The Implementation of Maximum Likelihood Estimation in Space Launch System Vehicle Design



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- 1. Background and problem definition
- 2. The response surface and maximum likelihood solution
- **3.** How well it worked



Background

- SLS design is a complex optimization problem
 - Many different groups with requirements and constraints
- Initial design had many sources of uncertainty
 - Large parameter space to search over
 - Manufacturing uncertainties
 - Day of flight uncertainties
 - Time and computational resources were limited
- How did we work through these problems?
 - Developed a response surface methodology coupled with a maximum likelihood estimation (MLE) process
 - Divide the uncertainty space into two groups
 - Manufacturing uncertainties
 - Flight day uncertainties





Trajectory Dispersed (TD) Vehicle Design

- The purpose of TD vehicles is to separate the manufacturing uncertainties from the day of flight uncertainties
- We do this because it helps qualify/quantify these effects from the flight day effects
- Allows for specifically constructed vehicles that stress critical parameters
 - Payload
 - Max Dynamic Pressure
 - Acceleration
 - Booster loading
- Explore different interactions without doing a worst on worst case coupling
 - This can lead to over design or lost performance

Month	Response Parameter	Applications
	Heavy Slow	
February	Thrust-to-Weight (10th Percentile)	Payload Performance
	Payload (10th Percentile)	Flight Performance
		Reserve Calculation
		Lift-Off Clearances
	Light Fast	·
July	Thrust-to-Weight (90th Percentile)	Vehicle Loads
	Max Dynamic Pressure (90th Percentile)	
	Max Heat Rate (90th Percentile)	
	Max 1st Stage Acceleration (90th Percentile)	
	Hybrid	
July	Max Dynamic Pressure (90th Percentile)	Payload Performance
-	Max Heat Rate (90th Percentile)	Inlet Pressure
	Max 1st Stage Acceleration (90th Percentile)	Clearances
	Payload (10th Percentile)	



Maximum Likelihood Design Process

- 1. Qualify/Quantify the manufacturing uncertainties
- 2. Choose a DOE method to produce a set of test cases from the design parameters
- 3. Fit response surfaces to the outcomes of the test cases
- 4. Use the response surfaces and the MLE optimization process to develop targets for the desired response offsets
- 5. Run a final simulation that compares its outcome to the response surface, to ensure the system closes





• Qualify/Quantify the manufacturing uncertainties

Design Parameters	Uncertainty mean, σ_{std}	Distribution shape
SRB Propellant Mass	0, 1	Normal
SRB Burn Rate	0, 1	Normal
SRB Burn out mass	0, 1	Normal
RS25 Thrust	0, 1	Normal
RS25 lsp	0, 1	Normal
Core Stage Dry Mass	0, 1	Normal
LAS Mass	0, 1	Uniform



Typically we encode the values to represent the width of the distribution in terms -1 to 1



- Choose a DOE method to produce a set of test cases from the design parameters
- Parameters are coded from -1 to 1 to represent minimum and maximum values
- The Central Composite method looks at coupled interactions at the vertices of the square
- The Latin Square looks at interior points that are well sampled
- After the design parameters are chosen and a search space produced we run a series of Program to Optimize Simulated Trajectories (POST) trajectories at these grid points



- Fit response surfaces to the outcomes of the test cases
- A standard least squares polynomial is fit

$$R(x_i) = \sum_{i=0}^{N} \beta_i x_i + \sum_{i=0}^{N} \sum_{j=0}^{N} \beta_{ij} x_i x_j + \beta_0$$

Minimizing the sum of the errors

$$e = \sum_{i=1}^{N} (y_i - R(x_i))^2$$

 Response surfaces allow for prediction of outcomes



Dependent Variable	TD Surface	Monte Carlo	Difference
Dependent variable	Coefficient	Surface Coefficient	Difference
SRB Propellant Mass	0.1562	0.1552	0.64%
SRB Burn Rate	0.6685	0.6720	-0.52%
RS-25 Specific Impulse	0.1835	0.1829	0.33%
RS-25 Thrust	1.0703	1.0714	-0.10%
Core Dry Mass	-0.2556	-0.2562	-0.23%
SRB Jettison Mass	-0.4999	-0.5030	-0.62%
LAS Mass	-0.0224	-0.0231	-3.03%



- Use the response surfaces and the MLE optimization process to develop targets for the desired response offsets
- Our goal is to optimize across a surface or surfaces to keep the chance of an offset occurring high while stressing key parameters for a TD vehicle
 - The objective function keeps the probability of occurrence high
 - The constraints become the response surfaces and the target of either 10th or 90th percentile

Objective Function

$$J(p) = max\left(\sum_{i}^{N} \ln P_{i}\right)$$

Constraints

 $R_{PAYLOAD} = -1.28\sigma_{PAYLOAD}$ $R_{LOTW} = -1.28\sigma_{LOTW}$

Notional Values

Design Parameters	Offset , σ_{std}
SRB Propellant Mass	0.25
SRB Burn Rate	1.38
SRB Burn out mass	0.36
RS25 Thrust	2.41
RS25 lsp	1.28
Core Stage Dry Mass	0.015
LAS Mass	0.003



- Run a final simulation that compares its outcome to the response surface, to ensure the system closes
- These offsets go into a final POST run for the **TD** vehicle
- Typically compare the final output back to the response surface to verify agreement

Notional Values		
eters	Offset, σ_{s}	

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Resulting Vehicle Altitude Time History





Grid Choice Considerations

- The Central Composite Design had a drawback
 - A dominant parameter would skew results
 - Use a Latin Square that samples the interior, which led to better response surface fits







Conclusions

- Reduce time and computational requirements by using statistically representative vehicles
- Response surfaces with a constrained MLE process can produce excursion vehicles for analysis
 - Provide a functional representation of a vehicle's outcome without further need of computational resources
 - Show relative sensitivity of design parameters
 - Process is applicable to other uncertain analyses besides launch vehicle design

