



# Using Advanced Design Methods to Optimize the Mars Ascent Vehicle First Stage Solid Rocket Motor

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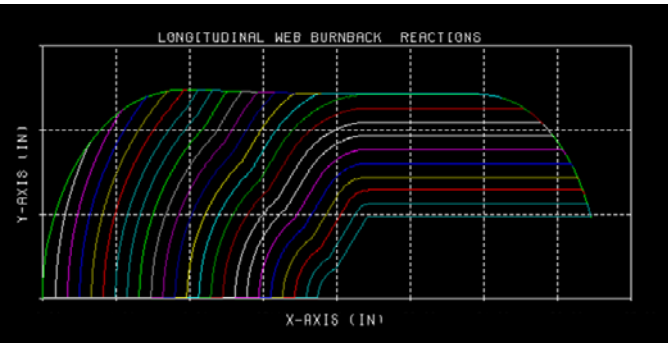
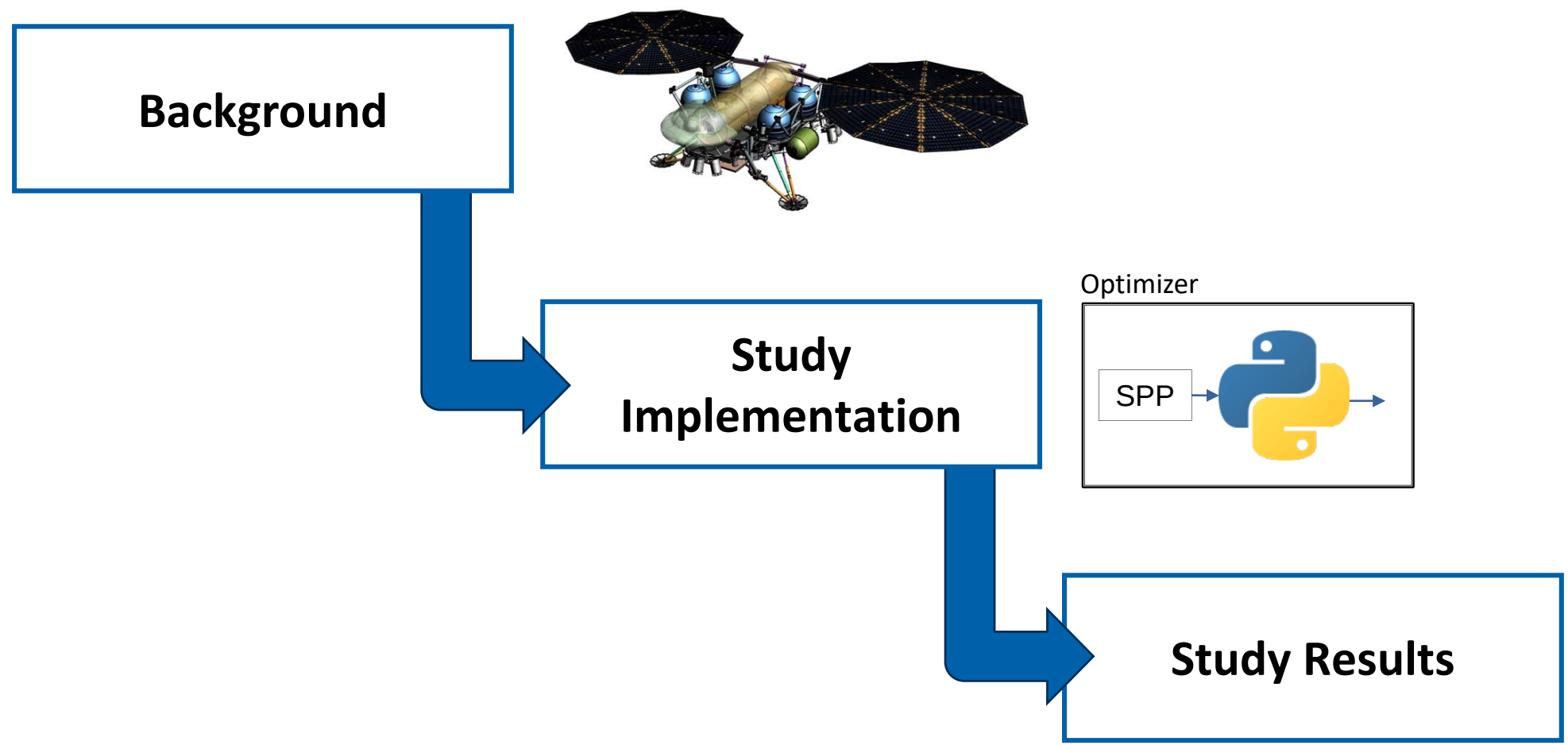
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# Agenda



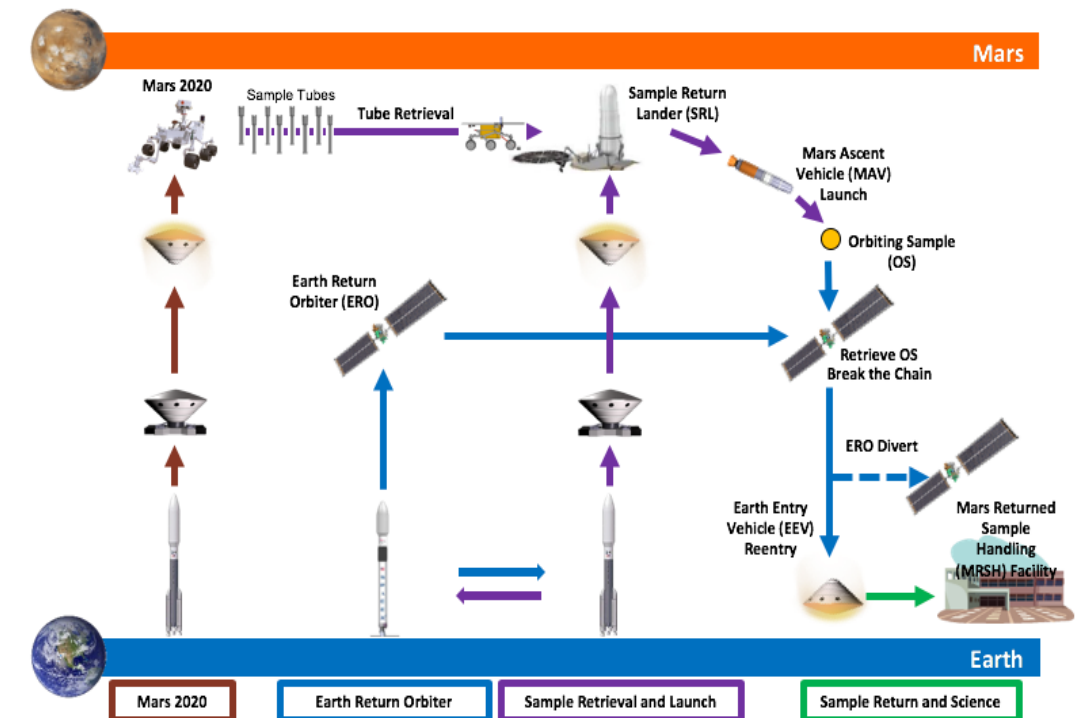
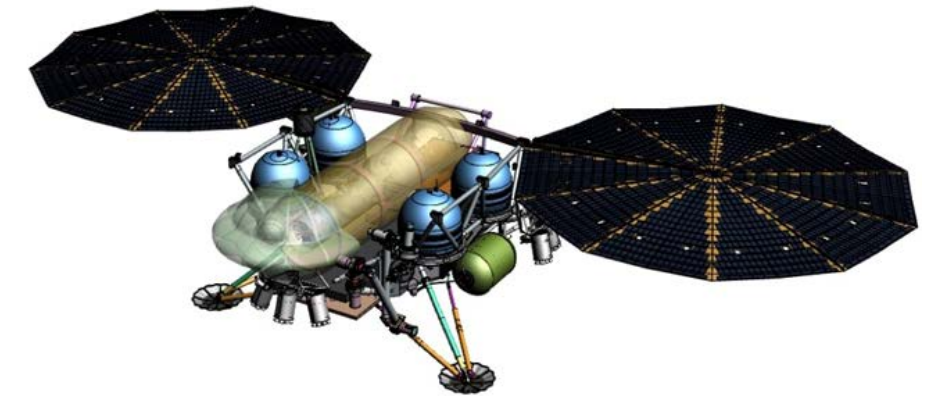
## ◆ Mars Ascent Vehicle (MAV):

- ◆ MAV is the portion of the sample return mission which brings the samples from the Martian surface to rendezvous with an orbiter
- ◆ At the time of this study, MAV was trading between hybrid and solid propulsion designs

## ◆ The MAV solid motor design had last been developed in October, so there was a need to update and improve the motor design

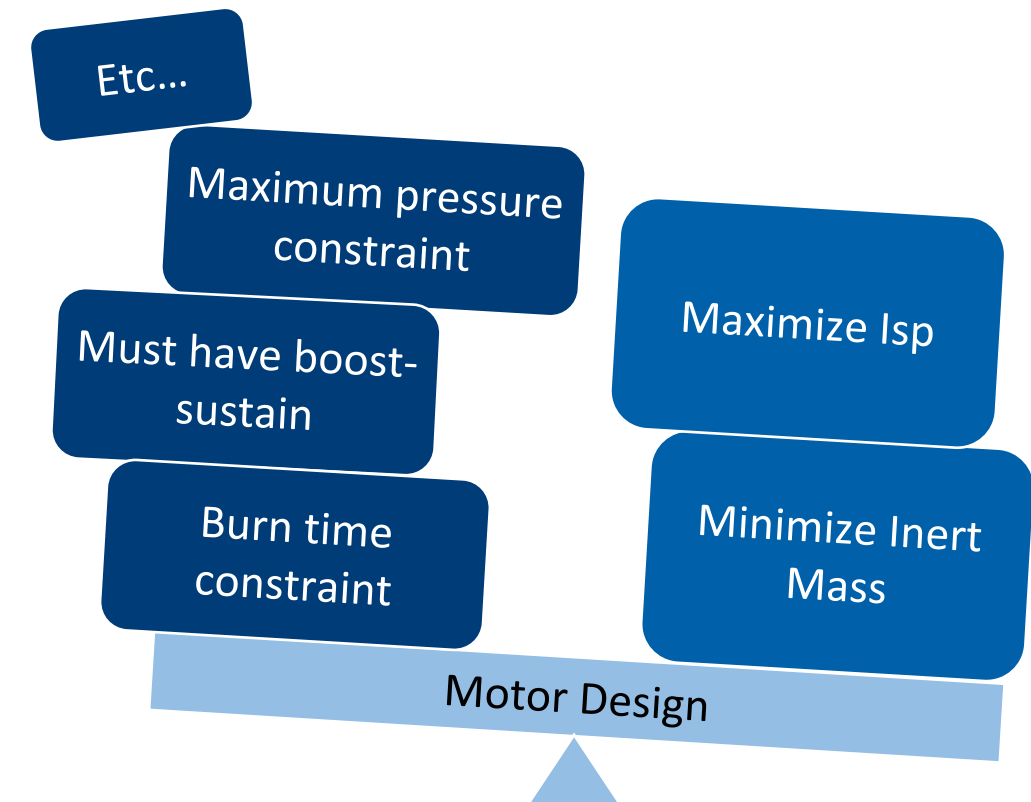
- ◆ This study was carried out under the mentorship of Tim Kibbey, from Marshall's solid propulsion group

**My primary task in this project was to carry out a design study for the MAV first stage SRM**



# Why does this study require optimization?

- ◆ Ultimately, we wanted to minimize the mass of the motor while maximizing its Isp and adhering to any design constraints
- ◆ Because we had conflicting needs and requirements, there was a need to optimize
- ◆ There are several discrete motors that Tim Kibbey wanted to design
  - ◆ Need to carry out a separate optimization for each discrete motor configuration

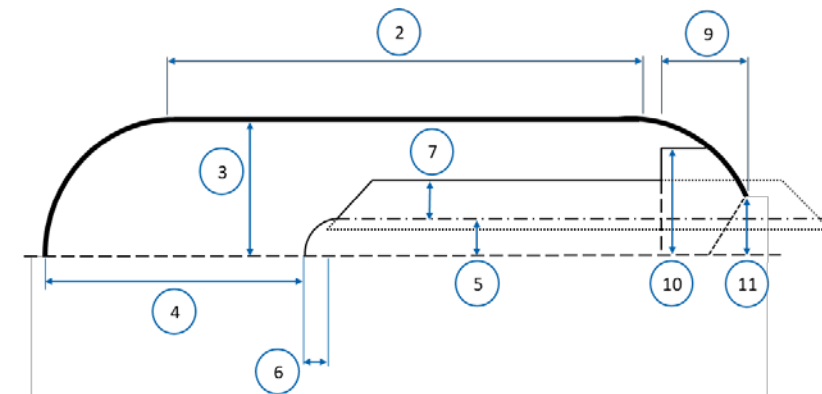


We can formulate the overall study goal and the steps to achieve that goal

**Use optimization to improve the grain and case design of each motor in a set of first stage Mars Ascent Vehicle (MAV) motor configurations, subject to given constraints**

To accomplish this goal we had to...

1. Parameterize the motor case and grain geometry

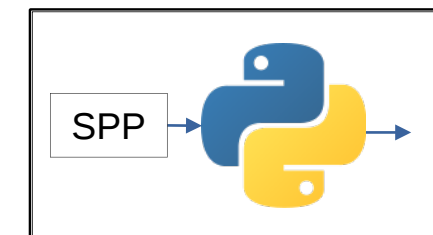


2. Define the optimization problem

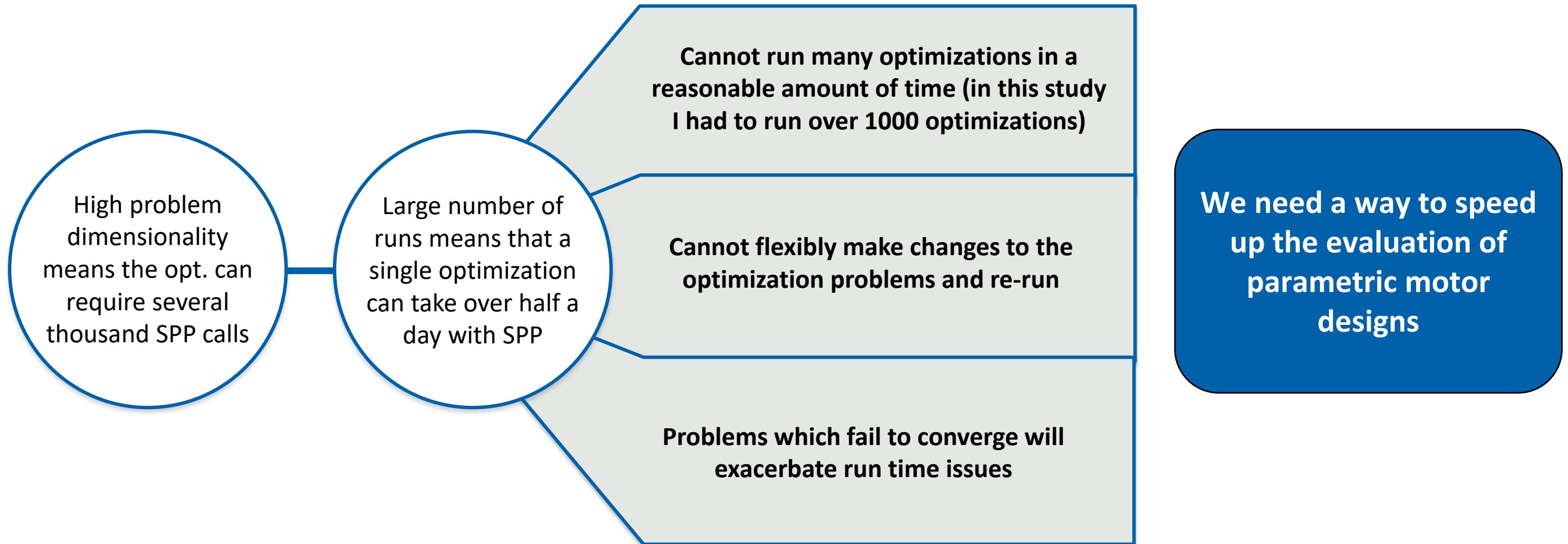
Maximize:  $\Delta V = g * I_{sp} * \ln \left( 1 + \frac{m_{prop}}{m_{inert}} \right)$

Subject to: max pressure  $\leq$  1000 psi  
propellant mass = target mass  
etc.

3. Wrap the motor simulation (Solid Performance Program - SPP) and run it quickly in an optimizer

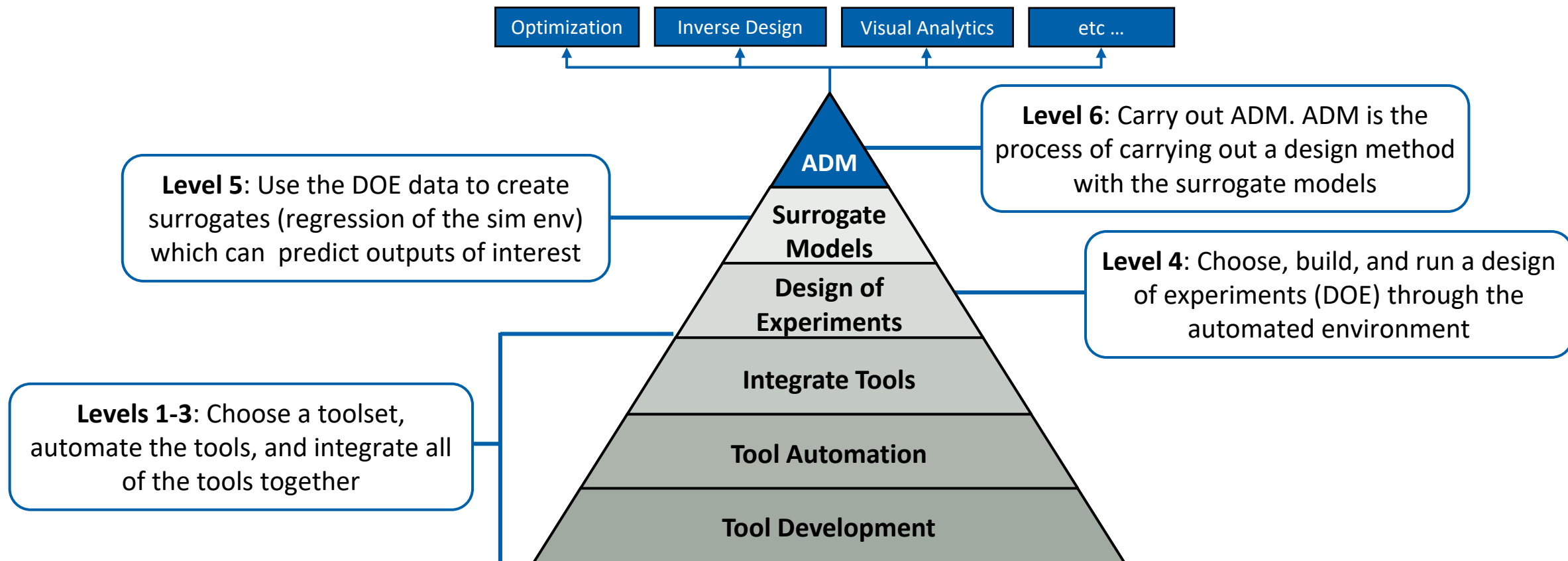


However, we found that solving the optimization problem with SPP in the optimization loop proved to be very difficult



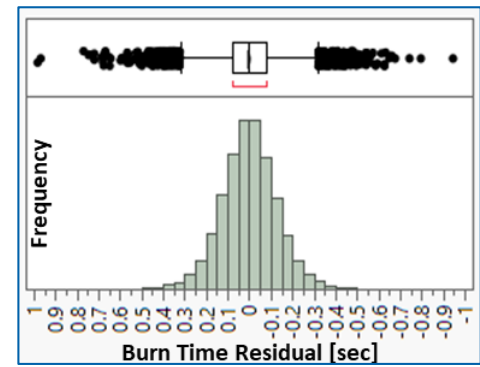
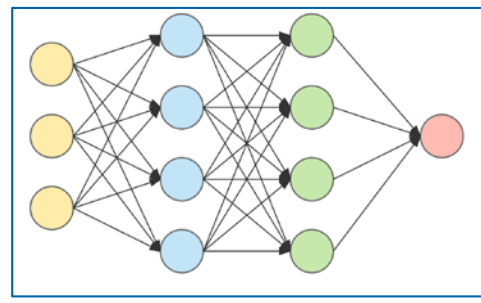
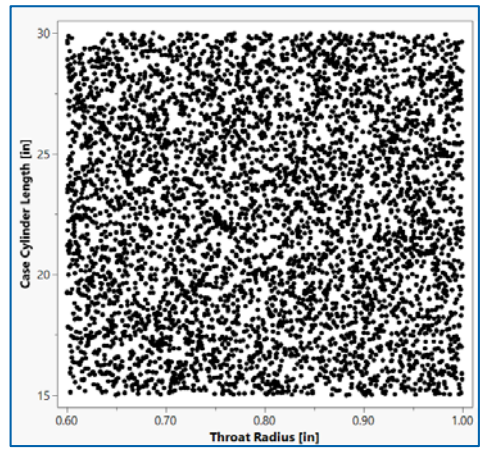
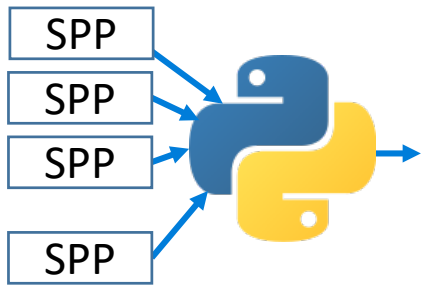
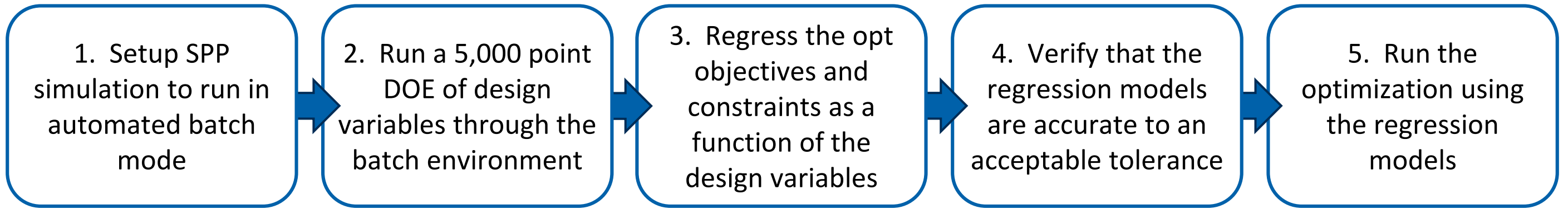
# For this design study we had to utilize Advanced Design Methods (ADM)

- ◆ ADM is very useful for when you have an automated toolset, but cannot feasibly carry out your design study due to long run time of the simulation environment



**With ADM, we can use surrogate models to carry out our optimizations since the surrogates can be evaluated very rapidly compared to the original simulation environment.**

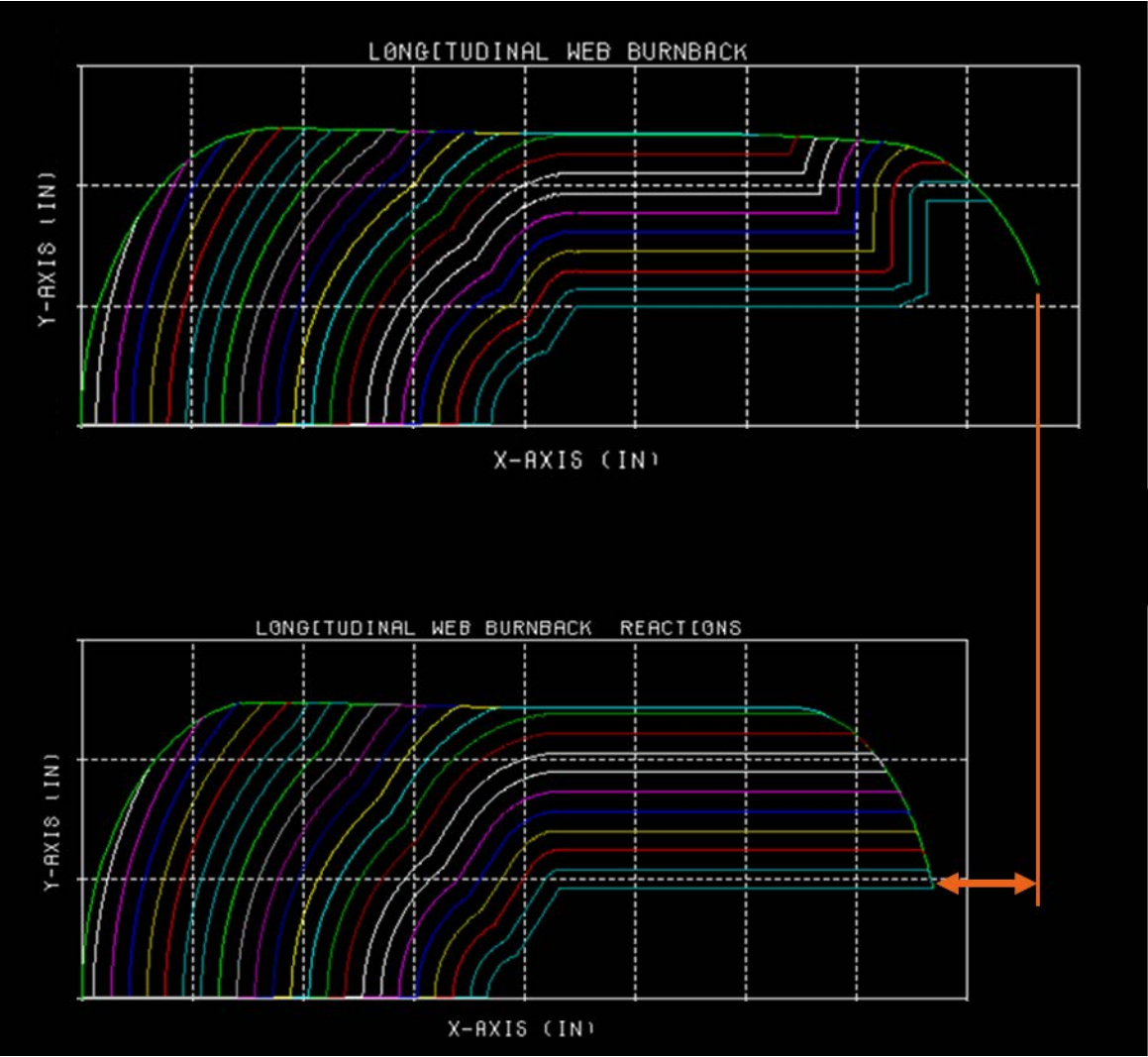
# We can now apply the ADM process to our study



**About a 1000 times improvement in optimization run time by using regression models while still accurately predicting SPP outputs within an acceptable tolerance**

With ADM, we were able to noticeably improve the design of each motor

Original Baseline



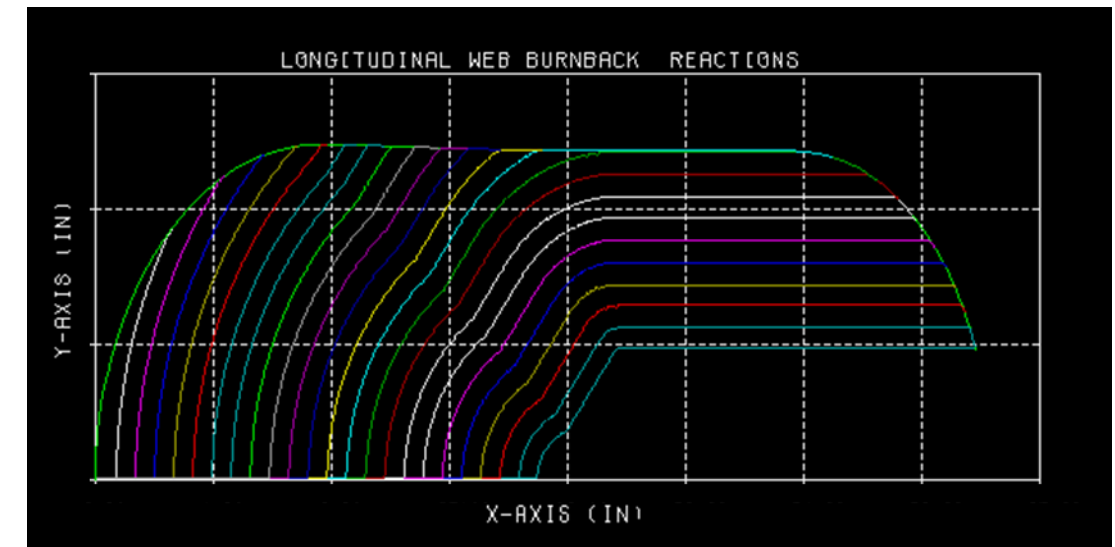
Optimized Baseline

| Output Variable Improvement        | Improvement |
|------------------------------------|-------------|
| Ideal $\Delta V$ Increase          | 2 %         |
| Insulation Mass Decrease           | 35 %        |
| <b>Total Motor Length Decrease</b> | <b>10 %</b> |
| <b>Stage 1 Inert Mass Decrease</b> | <b>7 %</b>  |
| Isp Increase                       | 1 %         |

# From the suite of optimized motors, Tim Kibbey was able to choose one as the new baseline



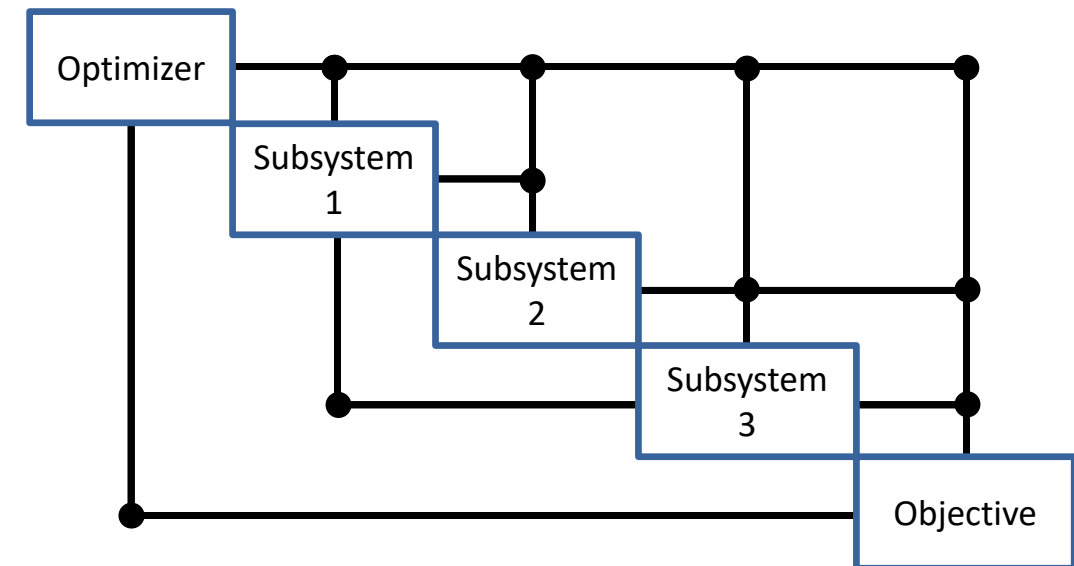
- ◆ With this optimization design study, I was able to provide Tim Kibbey with over 20 optimized motor configurations to choose from
- ◆ After the optimization study, Tim Kibbey made some additional, small tweaks to the motor design
- ◆ The final motor design which Tim Kibbey ultimately chose from the set of optimized motors was based on:
  1. Purposes of aerodynamic stability
  2. Good performance in 3 DOF trajectory analysis
  3. Favorable boost-sustain profile



| Output Variable          | Change from Original Baseline |
|--------------------------|-------------------------------|
| Ideal $\Delta V$ [m/s]   | - 2.15 %                      |
| Insulation Mass [lbm]    | - 32.29 %                     |
| Total Motor Length [in]  | - 13.29 %                     |
| Stage 1 Inert Mass [lbm] | - 6.89 %                      |
| Isp [sec]                | + 1.08 %                      |

# ADM can also be very useful for design studies outside of single discipline design

- ◆ These techniques can be even more powerful when used for multidisciplinary analysis and optimization (MDAO)
  - ◆ MDAO benefits even more from surrogate speed due to increased number of iterations
  - ◆ Surrogate models are very portable and easy to integrate
- ◆ These techniques can also be helpful for us to implement probabilistic design to quantify uncertainty
  - ◆ Can optimize or design to most probable performance

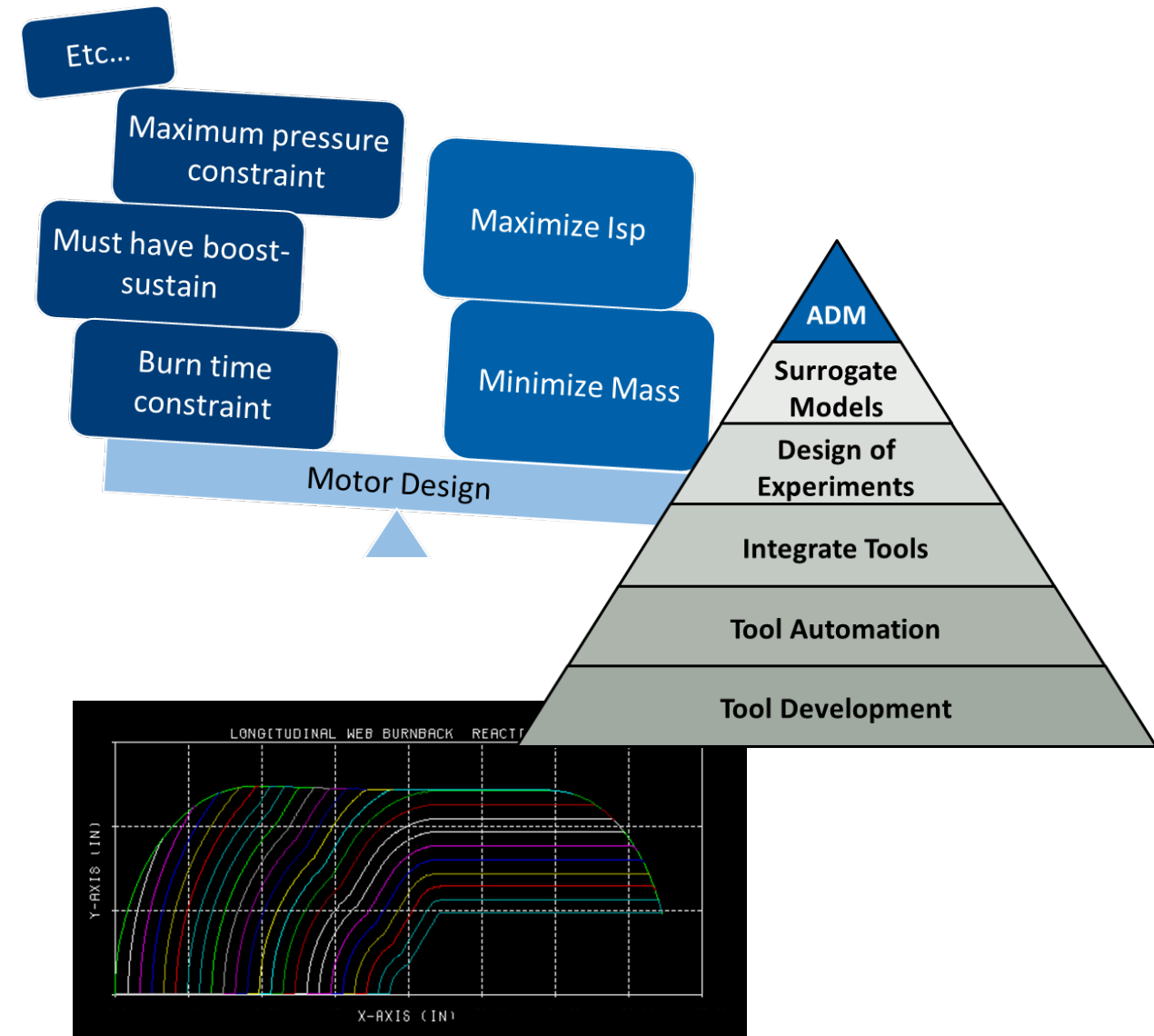


# Conclusion: We successfully used Advanced Design Methods to optimize the first stage motor design

**Study goal:** use optimization to improve the grain and case design of each motor in a set of first stage Mars Ascent Vehicle (MAV) motor configurations, subject to given constraints

Using ADM we were able to run an optimization design study to produce a new baseline design for the MAV first stage SRM with an improved length and mass

Use of ADM can further be extended to carry out multidisciplinary analysis / optimization and robust design



## Questions?

# Additional Information

# Defining the Optimization Problem

- ◆ With our parameterization of the motor, we can begin to form our optimization problem of interest

**Objective:** In this study we experimented with two different objectives. First we tried to minimize the total length of the case (to minimize mass of the interstage). Next we tried to maximize the ideal  $\Delta V$  of the MAV first stage.

$$\text{Minimize: } L_{case} = L_{cyl} + R_{cyl} \frac{b}{a} + R_{cyl} \frac{b}{a} \sqrt{1 - \left(\frac{R_{exit}}{R_{cyl}}\right)^2}$$

or

$$-\Delta V = -g * I_{sp} * \ln \left( 1 + \frac{m_{prop}}{m_{stage2} + m_{case} + m_{nozz} + m_{insulation} + m_{other}} \right)$$

Where...  $m_{case} = f \left( R_{cyl}, L_{cyl}, \frac{b}{a}, \rho_{case}, t_{case} \right)$   $L_{nozzle} = 56.97 - L_{case}$   
 $\rho_{case}, t_{case}, g, m_{stage2}, m_{other} = \text{constants}$   $m_{nozz} = f(L_{nozzle})$   
 $m_{prop}, m_{insulation} = \text{From SPP environment}$   $I_{sp} = f(L_{nozzle}, R_{throat})$

**Design Variables:** Use the previously defined parameterization of the motor as our design variables. The ranges are set such that we expect the optimum point to fall somewhere inside the ranges

By varying:

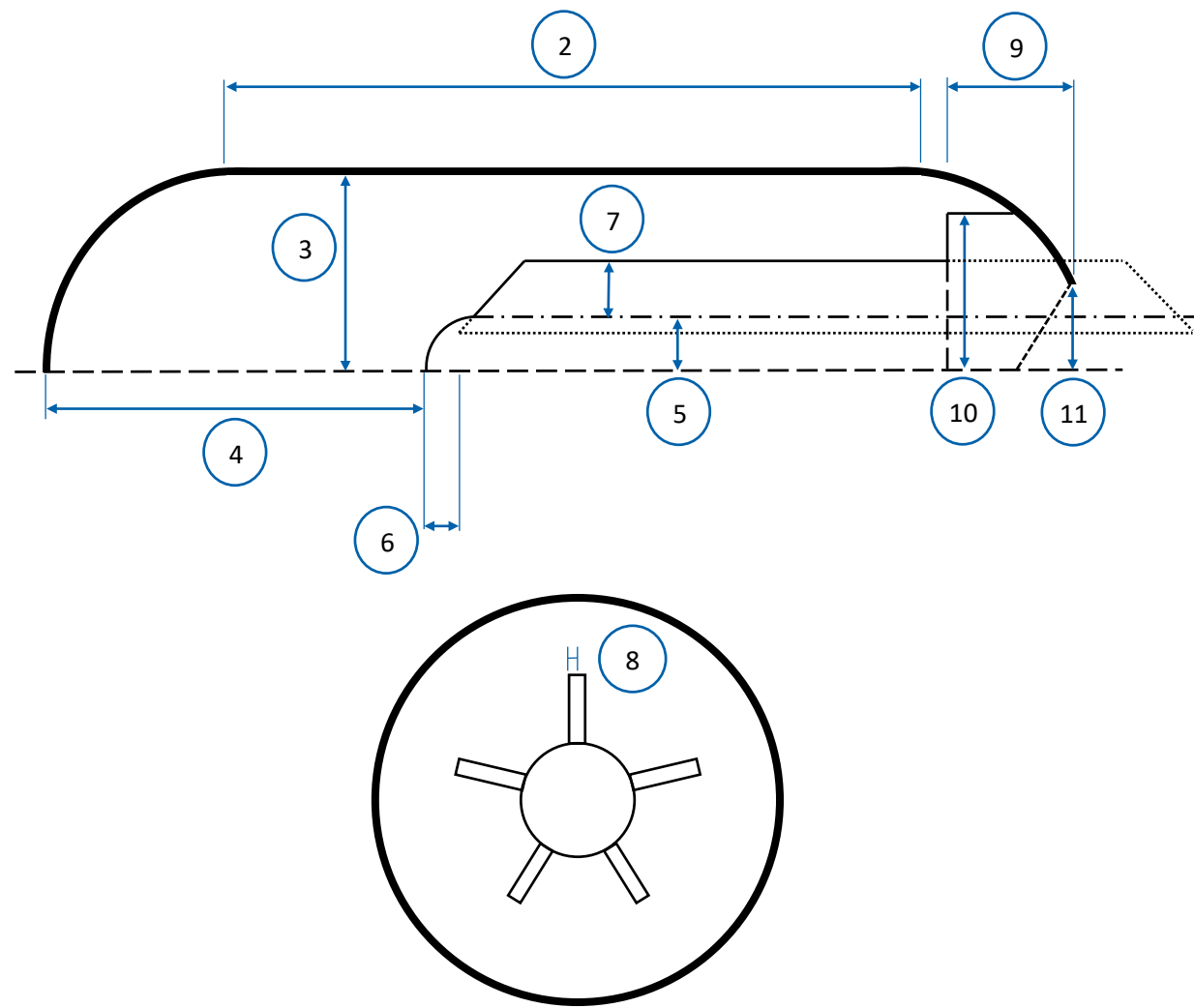
|                                                                         |                                                                         |
|-------------------------------------------------------------------------|-------------------------------------------------------------------------|
| $0.6 \text{ in} \leq \text{throat radius} \leq 1.0 \text{ in}$          | $0.045 \leq \text{grain fin start} \leq 1.0$                            |
| $15.0 \text{ in} \leq \text{case cylinder length} \leq 30.0 \text{ in}$ | $0.5 \text{ in} \leq \text{grain fin depth} \leq 4.0 \text{ in}$        |
| $0.5 \leq \text{case dome } b \text{ over } a \leq 0.999$               | $0.1 \text{ in} \leq \text{grain fin half width} \leq 0.5 \text{ in}$   |
| $3.0 \text{ in} \leq \text{case exit radius} \leq 7.0 \text{ in}$       | $0.0 \text{ in} \leq \text{grain aft slot length} \leq 6.0 \text{ in}$  |
| $0.25 \leq \text{grain bore start} \leq 0.60$                           | $4.0 \text{ in} \leq \text{grain aft slot radius} \leq 11.0 \text{ in}$ |
| $1.5 \text{ in} \leq \text{grain bore radius} \leq 5.0 \text{ in}$      | $3 \leq \text{grain number of fins} \leq 6$                             |

**Constraints:** Constraints were provided by Tim as requirements for the motor

Subject to:

- maximum head pressure  $\leq 1000 \text{ psi}$
- propellant mass = target mass
- impulse fraction at 30% time  $\geq 0.50$
- grain fin depth + grain bore radius  $\leq$  exit radius after applying insulation
- burn time  $\geq 72 \text{ sec}$
- time below 150 psi  $\leq 12 \text{ sec}$

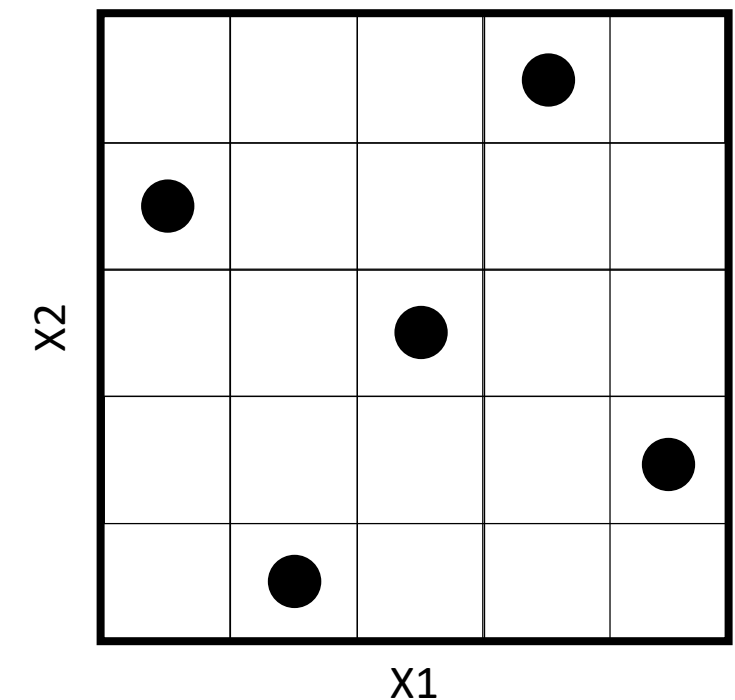
# Design of Experiments



| DOE Variables                                 | Min    | Max    |
|-----------------------------------------------|--------|--------|
| 1. Throat radius                              | 0.6 in | 1.0 in |
| 2. Case cylinder length                       | 15 in  | 30 in  |
| 3. Case cylinder radius                       | 8 in   | 11 in  |
| 4. Bore start point as percent of case length | 25%    | 60%    |
| 5. Bore radius                                | 1.5 in | 5 in   |
| 6. Fin start point as percent of bore length  | 4.5%   | 100%   |
| 7. Fin depth                                  | 0.5 in | 4 in   |
| 8. Fin half width                             | 0.1 in | 0.5 in |
| 9. Aft slot length                            | 0 in   | 6 in   |
| 10. Aft slot radius                           | 4 in   | 11 in  |
| 11. Exit radius                               | 3 in   | 7 in   |
| 12. Case dome b over a                        | 0.5    | 1.0    |
| 13. Number of fins                            | 3      | 6      |

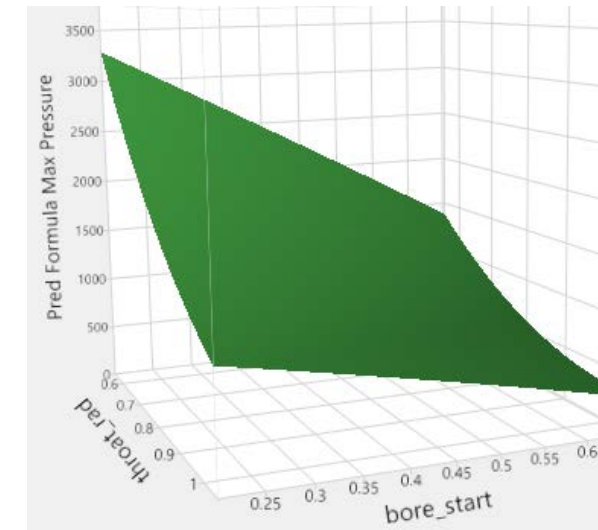
- ◆ Few things to consider when choosing a DOE for this study:
  - ◆ Our SPP simulations are deterministic and have very little noise
  - ◆ Our design space likely has higher order effects and non-linearities
  - ◆ Our optimized solution is likely to be on the interior of the design space rather than at the edges
- ◆ Therefore, for this study we want to use a design of experiments which will spread points over the design space and minimize replication of designs
- ◆ Chose to use a Latin Hyper Cube (LHC) space filling design
  - ◆ A LHC aims to maximize the minimum distance between design points, but requires points to be evenly spaced (like the uniform design)
  - ◆ Good balance between spacing of points and spread of points over the design space
  - ◆ Can be generated in a reasonable amount of time
- ◆ Training DOE for this study was built with 5,000 points
  - ◆ Run points through the batch SPP environment and collect the results for the optimization
  - ◆ Additional testing DOE was built with 1,000 points and run

Example of two variable LHC DOE with five points

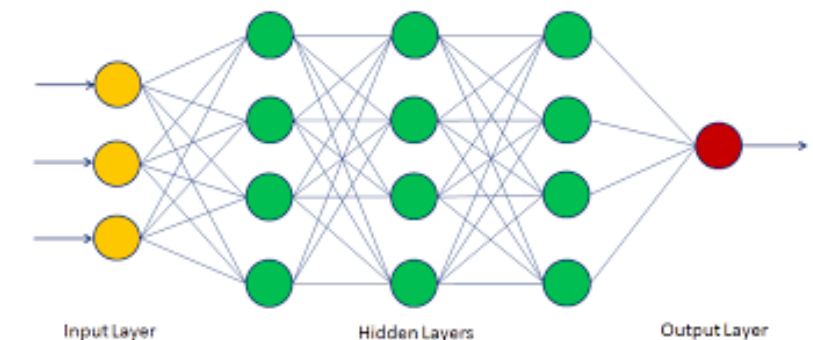


# Surrogate Models

- ◆ After creating the DOE, running the points through the batch SPP environment, and collecting outputs of interest, we can begin creating the surrogate models.
- ◆ Need to create seven different surrogate models:
  - Maximum head pressure
  - Propellant mass
  - Insulation mass
  - Impulse fraction at 30% time
  - Exit radius with insulation
  - Burn time
  - Time below 150 psi
- ◆ When I am creating surrogate models I generally try to start with the simplest model I can and see if it gives me a good enough fit
  - ◆ Continue to increase model complexity and move on to other model types until I reach a fit which I am content with
- ◆ For this study I ended up having to use neural networks for the majority of my models



Example 2D second order response surface model



Example artificial neural network diagram

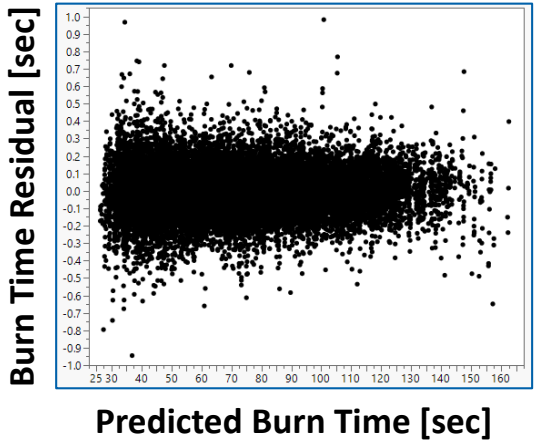
# Goodness of Surrogate Models

- ◆ For each of the seven surrogate models, we must carry out several checks to make sure that the models fit the data well and that we are not overfitting. For example, we can look at each check I carried out for the burn time surrogate model:

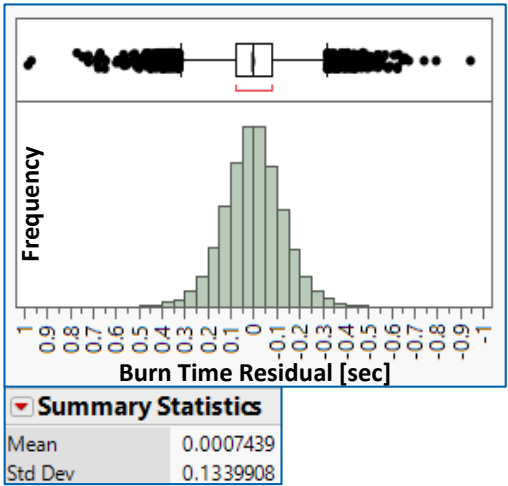
Check  $R^2$  & Root Mean Square Error (RMSE)

| Training  |           |
|-----------|-----------|
| Burn Time |           |
| Measures  | Value     |
| RSquare   | 0.9999756 |
| RMSE      | 0.128834  |

Check pattern of model residuals



Check distribution of model residuals



Check distribution of test point residuals

