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Processing of Experiments and Simulations into a Validated Failure Model (for a Device)

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FOREWORD

- The problem presented here is a real one having a rather full set of aspects and elements of Model Validation that may be encountered in practice
- The attraction of this talk is the interplay exemplified between experiments, modeling, and statistics that is typically present in Model Validation work
- The device operation, geometry, and finite-element thermal model cannot be presented for information sensitivity reasons, but this does not significantly impede the presentation of pertinent aspects of this problem

Introduction

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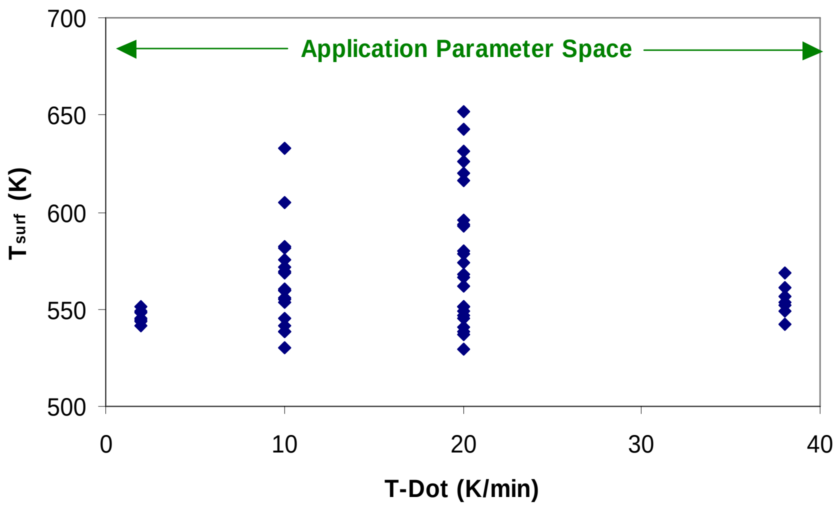
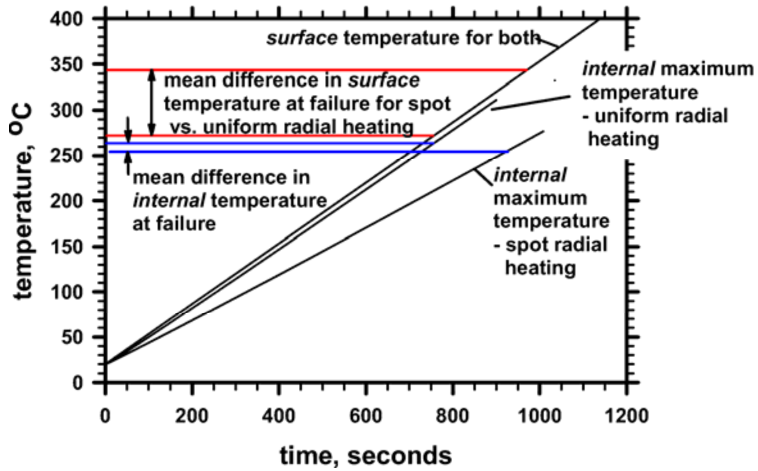
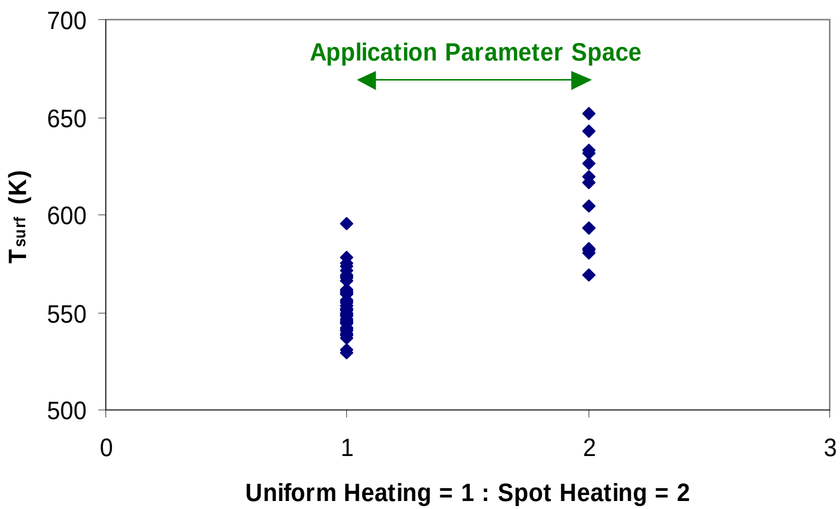
- A system-level thermal model containing the device is to be subjected to various fire accidents in a risk analysis
- From the device's predicted temperature response in a given fire accident, we need to assess the temperature at which the device will fail
- We cannot presently model the complex thermal/mechanical/ electrical failure mechanisms with a physics-based first-principles model
- This drives us to a statistical model of failure, based on failure testing and inference
- The 'model' to be developed and validated here is a Normal PDF model of failure temperature -- fits the distribution of failure temperatures reasonably
- Has uncertain parameters Mean and Standard Deviation
- Contributing uncertainties include both epistemic and aleatory (systematic and random) types.

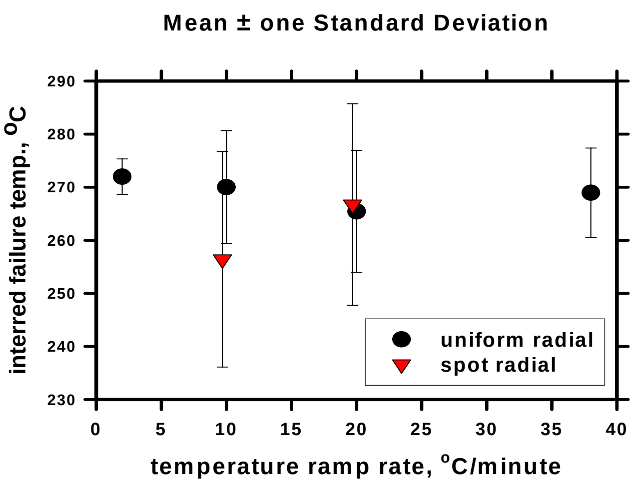
The Problem: *Experimental Realizations and Operational Space of the Application*

<u>Linking Variable</u>: Using <u>internal</u> component temperature rather than <u>surface</u> temperature collapses Failure Temperature variance & factor dependence







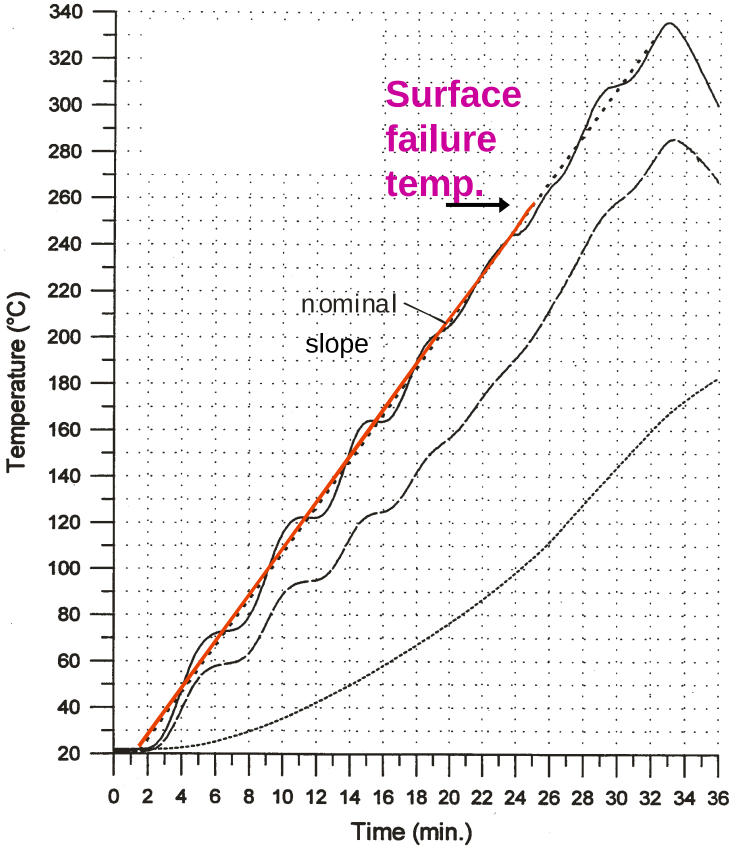


Processing the Experimental Results

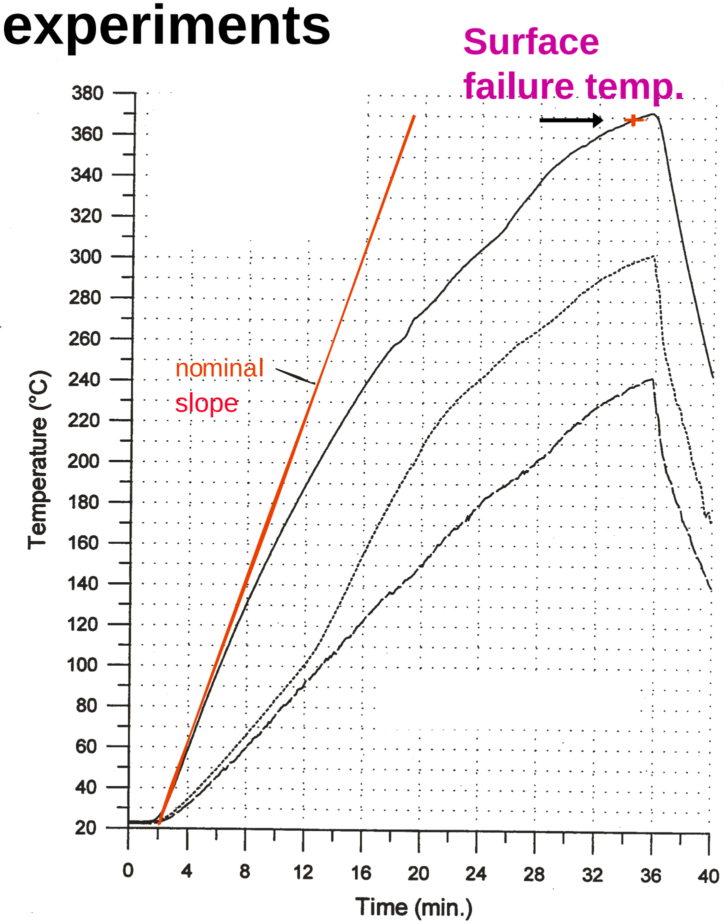
- Device failure temperature is the "linking variable" that ports information from failure characterization experiments to the system-level analyses
- Device internal temperature (where failure mechanism exists and failure occurs) is preferred to case temperature because the former significantly collapses the factor dependence and variance of failure temperature
- Thus, we must transform from measured case temperature at failure in the experiments, to inferred internal temperature at failure.
  - a nonlinear 3D thermal FE model is involved in this transform
- In the following we account for:
  - Sources of experimental error in "face-value" recorded case temperature at failure
  - Sources of FE model error in inferring internal temperature from case temperature

Example Effect not in Face-Value results:
Boundary Conditions – Heating Ramp Errors

Unaccounted-for <u>Variance</u> and <u>Bias</u> effects from heating rate approximations in modeled experiments



Variance effects

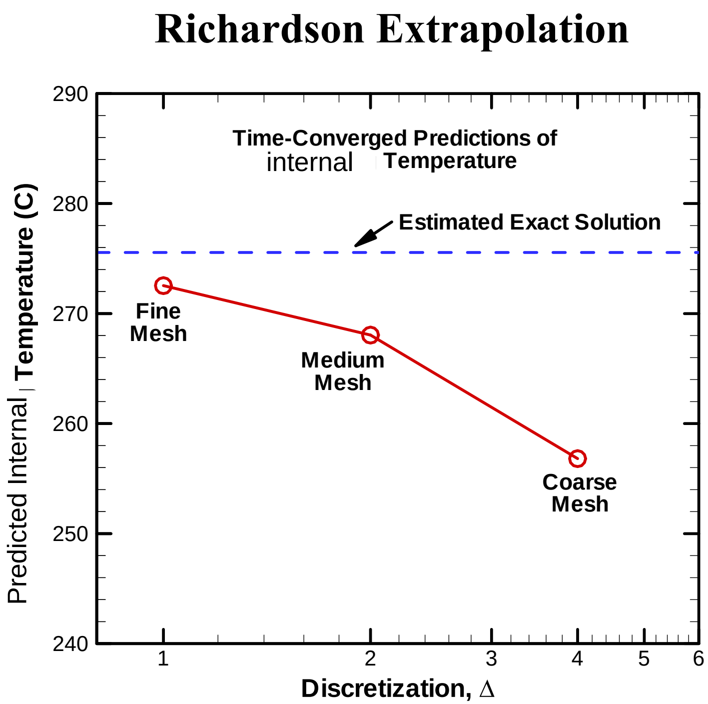


Systematic Bias

Example Effect not in Face-Value results:
Uncertainty of Model Discretization Error

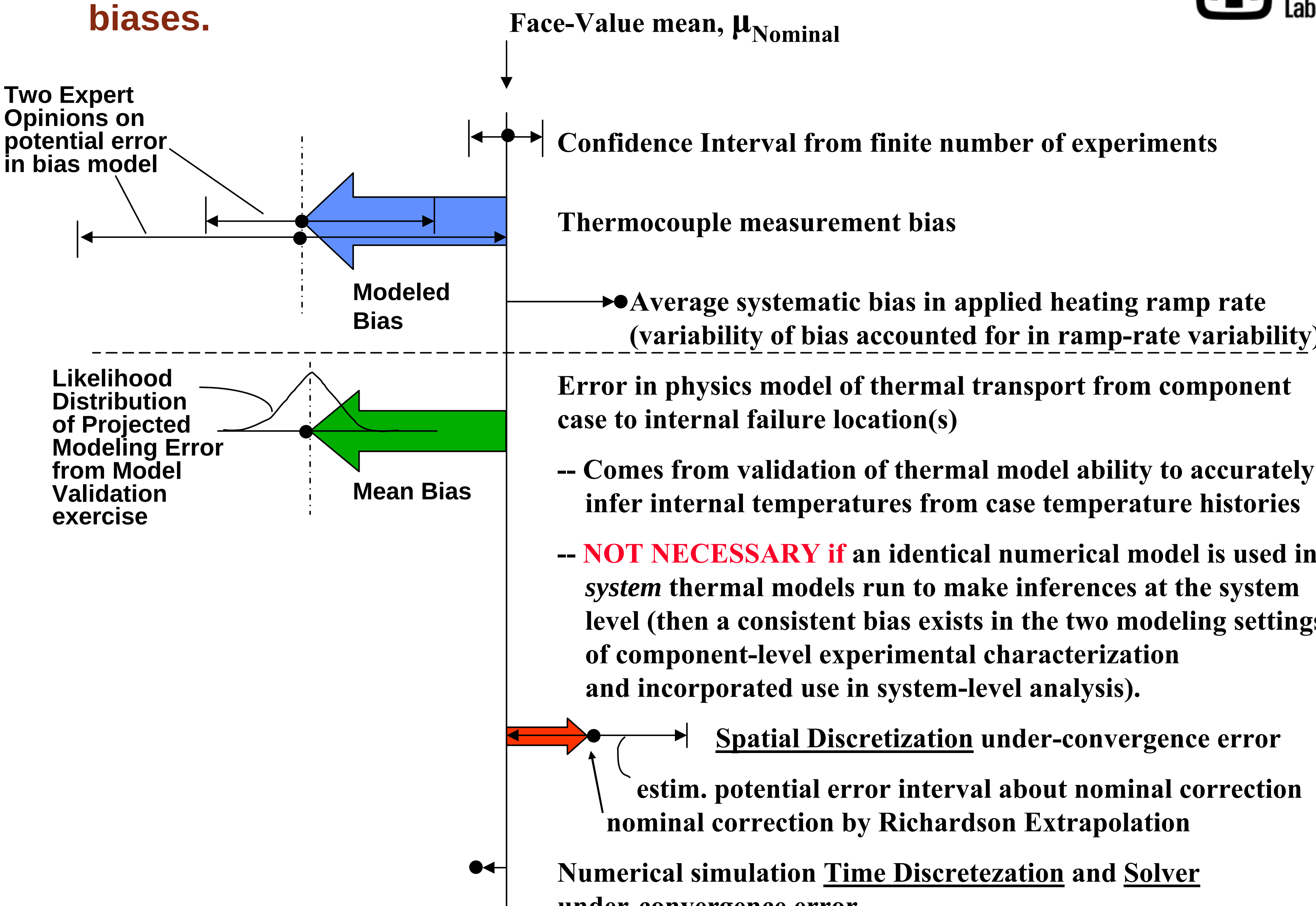
<u>Bias uncertainty</u> exists from unknown error in projected grid-converged results using Richardson Extrapolation

- Spot Heating boundary condition
- Predicted internal temperature (i.e., the inferred Failure Temperature) converges as spatial discretization in the finite-element mesh is refined
- Fine Mesh is 1.2 million linear-HEX finite elements and took a day to run on 64 Pentium-3 processors
- Fine-Mesh results still not converged, but more refined mesh was too expensive
- Used Richardson Extrapolation based on three different grid sizes
- Empirical convergence rate was 1.3 (not theoretically expected 2.0), so R. Extrap. result was somewhat suspect (***<u>uncertainty</u>***)



Bias corrections to inferred Failure Temperatures

– These are algebraically added or superposed on the Face-Value mean $\mu_{Nominal}$ by sampling for random values of the individual biases.



Variance Corrections to Face-Value Results: How things "add" for VARIANCE

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- **Adjustments for sources of variance in measured *case* failure temperatures, propagated to variance of inferred *internal* Failure Temperatures:**

$$\left(\sigma^2_{data} \pm Confidence\ Interval\right) = \sigma^2_{unit/unit} + \sigma^2_{setup/setup} + \sigma^2_{diagnostic}$$

$$\sigma^2_{unit/unit} = \sigma^2_{\substack{geometric \\ and\ thermal \\ transport \\ characterisitics}} + \sigma^2_{\substack{failure \\ \text{mode} \\ inducement}} = \left(\sigma^2_{data} \pm C.I.\right) - \left(\sigma^2_{setup/setup} + \sigma^2_{diagnostic}\right)$$

$$\sigma^2_{setup} + \sigma^2_{diagnostic} = \sigma^2_{\substack{applied \\ ramp\ rate}} + \sigma^2_{TC\ variance} + \sigma^2_{cooling\ BCs} + \sigma^2_{\substack{\text{others} \\ \text{we can't} \\ \text{deconvolve}}}$$

Case to Internal-Temperture transformations

$$\sigma_{j,\ \substack{\text{inferred} \\ \text{temperature}}} \approx \frac{\partial T_{\text{internal}}}{\partial T_{case}} \sigma_{j,\ \substack{case\ temperature \\ measurement}}; \quad where \frac{\partial T_{\text{internal}}}{\partial T_{case}} = f\left(ramp\ rate, heating\ \text{mode}\right)$$

{from FE thermal model}

$$\sigma_{\substack{case\ temp.@\ failure \\ due\ to\ BC\ ramp \\ rate\ variabilities}} \approx \frac{\partial T_{caseTemp.@\ failure}}{\partial \dot{T}} \sigma_{\dot{T}}; \quad \dot{T}\ \ represents\ \ ramp\ \ rate$$

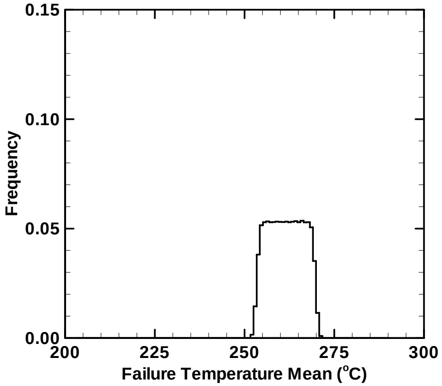
Uncertainty Aggregation Process

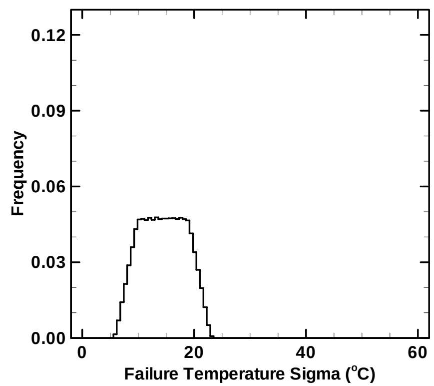
- A dual-loop Monte Carlo sampling approach is used for aggregating the various uncers. in the expers. & FE model:
  - The Bias factors are sampled and realizations are algebraically added to $\mu_{Nomnial}$ to get a point realization of Mean Failure Temp.
  - A realization from the interval $\left(\sigma_{data} \pm C.I.\right)$ is taken and inserted into the variance equation for $\sigma^2_{unit/unit}$, along with known variance quantities from the experiments which are used to decrement the magnitude of the conservative estimate for $\sigma_{unit/unit}$.
  - Many such random realizations of Failure Temperature mean and standard deviation define corresponding normal PDFs (realizations). Each PDF is then sampled and all samples are binned to form an aggregate PDF (next slide).

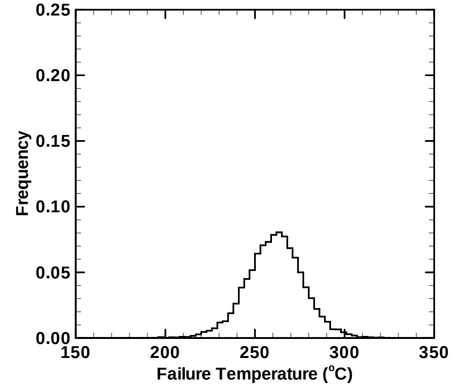
Monte Carlo Sampling Results for Aggregated Uncertainty

failure temp. Mean | Standard Deviation | Aggregate PDF

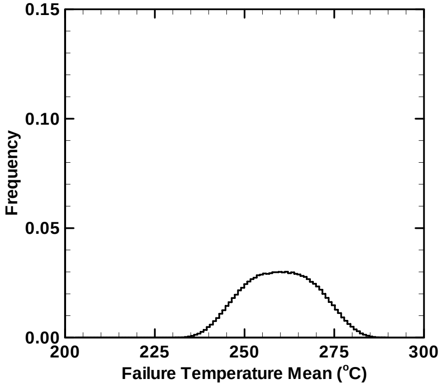
Uniform-20 Heating

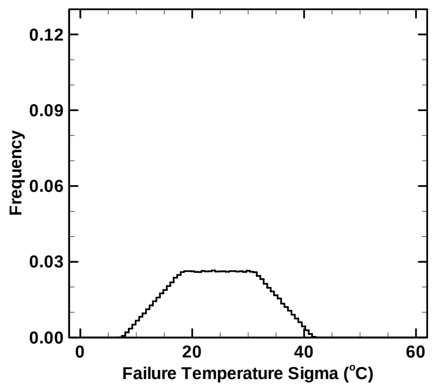


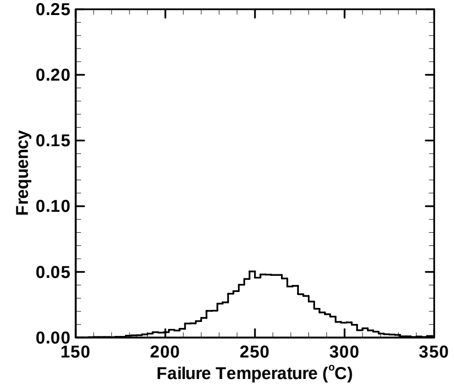




Spot-20 Heating







CLOSING

- The experimental failure data was appropriately processed and transformed into a failure criterion (model) in terms of linking variables optimal to the intended downstream use of the information derived from the experiments (i.e., for use in eventual system-level risk analyses).

- The statistical failure model faithfully replicates the failure data over the operational space of intended use. It predicts failure as accurately as the uncertainty in the experimental data and transforms allow. It is therefore a ***validated*** model for the intended use.

- If we had a physics-based (mechanistic thermal/mechanical/ electrical) failure model, it could certainly aspire to be as accurate as the statistical model…but it could not be validated to be any more accurate (in view of the uncertainty limit or *floor* present here).