National Aeronautics and Space Administration



#### **AIAA SciTech Forum 2015**

A Probabilistic Sizing Demonstration of a Flexible Thermal Protection System for a Hypersonic Inflatable Aerodynamic Decelerator

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- HIAD & Flexible TPS Background
- Margin Policy and Probabilistic Sizing Overview
- Sensitivity Analysis
- Thermal Model Correlation
- Uncertainty Analysis and Sizing
- Conclusions
- Future Work

### HIAD & Flexible TPS Background



- Potential missions have been identified that will require a planetary entry system to have an aeroshell much larger in diameter than the diameter of any feasible launch vehicle.
- The inflatable aeroshell of a HIAD entry system relies on a flexible thermal protection system (TPS) to prevent the underlying structure from exceeding its thermal limits.
- Candidate flexible TPS materials and layups have undergone extensive aerothermal arc jet testing in a stagnation configuration to evaluate thermal performance and provide boundary condition and in-depth temperature measurement data for thermal model correlation and validation.
- Outer fabric protects the underlying insulation layers from being directly exposed to the incident convective heat flux and the aerodynamic shear forces.
- The insulator layers reduce thermal soak back.
- Gas barrier prevents hot gas impingement on to the underlying structure.





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### **HIAD F-TPS Margin Policy Goals**



• Given uncertainties in material properties, environments, etc. Prevent bondline over temperature of the F-TPS

 Use probabilistic tools to enhance F-TPS performance and increase survivability during off nominal entry conditions, while reducing F-TPS margined mass

 Provide more knowledge and insight about the F-TPS design and its performance



### **End-to-End Monte Carlo Simulation**



- Uncertainties captured without stacking worst cases together
- Decoupled approach two separate Monte Carlo simulations are run
  - Trajectory
    - Output is a set of dispersed trajectories
  - Thermal model
    - Each resulting trajectory from the trajectory Monte Carlo is used as input to the thermal model Monte Carlo



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### Monte Carlo Simulation - Implementation



- Margin Process
  - Thermal Monte Carlo simulation run using several layups, each time increasing the number of insulation layers
  - Peak bondline temperature tracked and presented as a bondline temperature distribution
  - Margined thickness found by selecting the layup which satisfies mission reliability requirement for the F-TPS



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### **Probabilistic Sizing Process Overview**





![](_page_7_Picture_0.jpeg)

![](_page_7_Picture_2.jpeg)

#### **Sizing Objective**

- Bondline Temperature Limit: 400°C
- Margin Policy Dictates: 97% chance Bondline temperature will be maintained below 400°C (Predicted +2σ bondline temperature must be less than 400°C)

#### **Bondline Temperature Prediction Requirements**

![](_page_7_Figure_7.jpeg)

![](_page_8_Picture_0.jpeg)

![](_page_8_Picture_1.jpeg)

# Sensitivity Analysis (Monte Carlo #1)

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9

![](_page_9_Picture_0.jpeg)

![](_page_9_Picture_1.jpeg)

#### **Thermal Response Model Overview**

![](_page_9_Figure_3.jpeg)

![](_page_10_Picture_1.jpeg)

#### Parameters Dispersed in Monte Carlo Sensitivity Analysis

Parameter	Distribution Type	Mean or Nominal Value	Standard Deviation or Range
Insulator Virgin Conductivity (k <sub>vrg</sub> ) SF 1 (Low Temperature Range)	Normal	1.0	0.2
Insulator Virgin Conductivity (k <sub>vrg</sub> ) SF 2 (High Temperature Range)	Normal	1.0	0.2
Insulator Char Conductivity (k <sub>chr</sub> ) SF 1 (LowTemperature Range)	Normal	1.0	0.2
Insulator Char Conductivity (k <sub>chr</sub> ) SF 2 (High Temperature Range)	Normal	1.0	0.2
Insulator Specific Heat $(C_{ps})$ SF	Normal	1.0	0.15
Δρ (Virgin Density – Char Density) SF	Uniform	1.0	0.8 to 1.2
Gas Specific Heat (C <sub>pg</sub> ) SF	Uniform	1.0	0.1 to 1.0
Gas Viscosity $(\mu_{o})$ SF	Uniform	1.0	1.0 to 2.0
Latent Heat of Reaction 1(h <sub>R1</sub> ), SF	Uniform	1.0	-30 to 30
Insulator Porosity ( $\varphi$ ) SF	Uniform	1.0	0.575 to1.09
Insulator Permeability (k <sub>x</sub> ) SF	Normal	1.0	0.2
Outer Fabric Conductivity SF	Normal	1.0	0.2
Backing Material Conductivity SF	Normal	1.0	0.2

![](_page_11_Picture_0.jpeg)

![](_page_11_Picture_1.jpeg)

#### **Sensitivity Analysis Results**

#### Time Evolution of Input Parameter Contributions to Bondline Temperature Uncertainty

![](_page_11_Figure_4.jpeg)

![](_page_12_Picture_0.jpeg)

![](_page_12_Picture_1.jpeg)

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13

![](_page_13_Picture_1.jpeg)

#### **Correlated Model Predictions**

![](_page_13_Figure_3.jpeg)

#### **Correlation Parameters**

Parameter	Scaled Value
Insulator Virgin Conductivity (k <sub>vro</sub> ) SF 1	0.885
Insulator Virgin Conductivity (k <sub>vrg</sub> ) SF 2	1.09
Insulator Char Conductivity (k <sub>chr</sub> ) SF 1	0.97
Insulator Char Conductivity (k <sub>chr</sub> ) SF 2	1.01
Backing Material Conductivity SF	1.75
Outer Fabric Conductivity SF	1.70

#### Modeled Gen 1 Layup

Measured Surface Pressure Boundary Condition outer fabric \_TC-1R (BC) outer fabric -TC-2R (BC) insulation TC-3R • insulation TC-4K insulation TC-5K insulation -TC-6K (BL) -TC-7K gas barrier LI-900 **Bondline Temperature** 

Temperature (degC)

![](_page_14_Picture_1.jpeg)

![](_page_14_Figure_2.jpeg)

Markers => Arc Jet Data

#### Uncorrelated

Correlated

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![](_page_15_Picture_1.jpeg)

![](_page_15_Figure_2.jpeg)

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![](_page_16_Picture_0.jpeg)

![](_page_16_Picture_2.jpeg)

#### Error Analysis Results – 12 Arc Jet Cases Compared to Predictions (4 profile and 8 constant HF)

Error Indicator	Uncorrelated	Correlated
Average Max BL Temperature Difference °C	165	30
Average Normalize BL Temperature RMS %	27	5

![](_page_16_Figure_5.jpeg)

![](_page_16_Figure_6.jpeg)

![](_page_17_Picture_0.jpeg)

![](_page_17_Picture_1.jpeg)

# Uncertainty Analysis and Sizing (Monte Carlo #2, #3, & #4)

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18

![](_page_18_Picture_0.jpeg)

![](_page_18_Picture_1.jpeg)

#### Monte Carlo Input Parameters and Uncertainty Quantification

Parameter	Distribution Type	Mean or Nominal Value	Standard Deviation (1σ) or Range
Insulator Virgin Conductivity (k <sub>vro</sub> ) SF 1	Normal	0.885	0.106
Insulator Virgin Conductivity (k <sub>vrg</sub> ) SF 2	Normal	1.09	0.106
Insulator Char Conductivity (k <sub>chr</sub> ) SF 1	Normal	0.97	0.131
Insulator Char Conductivity (k <sub>chr</sub> ) SF 2	Normal	1.01	0.131
Insulator Specific Heat (Cps) SF	Normal	1.00	0.0738
Latent Heat of Reaction $1(h_{R1})$ SF	Uniform	1.00	0 to 2
Heat Flux (q <sub>cw</sub> ) SF	Normal	1.00	0.07
Bondline Temperature Bias	Uniform	0°C	0 to 50
Insulator Thickness SF	Normal	1.00	0.084
Insulator Density SF	Normal	1.00	0.083

![](_page_19_Picture_1.jpeg)

#### Monte Carlo Input Parameters: Trajectory Dispersions

![](_page_19_Figure_3.jpeg)

- Two thousand (2000) off-nominal trajectories were provided from a separate Monte Carlo simulation run using POST where initial orbital conditions, vehicle aerodynamic parameters, atmospheric conditions, and other parameters affecting the reentry trajectory were dispersed.
- The boundary condition parameters derived from each of the 2000 trajectory dispersions as inputs into each of the corresponding 2000 thermal model Monte Carlo samples.

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![](_page_20_Picture_1.jpeg)

#### Sizing: Nominal Case, Four Insulator Layers

![](_page_20_Figure_3.jpeg)

Maximum Bondline Temperature Histogram with Lognormal PDF Fit

![](_page_21_Picture_1.jpeg)

#### Sizing: Four and a Half Insulator Layers

![](_page_21_Figure_3.jpeg)

Maximum Bondline Temperature Histogram with Lognormal PDF Fit

![](_page_22_Picture_1.jpeg)

#### **Sizing: Five Insulator Layers**

![](_page_22_Figure_3.jpeg)

Maximum Bondline Temperature Histogram with Lognormal PDF Fit

![](_page_23_Picture_0.jpeg)

![](_page_23_Picture_1.jpeg)

#### Maximum Bondline Temperature Uncertainty Contribution Breakdown (5 Layer Case)

![](_page_23_Figure_3.jpeg)

![](_page_24_Picture_0.jpeg)

![](_page_24_Picture_1.jpeg)

- The probabilistic sizing methodology prescribes one additional insulation layer on top of the nominal thickness to mitigate parametric, stochastic, and structural uncertainties.
- A thickness margin of one layer of insulation was shown to result in a 99.87% probability of maintaining the bondline below 400°C, exceeding the given margin policy.
  - This thickness margin may shrink as knowledge is gained about the parameters which are contributing the significantly to the uncertainty in the maximum bondline temperature or by developing a higher fidelity thermal model, enabling a higher quality correlation and a lower maximum bondline temperature bias.
- The probabilistic sizing process works well and it has enabled the opportunity to make informed TPS design and mission risk tradeoffs.
  - A HIAD project may decide to decrease the TPS thickness margin to one half a layer of insulation resulting in a 5% probability of bondline over-temperature as determined by the second Monte Carlo simulation for uncertainty analysis.

# Conclusions

![](_page_25_Picture_1.jpeg)

- Lesson Learned: Sensitivity analysis showed that the gas specific heat (C<sub>pg</sub>) has a large influence on the maximum bondline temperature, this indicates that advection is a significant mode of heat transfer.
  - The specific heat of the gas, as well as other gas properties, can be better defined by introducing multi-species gas mass conservation into the thermal model and determining the properties of the mixture.
  - This will reduce the thermal response model structural uncertainty and allow for a better correlation to arc jet test data which will decrease the bondline temperature bias applied in the uncertainty analysis Monte Carlo simulations.
- This probabilistic sizing process can be readily implemented on other TPS layup designs provided a validated thermal response model, appropriate boundary condition dispersions, and thermal model input parameter uncertainty quantification.

![](_page_26_Picture_0.jpeg)

- Demonstrate this process using a higher fidelity model with multispecies-gas-mass conservation integrated in to the numerical solution approach.
- Further investigate uncertainties and the correlations between the thermal response model input parameters which were dispersed or not dispersed in this study.
- Employ automated correlation by inverse analysis (Grant Rossman work).

**Future Work** 

 Implement this process for sizing the TPS of the Terrestrial HIAD Orbital Reentry (THOR) aeroshell (HIAD technology demonstration flight test).

![](_page_27_Picture_0.jpeg)

![](_page_27_Picture_1.jpeg)

## **Back Up Charts**

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28

## Types of Uncertainties (1 of 3)

![](_page_28_Picture_1.jpeg)

## Parametric uncertainties

- Uncertainty that results from errors in the underlying physical models, or model input parameter estimates
  - ➢i.e. char thermal conductivity, pyrolysis gas enthalpy, decomposition kinetics constants

Properties that are difficult to measure are often estimated or theoretically calculated

This type of uncertainty can be reduced through testing and analysis but not eliminated

## Types of Uncertainties (2 of 3)

![](_page_29_Picture_1.jpeg)

## Stochastic variability

- Uncertainty that arises from natural fluctuations in the physical environment, or from material property variability
  - ➢i.e. Varying atmospheric conditions, lot-to-lot property variation
  - This type of uncertainty is always present and can not be reduced

Typically accounted for in the entry trajectory simulations using a Monte Carlo simulation

 These uncertainties are what most people think of when they think about uncertainties

## Types of Uncertainties (3 of 3)

![](_page_30_Picture_1.jpeg)

## Structural uncertainties

- Arise in numerical simulations due to the fact that simulations employ mathematical models to simulate physical phenomenon
- Mathematical models often make simplifying assumptions which are sometimes only valid over a limited range of conditions
- Computational truncation errors
- i.e. Tauber-Sutton radiative heating correlation, transfer coefficient-recovery enthalpy approach for convective heating boundary condition (FIAT/CMA), differential equation discretization method

![](_page_31_Picture_0.jpeg)

 Biases are factors applied to the nominal thickness to account for *known deficiencies* in the methodology used to calculate the nominal TPS thickness

**Biases and Margin** 

- Biases account for structural uncertainty and are applied to both nominal and margined thicknesses
- A bias should be applied if the thermal model shows a consistent difference between prediction and test data
- i.e. CEV TPS applied a bias to thickness based on the calculated recession
- For HIAD we need to add a bias to account for an uncorrelated model
- Margin is applied to the nominal thickness to account for the parametric and stochastic uncertainty types

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## **Random Variable Correlation**

![](_page_32_Picture_1.jpeg)

- Random variables are statistically correlated when the probability distribution of one depends on the value of another random variable
- The strength of the dependence between two random variable is assessed by calculating their correlation coefficient which varies between -1 and 1. A values of 0 means no correlation.
- In semi-plain English, when a functional relationship exists between two parameters, they are correlated and can not be treated as independent random variables

![](_page_32_Figure_5.jpeg)

![](_page_32_Figure_6.jpeg)

## **Random Variable Correlation**

![](_page_33_Picture_1.jpeg)

- This may seem like a problem, but its not.....
- For each sample in Monte Carlo simulation, a vector of random numbers are generated corresponding to the thermal model parameters of interest, {R}
- If there are parameter correlations present, {R} must be modified based on each parameters correlation with one another. The correlation coefficients are collected in a correlation matrix [C]
- The correlation matrix [C] can't be used directly, so an intermediate matrix [U] must be found such that:  $[U]^T[U] = [C]$
- Once [U] is found by using Cholesky decomposition, the correlated vector of random variables can be determined by:

 $\{R_c\} = [U]\{R\}$ 

## **Random Variable Correlation**

![](_page_34_Picture_1.jpeg)

- In reality there is a good chance that correlations exist between density and many other thermal model parameters, however ....
  - In the COMSOL model, we are not able to determine whether or not correlations exist between density and thermal conductivity, density and specific heat, density and permeability, etc, because there is no functional relationship established between these parameters in the COMSOL model
- The correlations can be determined experimentally, but at an expense
- By adding the degree of char to the COMSOL model, we may be able to computationally determine if there are correlations, but it is not as simple as just tracking the density change over temperature since gas conduction plays a significant role in the effective thermal conductivity of the material

## Current Root-Sum-Squared Approach

![](_page_35_Picture_1.jpeg)

- Currently TPS is sized using a root-sum-square (RSS) approach. Typically using three cases
  - Case 1: size heat shield to nominal bondline temperature, apply trajectory dispersion multiplying factors to heat flux
  - Case 2: size heat shield to nominal bondline temperature, apply trajectory dispersion *and* aerothermal uncertainty multiplying factors to heat flux
  - Case 3: size heat shield to *lower* than nominal bondline temperature, apply trajectory dispersion multiplying factors to heat flux
  - These three cases are RSS'ed together to arrive at the margined thickness

$$\tau_{RSS} = 1.10 * [\tau_1 + \sqrt{(\tau_2 - \tau_1)^2 + (\tau_3 - \tau_1)^2}$$