Uncertainty Quantification-driven Model-Based Engineering for DoD System Design and Evaluation

Sponsor: DASD(SE)

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Problem Statement

Problem:

There is currently significant emphasis on, and need for, the use of computational modeling & simulation (M&S) as a key component of development, test and evaluation of Warfighter systems within the Department of Defense [1].

This work focuses on developing a framework for integrating M&S and UQ-base probabilistic methods into the DoD systems engineering process, and leveraging M&S data to augment empirical models from 'live' testing/experimentation (especially when this testing is expensive or resource intensive) using Uncertainty Quantification techniques [2], with an emphasis on visual data assimilation methods.

The intent is to provide decision-makers with richer information for design decisions prior to prototype build, a simplified and credible approach to determine the utility of the M&S model in augmenting live testing, determine the need for additional testing, and determine the range of applicability for data augmentation relative to inherent system variation.

The purpose is to inform the SE process, particularly physical and functional decomposition, concept selection, system design-build-test with accurate M&S-based prediction and test results.

Definitions

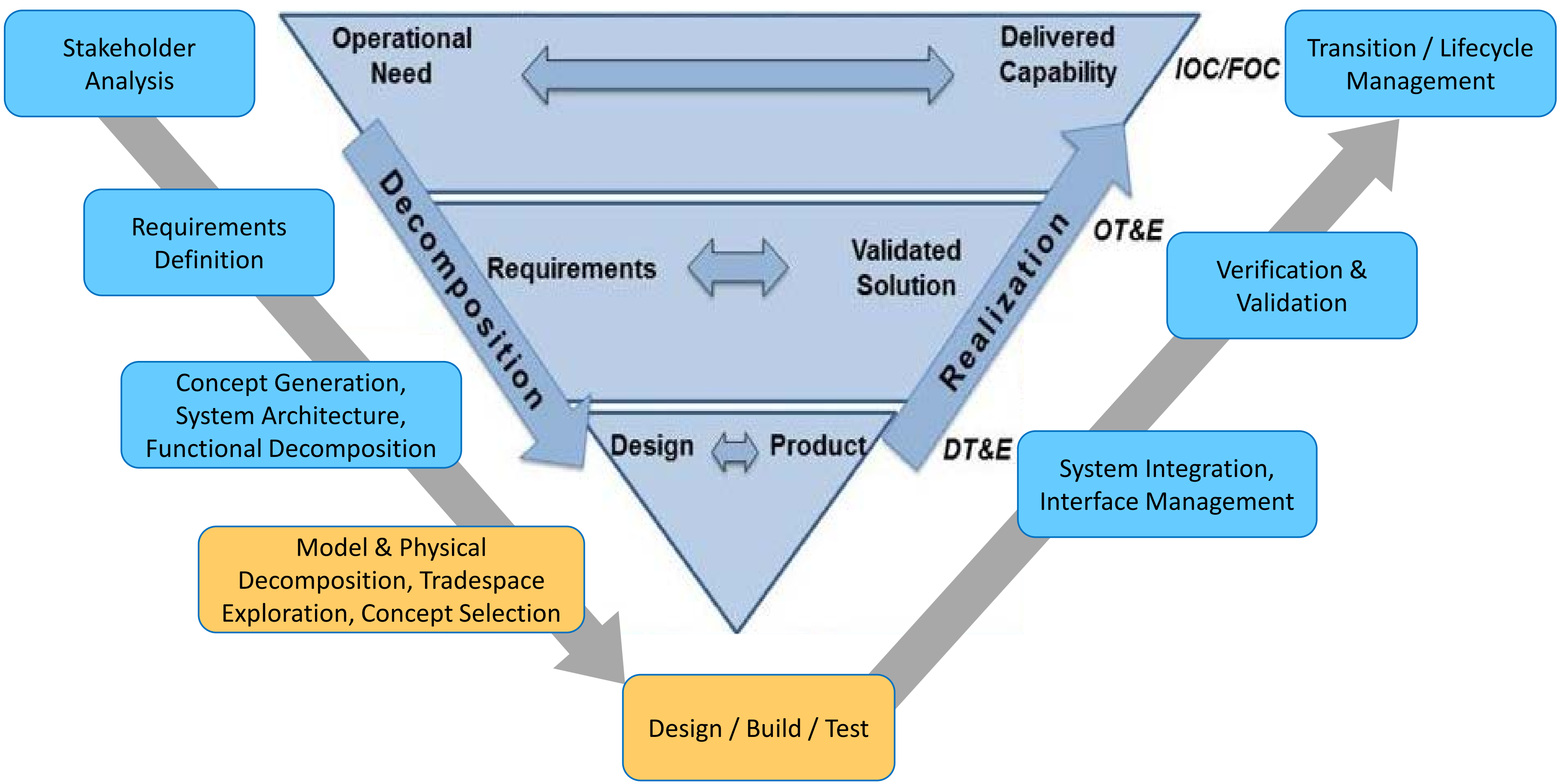
Model-Based Engineering (M&S):

An approach to engineering that uses models as an integral part of the technical baseline that includes the requirements, analysis, design, implementation, and verification of a capability, system, and/or product throughout the acquisition lifecycle.

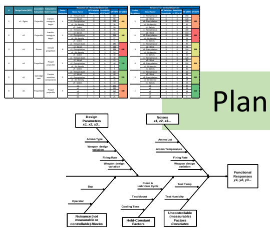
Uncertainty Quantification (UQ):

The process of identifying all relevant sources of uncertainties, characterizing them in all models, experiments, comparisons of M&S results and experiments, and of quantifying uncertainties in all relevant inputs and outputs of the simulation or experiment.

Systems Engineering Process



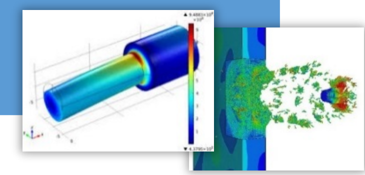
Overarching Probabilistic M&S Framework: Digital Engineering

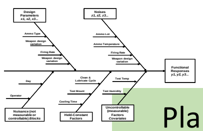


Planning

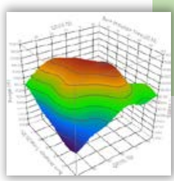
Computational Modeling & Simulation

- Aeroballistics
- Thermodynamics
- Materials & Additive Man.
- Reliability Availability POFA
- Structural Modeling
- Computational Chemistry
- Cost Modeling
- Throughput / Yield Forecast



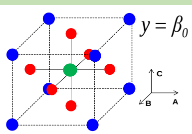


Planning



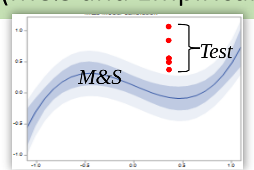
Computational M&S Emulation / Reduced-Order Modeling

'Live' Testing & DOE-based Empirical Modeling



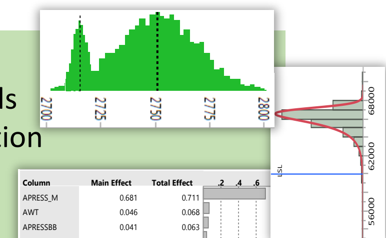
$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_{12} x_1 x_2 + \varepsilon$$

Data Assimilation / V&V (M&S and Empirical)



Sensitivity Analyses:

- Probabilistic Methods
- Numerical Optimization
- Error Propagation
- Capability Analysis
- Tradespace Studies
- Inverse Propagation
- Reliability-based design optimization

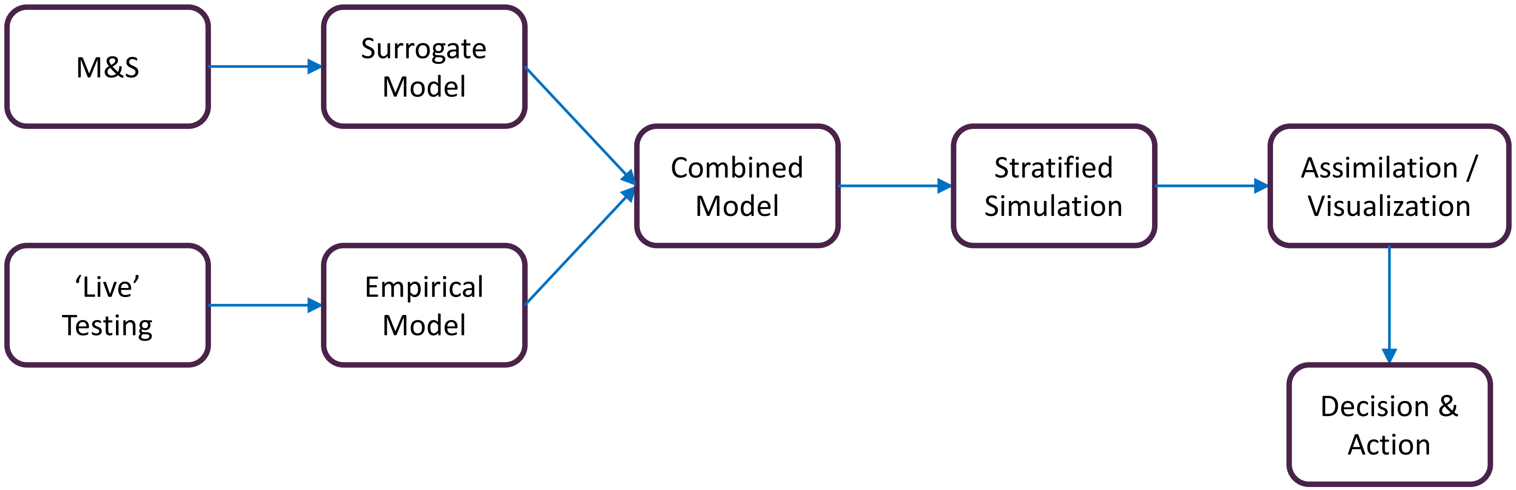


Column	Main Effect	Total Effect
APRESS_M	0.681	0.711
AWT	0.046	0.068
APRESSBB	0.041	0.063
BBANG	0.027	0.044
CANTLEN	0.026	0.042
BBSHAPE	0.018	0.03
ALENGTH	0.008	0.016
AIZZ	0.007	0.015

Results:

- ✓ Reliable, Robust, Optimized Products & Systems
- ✓ Credible and Defensible Engineering M&S Analytics
- ✓ Reduced Design Cycle Iterations; time to field
- ✓ ID'd opportunities to reduce manufacturing costs
- ✓ Reduced performance variation

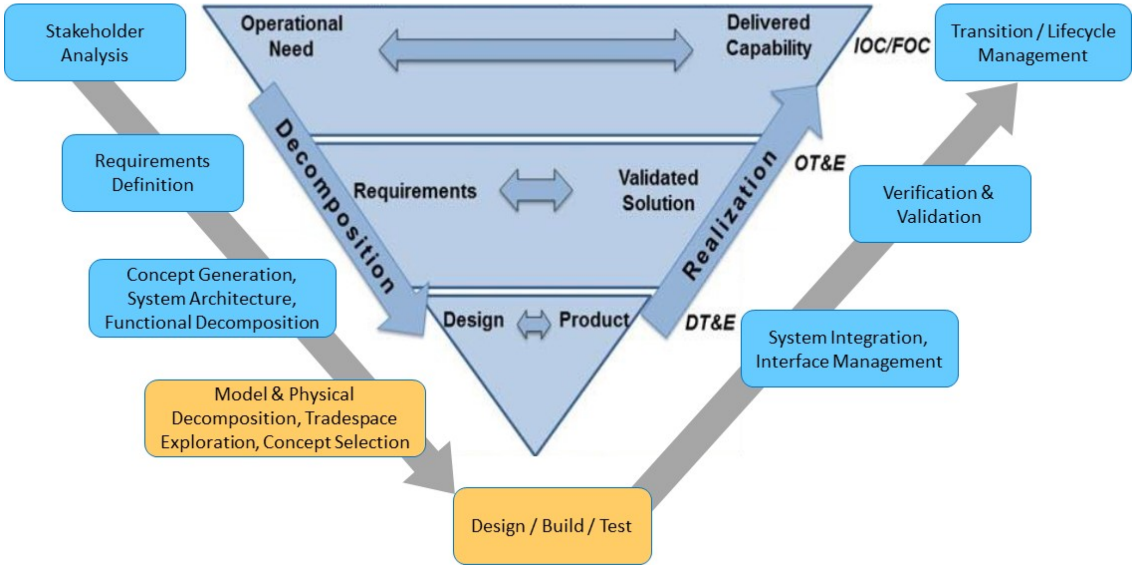
Area of Focus



- 'Data Assimilation' - integration of M&S and 'live' data
- How realistic and credible are the model predictions throughout the design space relative to estimated variation?
  - Decision-maker can ID low-reliance (high-risk) regions of the design space relative to random variation and propagated error across simulated model data
- Approach: Ensemble Modeling, Crossvalidation, Dimension Projection, Monte-Carlo Filtering, Multidimensional Data Visualization

Case Study

- Munition example (anonymized for operational security reasons):
  - —Key performance parameter: long-range target engagement capability
  - —Engineering team executes pre-prototype M&S of various subsystems:
    - o Aero, structural, interior ballistics, lethality, MBSE/functional architecture, etc



Aero Case Study - Background

- 6-DoF Aeroballistic model is developed to verify that tentative airframe design performs as intended across trajectory
- What happens to our ability to meet KPP (long-range target engagement capability, in terms of impact errors in the x- and y-directions and velocity) when we vary initial velocity, launch disturbances in the x- and y-axis, and spin rate of the munition (Hz); given tentative design (canard/fin geometry, projectile geometry, CG, etc)?
  - Resulting Velocity (velocity decay)
  - Other unintended consequences to the system (pressures required to achieve velocity/range, and impact of those pressures on system reliability / parts fatigue)

Case Study - Approach

- Objective: Study the impact of varying Aero inputs on the outputs, then explore tradespace to determine aero solution which minimizes x- and y-dispersion errors, and maximizes downrange velocity retention

- How: Simulate the model in various scenarios to support a DOE-based model emulator/surrogate model
  - —Can use emulator to rapidly execute what-if analysis, sensitivity analysis, optimization and robustness analysis

Case Study - Analysis

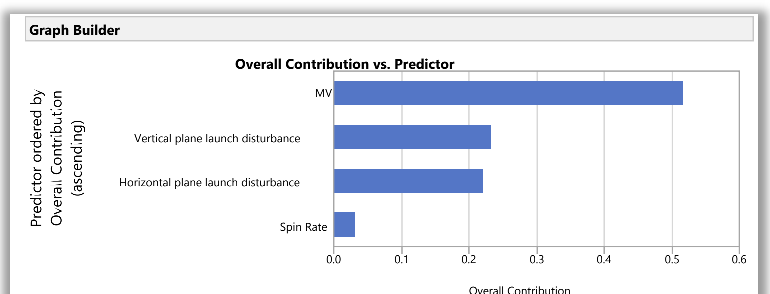
- Simulation DOE
- Emulation / Empirical Model Fitting
- Numerical Optimization & Propagation of Error
- Monte-Carlo Simulation, Sensitivity Analysis & KPP validation

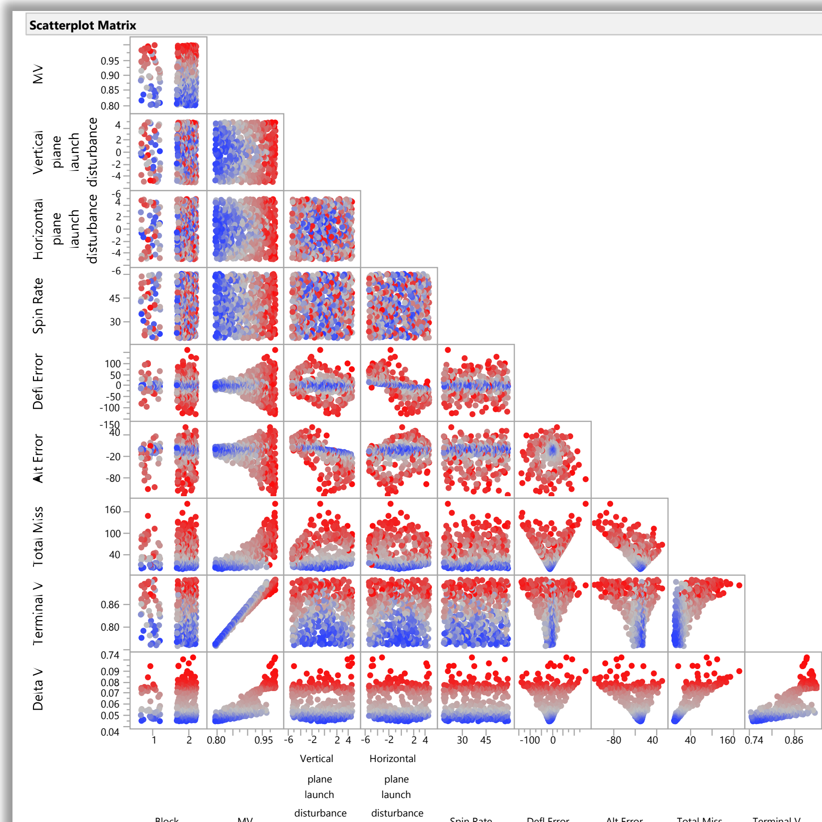
Simulation DOE

Input Variable	Factor	Units	Low	High
x1	MV	--	0.8	1.0
x2	Vert Launch Dist	Rad/sec	-6	6
x3	Horz Launch Dist	Rad/sec	-6	6
x4	Spin Rate	Hz	20	60

Output Variable	Response
y1	Delta Vel
y2	Final Vel
y3	Deflection Error (X)
y4	Altitude Error (Y)

- 400 run Sequential MaxPro Latin Hypercube Space-Filling DOE
- Colored by 'Velocity Delta' response (red = greatest velocity decay)





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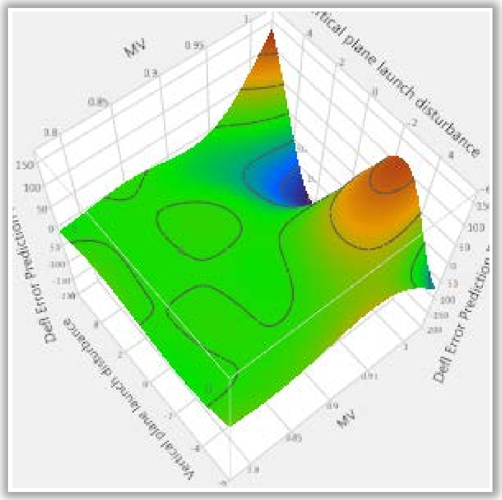
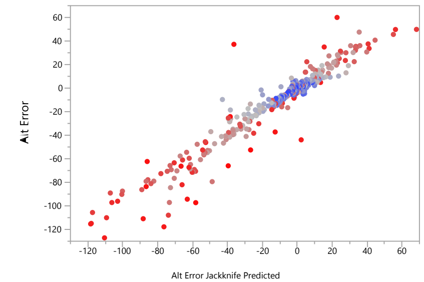
Response Emulator

- Fit the simulation data emulator for each response using Gaussian Process Model (Kriging model w/ Gaussian correlation function)
- MV contributes the most variation to responses, and SR contributes the least
- Strong interaction effect between MV and Launch Disturbances
  - ‘Hypersensitivity’ to launch disturbance as MV increases beyond ~0.95



Gaussian Process Model of Alt Error

Actual by Predicted Plot



Model Report

Column	Theta	Total Sensitivity	Main Effect	MV Interaction	Vertical plane launch disturbance Interaction	Horizontal plane launch disturbance Interaction	Spin Rate Interaction
MV	40.412336	0.3639803	0.0948706	.	0.166261	0.1027922	5.6512e-5
Vertical plane launch disturbance	0.0212357	0.6301243	0.4431235	0.166261	.	0.0174395	0.0033002
Horizontal plane launch disturbance	0.0319107	0.2123734	0.0869223	0.1027922	0.0174395	.	0.0052194
Spin Rate	1.2247e-5	0.0087911	0.0002149	5.6512e-5	0.0033002	0.0052194	.

μ	σ²	Nugget
-68.65742	48382.389	0.001

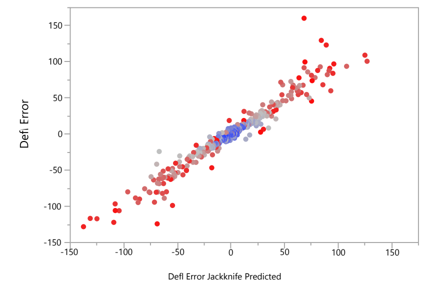
-2*LogLikelihood
3127.8517

Fit using the Gaussian correlation function.

Nugget parameter set to avoid singular variance matrix.

Gaussian Process Model of Defl Error

Actual by Predicted Plot



Model Report

Column	Theta	Total Sensitivity	Main Effect	MV Interaction	Vertical plane launch disturbance Interaction	Horizontal plane launch disturbance Interaction	Spin Rate Interaction
MV	50.014006	0.2981349	0.0002779	.	0.1171111	0.1804789	0.0002671
Vertical plane launch disturbance	0.0386488	0.2384236	0.089576	0.1171111	.	0.0264538	0.0052827
Horizontal plane launch disturbance	0.0349819	0.6789286	0.468418	0.1804789	0.0264538	.	0.0035778
Spin Rate	0.0000168	0.0091837	0.0000562	0.0002671	0.0052827	0.0035778	.

μ	σ²	Nugget
52.206007	58815.66	0.001

-2*LogLikelihood
3319.9344

Fit using the Gaussian correlation function.

Nugget parameter set to avoid singular variance matrix.

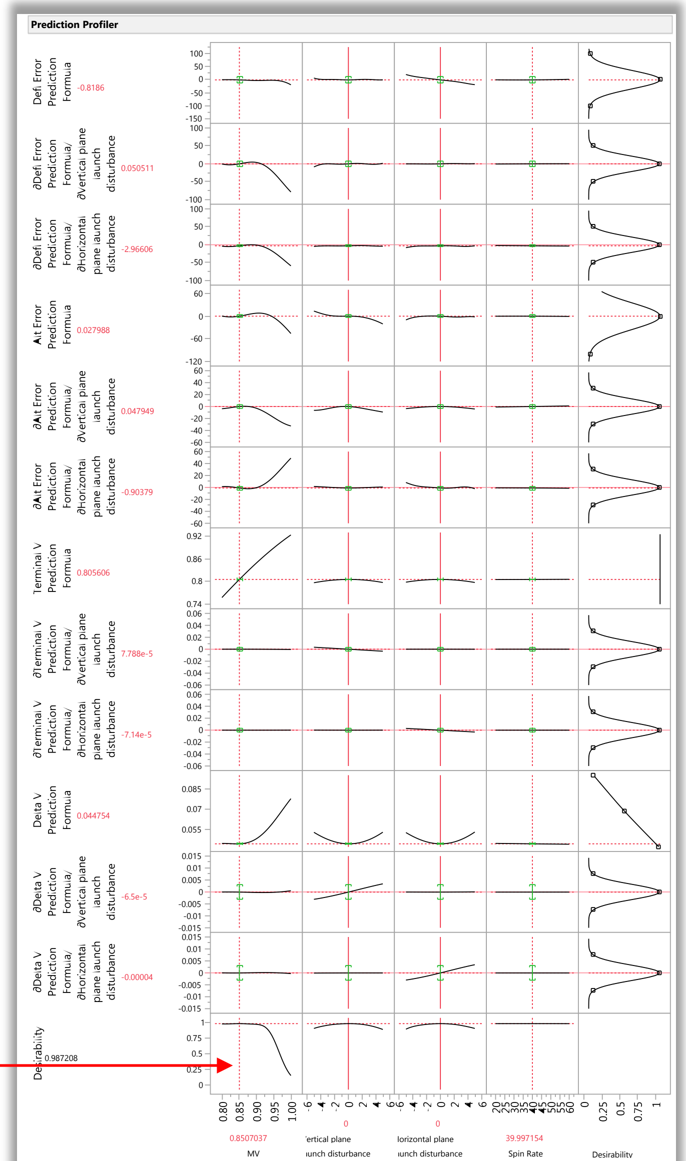
Robust Optimization

- Using Robust Parameter Design principles (related to 'Taguchi methods'), Propagation of Error (POE) analysis involves taking the partial derivative of response function wrt 'Noise' variables to minimize transmission of variability to responses

$$\underbrace{Var_Z\left[y(\mathbf{x},\mathbf{z})\right]}_{\text{Total Variation}} = \underbrace{\sigma_{z_i}^2}_{\text{Input variation}} \sum_{i=1}^{r} \underbrace{\left[\frac{\partial y(\mathbf{x},\mathbf{z})}{\partial z_i}\right]}_{\text{Input sensitivity}} + \underbrace{\sigma^2}_{\text{Output variation}}$$

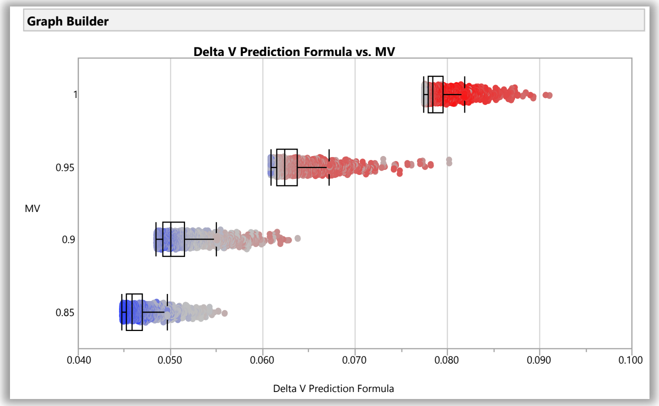
- Numerical optimization - setting the optimization goals and constraints such that:
  - — Launch Disturbances set as 'Noise' variables, with ***N~(0, 1.5)***
  - — Target zero value for Alt and Defl errors
  - — Maximize Final Velocity
  - — Target zero value for all partial derivatives (zero slope = flat/ insensitive regions)

- **Key Takeaway:** Robust-Optimal 'sweet-spot' setting is at MV = 0.85 when SR = 40 (giving terminal velocity of 0.80), with some margin in MV



Dispersion Error MC Simulation

- 20,000 Monte-Carlo simulations treat launch disturbances as random variables
- Downrange Dispersion Errors resulting from setting MV to 0.85, 0.90, 0.95, and 1.00
- Individual data points are colored by Velocity Decay (smallest to largest from blue to grey to red)



Case Study Outputs / Conclusions

- Results will inform:
  - —Tentative design and probability of meeting KPP
    - o Decreasing MV creates some performance margin wrt other performance parameters, and robustness/insensitivity to presence of system 'noises'
  - —Decisions regarding other attributes at the system-level (target effects, structural reliability, etc)
  - —Integration with other subsystem-level emulators to support system-level digital evaluation using hierarchical meta-model
    - o To overcome hypersensitivity to launch disturbances at higher launch velocities we can reconfigure projectile design (adjust CG to achieve better stability at higher MV, for example)
  - —Fusion of modeling data and predictions via emulator with 'live' test data at subsystem and/or system-level upon prototype design / build / test
    - o Visualization-based data assimilation (validation or calibration)

Literature

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