Statistical Design and Validation of Modeling and Simulation (M&S) Tools Used in Operational Testing (OT)

Kelly McGinnity, Laura Freeman

Institute for Defense Analyses

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Motivation

- **Models and simulations are increasingly becoming an essential element of operational test and evaluation**
  - Collecting sufficient data to evaluate system performance is often not possible due to time, cost, and resource restrictions, safety concerns, or lack of adequate / representative live threats
- **There is currently little to no DoD guidance on the <u>science</u> of validating such models**
  - Which / how many points within the operational space should be chosen for optimal ability to verify and validate the M&S?
  - What is the best way to statistically compare the live trials to the simulated trials for the purpose of validating the M&S?
  - How close is close enough?

Outline

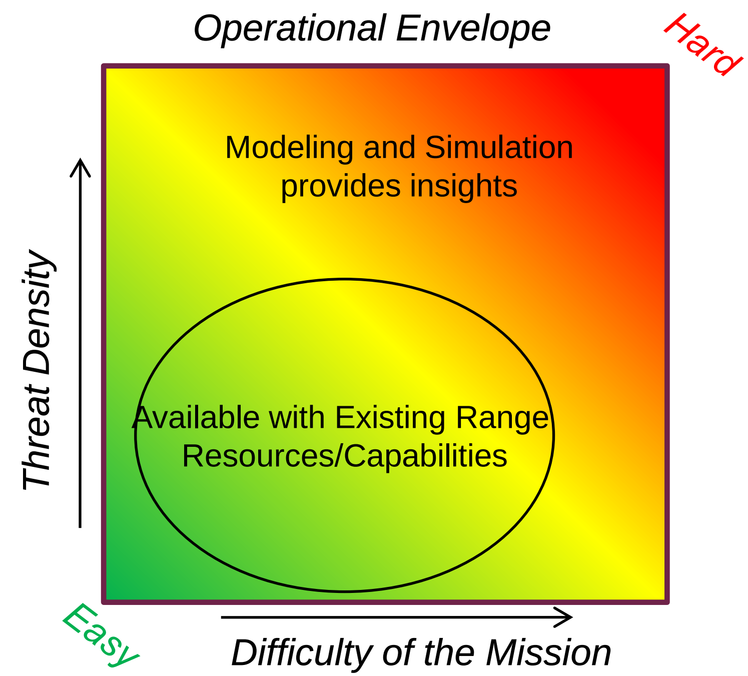
- **Examples of M&S in OT&E**
- **Validating the Simulation**
- **Designing the Simulation Experiment**

Why do I need M&S to assess Operational Effectiveness and Suitability?

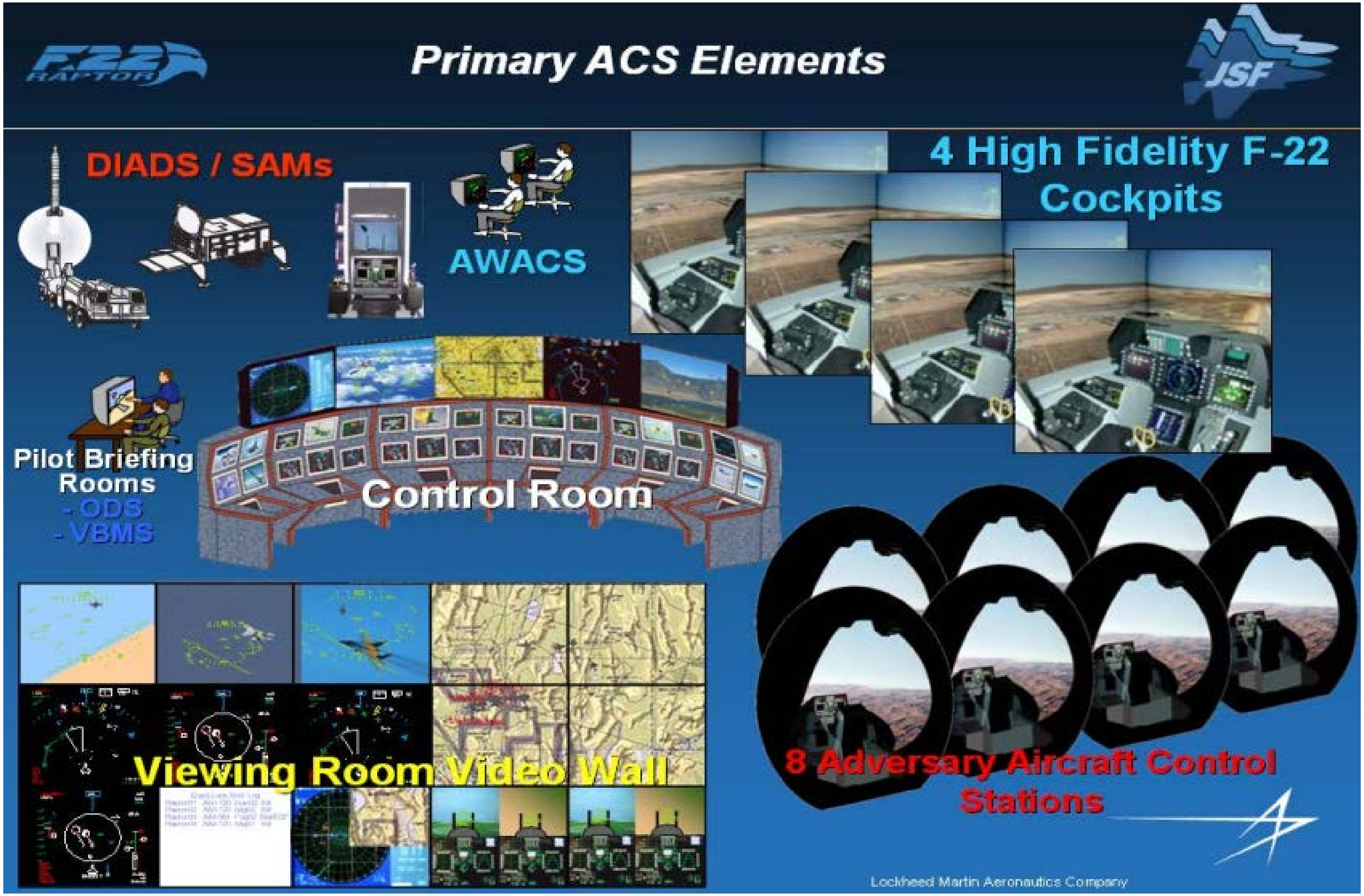
- **Expansion of the operational space from what can be done live**
  – High threat density (air and ground)
- **Frame the operational space**
  – Large number of factors contribute to performance outcomes
- **Improve understanding of operational space**
  – Limited live data available
- **End-to-end mission evaluation**
- **Translation of test outcomes to operational impact**

Expansion of the Operational Space: Air Combat Simulator F-22 Raptor

- **Why we need M&S:**
  - System is specifically designed to operate in higher threat densities and against more challenging threats then we can test open air (5th gen problems)
- **Expanding the Operational Space**
  - Higher air threat densities
  - Supports end-to-end missions with more fidelity than real time casualty assessments
- **M&S Solution:**
  - Complex, integrated simulation capability incorporating multiple simulation integration labs, operator-, hardware-, and software-in-the-loop
  - Allows for end-to-end mission conduct in a simulated environment



Expansion of the Operational Space: Air Combat Simulator (ACS) F-22 Raptor

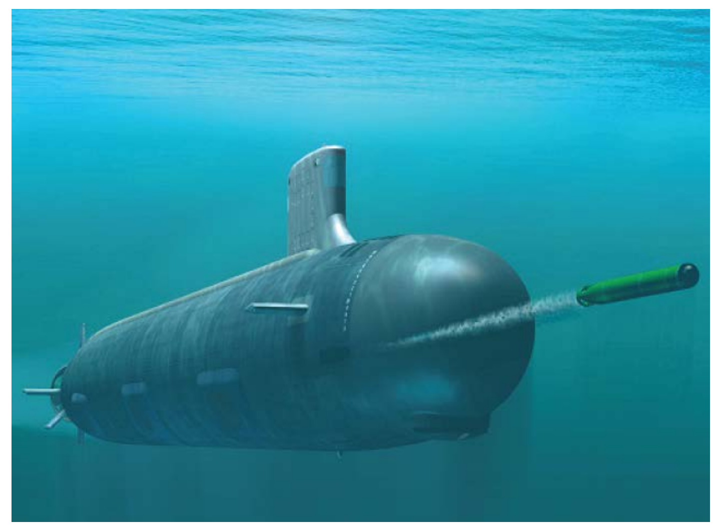


Expansion of the Operational Space: Air Combat Simulator (ACS) F-22 Raptor

- **Leave behind benefits of high fidelity M&S**
  - FOT&E - Large potential reductions in live flight testing if we understand the modeling capabilities
  - Training
  - Tactics Development

Frame the Operational Space: Weapons Assessment Facility (WAF)

- **Hardware-in-the-loop simulation capability for lightweight and heavyweight torpedoes**
- **Creates simulated acoustic environment**
  - Sonar propagation
  - Ocean features
  - Submarine targets
- **Interfaces with torpedo guidance and control scenarios**
- **Why we need M&S?**
  - Complex operational space where performance is a function of many environmental factors
- **Limitations**
  - Computer processing prohibits full reproduction of full ocean conditions which have limited prediction accuracy



Frame the Operational Space: Weapons Assessment Facility (WAF)

Run WAF Simulations

- Dozens of Factors
- Examine Complex Space

Characterize Operational Space

- Determine most important factors from WAF
- Highlight risk areas

Plan Operational Testing

- Use factors identified in WAF (subset of all possible)
- Informed scope

Even when Modeling and Simulation has limited predictive ability it can still be used to inform operational testing

Improve Understanding: PRA Test Bed

- **Question to be addressed:**
  - Self-defense requirements for Navy combatants include a Probability of Raid Annihilation (PRA) requirement
  - To satisfy the PRA requirement, the ship can defeat an incoming raid of anti-ship cruise missiles (ASCM) with any combination of missiles, countermeasures, or signature reduction

- **Why we need M&S:**
  - Safety constraints limit testing
  - No single venue where missiles, countermeasures and signature reduction operate together in OT

Improve Understanding: PRA Test Bed

- **PRA is a federation of models that is fully digital**
  - Many system models are tactical code run on desktop computers
  - Uses high-fidelity models of sensors including propagation and environmental effects
  - Incorporates high-fidelity six-degree-of-freedom missile models

- **Limited "live" data from the Self Defense Test Ship provides limited understanding of PRA**

- **Architecture will be useful for a variety of ship classes**
  - LPD 17 was the first successful implementation – provided more information on PRA under the same conditions as live testing
  - LHA 6, DDG 1000, Littoral Combat Ship, CVN 78 will be examined

End-to-End Mission Assessment: Common Infrared Counter Measures (CIRCM)

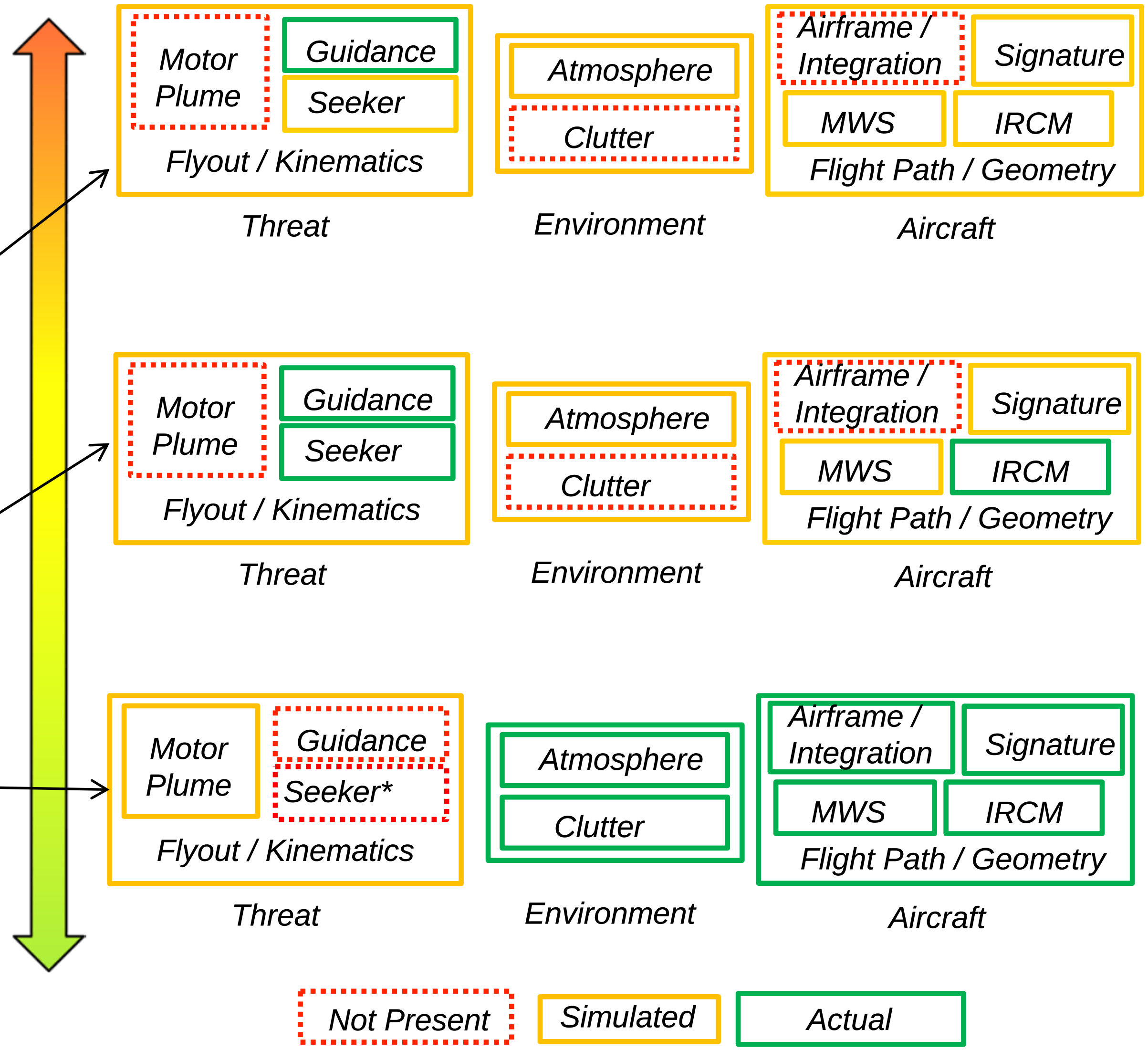
- **System Overview:**
  - Multiband infrared (IR) pointer/tracker/laser jammer for small/medium rotorcraft and small fixed wing aircraft

- **Why we need M&S:**
  - Shooting live missiles at aircraft is difficult

- **M&S Solution**
  - Simulate end-to-end missile engagements by combining results from multiple test facilities using identical initial conditions
  - Allows the full suppression chain to be assessed

End-to-End Mission Assessment: Common Infrared Counter Measures (CIRCM)

- **Integrated Threat Warning Lab**
  - Assess flight path/geometry
- **Threat Signal Processing in the Loop (T-SPIL)**
  - Actual Threat Tracking
- **Guided Weapons Evaluation Facility (GWEF)**
  - Inclusion of actual seeker and countermeasures supports wider operational space
- **Open Air Range, Missile Plum Simulators**
- **Free-Flight Missile Test**
  - Non-representative targets

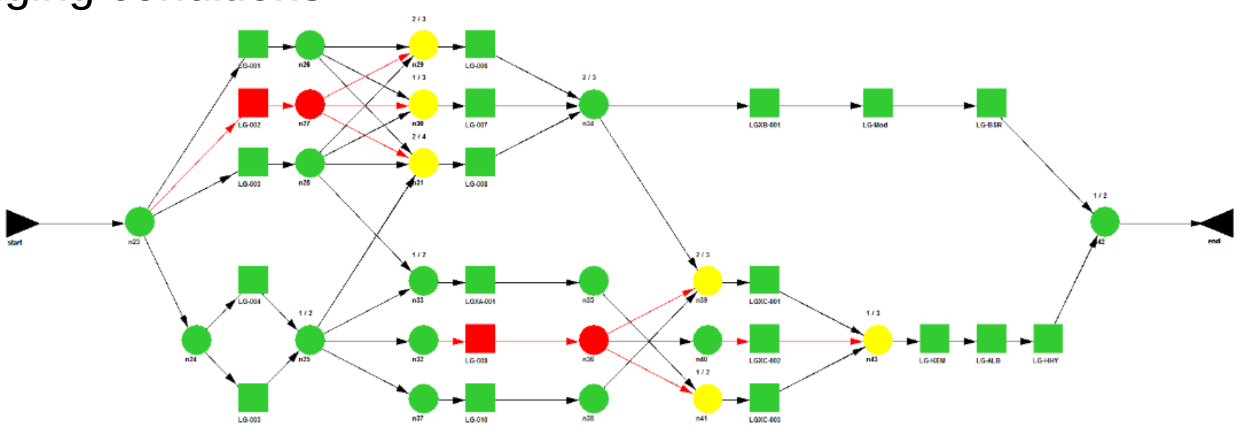


Acronyms this slide: Infrared (IR) Countermeasures (IRCM); Missile Warning System (MWS);

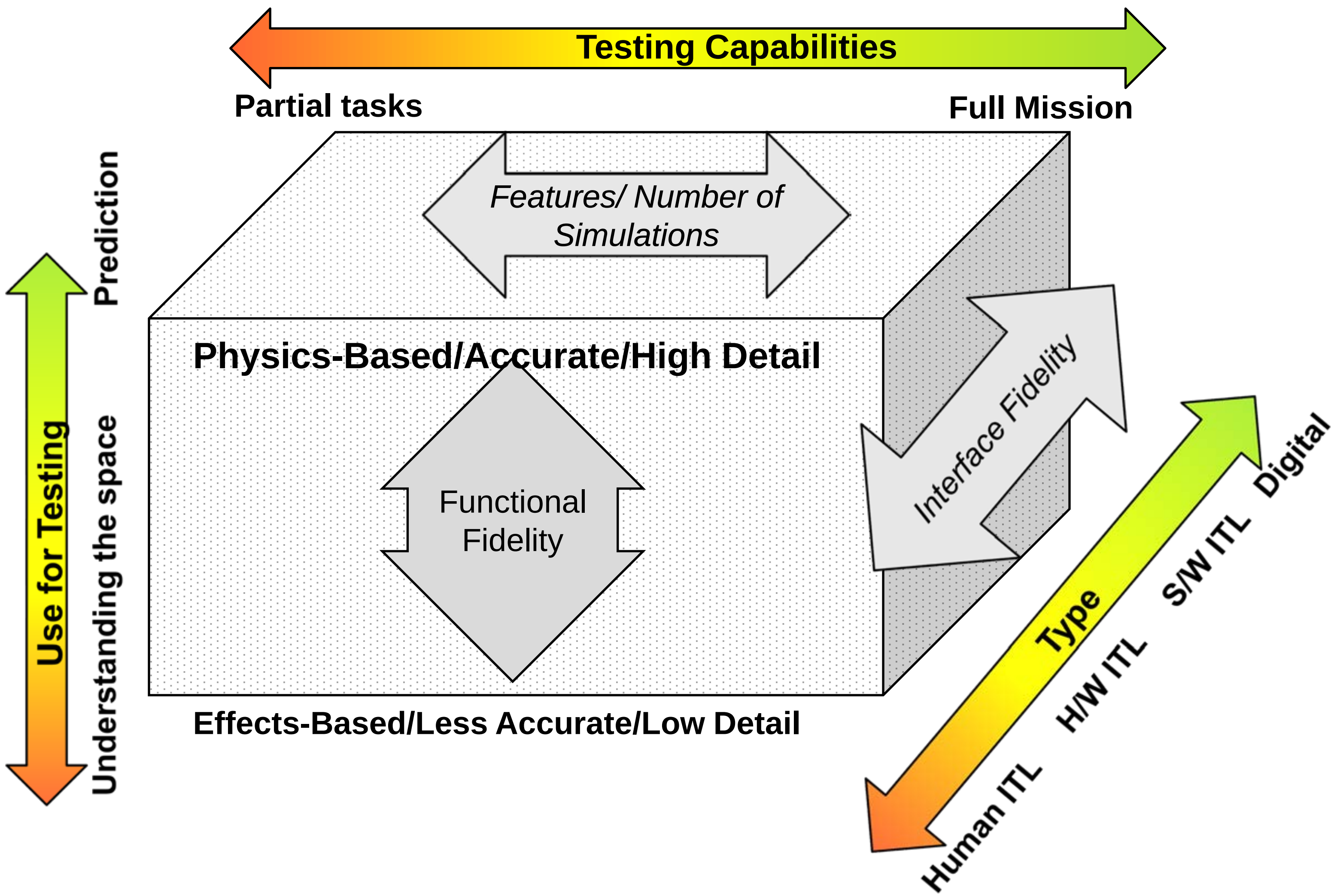
Translation to Operational Impact: Operational Availability

- **For complex systems, the Services use several M&S tools based on discrete event simulations (e.g., Raptor, LCOM) to model Operational Availability (A_O). These digital simulations are based on:**
  1. Reliability block diagrams
  2. Expected component reliability
  3. Expected maintainability

- **Why we need M&S:**
  - Operational Availability cannot be assessed across all mission types during live testing
  - Models are useful for assessing sensitivity of operational availability to changing conditions



Modeling Fidelity Terminology and the M&S Space

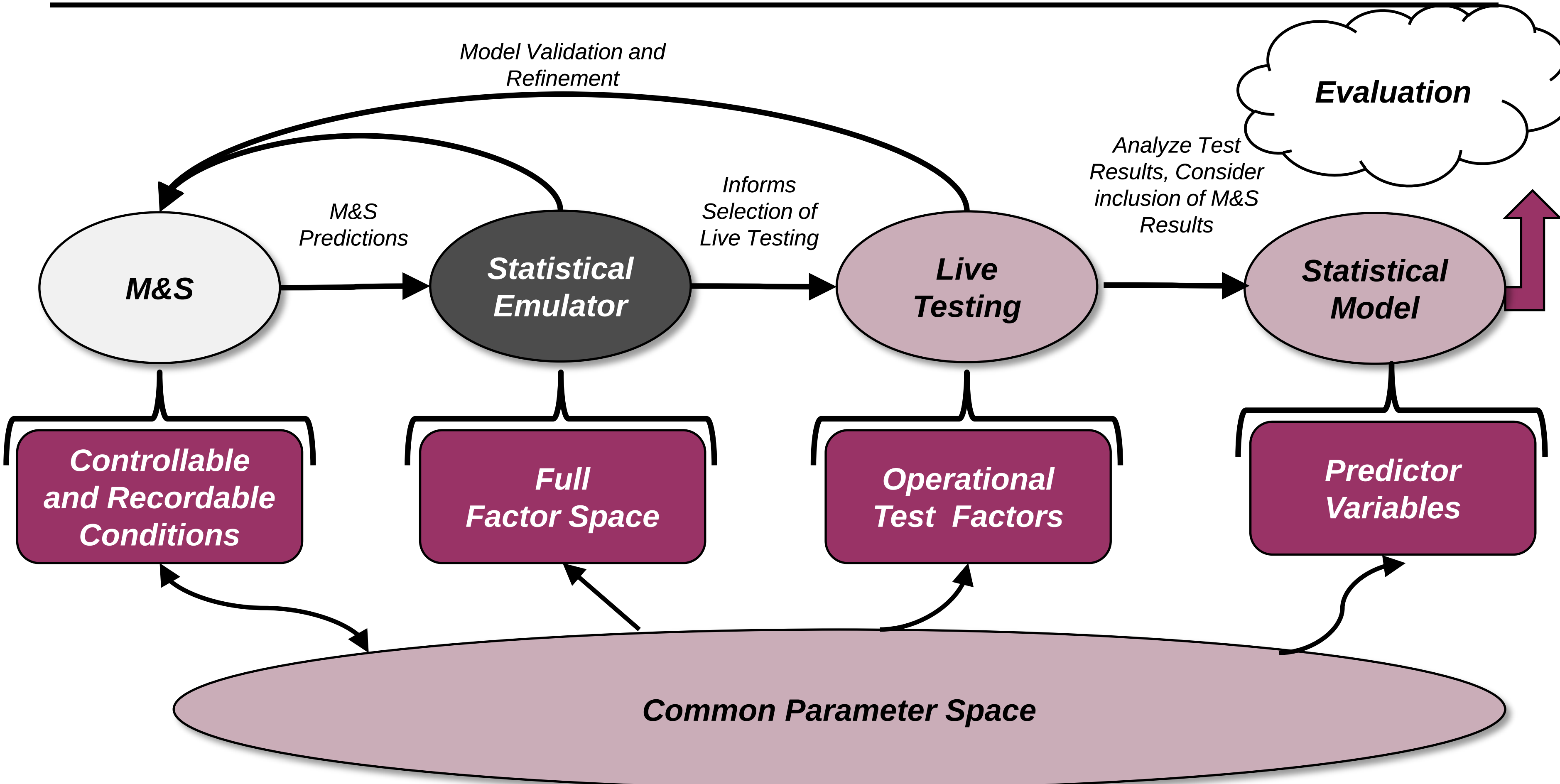


Key Questions

For each goal:

1. **What is the best analysis method for *validating* the simulation?**
2. **What is the best technique for designing the *simulation* experiment?**
3. **What is the best technique for designing the *live* experiment?**

Framework for M&S use in T&E



Identify the common set of variables that spans the operational space

Outline

- Examples of M&S in OT&E
- Validating the Simulation
- Designing the Simulation Experiment

Verification, Validation & Accreditation (VV&A)

- **All M&S used in T&E must be accredited by the intended user. The Director, Operational Test and Evaluation (DOT&E) determines if a model has been adequately VV&A'd to use in Operational Testing.**
- **"<u>Verification</u> is the process of determining if the M&S accurately represents the developer's conceptual description and specifications and meets the needs stated in the requirements document."**
- **"<u>Validation</u> is the process of determining the extent to which the M&S adequately represents the real-world from the perspectives of its intended use."**
- **"<u>Accreditation</u> is the official determination that the M&S is acceptable for its intended purpose."**

"A model should be developed for a specific purpose (or application) and its validity determined with respect to that purpose" (Sargent 2003)

Validation Methods Overview

- **Typically a combination of validation techniques will be used**
  - Comparison to other models
  - Event validity (does the simulation go through all necessary steps?)
  - Face validity (evaluation by subject matter experts)
  - Comparison to historical data
  - Extreme condition comparisons
  - Internal validity
- **Methods that should be used more frequently**
  - Sensitivity analysis – changes to inputs produce reasonable changes to outputs
  - Predictive validation – can the model predict live test outcomes

Challenges

- **Approaches will likely be different depending on:**
  - Type of model (deterministic vs. stochastic, continuous vs. discrete outcome, etc.)
  - Purpose of the model
  - Amount of data available

	Live	
Sim	1,1	1, m
	n, 1	n, m

- **What are the changes in outcomes as we move across test conditions? Do they match live testing?** [Factor Effects]

- **What is the variability within a fixed condition? Is it representative of live testing?** [Run-to-run variation]

- **What defines "matching live testing"? What is close enough?** [Bias and Variance]

- **How do we control statistical error rates?** [Type I and Type II errors]

Existing Methods (DoD)

1,1	1, m
n, 1	n, m

- **Graphical Comparison**
  - Graph test data vs. simulation data, is it a straight line?
- **Confidence Intervals**
  - Comparing confidence intervals about live data to those about sim data
- **Simple hypothesis tests**
  - Compare Means, Variances, Distributions
- **Limitations**
  - Averages over different conditions
    - Combine results and test aggregated data
  - Does not account for factor effects
  - No way to separate problems with bias vs. variance
- **Better Options:**
  - Fisher's combined probability test
  - Regression modeling
  - Logistic regression model emulator for cross-validation and classification

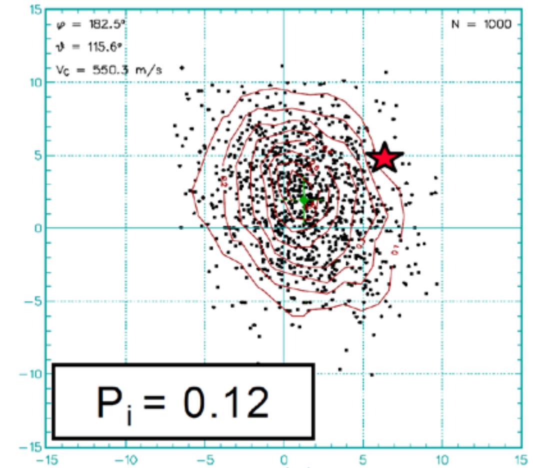
Fisher's Combined Probability Test

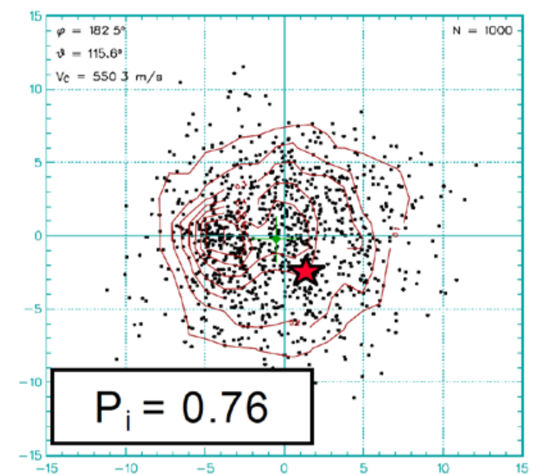
1,1	1, m
n, 1	n, m

- **Applied to validation of missile miss distance**
  - 1 live shot per condition
  - Null hypothesis is that the live shot comes from the same distribution as the simulation "cloud"
  - Tail probabilities under each condition combined using a chi-squared test statistic
    - » $X = -2\,\Sigma \ln(p)$ follows a chi-square distribution with 2N degrees of freedom

- **Strengths**
  - Intuitive way to handle limited data
  - Preferred to the t-test which ignores the variability of the "cloud"
  - Preferred to goodness-of-fit tests for most alternative hypotheses

- **Limitations**
  - Sensitivity to one failed test condition
  - Method requires adjustment if more than 1 live shot per condition is obtained
  - No formal test of factor effects





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Regression Modeling

1,1	1, m
n, 1	n, m

- **Developed for validating the Probability of Raid Annihilation (PRA) Test Bed**
  - The Navy's modeling and simulation venue used to examine the ability of shipboard combat systems to defend a ship against a cruise missile attack
  - Only 1 live shot per test condition (4 threat types)
  - Build a statistical model to compare the M&S results to the live test results and test for significant differences
  - *Detection Range* $= \beta_0 + \beta_1 TestType + \beta_2 TestThreat + \beta_3 (TestType * TestThreat) + \epsilon$

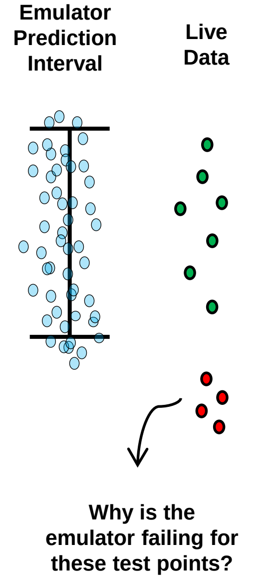
- **Strengths**
  - PRA Testbed runs can be formally compared to the live test events, even when there is limited live data
  - The model allows analysts to test for a Test Type effect, a Test Threat effect, and an interaction effect
    - » If the Test Type effect is not statistically significant then the PRA Testbed runs are providing meaningful data
    - » If the interaction term is significant, there many be a problem with the simulation under some conditions but not others

- **Limitations**
  - Relatively weak test
  - Limited data; cannot differentiate between problems with bias vs. variance
  - Parametric model assumptions questionable

1,1	1, m
n, 1	n, m

Model Emulator for Cross-Validation and Classification

- **Build an empirical emulator (e.g. a logistic regression model) from the simulation**
  - As a new set of live data becomes available, compare each point with the prediction interval generated from the emulator under the same conditions
    - » If a live point falls within the prediction interval, that is evidence that the simulation is performing well under those conditions
  - Compare/model the live points that do vs. don't fall within the emulator prediction intervals and test for any systematic patterns
    - » Will help explain where / why the simulation is failing in certain cases
  - Once the live data is classified or "tested", it can then be used to update the simulation and continue to "train" the model



- **Strengths**
  - Applicable to any amount of live data
  - Can test for factor effects, as well as differentiate between problems with bias and variance (in the case of >1 live shot per condition)
  - Live data serves dual purposes of validating and updating the model
  - Emulator can help inform the live test

- **Limitations**
  - Not reasonable in the case of 1 or very few simulation runs per condition

Validation Recommendations

- **Avoid using basic hypothesis tests or averaging results across conditions**
- **Given limited data and no real factors, Fisher's Combined Probability Test is a reasonable and intuitive approach**
- **Otherwise, one of the modeling approaches is recommended**
  - Allows for rigorous testing of factor effects
- **More advanced methods may become feasible as statistics in the DoD advances and M&S test designs are developed appropriately**

Outline

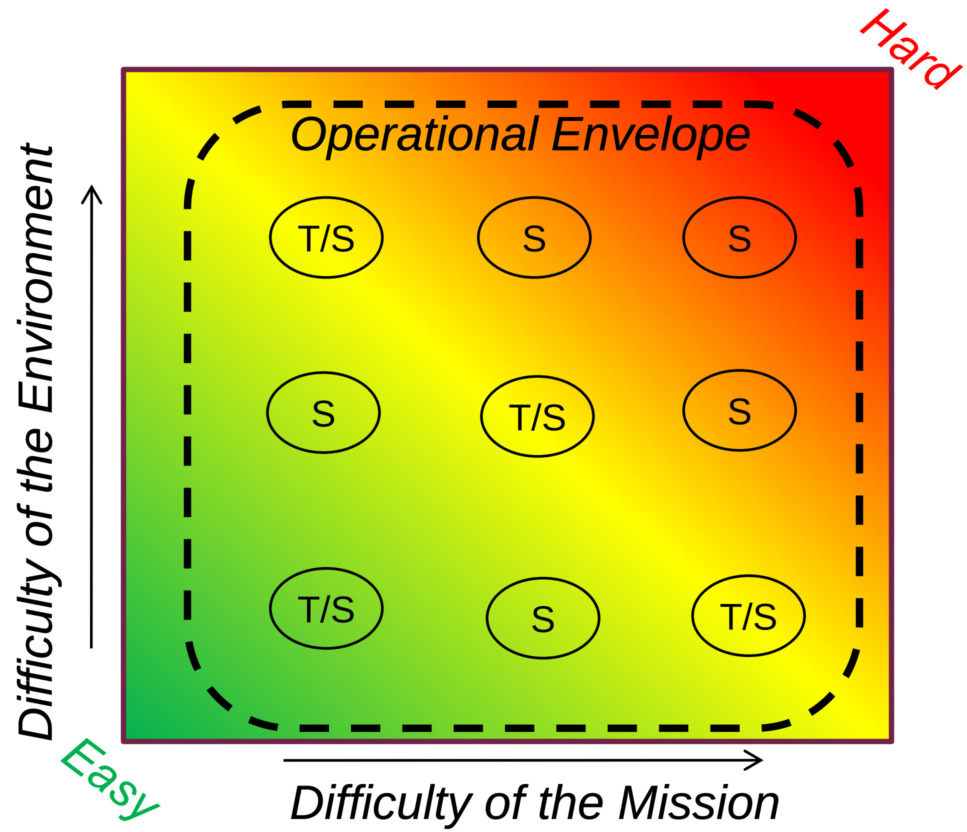
- **Examples of M&S in OT&E**
- **Validating the Simulation**
- **Designing the Simulation Experiment**

DOE for Modeling and Simulation

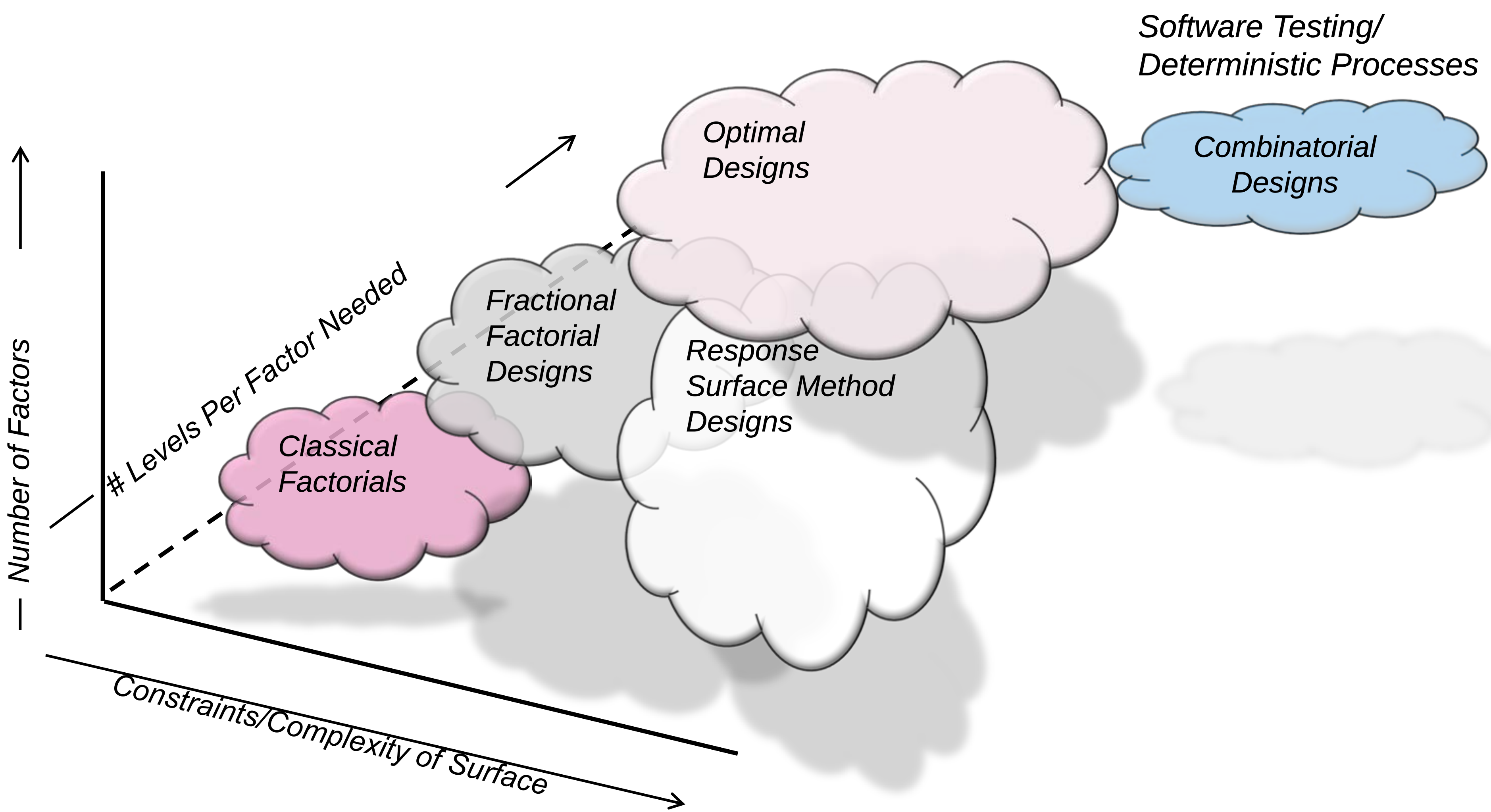
- **Design of Experiments (DOE) provides a framework for selecting:**
  - Which simulation runs?
  - Which live runs?
  - How to validate?

- **Facilitates answering the key validation questions**

1. *What are the changes in outcomes as we move across test conditions? Do they match live testing? [Factor Effects]*
2. *What is the variability within a fixed condition? Is it representative of live testing? [Run-to-run variation]*
3. *What defines "matching live testing"? What is close enough? [Bias and Variance]*
4. *How do we control statistical error rates? [Type I and Type II errors]*



Types of Designs – Overview



How do we choose the best design?

- **Most appropriate design choice depends on:**
  - The purpose of the M&S / goal of the validation analysis
  - The type of simulation (deterministic vs. stochastic)
  - The nature of the data (categorical vs. discrete)
  - The model terms desired to be estimated (e.g. what the “emulator” should look like)

- **Various selection criteria for design evaluation:**
  - High statistical power for important effects
  - Robustness to missing data
  - Low correlation between factors
  - Maximize the number of estimable main effects, two factor interactions and other higher order terms (depending on the goal of the test)
  - Minimize correlation between two-factor interactions and main effects

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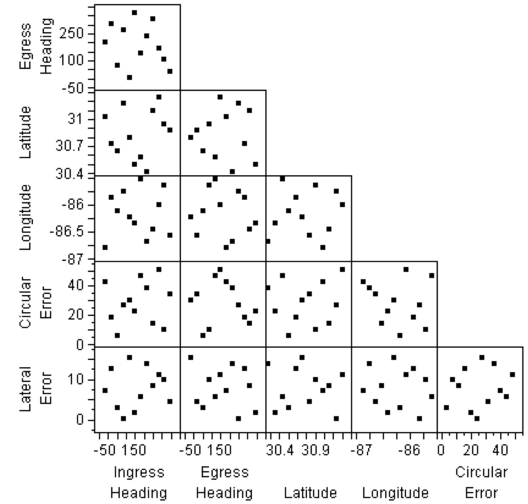
DOE for Deterministic M&S

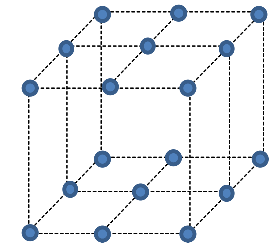
- **Space Filling Designs**
  - An efficient way to search or cover large continuous input spaces
  - Algorithms spread out test points using tailored optimality criteria
  - Analyzed via Gaussian process models
- **Factor Covering Arrays**
  - Type of combinatorial design; used to find problems
  - An efficient way to test when the space is large and made up of combinations of selections (categorical / binary input)
- **Computer simulation experiments**
  - Many recent methods in academic literature
  - Parameter calibration using Gaussian Stochastic Process Models
  - Bayesian techniques



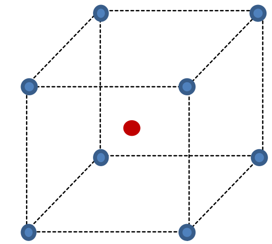
0	0	0	0	0	0	0	0	0	0
1	1	1	1	1	1	1	1	1	1
1	1	1	0	1	0	0	0	0	1
1	0	1	1	0	1	0	1	0	0
1	0	0	0	1	1	1	0	0	0
0	1	1	0	0	1	0	0	1	0
0	0	1	0	1	0	1	1	1	0
1	1	0	1	0	0	1	0	1	0
0	0	0	1	1	1	0	0	1	1
0	0	1	1	0	0	1	0	0	1
0	1	0	1	1	0	0	1	0	0
1	0	0	0	0	0	0	1	1	1
0	1	0	0	0	1	1	1	0	1

DOE for Stochastic M&S

- **Classical Factorial Designs**
  - Full coverage
  - Highest fidelity
  - All model terms estimable
- **Screening Designs (e.g. Fractional Fact.)**
  - Good for testing many factors at once
  - Lower fidelity
  - Some aliasing / inestimable terms
- **Response Surface Designs**
  - Best for a characterizing a few continuous factors
  - Allows testing for curvature
- **Optimal Designs**
  - Most efficient and flexible
  - Allows for constrained spaces, disallowed combinations, etc.



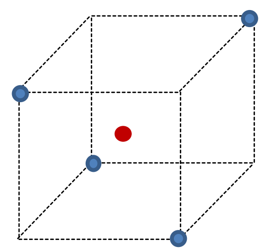
General Factorial
3x3x2 design



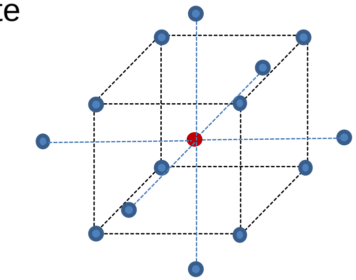
2-level Factorial
2^3 design

single point

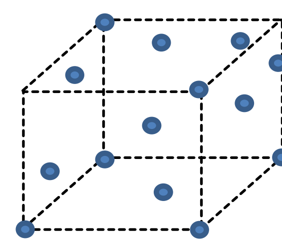
replicate



Fractional Factorial
2^{3-1} design



Response Surface
Central Composite design



Optimal Design
IV-optimal

Design Recommendations by Goal

- **Expansion of the operational space from what can be done live**
  – Need to facilitative extrapolation across the space
  – Classical factorial designs, Response Surface, Optimal
  – Ensure there is some overlap (anchor points) between live test and simulation experiment if possible

- **Frame the operational space**
  – Many potential factors
  – Screening or Optimal designs

- **Improve understanding of operational space**
  – Limited live data
  – Replicate live points
  – Space Filling (if deterministic), Response Surface or Optimal otherwise

- **End-to-end mission evaluation**
  – Design must be repeatable across venues
  – Factorial or Response Surface

- **Translation of test outcomes to operational impact**
  – Test for sensitivity to changing conditions
  – Space Filling / Covering Arrays (if deterministic), Response Surface or Optimal otherwise

Conclusions

- **Statistical rigor of M&S validation in OT needs improvement**
- **The goal of the M&S and its role in OT evaluations should inform both the design of the simulation experiment and the analysis method used to validate it**
- **Design of experiments techniques can improve the efficiency of testing and optimize the information gained**
  - The dual purpose of live testing (characterization and validation) needs to be considered
- **Rigorous statistical analyses can characterize the extent to which the simulation matches the live data**
  - Process should be iterative
- **More work to be done via future research, case studies, and policy guidance**

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BACK UP

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Existing Advanced Statistical Methods

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n, 1	n, m

- **Bayesian parameter calibration using Gaussian Stochastic Process Models (Johnson et al. 2008, Bates et al. 2006, Kennedy and O'Hagan 2001)**
  - Use physical data to calibrate the computer experimental data and estimate unknown parameters
  - Uses basis functions for computing mean and variance

- **Modified calibration of models (Rui Tuo & C.F. Jeff Wu 2013)**
  - Modified Kennedy & O'Hagan (2001) – Kernel based, not Bayesian
  - Find parameter which minimizes L2 distance between computer model and "reality"
  - Estimate "real" model from Kernel interpolation and Gaussian Process Prediction

- **Recursive Bayesian Hierarchical Modeling (Shane Reese et al 2004)**
  - Use computer model outputs and expert opinion to improve estimation and predication of a physical process

- **Hierarchical linear models**
  - Remove the variation due to covariates first, then test live vs. sim

- **Limitations**
  - Complex methodologies limit DoD application
  - Current M&S designs do not support Gaussian Stochastic Process models
  - Focus is on improving prediction, we simply need to validate and state limitations