SoSECIE Webinar

Welcome to the
2022 System of Systems Engineering Collaborators
Information Exchange (SoSECIE)

We will start at 11AM Eastern Time

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NDIA System of Systems SE Committee

- **Mission**
  - To provide a forum where government, industry, and academia can share lessons learned, promote best practices, address issues, and advocate systems engineering for Systems of Systems (SoS)
  - To identify successful strategies for applying systems engineering principles to systems engineering of SoS
- **Operating Practices**
  - Face to face and virtual SoS Committee meetings are held in conjunction with NDIA SE Division meetings that occur in February, April, June, and August

NDIA SE Division SoS Committee Industry Chairs:
Mr. Rick Poel, Boeing
Ms. Jennie Horne, Raytheon
OSD Liaison:
Dr. Judith Dahmann, MITRE

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- **I have muted all participant lines for this introduction and the briefing.**
- **If you need to contact me during the briefing, send me an e-mail at sosecie@mitre.org.**
- **Download the presentation so you can follow along on your own**
- **We will hold all questions until the end:**
  - **I will start with questions submitted online via the CHAT window in Teams.**
  - **I will then take questions via telephone; State your name, organization, and question clearly.**
- **If a question requires more discussion, the speaker(s) contact info is in the brief.**

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2022 System of Systems Engineering Collaborators Information Exchange Webinars

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June 14, 2022
Leverage Set-Based Practices to Make Agile Practices More Effective for System-of-Systems Engineering
Brian Kennedy

June 28, 2022
Model Based Systems Engineering in a Digital Environment: Creating a Virtual Testbed for Complex System Architectures
Claudeliah Roze

July 12, 2022
TBD

July 26, 2022
TBD

https://www.mitre.org/capabilities/systems-engineering/collaborations/system-of-systems-engineering-collaborators

Mission-Level Optimization: A New Method for Designing Successful Systems

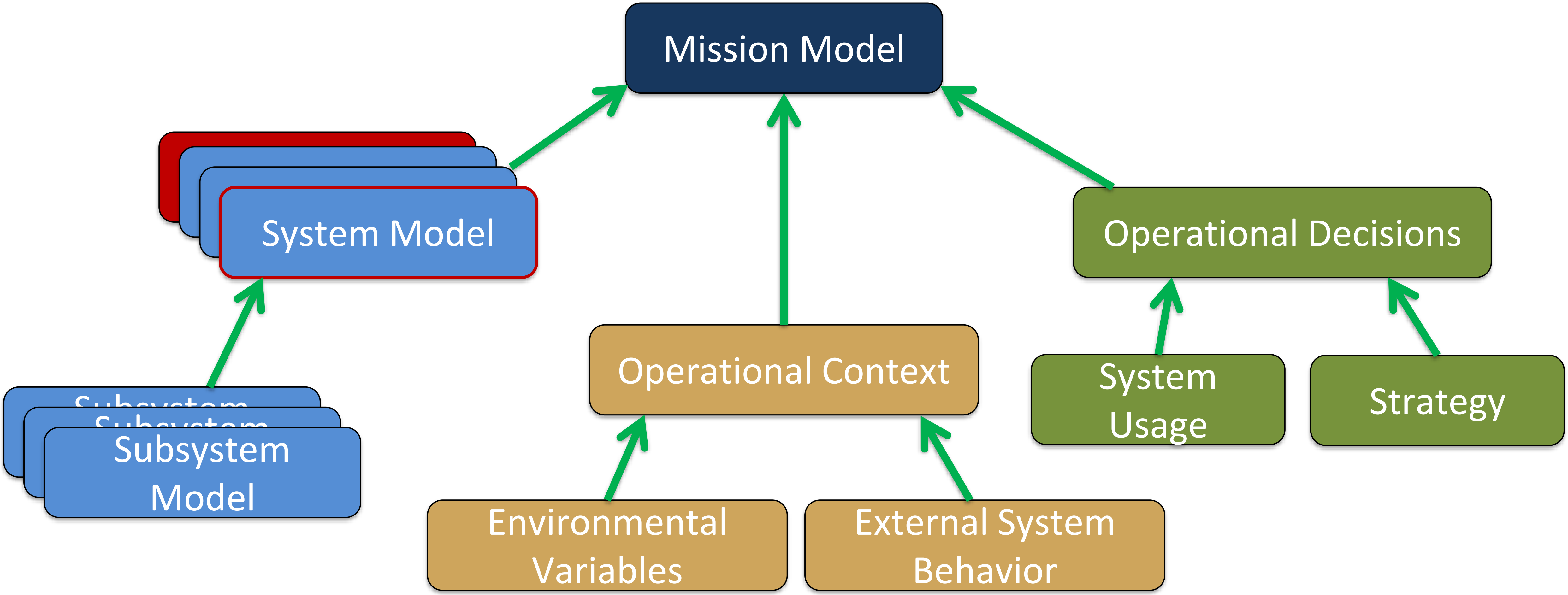
Brian Chell, Ph.D.
Steven Hoffenson, Ph.D.
Mark R. Blackburn, Ph.D.

National Defense Industrial Association
Virtual Systems & Mission Engineering Conference
December 8th, 2021

Introduction

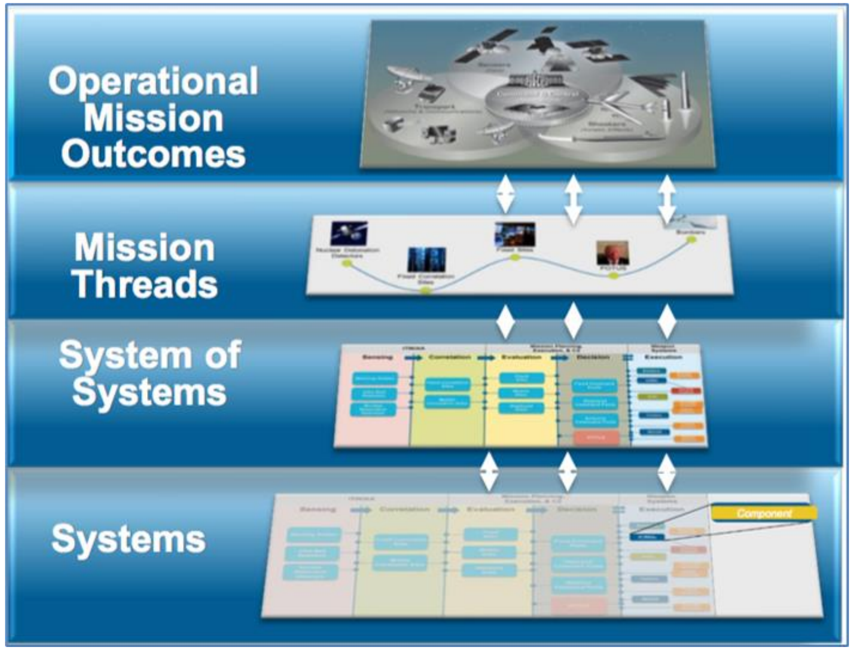
- Mission models are becoming more prevalent and capable
- Established multiobjective optimization (MOO) approaches using key performance parameters (KPPs) are insufficient
- Missions present many difficulties for MOO methods
    - High amounts of uncertainty and complexity
    - Binary success/failure objectives
    - Subjectivity in objective weighting
    - Subjectivity in selecting design from a Pareto set
- ***This project motivates, proposes, and tests a new method for mission-level optimization (MLO)***

Mission-Level Optimization Context



MLO Background

- Mission Engineering
  - Systems engineering at a high level of abstraction
  - Combines capabilities with desired effects
- Mission modeling methods and tools
  - Top-down/Bottom-up
  - Combination of models or an analysis suite
  - Mission-level tools still immature
- Metrics for mission-level analysis
  - Cost and value often used
  - New measures necessary



Zimmerman, 2019

Related Optimization Techniques

Method	Value	Limitations
Robust design optimization (*Park, 2006; Beyer, 2007*)	Handles uncertain inputs while limiting uncertainty in objective	Intended for low levels of uncertainty, e.g., dimensional tolerances
Reliability-based design optimization *(Enevoldsen, 1994; Tu, 1999; Madsen, 2006)*	Maintains feasible design points if constraints are well-defined	Assumes continuous reliability-based objectives/constraints
Heuristic optimization *(Tanese, 1989; Kennedy, 1995; Dorigo, 2006; Olafsson, 2006)*	Does not require gradient information, many algorithms well-suited to find global optima	Many function evaluations, typically has no optimality guarantee, and does not explicitly handle uncertainty
Surrogate-based optimization *(Jones, 1998; Jones, 2001; Queipo, 2005; Barton, 2006; Shan, 2010)*	Very low computational expense when solving	Requires preliminary dataset, difficult to fit stochastic models well, results based on simplified model

Related Mission Applications

- Aerospace systems
  - Largely semantic similarities
  - Mission thread studies
- Autonomous robots
  - Task optimization has binary outcomes
  - Route planning
- Wargames

None of this previous work optimizes mission models with high amounts of uncertainty and a binary pass/fail objective

MLO Approach

Mission model input

- Takes in design decisions
- Contains operational and environmental uncertainty
- Outputs success/failure

→

Mission-level optimization

- Formulate to maximize probability of success
- Include large enough Monte Carlo simulation in-the-loop
- Select algorithm
- Run optimization routine
- Compute success rate with very large Monte Carlo simulation

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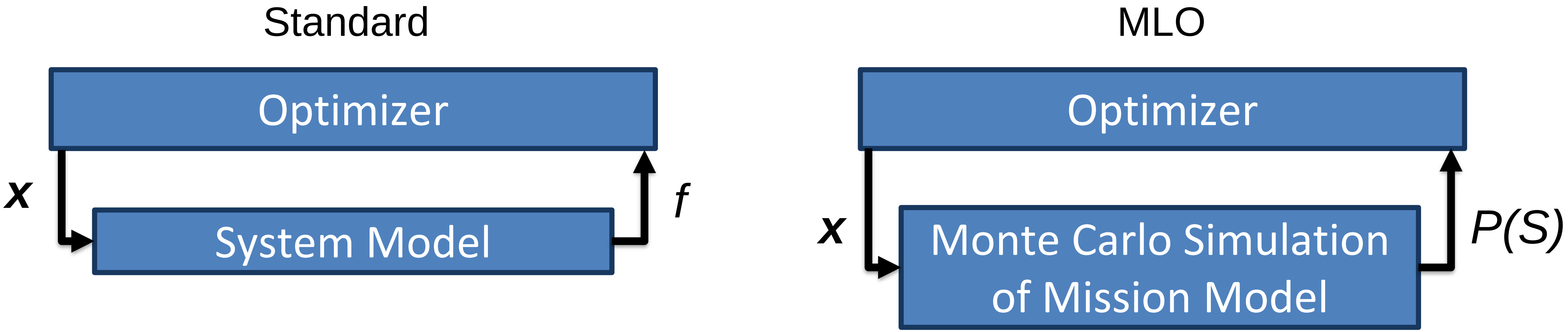
Optimal solution output

- Mission-optimal decision input variables
- Estimated probability of mission success

MLO Approach Comparison

How is this different from standard approaches?



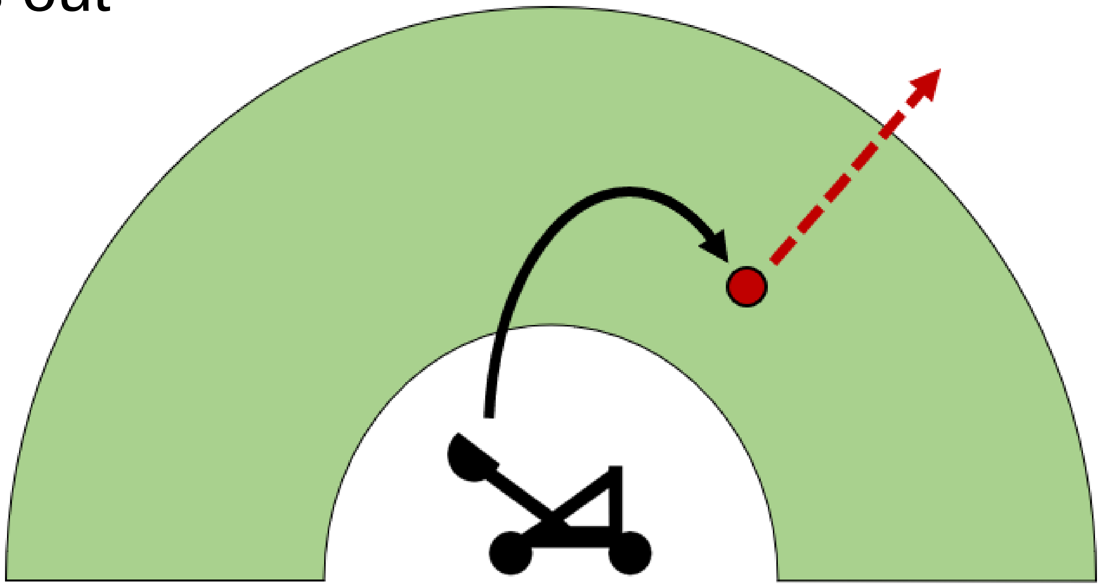
Research Questions

1. How does an MLO solution compare to Pareto-optimal designs from a traditional multiobjective optimization approach, with respect to mission success probability, key performance parameters, and computational resources required?

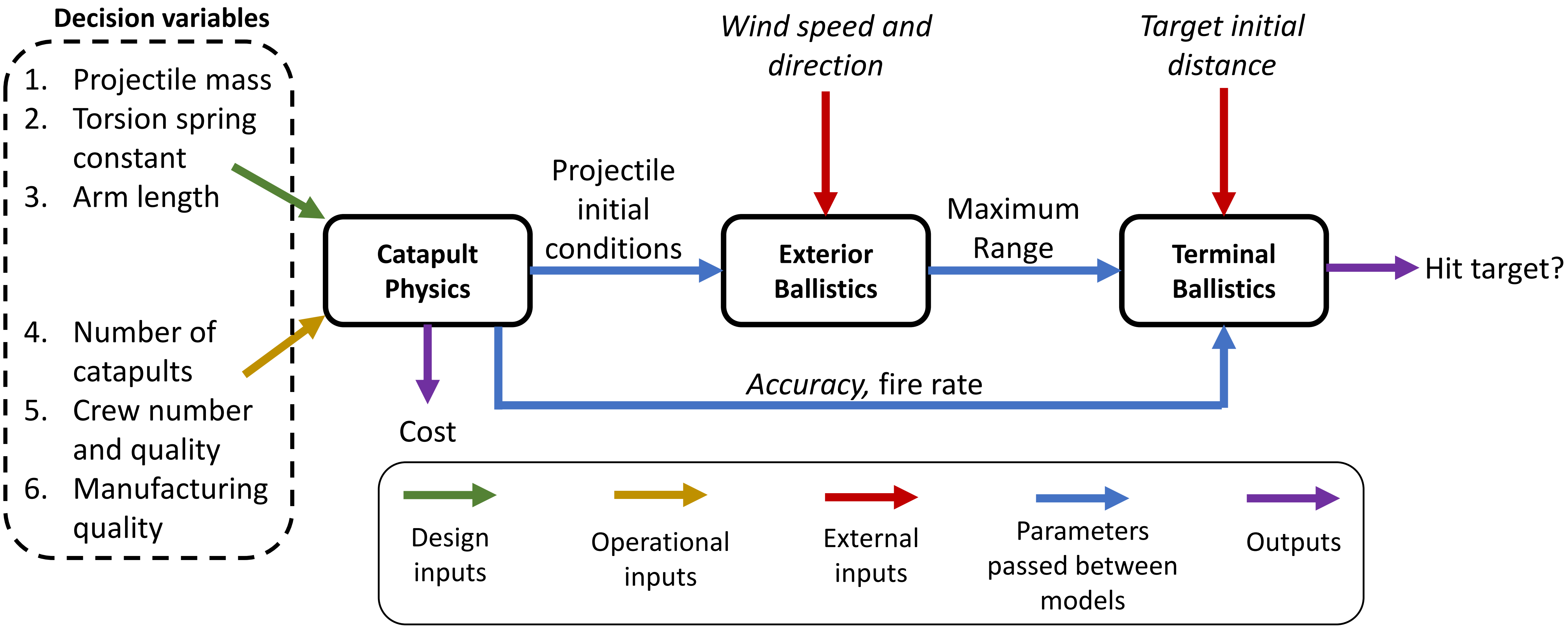
2. How do the choices of optimization algorithm and number of mission model samples affect MLO results?

Catapult Mission Model

- One or several catapults firing at escaping target
- Target appears at random location in front of catapults and escapes directly away
- Very fast run times
- Success: Hitting the target before it escapes out of range
- Physics-based simulations
- Developed with Matlab

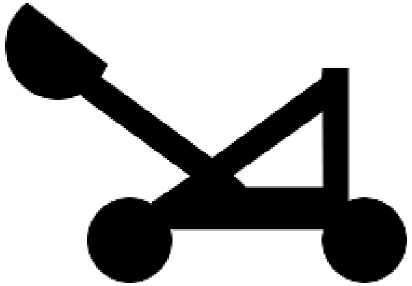


Catapult Model Data Flow



Catapult Decision Variables and Bounds

Input	Symbol (Units)	Lower Bound	Upper Bound	Cost Weight
Number of catapults	$\boldsymbol{n_{cat}}$ (#)	1	8	$\boldsymbol{n_{cat}}$
Mass of projectile	$\boldsymbol{m_p}$ (kg)	1	300	0.1
Spring constant	$\boldsymbol{k}$ (N*m/rad)	10,000	40,000	0.5
Arm length	$\boldsymbol{l}$ (m)	1	15	0.15
Manufacturing quality	$\boldsymbol{q_m}$ (unitless)	0	1	0.5
Crew quality	$\boldsymbol{q_c}$ (unitless)	0	1	0.5

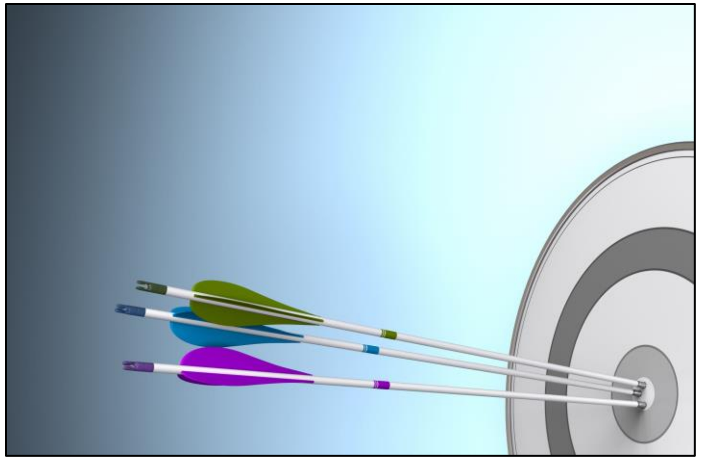


MLO Methodology

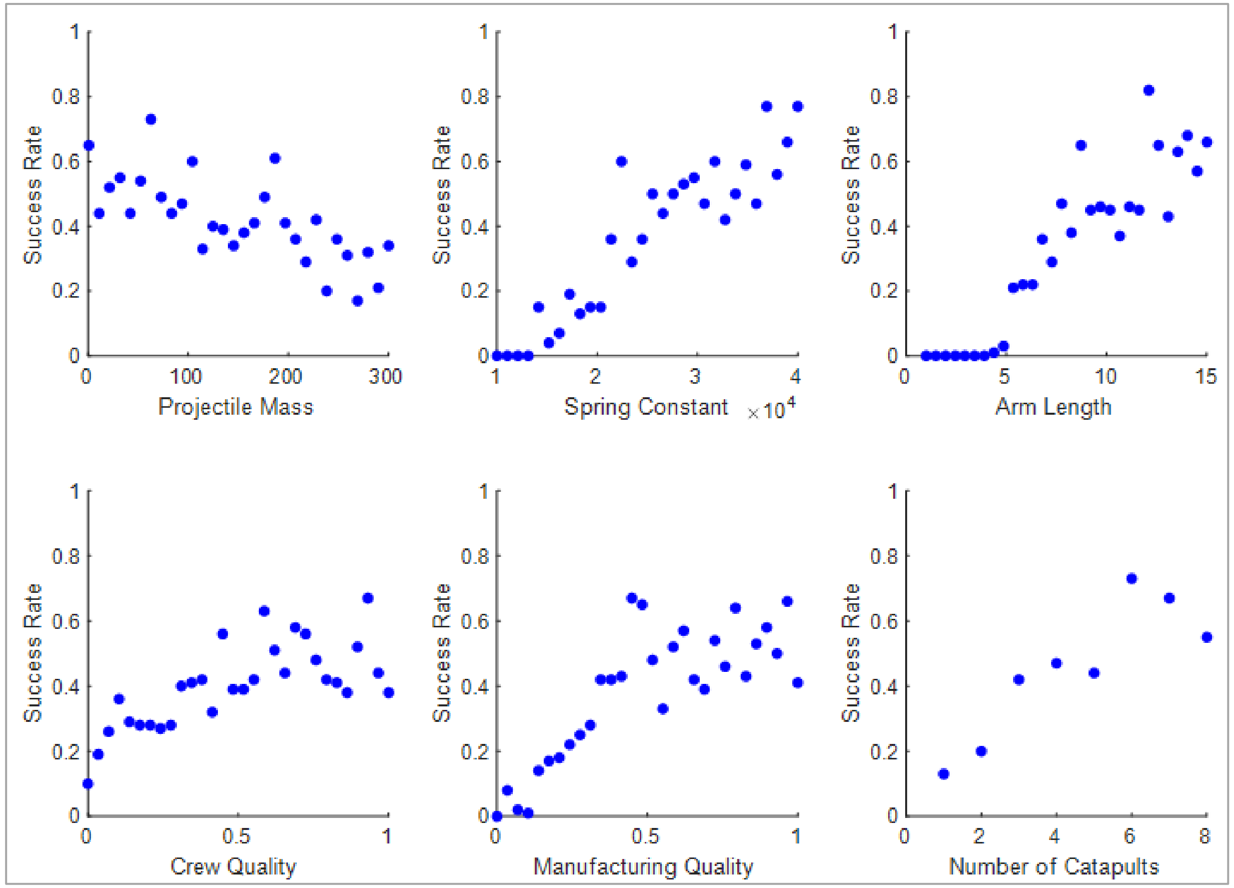
- Three levels of Monte Carlo samples per design tested $(\boldsymbol{n_{samp}})$: 100, 500, 2000
- Genetic (GA) and pattern-search (GPS) optimization algorithms
- Parametric formulation – one routine per $\boldsymbol{n_{cat}}$
- Objective: Maximize *P(S)*
- Constraint: Less than 5 “cost units”
- Probability of success *P(S)* evaluated with 100,000 sample Monte Carlo simulation

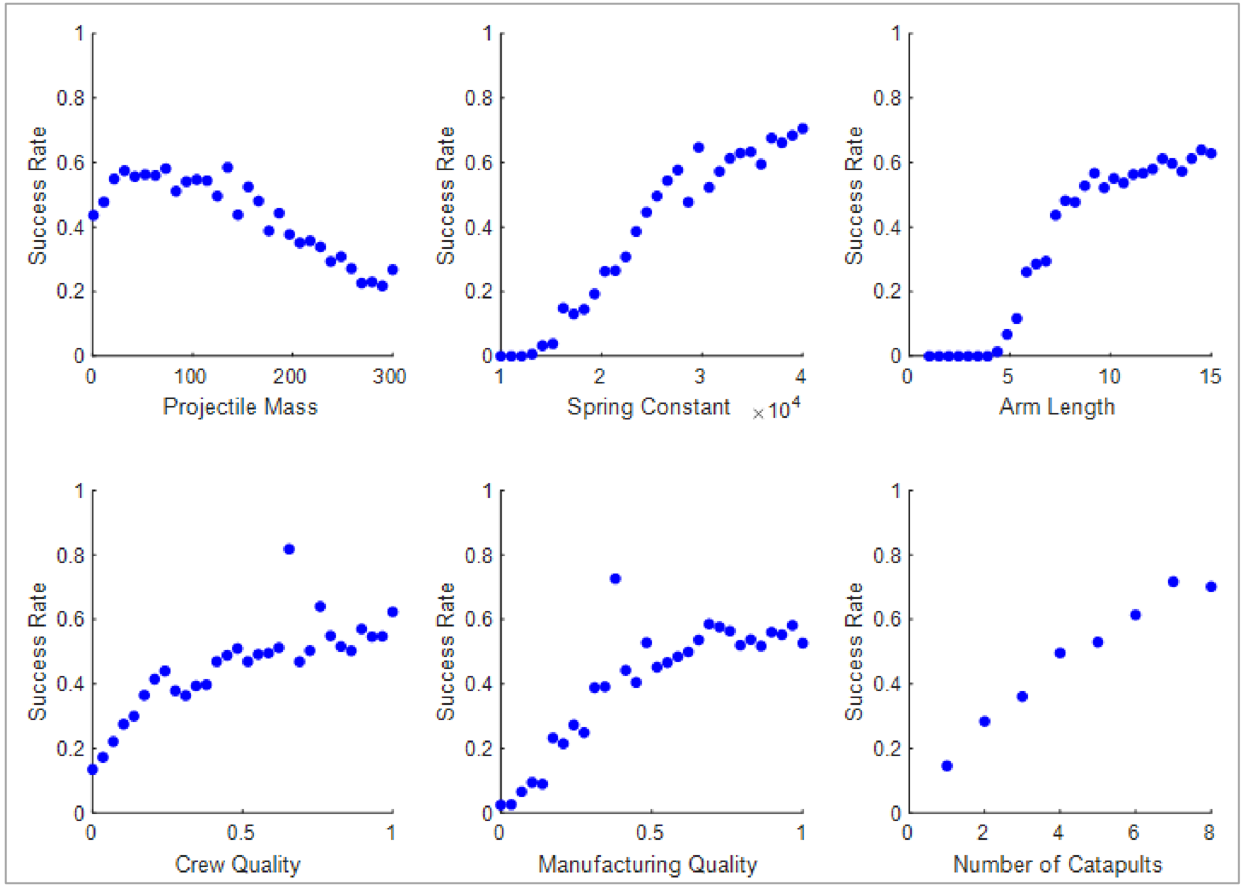
MOO Benchmark Methodology

- Four KPP's used as objectives
  - Minimize targeting error
  - Maximize fire rate
  - Maximize launch distance
  - Maximize projectile radius
- Solved with NSGA-II
- Resulted in 70 Pareto-optimal designs
- Pareto set evaluated with mission model to find *P(S)* for comparison



Sensitivity Analyses





100 Samples per Design

2,000 Samples per Design

Best Design Results

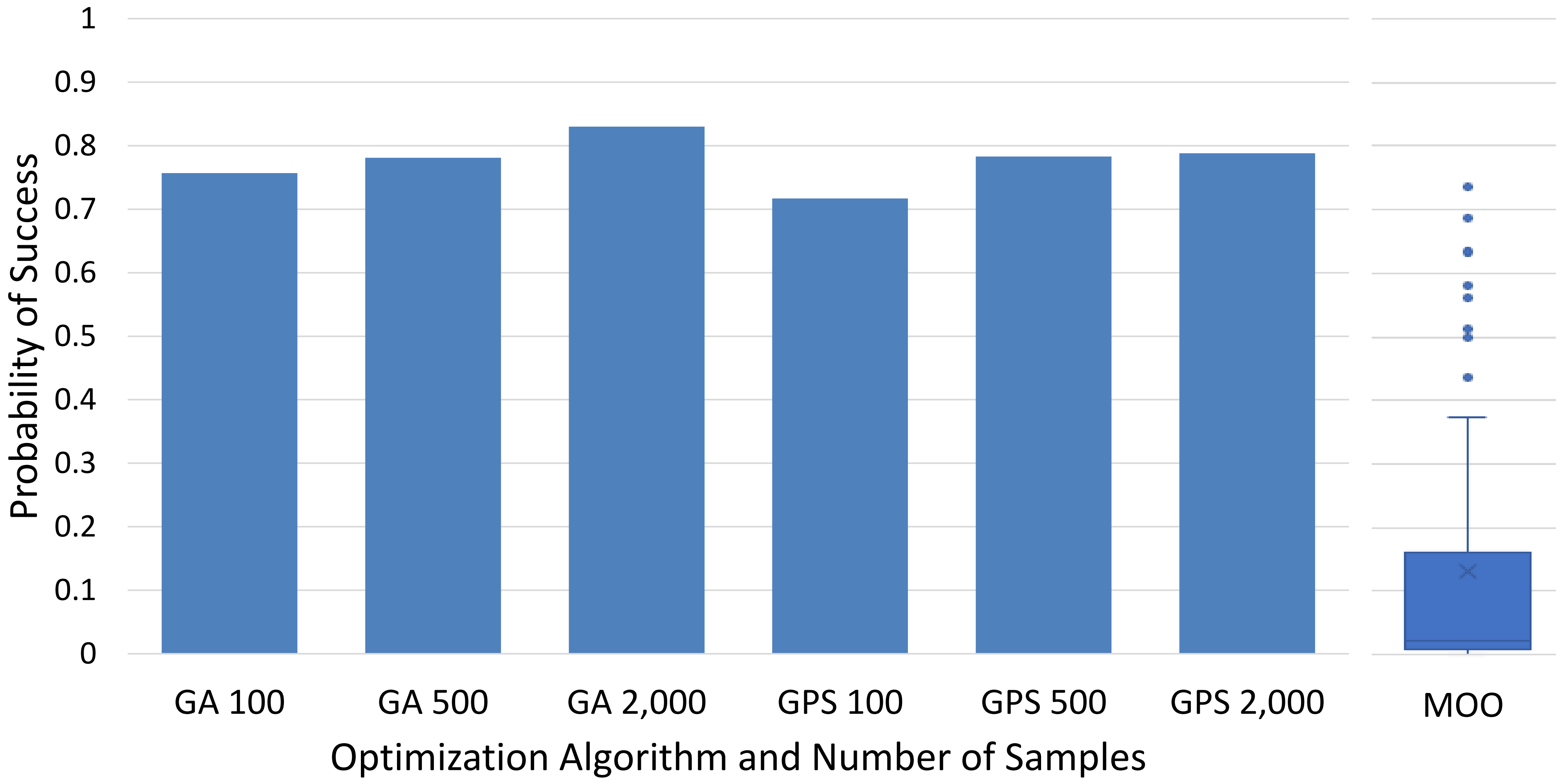
Optimizers

Formulation	n_{cat}	m_p	k	l	q_m	q_c	Fn. Eval.	P(S)
MOO best	4	14.7	37540	5.36	0.589	0.914	7.24×10^6	**0.735**
MLO GA	3	219.3	37460	14.99	0.912	0.882	1.04×10^9	**0.830**
MLO GPS	4	126.2	39720	10.13	0.531	0.746	1.10×10^7	**0.788**

Key Performance Parameters

Formulation	Fire Rate (shot/s)	Accuracy (CEP)	Range (m)	Proj. Rad. (m)	Cost (constraint=5)
MOO best	0.114	8.27	359.7	0.112	4.93
MLO GA	0.118	8.26	375.6	0.276	4.73
MLO GPS	0.110	8.34	373.7	0.229	4.97

Monte Carlo Sample Size and Algorithm Results

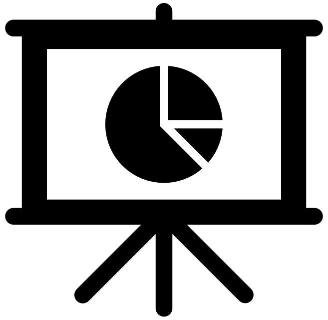


Monte Carlo Sample Size and Algorithm Results

Formulation	Algorithm	n_{samp}	Fn. Eval. (x10^6)	*P(S)*
MOO	NSGA-II	N/A	7.24	**0.735**
MLO	GA	100	21.7	**0.757**
MLO	GA	500	166	**0.781**
MLO	GA	2,000	1040	**0.830**
MLO	GPS	100	1.28	**0.717**
MLO	GPS	500	3.27	**0.783**
MLO	GPS	2,000	11.0	**0.788**

Interpretation of Results

- MLO overall found highly successful designs
- All but one MLO routine found a better *P(S)* than benchmark
- MOO benchmark overall much worse
    - Average *P(S)* = 0.13
    - Only 7 out of 70 solutions had *P(S)* > 0.5
    - Choosing MOO design requires subjective criteria
    - Shows value of both mission modeling and MLO
- MLO is computationally expensive

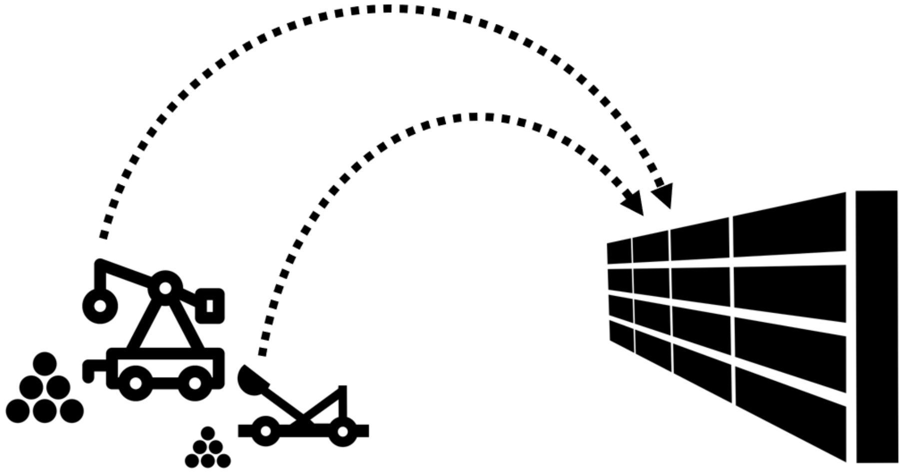


Summary and Contributions

- MLO is straightforward to set up
- Mission model development requires a substantial effort
- MLO routines were able to find successful designs more easily
- High-sample *P(S)* evaluation runs are important to find best designs – without this some parametric MLO solutions would have been suboptimal
- Contributions
  - Formulated and demonstrated a novel method for optimizing mission-level problems
  - MLO approach finds successful designs without subjective decisions

Future Research Opportunities

- Further quantify the influence of optimization algorithm choice and Monte Carlo simulation size on MLO
- Test MLO with more efficient optimization techniques
  - Surrogate-based optimization
  - Multifidelity optimization
- Evaluate MLO with more diverse and complex mission models
- Identify the most suitable methods and tools to create and validate mission models



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Thank you!

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