Robust heavy armor	70%	\$5000	–	–	–	\$5000

per vehicle. We assume that this is a development project with new technologies and these types of projects carry additional risk, such as the joint strike fighter [51].

3.1.2 Mission Operations. In the original model, at each time-step, a vehicle is either deployed or not, and if deployed faces one of three MTs. These types are based on Army Doctrine. The first is large-scale combat operations (LSCOs). These include heavy combat over an extended period of time. Operation Iraqi Freedom from 2003 to 2009 is an example. The second type of mission is crisis response and limited contingency operations (CRLCOs). These are more limited operations over a shorter time period. These may or may not involve combat. Examples include operation restore hope in Somalia in the early 1990s or hurricane relief operations. CRCLOs lack both the frequency of deployments and the intensity of combat of LSCOs. The final type of mission is military engagement, security cooperation, and deterrence (MESCD). This operation type is designed to maintain global influence through cooperation with allies and the deterrence of potential adversaries. It will be assumed that these types of missions do not require combat [52]. The initial scenario will provide an equal probability to each MT; sensitivity to this parameter choice will be examined separately. The deployment cycle is based on Department of Defense (DoD) targets for boots on the ground:dwell time (BOG: dwell). BOG:dwell is related to the MT as shown in Table 3. In the original simulation, each MT receives equal weight. All the assumptions made in choosing these figures are detailed in Ref. [7].

3.2 Fleet-Level Model: Overview of Modifications to Enable Fleet-Level Analysis. To enable the fleet-level analysis core to this study, modifications to the original model were required. A comparison between the two models can be seen in Fig. 1. The fleet-level model adopts the same basic parameters for the vehicle types and mission operations scenarios. Vehicles still deploy to three MTs of varying threat levels and performance is still measured by TENPC. However, since the original model focused at the vehicle level, some modifications to the structure were needed in order to allow for the fleet to be studied and a few modeling assumptions were changed to improve the model based on new data. The changes to the model are outlined in the following sections. The corresponding sections are also enumerated in the boxes in Fig. 1 to provide a graphical reference of the flow of the simulation.

At a high-level, where the original model sought to pick the vehicle-level armor that maximized TENPC, the fleet-level model aims to pick the fleet-level strategy (which includes an armor choice) that minimizes TENPC. Here the assumption is that the Army is making a decision to purchase a new fleet of vehicles that will be used over the next many years. Each deployment will only involve a relatively small subset of the total fleet giving significant leverage on the specific composition for any particular deployment. For reference, even at the height of the Irag War, approximately 15% of the total fleet was deployed at any one time [12].

Table 3 Operational scenario overview

Scenario	MT	BOG: dwell	Months deployed	Enemy effectiveness	Scenario probability
Scenario 1	LSCOs	1:1	60	25%	1/9
Scenario 2	LSCOs	1:2	48	25%	1/9
Scenario 3	LSCOs	1:3	36	25%	1/9
Scenario 4	CRLCOs	1:3	36	25%	1/6
Scenario 5	CRLCOs	1:4	24	25%	1/6
Scenario 6	MESCD	1:4	24	0%	1/3

3.2.1 Generate Total Demand. The primary change of the model is the difference in the number of vehicles in each trial, and many of the changes in the following paragraphs allow this change in the model structure. In the original simulation, only one vehicle was simulated in each trial and it could only deploy to one MT at a given time. This modeling decision did not allow for flexibility "of" approach to be tested, and therefore the model required modification. In this simulation a fixed fleet size of 1000 vehicles is simulated, with subsets of the overall fleet deployed at any given time-step.

This change also prompted a change in the utilization rate for the vehicles. In the previous study, a 100% utilization rate was assumed. This means that for each trial the vehicle, if deployed, deployed to one of the three MTs. In reality, this is rarely the case. For instance, the requirement for HMMWVs during the Iraq War was far less than the total inventory (10–15%) [12].

For this reason, we randomly generated total demand for all three theaters using a $U(0{,}600)$ distribution. This is shown in the left facet in Fig. 2 as an example of 20 demand distributions. Therefore, in each trial, the total demand can be as low as zero vehicles to as high as 600 total vehicles. As part of our initial analysis, we identified a requirement of 1000 vehicles (approximately 32 vehicles in each of the 31 active-duty Army brigade combat teams) [53]. An upper bound of 600 is selected as it represents an upper bound of approximately 20 brigades, which approximates the Army's maximum number of soldiers deployed to Iraq and Afghanistan in the 2000s [54]. This upper bound will be varied as part of the sensitivity analysis.

3.2.2 Generate Mission Demand. As described earlier, the previous model consisted of one vehicle deployed to one of the three

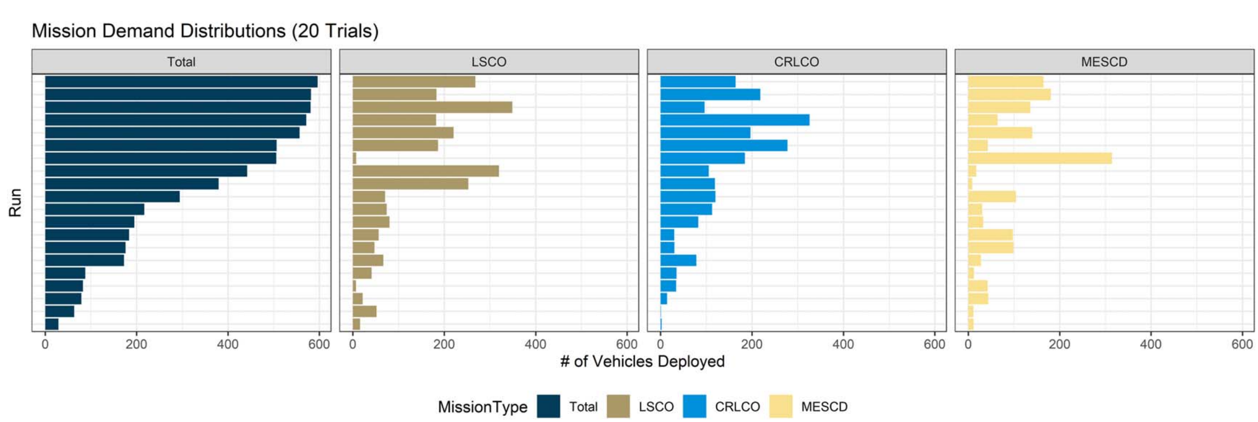

Fig. 2 Mission demand distribution. The left most facet shows the total mission demand for 20 trials which are drawn from a *U*(0600) distribution. The three facets to the right demonstrate the random allocation of the respective total demand across the three MTs.

MTs. In this model, vehicles can be deployed to each of the three theaters in each trial. The three MTs, based in Army doctrine, remain the same. These are (1) LSCOs, which we consider as high intensity, (2) CRLCOs, which we consider as moderate intensity, and (3) MESCD, which is low intensity and therefore, we assume that it does not involve combat operations [52].

In this simulation, we randomly distribute the total demand, generated from the $U(0,600)$ distribution across the three MTs and 20 simulated runs can be found in Fig. 2. Each MT has equal probability of vehicle assignment. This approach allows for a wide range of MTs to be analyzed. We recognize that there may not be equal probability between the three MTs and will perform a sensitivity analysis on MT distribution to explore the impacts of different allocations.

Additionally, the previous model allowed for uncertainty in the deployment schedules. As it only considered one vehicle, we incorporated deployment and redeployment schedules. In this model, since we are considering the entire fleet, we do not have vehicles redeploy in and out of theater. We assume a constant presence based on the specific mission demand of each trial. The impact of this decision balances across the armor types and therefore does not negatively impact any armor type more than another.

3.2.3 Calculate Combat Losses. The method in which the losses are calculated was modified based on the increased fleet size. Loss calculations in the previous model were binary. A probability of loss was calculated for each month. This value is then compared to a random number generated from a $U(0,1)$ distribution. If the random number was less than the probability of loss, the vehicle was considered lost and a replacement is purchased. In this simulation, the vehicle loss model is adapted to account for the fleet. To calculate losses, the number of attacks per vehicle per month are multiplied by the number of vehicles deployed and the enemy effectiveness level. This number is reduced by the armor effectiveness levels for the respective armor types.

We recognize that in reality all vehicles will not have an identical mission profile. Since our historical data were aggregated across different threat levels across Iraq, we felt the aggregation of this variable is acceptable. Due to the limitations of effectiveness data, we assume 25% and will perform sensitivity analysis on the variable later.

The number of attacks is the key operational uncertainty in both models. When uncertainty is incorporated, there is, in theory, an unlimited number of attacks, but it possesses a lower bound of zero. While this upside is constrained through the modeling of the uncertainty as will be described below, the difference between the floor and upside is demonstrated in Fig. 3. This leads to an underestimation of the threat if only the expected number of attacks is used. This demonstrates why a deterministic approach is not preferred, as it underestimates the threat.

In this model, a slight modification to the initial attack parameters was undertaken. Utilizing the same historical estimates from the Iraq War, an average of 0.08 attacks/month was modeled using attack and troop level data from the Brookings Institute [55]. In this simulation, we modeled the initial attack parameter for the LSCO MT as a random value as much as 50% over the historical average using a $U(0.08, 0.12)$. For the CRLCO MT, we assume as much as a 50% decrease from the historical average and use $U(0.04, 0.08)$ distribution. We considered the historical Iraq data as a middle ground between the LSCO and CRLCO MTs. It was not as dangerous as a full conflict such as LSCO but more dangerous than other types of CRLCO missions, such as Somalia. Therefore, we then varied 50% in each direction for the parameters for each MT.

While this is a slight modification to the initial conditions, the same model is used to model noise in the number of attacks. Arithmetic Brownian motion is incorporated into the number of attacks. This is a suitable method as the number of attacks in each month can be predicted using the number of attacks in the prior month ($R^2 = 0.99$) with the residuals being normally distributed (Shapiro–Wilk p-value >0.05), where $\mu = 0$ and $\sigma = 0.009$ [4]. Random error based on historical estimates is included, creating noise in the number of attacks per month. Uncertainty in the number of attacks is incorporated in the model as shown in Fig. 3.

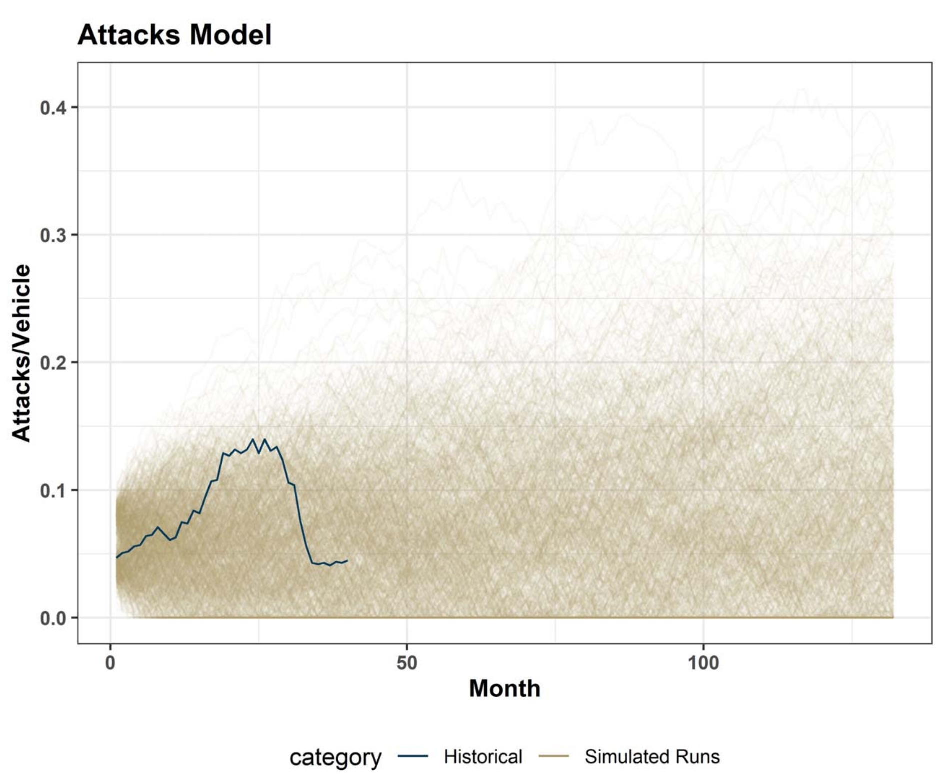

Fig. 3 Attacks model

For vehicles with additional armor, this number reduced by the armor effectiveness level. Please note that due to the size of the fleet, a continuous loss model is used, allowing for fractional losses. We recognize that for smaller fleets, a discrete model may be more appropriate. Additionally, the same enemy effectiveness level is used in this simulation (25%) as the previous study. Due to the uncertainty in this value, as there limited publicly available data on this variable, a sensitivity analysis will be conducted on this variable.

Additionally, there were slight modifications in the system parameters. In this study, there is a slight decrease in the effectiveness for the advanced armor type from 40% to 35% improvement over the baseline system. This was done to make it proportional to the benefits of the robust system. In this case, the advanced add-on armor costs \$0.5M for a 35% improvement and the robust armor cost \$1.0M for a 70% improvement.

3.2.4 Calculation of Expected Net Present Cost. As described earlier, the previous model determined the expected net present cost (ENPC) for a single vehicle, then multiplied that amount across the fleet to determine the TENPC. Since the full fleet is represented in this simulation, there is no need to multiply the simulation result by the fleet size (TENPC in the original model); the ENPC calculated at the end of each scenario is the ENPC for the fleet. Additionally, there was a slight modification of the cost of the simple add-on armor. It was reduced from \$100K to \$50K, putting it more in line with the costs associated with similar armor efforts [56].

3.3 Fleet-Level Model Formulation. Monte Carlo simulation is a common method to analyze flexible design, as it allows for both the implementation of uncertainty and the ability to customize decision rules [4,9]. The ENPC is calculated for each fleet type and scenario by taking 10,000 trials for each ($M = 10{,}000$). In each scenario, the fleet with the lowest ENPC is the preferred alternative in each simulation scenario. The following paragraphs outline the formulation of the model. An overview of the simulation is provided in Fig. 1.

The first step is the generation of the total vehicle demand for each trial. This is generated using the following distribution:

$$D_{\text{total}} = U(0, 600) \tag{1}$$

Once the total demand is generated, the allocation to each MT is generated as a percentage of total demand using the following series of equations to determine the initial demand for vehicles in each MT. The first step is to generate random numbers for demand for each MT, annotated by the variable MDRV_{MT}, where MT is each mission type (L = LSCO, C = CRLCO, M = MESCD).

$$\text{MDRV}_{\text{L}} = U(0, 1) \tag{2}$$

$$\text{MDRV}_{\text{C}} = U(0, 1) \tag{3}$$

$$\text{MDRV}_{\text{M}} = U(0, 1) \tag{4}$$

These variables are then used to calculate the mission demand ratio (MDR) for each MT. First, the percent of total demand for each MT is calculated by finding the percentage of each MT random variable divided by the sum of all three random variables. The equations are provided as follows:

$$\text{MDR}_{\text{L}} = \frac{\text{MDRV}_{\text{L}}}{\text{MDRV}_{\text{L}} + \text{MDRV}_{\text{C}} + \text{MDRV}_{\text{M}}} \tag{5}$$

$$\text{MDR}_{\text{C}} = \frac{\text{MDRV}_{\text{C}}}{\text{MDRV}_{\text{L}} + \text{MDRV}_{\text{C}} + \text{MDRV}_{\text{M}}} \tag{6}$$

$$\text{MDR}_{\text{M}} = \frac{\text{MDRV}_{\text{M}}}{\text{MDRV}_{\text{L}} + \text{MDRV}_{\text{C}} + \text{MDRV}_{\text{M}}} \tag{7}$$

Initial demand, at month 13, for each MT is then calculated by multiplying the percent demand by the total demand, as shown as follows:

$$\text{MD}_{13,\text{L}} = D_{\text{total}} * \text{MDR}_{\text{L}} \tag{8}$$

$$\text{MD}_{13,\text{C}} = D_{\text{total}} * \text{MDR}_{\text{C}} \tag{9}$$

$$\text{MD}_{13,\text{M}} = D_{\text{total}} * \text{MDR}_{\text{M}} \tag{10}$$

The number of losses in each time period for each MT ($L_{t,\text{MT}}$) is calculated using the attack variable described above, annotated $A_{(t,\text{MT})}$ MT where t is the time period and MT as the MT. The enemy effectiveness is annotated as EE_t and the armor effectiveness is identified as $I_{t,\text{AT}}$ where AT is the armor type. The loss in a given month for each MT is calculated in Eq. (11).

$$L_{t,\text{MT}} = \text{MD}_{t,\text{MT}} * A_{t,\text{MT}} * \text{EE}_t * (1 - I_{t,\text{armor type}}) \tag{11}$$

For instance, a trial where 100 advanced add-on armored vehicles are needed for a MT of LSCO with 0.08 attacks per vehicle in month 20 leads to 1.3 losses for that month, as calculated below.

$$\begin{aligned} L_{20,L} &= V_{20,L} * A_{20,L} * \text{EE}_{20} * (1 - I_{20,\text{advanced}}) \\ L_{20,L} &= 100 * 0.08 * .25 * (1 - 0.35) \\ L_{20,L} &= 1.3 \end{aligned}$$

The loss variable for each MT is added together to determine a total loss variable for each month.

$$L_{t,\text{total}} = L_{t,L} + L_{t,C} + L_{t,M} \tag{12}$$

Using this total loss variable, replacement costs can be calculated by multiplying the number of losses by replacement costs for each vehicle (RC_{AT}) and discounting by the time period, using a 2.1% (r) discount rate based on the Office of Management and Budget (OMB) guidance for government projects [57].

$$\text{RNPC}_t = \frac{L_{t,\text{total}} * \text{RC}_{\text{AT}}}{(1 + (r/12))^t} \tag{13}$$

The replacement costs for all time periods in the trial are then calculated by taking the sum of all time periods.

$$\text{RNPC}_m = \sum_{i=1}^{132} \text{RNPC}_t \tag{14}$$

For vehicles deployed to LSCO or CRLCO MTs, the call costs (CA_t) are calculated, discounted, and summarized as the OPNPC_m, where m is the trial number, as shown below.

$$\text{OPNPC}_m = \frac{V_{0,L} * \text{OC}_L}{(1 + (r/12))^{13}} + \frac{V_{0,C} * \text{OC}_C}{(1 + (r/12))^{13}} \tag{15}$$

The initial purchase price (CI) times the total number of vehicles purchased (1000) is added to the sum of the replacement net present costs (NPCs) and the total call costs to calculate the NPC for the trial.

$$\text{NPC}_m = 1000 * \text{CI} + \text{RNPC}_m + \text{OPNPC}_m \tag{16}$$

The ENPC is then determined by calculating the mean of the NPCs for all trials (M).

$$M = 10{,}000 \tag{17}$$

$$\text{ENPC}_{\text{Scenario,AT}} = \frac{\sum_{i=1}^{M} \text{NPC}_m}{M} \tag{18}$$

The ENPC is used for each simulation scenario to select the preferred armor type. For each scenario, the vehicle with the lowest ENPC is the preferred alternative.

3.3.1 Verification of Model Updates. After implementing the changes described in the previous section, we wanted to ensure that none of the modifications affected the main results of the original analysis. Therefore, we checked that we could replicate the results of our previous study with the four homogeneous fleets. The updated model replicates the main findings of the initial simulation as shown in Fig. 4. First, delays negatively impacted the value of flexibility. Second, the more expensive armor type was more sensitive to delays and lost value more quickly than the less expensive option. Therefore, we are confident that the modifications needed to conduct fleet-level analysis did not change the key dynamics of the previously validated model.

3.4 Generalized Model: Overview of Modifications Needed to Compare Flexibility Strategies in a More Generalized Scenario. To support the second analysis, we adopted the fleet-level model and made a few modifications to the model parameters in order to remove some of the contextual specificity of the LUMAV case. In the first analysis, the alternative systems were calibrated to match realistic expectations of armor alternatives. However, this created a significant cost and performance disparity between the robust and flexible alternatives. To focus the present comparison on the alternative flexibility strategies themselves, we generalized the model to consider different strategies for implementing the same performance gain.

This resulted in the creation of three modified vehicle types, summarized in Sec. 5. Now, the flexible and robust option have equal protection once the option has been called and their total costs are identical. The simulation is setup to vary that level of protection and also the fraction of upfront costs to buy the flexible option.

4 LUMAV Case Study: Assessing to Potential for a Flexibility “of” Strategy

This section presents the results from the first analysis which assesses whether flexibility “of” can be a viable strategy in the context of a fleet of LUMAVs. All the results presented here are based on Monte Carlo simulation of a 1000 vehicle fleet using the fleet-level model described earlier. Specifically, we compare the ENPC of five alternative fleets:

(1) *Baseline fleet*: The model instantiates a homogeneous fleet of 1000 baseline vehicles as defined in Table 2. Vehicles are deployed as needed.
(2) *Flexibility “in” (simple) fleet*: The model instantiates a homogeneous fleet of 1000 baseline vehicles equipped to accept simple add-on armor if needed as defined in Table 2. The option to call is managed consistent with the original model.
(3) *Flexibility “in” (advanced) fleet*: The model instantiates a homogeneous fleet of 1000 baseline vehicles equipped to accept advanced add-on armor if needed as defined in Table 2. The option to call is managed consistent with the original model.
(4) *Flexibility “of” fleet*: The model instantiates a heterogeneous fleet of 1000 vehicles including both baseline and robust heavy armored vehicles. The initial analysis is run with a 50–50 split but other mixes are also explored. Deployment options are managed through rules for when to assign a particular vehicle to a particular MT as they arise are summarized in Fig. 5. The logic is as follows: the robust vehicles are prioritized for the most dangerous mission (LSCO), then any remaining robust vehicles are deployed to next most dangerous mission (CRLCO) as required. The baseline vehicles are prioritized for the least dangerous MT (MESCD). Any shortfall of preferred vehicles and MT combinations will be filled by the other vehicle type. Any lost vehicles will be replaced by robust vehicles if available, as vehicles will only be lost in scenarios where the robust vehicles are preferred.
(5) *Robust fleet*: The model instantiates a homogeneous fleet of 1000 robust heavy armor vehicles as defined in Table 2. Vehicles are deployed as needed.

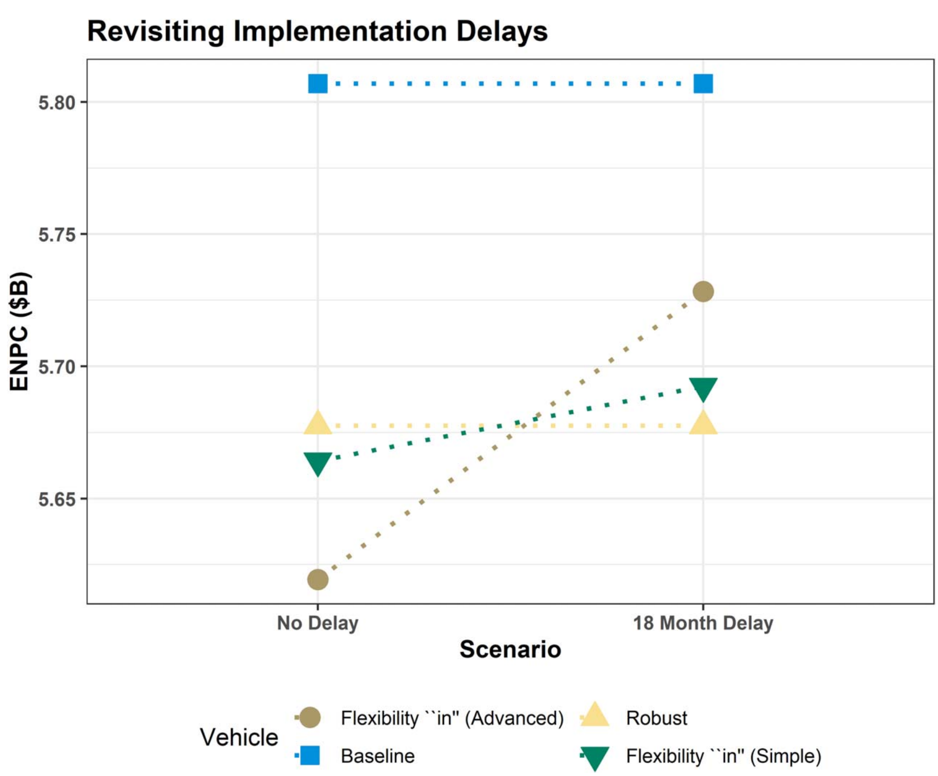

Fig. 4 Updated model results

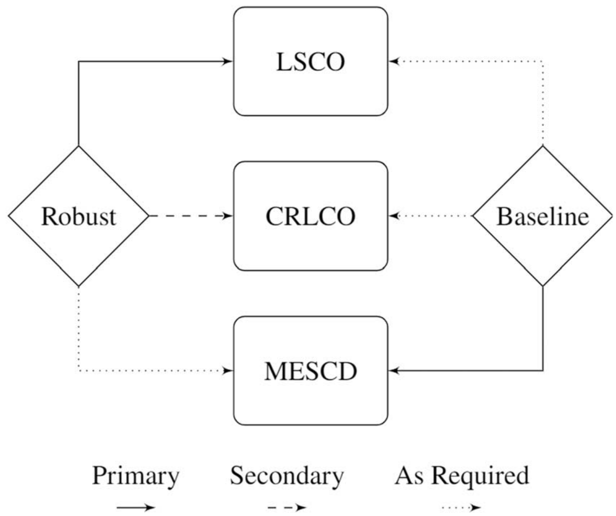

Fig. 5 Deployment options. The "primary" line defines the vehicle type and MT combination which fills first. The "secondary" line defines the robust vehicles which are the preferred alternative for the CRLCO MT over the baseline. The "as required" line shows the allocation when the "primary" or "secondary" are unavailable.

In the subsections below, we begin by presenting the main result from the model with the initial parameters as defined. We then elaborate the analysis by considering the optimized fleet composition, and we perform an extensive sensitivity analysis, varying key parameters to ensure that the main result is robust to model assumptions.

4.1 Main Results. The main model results are presented in Fig. 6. They compare the five alternative fleet strategies with no delay and a representative 18-month delay. The results demonstrate that even with a naive mixture, flexibility "of" provides a significant improvement, with savings of 7%. Additionally, this result is robust to delays, as the flexibility "of" strategy does not require a change to be enabled "in" the system. In the remainder of the analysis, all results report the no implementation delays condition, since this is the scenario where "in" is most favorable. This is a conservative lower bound of benefit since any observed benefits of an "of" approach will be even more significant with practical delays.

4.2 Improvements Due to Optimizing Fleet Composition. These results can be further improved through the optimization of the composition of the fleet. While the optimal mixture is specific to this scenario and perfect knowledge of future demand is unreasonable, demand forecasts based on historical trends are likely sufficient to improve upon the naive 50–50 assumption explored above. Therefore, this result is useful to show the upper bound of improvement through flexibility "of."

By modifying the fleet composition, Fig. 7 shows how performance improvement varies with fleet composition. The simulation was rerun, changing the distribution by 25 vehicles in each run, represented by each point in the graph. In this case, the optimal results come from a fleet with 225 robust vehicles and 775 baseline vehicles. This fleet composition reduces costs an additional $170M from the initial results with 500 of each vehicle type. This optimized flexibility "of" the fleet achieves a 10% savings over the preferred alternative with flexibility "in" the system.

The U-shaped distribution can be explained in terms of two competing forces: extra cost due to carrying unused robust vehicles and losses due to insufficient armor if you do not have enough robust vehicles. Performance is worse to the right of the optima (>225) because extra (expensive) robust vehicles are purchased upfront and not used. Performance is worse to the left of the optimum (<225) because an inadequate supply of robust vehicles leads to substantial losses of baseline vehicles. This logic also emphasizes that a key part of what makes the flexibility "of" strategy work is the nature of an FBS system, where a large pool of vehicles is maintained with only subsets deployed at any one time. This issue of utilization will be explored further in the generalized analysis below.

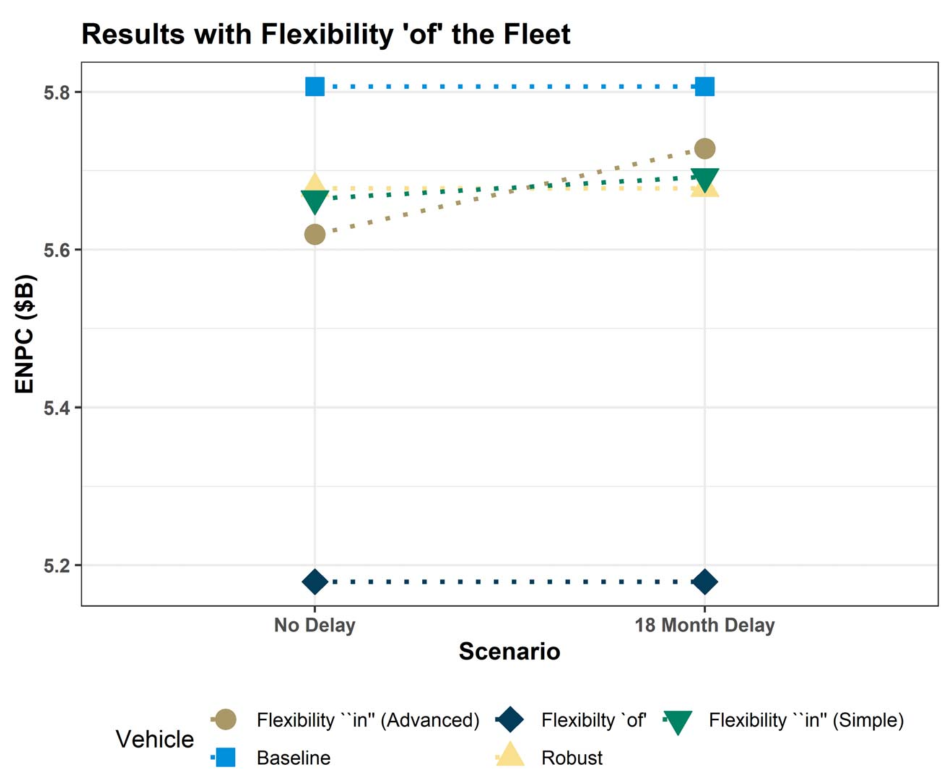

Fig. 6 Results with flexibility "of" the fleet

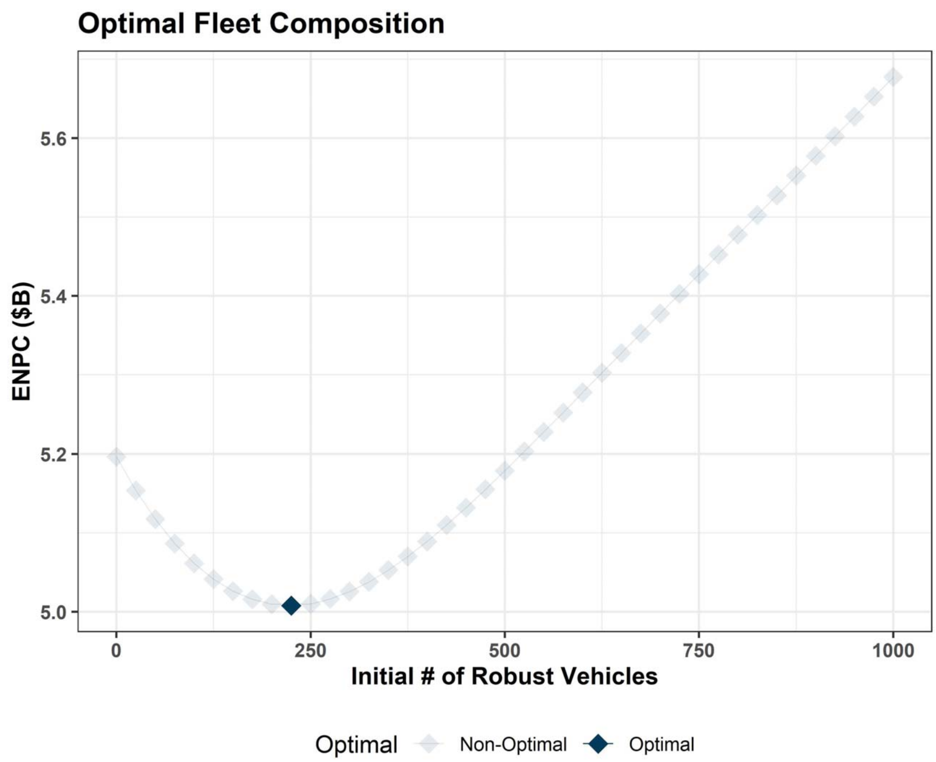

Fig. 7 Optimal distribution for flexibility "of". The x-axis provides the number of robust vehicles in the flexibility "of" alternative. For instance, the optimal distribution is 225 robust and 775 baseline vehicles.

4.3 Sensitivity Analysis. While the model was calibrated with the best available data, we recognize that our results could depend upon several assumptions for which we were not able to identify definitive literature or empirical support. Due to the limitations of data collection in military operations, sensitivity analysis is required to understand how different assumptions impact the results. Here, our focus is not on the specific numerical solutions, rather the overall trends that constitute our findings. In order to establish the robustness of the core finding that flexibility "of" is the dominant strategy in an FBS's similar to LUMAV fleets, in the following sections, we conduct a one-at-time sensitivity analysis on four key assumptions: (1) the enemy effectiveness level, (2) the MT distribution, (3) the maximum number of vehicles required, and (4) the robust vehicle effectiveness. Results for the four sensitivity analyses can be found in Fig. 8.

4.3.1 Enemy Effectiveness. The first operational assumption to perform sensitivity analysis on is the enemy effectiveness. The results are shown in the upper left graph in Fig. 8. The enemy effectiveness used throughout the previous simulations was 25%. For the sensitivity analysis, the effectiveness was varied by $\pm5\%$ and $\pm10\%$ to see if either of the flexible alternatives (simple and advanced) were preferred as effectiveness changes. The results show that as enemy effectiveness decreases (lower threat), the gap between the alternatives with flexibility "in" and flexibility "of" decreases too, but the flexibility "of" strategy is still preferred. On the other hand, as the enemy effectiveness increases, the gap becomes larger. These results show the preferred alternative is not sensitive to the enemy effectiveness over any reasonable range.

4.3.2 Distribution of Demand Over Mission Type. One of the key assumptions is the distribution of MTs. The results are shown in the top right graph in Fig. 8. Recall that the base case simulation assumed an equal probability of each MT. In practice, it is unlikely that there would be equal levels of combat and peacekeeping, for example. To understand if our baseline assumption drove the result, we vary the weights for each MT. To do this, weights applied to each MT are varied by 10%. In this figure, the *x*-axis varies the fraction of LSCO missions, the *y*-axis varies the fraction of CRLCO missions, with the remainder being MESCD (i.e., $1-$ (LSCO weight + CRLCO weight)). Each geom represents a specific mix, for example, the bottom left dot is from a simulation where all deployments are to a MESCD mission. The geom at each point is the preferred fleet strategy in that scenario.

The results show that the main result is insensitive to the MT distributions except when the likelihood of combat is extremely low (MESCD at or close to 100%). The flexibility "of" strategy is preferred in all other combinations, and therefore, the conclusion is robust to different MT distributions.

4.3.3 Fleet Utilization: Maximum Vehicles Deployed. As noted earlier, a core aspect of the flexibility "of" strategy relies on the initial fleet being relatively large compared to each deployment. The base case simulation assumed a maximum of 600 vehicles to be deployed of the 1000 total vehicles purchased, which is high compared to available historical data. To understand how the results change if the number of vehicles differs from 600, the simulations were run again, varying the maximum number of vehicles by 200, from 0 (no vehicles will deploy) to 1000 (all vehicles may deploy) and are shown along the *x*-axis. Results are provided in the bottom left graph in Fig. 8.

The results show that with low utilization (few vehicles are deployed), the simple add-on armor is preferred where the maximum number of vehicles is 125 or less. Above 125 (12.5%), the flexibility "of" strategy is consistently preferred. Additionally, the results show that fleets with the robust vehicles (pure and flexibility "of") are both less sensitive to increases in the maximum vehicle requirement.

Under these conditions, the flexibility "of" strategy remains the dominant strategy as long as the maximum vehicles deployed are greater than approximately 12.5%. This is an important consideration based on the expected fleet utilization. In fleets where a

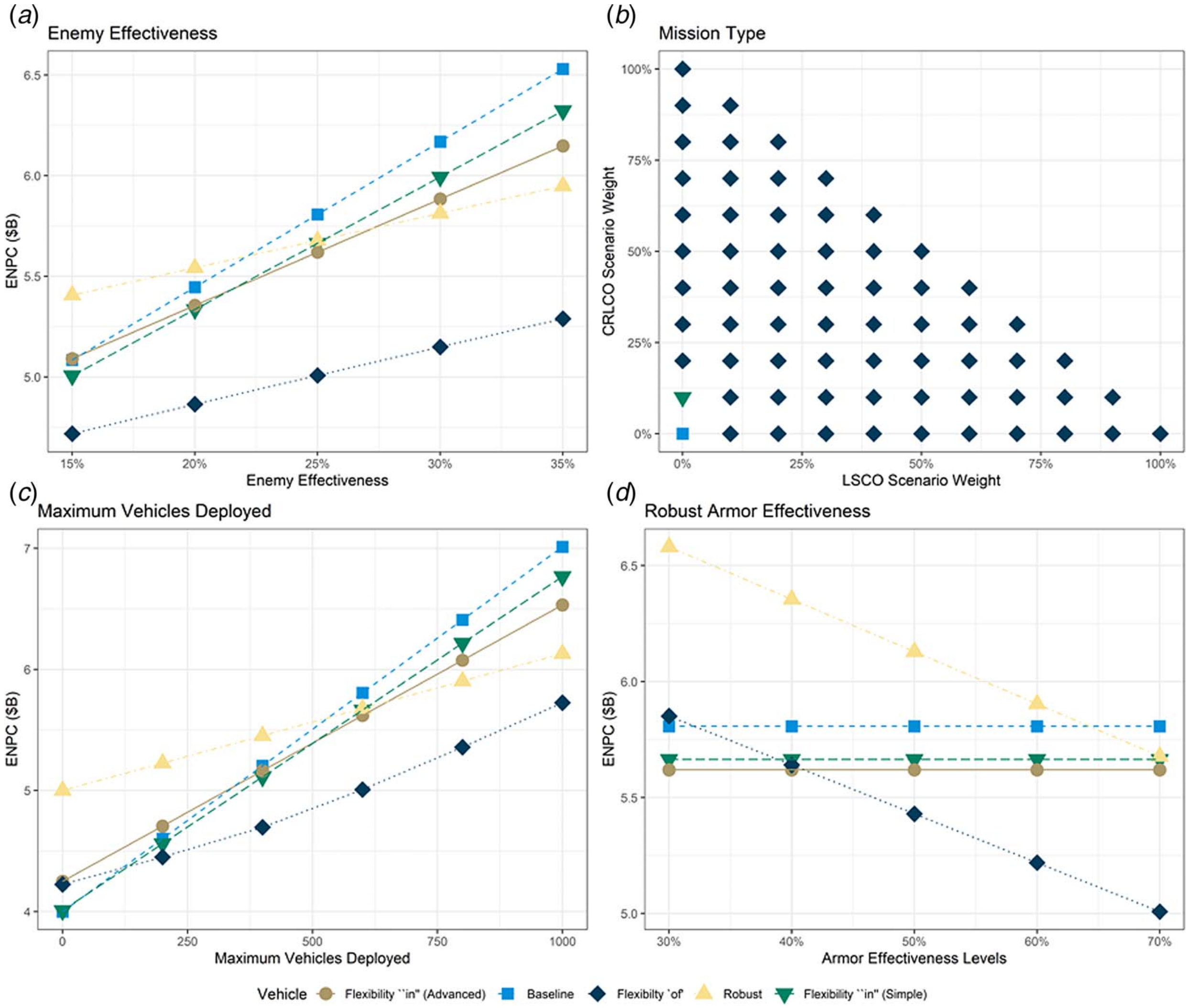

Fig. 8 Sensitivity analysis. Each of the facets present the results of a separate parameter sweep on the variables of interest. Clockwise, starting from top left (*a*) performance of each fleet as enemy effectiveness increases from 15% to 35%, (*b*) preferred fleet strategy as proportion of each MT changes, (*c*) performance of each fleet demand for deployed vehicles increases from 0% to 100%, and (*d*) performance of each fleet as armor effectiveness of the robust vehicle increases from 30% to 70%.

high percentage of vehicles are anticipated to change, an "of" strategy may be preferred, with the robust strategy becoming a better alternative than the other fleets. On the other hand, less expensive strategies, such as the baseline alternative of the inexpensive flexibility "in" strategy, may be preferred.

4.3.4 Robust Vehicle Effectiveness. An important modeling assumption involved setting the relative performance of the alternative armor types. Initially, robust armor improved performance by 70%, while the advanced add-on improved performance by 35%, and simple add-on improved 10%. While it is reasonable to assume that an integrated armor system would significantly outperform add-on kits, we wanted to understand how much better the robust system needed to be before a flexibility "of" strategy is preferred. Therefore, we examined how varying robust performance levels impacted which flexibility strategy was preferred. The robust vehicle effectiveness was decreased by 10% increments as shown in the bottom right graph in Fig. 8. In this case, both flexible alternatives are preferred when the robust armor effectiveness drops below 40%. This specific tipping point is also driven by relative costs, which were held constant. Therefore, flexibility "of" is still dominant under reasonable conditions but might not be preferred if an expensive robust vehicle is only minimally more effective than the add-ons.

4.4 Case-Specific Insights. These results clearly demonstrate the potential of flexibility "of" the fleet when designing FBS like the LUMAV fleet. In the context studied, we found very few conditions where investing in flexibility "in" in a particular vehicle was preferred over applying deployment options to achieve flexibility "of" the fleet. This has significant implications for how designers think about designing for flexibility. Flexibility "in" involves creating change paths within each system, while flexibility "of" emphasizes designing multiple levels of fixed capability and achieving systems level change through operational allocation. It is possible to do this in much more sophisticated ways than the one presented here, including a vehicle-level flexibility "in" strategy within the fleet mix. These details should be explored, but for now, this analysis demonstrates the concept of flexibility "of" and shows great potential for future refinement.

5 When to Adopt a Flexibility "of" Approach: General Considerations

In the previous section we established flexibility "of" as a dominant strategy in the context of the military's development of a fleet of light combat vehicles. In our second analysis, we explore the attributes of an FBS that determine which design approach makes

Table 4 Generalized vehicle type overview

Armor type	Improvement over standard	Baseline cost ($K)	Option design cost ($K)	Option call cost ($K)	Total option cost ($K)	Total cost ($K)
Unarmored	0%	$4000	–	–	–	$4000
Flexibility "in"	0–100%	$4000	$X = \$\ 0 - 1000$	$\$1000 - X$	$1000	$5000
Armored	0–100%	$5000	–	–	–	$5000

sense, with the goal of providing more general guidance. To do this, we leverage the generalized model defined in Sec. 3, which modifies the vehicle types used in the fleet-level formulation to enable a more general comparison. Specifically, in the first analysis, the alternative systems were calibrated to match realistic expectations of armor alternatives. However, this created a significant cost and performance disparity between the robust and flexible alternatives. To focus the present comparison on the flexibility strategies themselves, we generalized the model to consider different strategies for implementing the same performance gain. In the below sections, we compare the ENPCs of three alternative flexibility strategies:

(1) *Unarmored fleet*: The model instantiates a homogeneous fleet of 1000 unarmored vehicles as defined in Table 4. Vehicles are deployed as needed. If lost, they are replaced with unarmored vehicles since we assume that no armored vehicles were developed.
(2) *Generalized flexibility "in" fleet*: The model instantiates a homogeneous fleet of 1000 unarmored vehicles equipped to accept add-on armor if needed as defined in Table 4. The option to call is managed consistent with the original model.
(3) *Flexibility "of" fleet*: The model instantiates a heterogeneous fleet of 1000 vehicles including a mix of 500 armored and 500 unarmored vehicles. The deployment options are consistent with earlier analysis. Any lost vehicles will be replaced by armored vehicles, as vehicles will only be lost in scenarios where the robust vehicles are preferred.
(4) *Armored fleet*: The model instantiates a homogeneous fleet of 1000 armored vehicles as defined in Table 4. Vehicles are deployed as needed. If lost, they are replaced with armored vehicles.

In the below analysis, we explore the impact of three key parameters that define an FBS (as distinct from LMS or other classes of complex systems).

Three variables will be changed as part of the experiment, the armor effectiveness, the cost to enable flexibility, and the utilization rate. Each of these values are varied in 10% increments, from 0% to 100%, for a total of 1331 scenarios. A simulation of each fleet is performed and the preferred alternative is selected. A description overview of these three variables is provided below.

(a) *Armor effectiveness*: The armor effectiveness percentage limits the effectiveness of the enemy attacks, leading to fewer losses. We vary this value to understand two elements. First, an understanding of what effectiveness levels are needed for each of the alternatives to be desirable. Second, to understand any shifts in the preferences as the effectiveness changes. This amount will vary from 0% to 100%.
(b) *Enabler cost*: The cost to enable the system to easily change is an important variable in any flexibility study. As the cost to enable flexibility increases, the option becomes less desirable, and at some point, the preference transitions to a static alternative, as demonstrated in LMS studies. For example, using the well-known parking garage example, as the cost to enable flexibility increases, flexibility loses value, and at some point, building additional floors up front becomes a preferred alternative. The variation of this variable allows us to identify these transition points at different effectiveness and utilization levels. These costs will be varied in 10% increments to explore the decision space.
(c) *Fleet utilization*: Varying fleet utilization provides an opportunity to understand how to bound the "fleet" nature of an FBS. In the LUMAV context, only about 20% of the fleet was needed even at the height of war, which creates a large pool of resources to flexibly reallocate as needed. However, in other contexts, a much higher utilization might be expected. Here, we explore how preferences for flexibility strategies change at different utilization levels, as not all vehicles are always needed in a fleet. In traditional LMS studies, this opportunity is not available as there is only one system. In the initial case study, we assumed a random total vehicle distribution, modeled using a $U(0,600)$ distribution. In this simulation, the total demand

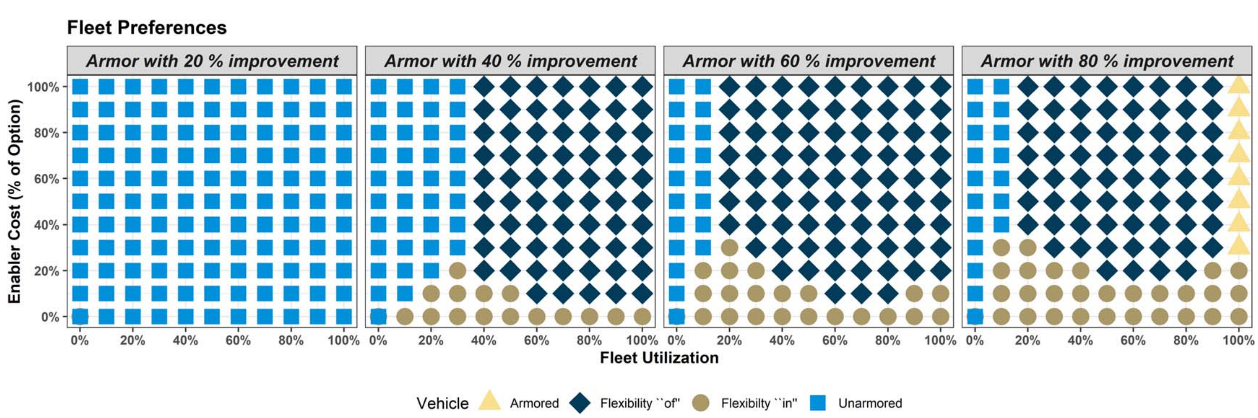

Fig. 9 Results. Each facet represents varying levels of the improvement provided by armor. The *x*-axis represents different fleet utilization percentages and the *y*-axis represents cost to enable flexibility. Each point represents the preferred alternative for that combination of armor armor effectiveness, fleet utilization, and enabler costs. As effectiveness increases, flexibility "of" is preferred when utilization and enabler costs are high.

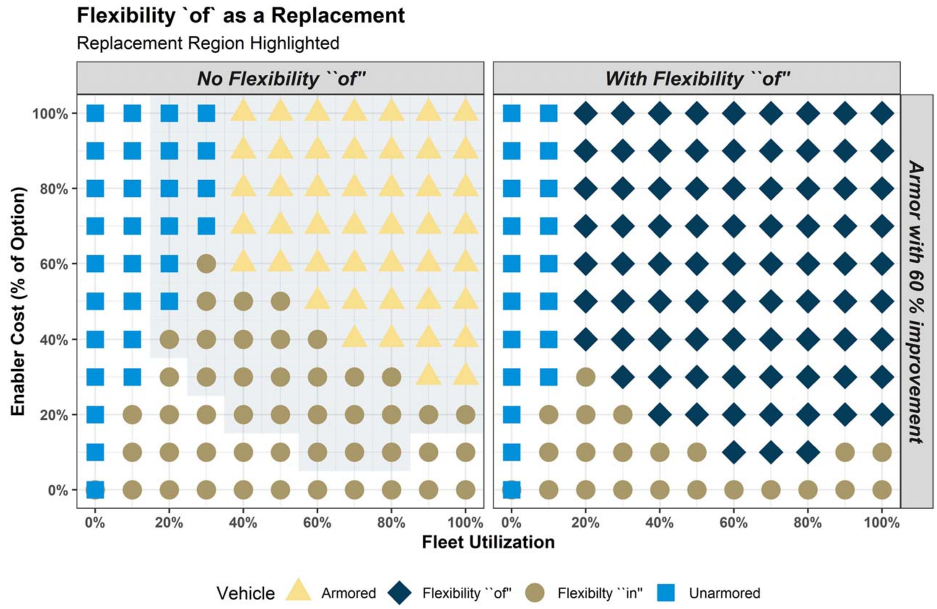

Fig. 10 Comparison of results with and without flexibility "of." The left facet shows the system preferences when flexibility "of" is not an option. When flexibility "of" is incorporated, it replaces all robust armor and a majority of flexibility "in" preferences.

is static and is varied in 10% increments. Therefore, a utilization rate of 30% means that the total demand for all of the runs at that value is 300. There is still random allocation of the total demand to each of the three MTs with equal probability.

5.1 Results. The results of the computer experiment are provided in Fig. 9. The armor effectiveness is indicated in the gray header in each facet from left to right. The values 20%, 40%, 60%, and 80% effectiveness levels are provided in order to streamline for conciseness but still provide a representative sample to demonstrate the behavior as effectiveness changes. The cost to enable is the y-axis in each facet, and the fleet utilization is the x-axis. First, as the effectiveness increases, the flexible alternatives (both "in" and "of") clearly dominate the decision space. At the same time, preferences for when each should be selected begin to emerge.

In areas where both fleet utilization are high and the cost to enable flexibility "in" is high (upper right quadrant of each subplot), the flexibility "of" quickly becomes the dominant preference. As the cost to enable flexibility "in" increases (y-axis), flexibility "in" becomes less desirable, and flexibility "of" becomes the preferred alternative. Additionally, when the utilization (x-axis) is low, there is over-investment in the armored vehicles for the flexibility "of" strategy and the unarmored variant becomes the preferred alternative. Only when the armor effectiveness level is extremely high ($\geq$80%) and utilization is at 100%, does the additional premium to buy the pure armored fleet pay off.

When the cost to enable flexibility "in" the system is low, it is preferred across all utilization levels, with the transition point along the cost to enable varying at different effectiveness and utilization levels. There appears to be a U-shaped distribution for flexibility "in." This is likely due to the MT distributions and fleet composition. When fleet utilization is low, 500 armored vehicles are an over-investment. When the utilization level is high, it is an under-investment in armor, these both make flexibility "in" more preferred, as it can provide the exact armor amount to all vehicles.

Next, we synthesize these insights to highlight that the introduction of a flexibility "of" strategy changes the flexibility decision space. To do this, we compare the results when flexibility "of" is available and when it is not to see what flexibility "of" replaces. The results are shown in Fig. 10, using an armor effectiveness of 60%. This effectiveness level was chosen as a representative example as the results are similar across other armor effectiveness levels.

First, it is clear that the flexibility "of" fully replaces the armored alternative when included as an alternative. When there is no flexibility "of" alternative, as is the case with LMS, the pure armor fleet is the preferred alternative as the cost to enable flexibility increases. It is important to note that for the utilization level that best replicates LMS (when utilization is at 100%), the transition point where the preferences change from flexibility "in" to the pure armored fleet or flexibility "of" fleet is similar in both scenarios. Second, and more importantly, flexibility "of" the fleet is preferred in many of the scenarios where flexibility "in" would have been preferred if "of" is not an alternative. Flexibility "of" not only replaces the pure armored fleet, but it also replaces a significant portion of the preferences for flexibility "in".

6 Conclusion

The design of flexibility "in" systems is a popular and effective strategy for incorporating the ability to change into complex systems. Despite the power of the idea, identifying and implementing these options has proven difficult in practice [4,7,9,20]. With this study, we offered and demonstrated a complementary strategy for implementing flexibility in a particular class of systems, which we name FBS. Our strategy exploits the portfolio nature of the system, introducing a new approach called flexibility "of" the system. Flexibility "of" leverages both the design of the system and the operational flexibility the fleet enables.

Rather than seeking flexibility by only enabling each unit to change its capability (i.e., building an option into each HMMWV), a flexibility "of" approach focuses on capability at the fleet level. Specifically, by initially procuring a mixed fleet that includes some high and lower capability units, the fleet-level capability of a specific deployed unit can be altered quickly by resourcing it with different vehicles from the full fleet. This strategy is relevant to many modern complex system managers, from the military to airlines, to public transit operators.

Our first analysis demonstrates that a flexibility "of" strategy dominates for fleets similar to the LUMAV context studied.

Our second analysis further elaborates the value of a flexibility "of" strategy to support flexible design of FBS more generally. Even in the most favorable case of flexibility "in" (where performance of the option matches an optimized robust solution, there are no delays and no mix optimization was performed), flexibility "of" is still preferred in most cases. Except when utilization and/or option costs are very low, flexibility "of" is the best strategy. This is not to suggest that flexibility "of" should replace "in." Rather it highlights the value of a new tool and identifies a broad set of conditions where it might be particularly valuable.

This result is important for designers because it helps bound the conditions under which it makes sense to invest in making the system itself flexible, designing multiple different systems to span the capability space or using a combined strategy. Our results highlight the importance of a flexibility "of" approach and provide initial guidance for designers to consider which flexibility path to pursue. While additional work is needed to elaborate the details of the tradeoff in any given design context, the strength of the results gives confidence that this approach will often be productive.

As noted, flexibility "of" is considered a complementary strategy for flexible design, and with that, an area for future work is the nesting of flexibility "in" design within a flexibility "of" construct. In this initial example, we only considered flexibility "of" with two inflexible alternatives. For instance, under certain conditions, it is likely that flexibility "in" the systems (vehicles which can add armor later) can be leveraged combined with deployment options outlined in the flexibility "of" scenario to further improve results. This ultimately can lead to a portfolio optimization approach within the fleet.

We hope that future work will extend these ideas to consider more sophisticated fleet management strategies and apply it to other classes of complex systems, for example, networked systems. This work lays the foundation for a continued expansion of flexible design strategies to new types of complex systems.

Conflict of Interest

There are no conflicts of interest.

Data Availability Statement

The datasets generated and supporting the findings of this article are obtained from the corresponding author upon reasonable request.

Nomenclature

r = discount rate
M = maximum number of runs of Monte Carlo simulation
A_t = attacks/month at time t
D_{total} = total vehicle demand for a trial
I_{AT} = improvement, as a percentage, for given armor type
$L_{t,\text{MT}}$ = lost vehicles at time t for each mission type
$V_{0,\text{MT}}$ = initial vehicles deployed to specific mission type
MDRV_{MT} = mission demand random variable
MDR_{MT} = mission demand ratio
$\text{MD}_{0,\text{MT}}$ = initial mission demand
OC_{MT} = option call cost for each mission type
OCNPC_t = option call net present cost
RC_{AT} = replacement cost for an armor type
RNPC = replacement net present cost

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