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

Sponsor: DASD(SE)

By
Mr. Douglas Ray
5th Annual SERC Doctoral Students Forum
November 7, 2017
FHI 360 CONFERENCE CENTER
1825 Connecticut Avenue NW
8th Floor
Washington, DC 20009

www.sercuarc.org
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

Stakeholder Analysis

Requirements Definition

Concept Generation, System Architecture, Functional Decomposition

Model & Physical Decomposition, Tradespace Exploration, Concept Selection

Operational Need

Requirements Decomposition

Delivered Capability

Validated Solution

Design / Build / Test

System Integration, Interface Management

Transition / Lifecycle Management

Verification & Validation
Overarching Probabilistic M&S Framework: Digital Engineering

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

Reliability
- Availability
- POFA

Planning
- ‘Live’ Testing & DOE-based Empirical Modeling

Computational M&S
- Emulation / Reduced-Order Modeling

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

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

UNCLASSIFIED
DISTRIBUTION A. Approved for Public Release; Distribution is unlimited.
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:
    - 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

- 400 run Sequential MaxPro Latin Hypercube Space-Filling DOE

- Colored by ‘Velocity Delta’ response (red = greatest velocity decay)

<table>
<thead>
<tr>
<th>Input Variable</th>
<th>Factor</th>
<th>Units</th>
<th>Low</th>
<th>High</th>
</tr>
</thead>
<tbody>
<tr>
<td>x1</td>
<td>MV</td>
<td></td>
<td>0.8</td>
<td>1.0</td>
</tr>
<tr>
<td>x2</td>
<td>Vert Launch Dist</td>
<td>Rad/sec</td>
<td>-6</td>
<td>6</td>
</tr>
<tr>
<td>x3</td>
<td>Horz Launch Dist</td>
<td>Rad/sec</td>
<td>-6</td>
<td>6</td>
</tr>
<tr>
<td>x4</td>
<td>Spin Rate</td>
<td>Hz</td>
<td>20</td>
<td>60</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Output Variable</th>
<th>Response</th>
</tr>
</thead>
<tbody>
<tr>
<td>y1</td>
<td>Delta Vel</td>
</tr>
<tr>
<td>y2</td>
<td>Final Vel</td>
</tr>
<tr>
<td>y3</td>
<td>Deflection Error (X)</td>
</tr>
<tr>
<td>y4</td>
<td>Altitude Error (Y)</td>
</tr>
</tbody>
</table>

Graph Builder

Overall Contribution vs. Predictor

Output Variable Scatterplot Matrix

Input Variables:
- Block
- MV
- Vertical plane launch disturbance
- Horizontal plane launch disturbance
- Spin Rate
- Defl Error
- Alt Error
- Total Miss
- Terminal V

Overall Contribution

0.0 0.1 0.2 0.3 0.4 0.5 0.6

Predictor: Overall Contribution

Graph Builder Output

Overall Contribution vs. Predictor

Overall Contribution

Output Variable

Delta Vel

Terminal V

Total Miss

Terminal V
• 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
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

\[
Var_z [y(x,z)] = \sigma^2 \sum_{i=1}^{r} \left[ \frac{\partial y(x,z)}{\partial z_i} \right]^2 + \sigma^2
\]

- Numerical optimization - setting the optimization goals and constraints such that:
  - Launch Disturbances set as ‘Noise’ variables, with \( N \sim (0, 1.5) \)
  - 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)


