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Combat Vehicle Program Management and Product Development Resilience through Set-Based Design

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ABSTRACT

Product Development (PD) remains a highly uncertain process for both commercial and DoD programs. The presence of multiple stakeholders (e.g., DoD and allied agencies, soldiers/users, PEO, contractors, manufacturing, service, logistics) with varying requirements, preferences, constraints, and evolving priorities make this particularly challenging for the DoD. These risks are well recognized by agencies, and it is widely understood that acquisition is about risk management and not certainties. However, almost all the DoD acquisition processes still require critical reviews, and most importantly, structured decision support for the fuzzy front-end of the acquisition process. What is lacking, are effective decision support tools that explicitly recognize the sequential milestone structure embedded with multi-stakeholder decision making in all acquisition programs. We describe the Resilient Program Management & Development (RPMD) framework to support complex decision making with set-based design approach.

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1. INTRODUCTION

Product Development (PD) remains a highly uncertain process for both commercial and Department of Defense (DoD) programs. The presence of multiple stakeholders (e.g., DoD and allied agencies, soldiers/users, program executive office, contractors, manufacturing, service, logistics) with varying requirements, preferences, constraints, and evolving priorities make this

particularly challenging for the DoD. These risks are well recognized by the agency and it is widely understood that acquisition is about risk management and not certainties.

However, almost all the DoD acquisition processes still require critical reviews, and most importantly, structured decision support for the fuzzy front-end of the acquisition process. Historically, there is great reliance on Trade-Space Exploration and Optimization (TSE&O) tools to enable structured analysis of alternatives and identification of concepts that best balance



Figure 1: Complex Decision-Making.

time, cost, risk and capability. However, there is lack of integrated decision support tools for program managers and systems engineers that explicitly recognize the sequential milestone structure embedded with multi-stakeholder decision making in all acquisition programs.

This paper presents and describes a framework, identifies its core capability requirements, and illustrates with results from a pilot study.

2. BACKGROUND

The complexity, uncertainty and risks associated with the DoD acquisition process are well documented (Bond et al., 2015). The acquisition process is fraught with development uncertainties and outside factors changing over the timeline of the program. Multiple stakeholders with different preferences and concerns, constraints, evolving priorities, and uncertainties in engineering of subsystem technologies and their readiness levels (technology, integration, manufacturing), all impact the total system choice throughout the program management life-cycle. Arena et al. (2006) provide an excellent summary of research on the subject of cost growth since the 1950s, with total average cost overages

relative to estimates at Milestone B estimated at a staggering 46 percent. These cost overages are due to the uncertainty inherent in the acquisition and technology-development processes (Bond et al., 2015).

Bolten et al. (2008) classified these sources of uncertainty into four major categories: 1) errors in estimation and planning; 2) decisions by the government, including changes in requirements and other programmatic changes; 3) financial matters, including changes in the macroeconomic environment; and 4) miscellaneous sources. Within the literature on cost growth, there appears to be consensus that technical, schedule, and cost risks are interconnected, with technical and schedule outcomes feeding into resultant costs.

Younossi et al. (2008) state that technical risks, such as immature technologies or a compressed testing schedule, lead to technical difficulties that could eventually result in failures in meeting the technical performance. Overall, presence of multiple stakeholders with varying preferences, budgetary and other resource constraints, evolving priorities and requirements, all

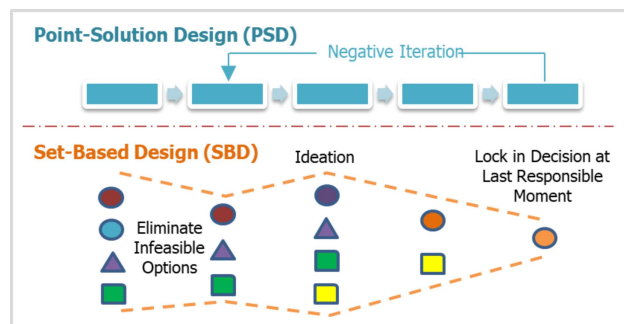


Figure 2: Point-Solution Design vs Set-Based Design.

contribute to program acquisition challenges.

Design and development of complex engineered systems is an exemplar of the complex-decision making under uncertainty with multiple conflicting objectives (Figure 1). Complex decision making requires a detailed planning and real-time orchestration of a capable decision analytics program and

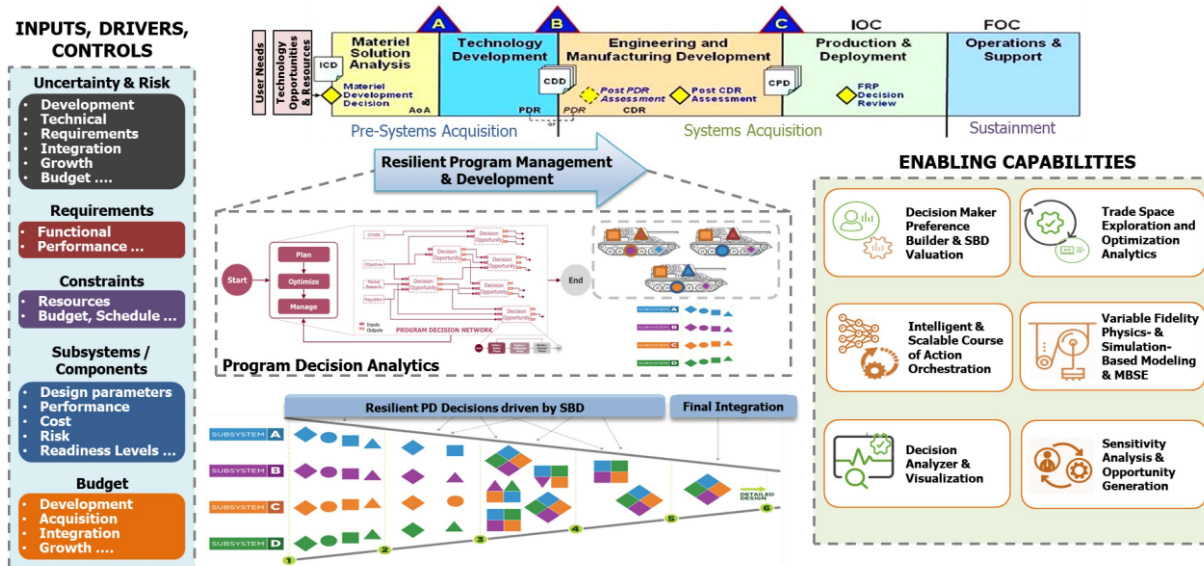


Figure 3: Resilient Program Management & Development (RPMD) framework.

facilitation of the decision-making steps with intelligent guidance to build confidence and trust in decisions.

The traditional and pre-dominant approach to product development (PD) is the so-called Point-Solution Design (PSD). It forces program managers to identify and commit to a single promising concept solution early in the acquisition cycle and all effort is spent to realize that very solution, irrespective of the evolving uncertainties and realities of PD. There is strong recognition that PSD limits PD Program Management (PM) resilience. Set-Based Design (SBD) overcomes these risks by maintaining sets of technology options (redundancy) for risk-prone (sub-)systems, and hence, adds resiliency to best counter risks and uncertainties while seeking cost efficiency (Figure 2).

While SBD has been explored in practice, there exist no scalable/robust SBD decision support platforms to guide decision making in support of multi-stage multi-criteria program management and development. Intrinsic to PD and PM is “sequential” decision making, where the ‘best choice now’ depends critically on future situations. There are powerful and ideal analytical tools for

sequential decision making under uncertainty.

To account for the limited but directionally useful knowledge on the technical and programmatic uncertainties and ability to plan with courses of actions (parallel development, off-ramp, risk reduction through testing and prototyping, etc.), there is need for an integrated framework. This framework should support comprehensive multi-stage multi-criteria SBD approach to support DoD’s acquisition processes at different life cycle stages.

3. RESILIENT PROGRAM MANAGEMENT & DEVELOPMENT FRAMEWORK

Resilient Program Management & Development (RPMD) framework (Figure 3) is a comprehensive multi-stage multi-criterion SBD approach to support DoD’s acquisition processes during the pre-systems acquisition phase. The framework identifies optimal courses of actions (decision “policies”) to explicitly guide decision making at each critical stage/milestone of the program as a function of program “state” (e.g., accounting for risks, budget revisions,

readiness levels of technologies, and consideration for past decisions) and program goals. The framework developed is flexible, intelligent, and scalable for complex DoD programs.

RPMD framework considers both the program management and the product development processes executed concurrently. It enables program managers and systems engineers to account for reducible and irreducible uncertainties and mature the system design. There are six enabling core capabilities of this framework.

1. Decision Maker Preference Builder & SBD Valuation: This capability requirement is a rich, flexible/configurable, and robust trade space preference builder module to capture the stakeholders’ and decision makers’ preferences and utilities for risks in cost, performance, and schedule to inform the set-based trade studies, i.e., used in the PM’s management of risk, budget allocations, requirements, and schedule, and in the generation of alternatives for trade studies (Figure 4).

2. Trade Space Exploration and Optimization Analytics: Unlike traditional TSE&O approaches, RPMD’s requirements for trade study exploration of the design spaces are complicated by the presence of uncertainty and multiplicity of outcomes due to integrated risk management and courses of action planning. This capability consists of scalable set-based TSE&O algorithms that can account for uncertainty in the cost, performance, schedule spaces, risk-informed value preferences, set-based design decisions, and a very large number of programmatic and design outcomes.

3. Intelligent & Scalable Course of Action Orchestration: RPMD features a forward-looking risk-management approach with explicit consideration for set-based design

alternatives enabled with courses of actions (delaying decisions, parallel tracks, switching in/out technologies, risk reduction actions, etc.). This capability allows the program management office (PEO/PM) to assess, transfer, control and mitigate risk by using various strategies, i.e., allocating and investing resources (i.e., budget, schedule), creating multiple pathways and start new contracts, allocating requirements between subsystems, and so on. In addition, it is also able to support early concept generation studies (i.e., AoA studies’ alternative development) by not only looking at what is available “today” in terms of baseline, its optimizations, and other alternative concepts

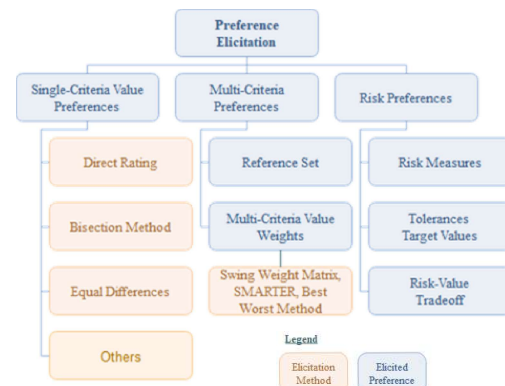


Figure 4: Preference elicitation for Value and Risk.

but also by explicitly incorporating various risks and uncertainties (technical, programmatic, schedule and cost) as well as technical maturation opportunities in identifying suitable and effective system alternatives.

4. Variable Fidelity Physics- & Simulation-Based Modeling & MBSE: Evaluation of design alternatives and exploration of design space using TSE&O require resources and could be prohibitive if highest fidelity analysis is pursued. At the same time, there is need for accuracy and confidence in the effectiveness and performance evaluations of system designs.

RPMD should integrate multi-disciplinary physics- and simulation-based models of variable fidelity using model-based systems engineering (MBSE) to reduce program and technical risk, ensure requirements satisfaction and maximize realized performance. Variable fidelity can be achieved through reduce-order models enabled by machine learning models (i.e., deep neural-network models) for intelligent and efficient surrogate modeling of physics- and simulation-based engineering modeling and simulation (M&S) tools. To exploit the power of exact optimization approaches, it should implement methods to further approximate the surrogate models for linearized optimization formulation generation and injection into Mixed Integer Programming (MIP) based TSE&O models for scalability.

5. Decision Analyzer & Visualization:

Overarching scope of the RPMD (program management and product development) and explicit consideration of SBD, decision program networks, courses of action, and risk-management calls for novel characterization and visualization of the program and technical management decisions.

Examples of these decision-aid tools are risk-informed trade-space visualizations, set-based trade spaces, and courses of action decision pathways. This capability provides the interpretability of optimal sequence of program management and development decisions for risk management in terms of attainable system configurations, program and technical management criteria, development, and investment costs, schedule, and risks.

In addition to visualization and decision guidance/feedback, it should evaluate the benefits, costs and risks associated with managing risk through an evolving set-based

design approach over the point-based approaches.

6. Sensitivity Analysis & Opportunity

Generation: RPMD framework should the capabilities of assessing the sensitivity and impact of requirements (cost, key performance parameters), schedule, changes in stakeholder preferences, budget allocations, and program decisions of set-based approach for PM/PD resilience.

Another requirement is the discovery of opportunities to drive the generation of viable courses of actions. This requirement assesses and quantifies the impact of the risk-management decisions in real-time and sensitivity of outcomes with respect to budgets (development, engineering, growth), schedule, design requirements, initial state of subsystem options (i.e., design readiness, reliability, and manufacturability), risk and uncertainties (transition probabilities, budgets, and requirements).

4. ANALYTICAL REQUIREMENTS OF RPMD

In this section, we detail the second and third capabilities' (TSE&O and course of action orchestration) analytical requirements for integrated analytics treatment of the available design, technology, maturity, uncertainty data.

4.1. Risk-Informed Variable Fidelity Trade Space Exploration and Optimization

RPMD framework requires a scalable variable-fidelity trade space exploration and optimization algorithms that can explore the risk-informed design space in terms of PBD and SBD strategies.

The task of finding the non-dominated set-based design solutions is, given a future realization of program and design uncertainties, to identify those system design solutions that are not inferior to any other

system design solution in at least one of the criteria. Given the discrete nature of the system design decisions, i.e., selection of one technology option for each subsystem, this problem belongs to the domain of multi-criteria (multi-objective) integer programming. It is commonly used in the trade-space exploration and optimization tasks and there exist several tools capable of solving this problem exactly and heuristically (i.e., using meta-heuristic algorithms).

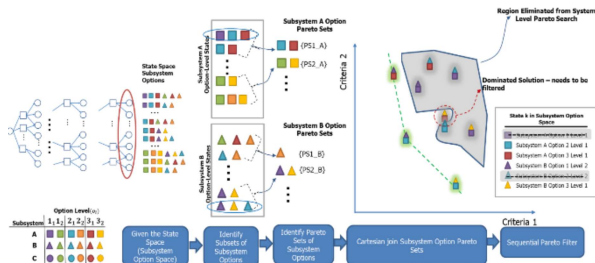


Figure 5: Design decomposition strategy.

These algorithms are designed and implemented for the purpose of finding Pareto optimal designs for a single realization of the future milestone. However, RPMD framework requires consideration of many future state scenarios due to the consideration of uncertainty (risk-informed) and set-based design approach. Hence, the framework evaluates a very large number of states in the design space and treating the problem of finding non-dominated design solutions in each state as an independent problem is rather inefficient. Instead, RPMD exploits the similarity of future state realizations in terms program outcomes, design outcomes, and other uncertainties to identify the efficient sets of designs in a scalable manner. One example of such strategies is to leverage the similarity of design space structure of future states and analyze the trade-spaces of future in coordination rather than independently using design space decompositions (Figure 5).

The impact of uncertainty could be significant for PM's value space and

stakeholder's design space (Figure 6). Further, the risk preference of decision makers is critical for identifying robust efficient designs. RPMD's TSE&O capabilities addresses these requirements by explicitly accounting for the uncertainties and decision maker's risk preferences in the

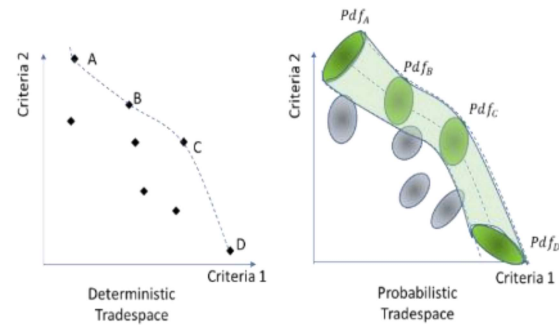


Figure 6: Illustrative comparison of deterministic and probabilistic trade-spaces.

exploration of the decision space. The impact of the uncertainty in the design and program trade-spaces can be paramount and capturing independent and correlated risks are critical for not only the SBD decision in the design and program decision space but also crucial for effective courses of action planning.

These novel TSE&O approaches should also support variable-fidelity modeling and simulation of system performance in a scalable manner using machine learning based surrogate modeling for decision-context specific fidelity and local linearization techniques to take advantage of powerful exact optimization algorithms (Figure 7).

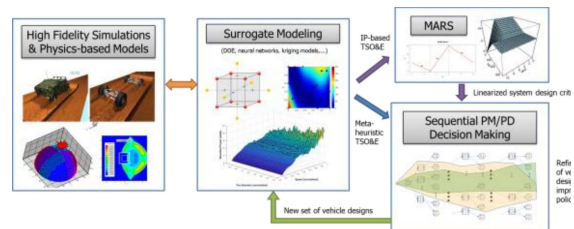


Figure 7: Variable-fidelity modeling for scalable trade space exploration.

4.2. Course of Action Orchestration for Risk and Opportunity Management

RPMD framework should flexibly and accurately capture the impact of multi-stage SBD and development decisions on attainable system configurations under different sources of uncertainty. SBD entails sequential decision making, where the evolving dynamics of the decision-making environment need to be taken into consideration through actions at different discrete decision milestones/reviews, where new information might be revealed for course correction (or staying the course) and by delaying as appropriate. Sequential decision making is at the heart of all product development with milestones, and DoD acquisition program management is no exception. There are powerful analytical tools used for sequential decision making under uncertainty, are most appropriate for promoting optimal set-based design practices during program management.

RPMD framework should facilitate a continuously evolving decision process where SBD solutions are implicitly carried forward through design development milestones/reviews (epochs), by means of subsystem options that are being actively developed. Such a framework focuses on “necking down” of potential subsystem option sets at every milestone for cost efficiency. However, it should also keep options longer into the process if necessary and allows for “necking up” to avoid early mistakes as the risk and uncertainty veil lifts and if an earlier “neck down” in the set solution proves to be disadvantageous. This is achieved by designing the modeling constructs (program development “state”, program manager’s “action” space, and program development uncertainty) of the framework in terms of subsystem options and utilization of “recovery” penalties for subsystem options.

Meeting such requirements for complex decision making as in RPMD is possible through a combination of proper view of the world representation through uncertainty modeling and in-context state representation, state-of-the-art sequential decision modeling. Design, manufacturing, integration Readiness Levels (RL) are candidates for representing the states in such a modeling effort. Similarly, course of actions can be modeled through the PM/PD decision portfolios while capturing their impact on the value space (cost, schedule, and performance). Also needed is the representation of the uncertainty and how it effects the key decision drivers in the state space and value space.

A key requirement for sequential decision making is the notion of “reward” associated with “courses of actions” (i.e., decisions) taken at any given epoch given the current “state”. In the context of SBD, for example, an action at a given epoch and development state could entail decisions about the different technology options we choose to continue the development, drop, maintain, or recover, etc. Hence there is a need to quantify the “value” attainable from taking these discrete actions.

In the context of DoD acquisition, the value should be estimated from the quality or utility of the eventual design solution(s) that can be realized at the end of the program development cycle. If one were to pursue a single-point solution, the overall utility of the eventual solution should be derived from the design criteria (both performance and burdens), which is multi-criteria in nature (e.g., low cost, low weight, high fuel efficiency, high availability, high force protection etc.). When it comes to SBD, it is possible that at the end of the development cycle, more than one viable design solution (i.e., a “set” of optimal solutions) might be available for the “down-select” process (Figure 8).

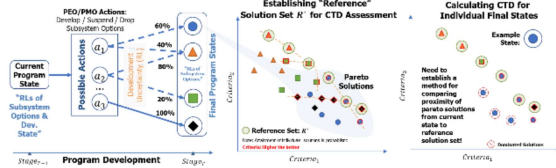


Figure 8: Illustrative comparison of deterministic and probabilistic trade-spaces.

For tractability of analysis, the value function at any given epoch and design state should be scalar and capture the collective utility of the eventual design solution set in terms of the stated design criteria. Overall, this presents several requirements for the value function: 1) Scalar; 2) Support multiple design evaluation criteria; 3) Account for the possibility of realizing multiple Pareto optimal solutions; 4) Account for uncertainty (i.e., probability) in realizing different design solutions; and 5) Account for preferences of decision makers (such as threshold and objective levels for each criterion).

There is no single best approach to establish the value function. An example approach is the Contribution-to-Design (CTD) proposed by Rapp (2017). This function is a “weighted” sum approach to calculating CTD for individual subsystems, where weights are assigned to different criteria and rolled into a scalar value using the notion of “Design Readiness Levels” (DRL), which is an expansion of the DoD’s Technical and Material Readiness Levels. In the context of the framework, the DRL reflects the maturity of the design relative to each of the required target levels in a program. The general expectation for DRL is that, if an option is invested in for development during the next phase, its readiness should generally improve. Rapp (2017) also recommends a weighted sum approach to estimate the CTD for the overall design solution or solution set.

To support the SBD, the CTD value function of Rapp (2017) can be generalized by allowing the value function to be determined in terms of the quality of the design solution set attainable at the end of the

program development cycle. This can be done by measuring the value of a system design state in relation to a global “reference” design set in the trade space (Figure 8).

5. ILLUSTRATIVE EXAMPLE

We describe an illustrative case-study to demonstrate the RPMD framework. The goal is to manage the Technology Maturation & Risk Reduction (TMRR) development of a system with three critical technology subsystems, (1) Powerplant, (2) Energy Storage, and (3) Propulsion (Wheel vs Track), using an SBD approach with multiple courses of actions. Each subsystem has two alternatives under consideration for a down-select at the system level.

5.1. Description and Data

The three design criteria considered are: 1) Performance (aggregated); 2) Weight; and 3) AUPC (i.e., unit production cost). The design criteria probabilistically depend on the technology readiness levels of the subsystem options and improve (can remain unchanged) with their readiness level. There are three technical reviews in the TMRR, i.e., three development stages. Given the initial readiness levels for all subsystem options, the subsystem option development and maturation (engineering design, testing, verification, etc.) decisions at each stage evolves the technology options’ readiness levels probabilistically over time. Program budgets and PEO/PM constraints further limit the development and testing actions taken at each stage.

State Space

In capturing the design and program evolution, we consider two state sets of tuples: 1) Development states and 2) Readiness level (RL) states. Development States (DS) accounts for such programmatic stats as the budget (total development budget, carryover budget, management reserve),

active/inactive development status of each technology option, etc.

Readiness Level (RL) states are considered as individual option's baseline readiness level plus of three discrete levels, i.e., readiness levels RL 1-3 for an option at Technological Readiness Level (TRL) 4 would correspond to TRL 4,5,6. Readiness levels may remain same or improve with the courses of actions according to a probabilistic transition given the current development stage and course of action taken.

Courses of Actions

Courses of Actions (CoA) include SBD decisions in terms of constricting and expand the design set, engineering development, and program actions. CoA(s) impact the individual subsystem options in terms of maturation as well as the overall program in terms of program resources such as the budget and reserve. Development CoA(s) of subsystems' technology options may improve their readiness levels. Their programmatic dependencies are captured through the budget implications and PEO/PM constraints. It is possible to constrict the design set by pausing the development of an option, maintaining at a low rate, or completely dropping from the option set. It is possible, however, to recover a technology option previously removed from consideration through catchup development courses of actions. Catchup CoA(s) (after being dropped or low-rate development) are not feasible for all options at all stages, rather they are specified by the PM and carry cost penalties reflecting the need for accelerated development, and/or re-integration into the development process, etc. option after being dropped.

Constraints

We consider various PEO/PM constraints to allow for various program management controls over the CoA(s). Some of these

constraints are tailored to target individual options by DRL and stage, individual subsystems by stage and DRLs of their options as well as enforce CoA jointly for multiple options and/or subsystems.

State Transitions

State transitions, given the current state and design development and program actions, probabilistically maps to the next stage state. Without loss of generality, we assumed the options' state transitions are independent of one another, i.e., development and maturation of each technology option is independent of the other option. The probabilistic models account for the impact of CoA(s) on the readiness levels considering the current level of maturity (readiness levels), program state, and resource allocations. These probability models are stage dependent and reflect the impact on schedule constraints on the maturation success likelihood.

Budget and Cost

In terms of budget, we consider different budget categories such as engineering development, testing and integration and management reserve. Integration efforts are stage and readiness level dependent and consume integration budget resources. We account for budget carry over to capture effect of variances, i.e., target vs actualized costs subject to certain limits. Each subsystem option has an associated baseline development cost in each development stage (the PM's planned and allocated levels). These costs are further parametrized to account for the design readiness level of the option at the time of development and the stage when the development takes place. Courses of actions at the program level effect multiple budget categories depending on the development design development state, program state and stage in TMRR.

Data

The critical subsystem technologies are:

Engine/Powerplant: Modern diesel engine (HD) is heavier than the High Energy (HE) density diesel engine but cheaper and has better performance.

Energy Storage: Lithium-Ion (T2) based energy storage weighs more than the Nickel-Metal Hydride (M4) based unit. However, Lithium-Ion (T2) offers a much better performance albeit being significantly more expensive.

Propulsion: Track system (EM) is more expensive and heavier than the wheel-based system (RL) but offers significantly more performance.

Baseline scenario has a total budget of \$63M, of which \$61M is allocated across three stages and \$2M is set aside as a “reserve” budget. This reserve budget can be spent in any of the stages. Development actions are restricted with the available development and integration budget at the beginning of each stage. Available budget includes stage’s allocated budget, a percentage of any carryover of unspent budget from the previous stage, and reserve budget remaining. The cost modeling of option development and integration account for the dependency on DRL. Budget for stages 1 and 2 are mostly for engineering development and testing and stage 3 budget is shared between development and integration. In terms of subsystem technology options, some of the cost differences are summarized below:

Engine/Powerplant: Modern diesel engine (HD) costs more to develop in Stage 1 than any other option. Initial HE development cost is lower but increases with stages.

Energy Storage: Lithium-Ion (T2) based energy storage is costlier to develop and integrate than the Nickel-Metal Hydride (M4) based unit.

Propulsion: Wheel subsystem option (RL) is more costly to develop as the EM track is currently the subsystem option in use.

We consider different design and programmatic uncertainties. An illustration of the readiness level uncertainty by subsystem option and criteria is shown in Figure 9.

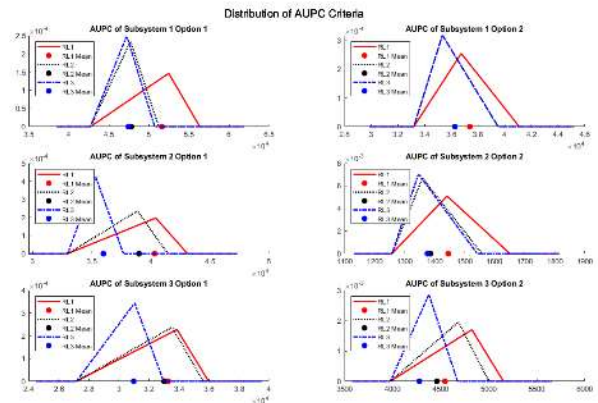


Figure 9. Triangular distributions of Subsystem Option “AUPC” at different design readiness levels.

RPMD framework allows developing and comparing different strategies given the requirements and programmatic scenarios. In the baseline scenario, the program allows for some level of redundancy in the development efforts as the budget levels accommodate the development of approximately 3 options per stage. This corresponds to the point-solution design where 3 options (1 option per subsystem) will be developed per stage. Unlike the point-solution design, the set-based approach has the flexibility to adjust the set designs and can switch the development of different sets of options at each stage. we compared the SBD approach with a PBD approach where the CoAs are limited to the selection of a single optimal design solution that can be afforded without off-ramping.

Results

Figure 10 shows the Pareto optimal PBD design solutions across all future state

possibilities (before down-select) and ignoring the program considerations. Global Pareto optimal solutions across these future state dependent design solutions are shown with red colored star.

Figure 11 shows the distribution of expected readiness levels for the option set (all six options) at the end of the program under set-based design (SBD) and point-solution design (PSD) solution development in the baseline scenario. The first column of Figure 11(a), SBD results, corresponds to option set RL state “3,3,3,1,3,1”. This RL state coding, for example, indicates the readiness level of the HD and HE options of the engine to improve 2 levels, T2 of Energy storage improve to improve 2 levels but M4 to remain unchanged. In this example, both options for engine subsystem are fully developed here to RL state “3”, yielding at least two design solutions (SBD). Given the shared development budgets for each stage and the overall program, RL development paths for individual subsystems are not independent. Figure 8 allows us to visualize these dependencies and reports the option set RL states at the end of the program. The PBD

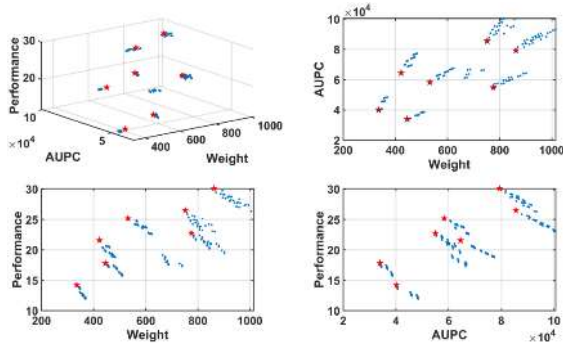


Figure 10. Pareto optimal solutions for Case Study in joint criteria space along with reference set R^* .

solution (Figure 13b) shows that the optimal PBD is HD, M4 and EM and only achieve the highest maturation possible, i.e. RL 3,1,1,3,3,1, in about 57% of the time.

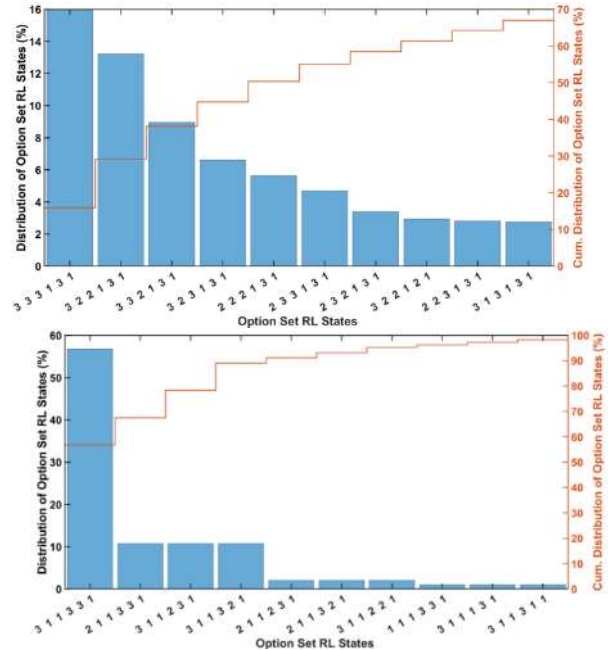


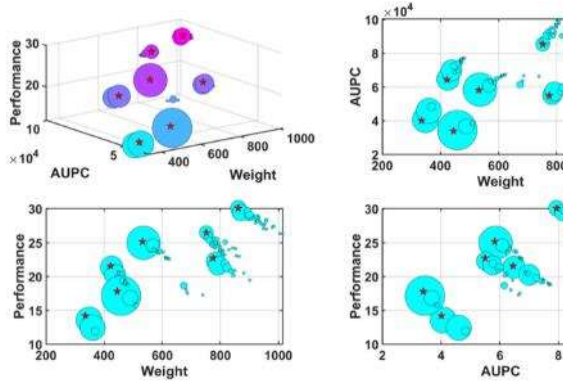
Figure 11. Distribution of expected readiness levels for the option set (all six options) at the end of the program under SBD and PBD solution development.

Figure 12 reports the solution results at the end of the program management in terms of likely criteria attainment by design solutions. The global reference points R^* are highlighted as red stars in these plots and are identified using the Average set-based CTD measure.

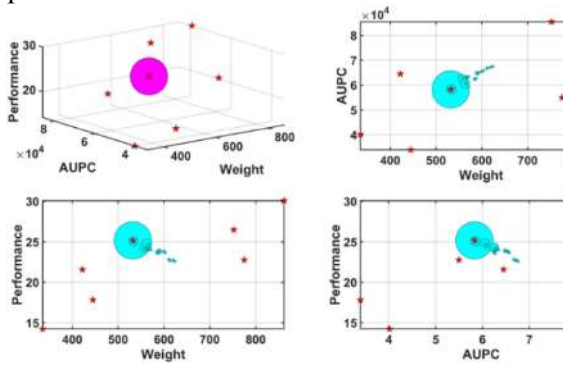
The different circles denote the distinct design solutions while their diameter denotes the probability of attainment. In the case of PBD, there is, by definition, a single design solution in terms of the subsystem option choices. However, the different circles correspond to the different option set readiness levels (as seen in Figure 12(b)). When it comes to SBD, as discussed earlier, there exist several design solutions in terms of the subsystem choices (as seen in Figure 11a). Under SBD, each option set RL state from Figure 11a can lead to multiple design solutions. We first identify the Pareto solutions for each option set RL state and their corresponding probabilities of attainment. The probabilities corresponding to each distinct design solution including

their option RL levels are then aggregated across all the final option set RL states. It is these attainment probabilities that are plotted in Figure 12a.

There are several observations that can be



(a) Set-based designs come close to all points of R^* .



(b) Point-solution design comes close to one point of R^* .

Figure 12. Comparison of trade-spaces of SBD and PBD by the end of TMRR.

made from Figure 12:

The global reference Pareto set R^* is rather diverse covering much of the criteria space allowing the PEO/PM to recognize the vastly distinct design solution possibilities.

In spite of the relatively small surplus in the program budget (over funds necessary to pursue the best single-point solution), CoA enabled set-based design approach to effectively utilize the surplus funding to attain good and balanced solutions that are relatively close to all points of R^* .

CoA enabled set-based design approach allows the possibility of several Pareto or near Pareto optimal design solutions nearing all the eight global reference points R^* with high likelihood of attainment for the final down-select process.

Figure 13 illustrates the effect of including trade space uncertainties and risk preferences. In this frequency plot, we compare the set-based CTD values obtained through the SBD approach described but assuming the criteria (i.e., Performance, Weight, AUCP) space is deterministic and by explicitly accounting for the uncertainties in the criteria (coupled) and decision maker's risk preferences. Clearly, accounting for the uncertainty with risk preferences results in SBD development and program decisions differently. Further, such an approach values the future design states differently than those of the deterministic treatment, i.e., deterministic treatment appears to uniformly distribute the SB-CTD values compared to stochastic based approach. This is a very valuable observation in that the risk preference modeling and Risk-Informed TSE&O of RPMD are critical for programs where there are significant variabilities in the criteria set and coupled trade space uncertainties. In such cases, RPMD framework focuses more on those states that captures the decision maker's risk preferences better.

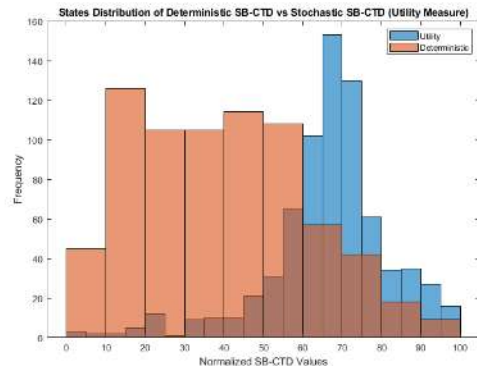


Figure 10. Frequency distribution of set-based CTD with deterministic and uncertain criteria.

6. CONCLUSION

SBD as a design method has been explored in practice and studied extensively by the research community. There is still need for further investigations as to how to integrate SBD into the DoD's acquisition processes from a design point of view. However, we believe SBD's full potential is realizable if it is integrated as not only a design method but as an integrated decision analytics framework concurrently supporting the PEO/PM and DoDI 5000.02's SE workflows. To that end, we described the RPMD framework, its capability requirements, and presented results of an illustrative application.

7. REFERENCES

- Arena, M. V., Leonard, R. S., Murray, S. E., & Younossi, O. (2006). Historical Cost Growth of Completed Weapon System Programs (Vol. TR-343-AF). Rand Corporation. Link
- Bonet, B., & Geffner, H. (2003, June). Labeled RTDP: Improving the Convergence of Real-Time Dynamic Programming. In ICAPS (Vol. 3, pp. 12-21).
- Bernstein, J. I. (1998). Design Methods in the Aerospace Industry: Looking for Evidence of Set-Based Practices (Doctoral dissertation, Massachusetts Institute of Technology).
- Bilbro, J. W. (2007). A Suite of Tools for Technology Assessment. In Technology Maturity Conference: Multi-Dimensional Assessment of Technology Maturity. Virginia Beach, VA: AFRL.
- Bolten, J. G., Leonard, R. S., Arena, M. V., Sollinger, J. M., & Younossi, O. (2008). Sources of Weapon System Cost Growth: Analysis of 35 Major Defense Acquisition Programs (No. MG-670-AF). Rand Corporation. Link
- Bond, C. A., Mayer, L. A., McMahon, M. E., Kallimani, J. G., & Sanchez, R. (2015). Developing a Methodology for Risk-Informed Trade-Space Analysis in Acquisition (No. RAN136454). Rand Corporation. Link
- DoD, U.S. (2009). Technology Readiness Assessment (TRA) Deskbook. Defense Research and Engineering. Link
- DoD, U. S. (2011). Technology Readiness Assessment (TRA) Guidance. Defense Research and Engineering. Revision posted, 13. Link
- Hoffenson, S., Kokkolaras, M., Papalambros, P., & Arepally, S. (2011). Ground vehicle safety optimization considering blastworthiness and the risks of high weight and fuel consumption (No. TARDEC-21999). Army Tank Automotive Research Development and Engineering Center Warren MI. Link
- NAVSEA – Naval Sea Systems Command. (2019). Ship to Shore Connector: Program Summary. Link
- Rapp, S. (2017). Product Development Resilience Through Set-Based Design. Doctoral Dissertation. Detroit, MI: Wayne State University. 1861. Link
- Rapp, S., Chinnam, R., Doerry, N., Murat, A., and Witus, G. (2018). Product Development Resilience Through Set-Based Design. Systems Engineering Journal. 21(5), 490-500.
- Singer, D. J., Doerry, N., & Buckley, M. E. (2009). What Is Set-Based Design?. Naval Engineers Journal, 121(4), 31-43.
- Small, C., Buchanan, R., Pohl, E., Parnell, G. S., Cilli, M., Goerger, S., & Wade, Z. (2018, July). A UAV Case Study with Set-based Design. In INCOSE International Symposium (Vol. 28, No. 1, pp. 1578-1591).
- Sobek II, D. K., Ward, A. C., & Liker, J. K. (1999). Toyota's Principles of Set-Based Concurrent Engineering. MIT Sloan Management Review, 40(2), 67.

Younossi, O., Arena, M. V., Jain, A., Leonard, R. S., & Roll Jr, C. R. (2007). Is Weapon System Cost Growth Increasing? A Quantitative Assessment of Completed and Ongoing Programs (Vol. MG-588-AF). Rand Corporation. [Link](#)

Younossi, O., Lorell, M. A., Brancato, K., Cook, C. R., Eisman, M., Fox, B., Graser, G. C., Kim, Y., Leonard, S. L. P. & Sollinger, J. M. (2008). Improving the

Cost Estimation of Space Systems. Past Lessons and Future Recommendations (Vol. MG-690-AF). Rand Corporation. [Link](#)

Zitzler, E., Thiele, L., Laumanns, M., Fonseca, C. M., & Da Fonseca, V. G. (2003). Performance Assessment of Multiobjective Optimizers: An Analysis and Review. *IEEE Transactions on Evolutionary Computation*, 7(2), 117-132.