

Surrogate-Based V&V

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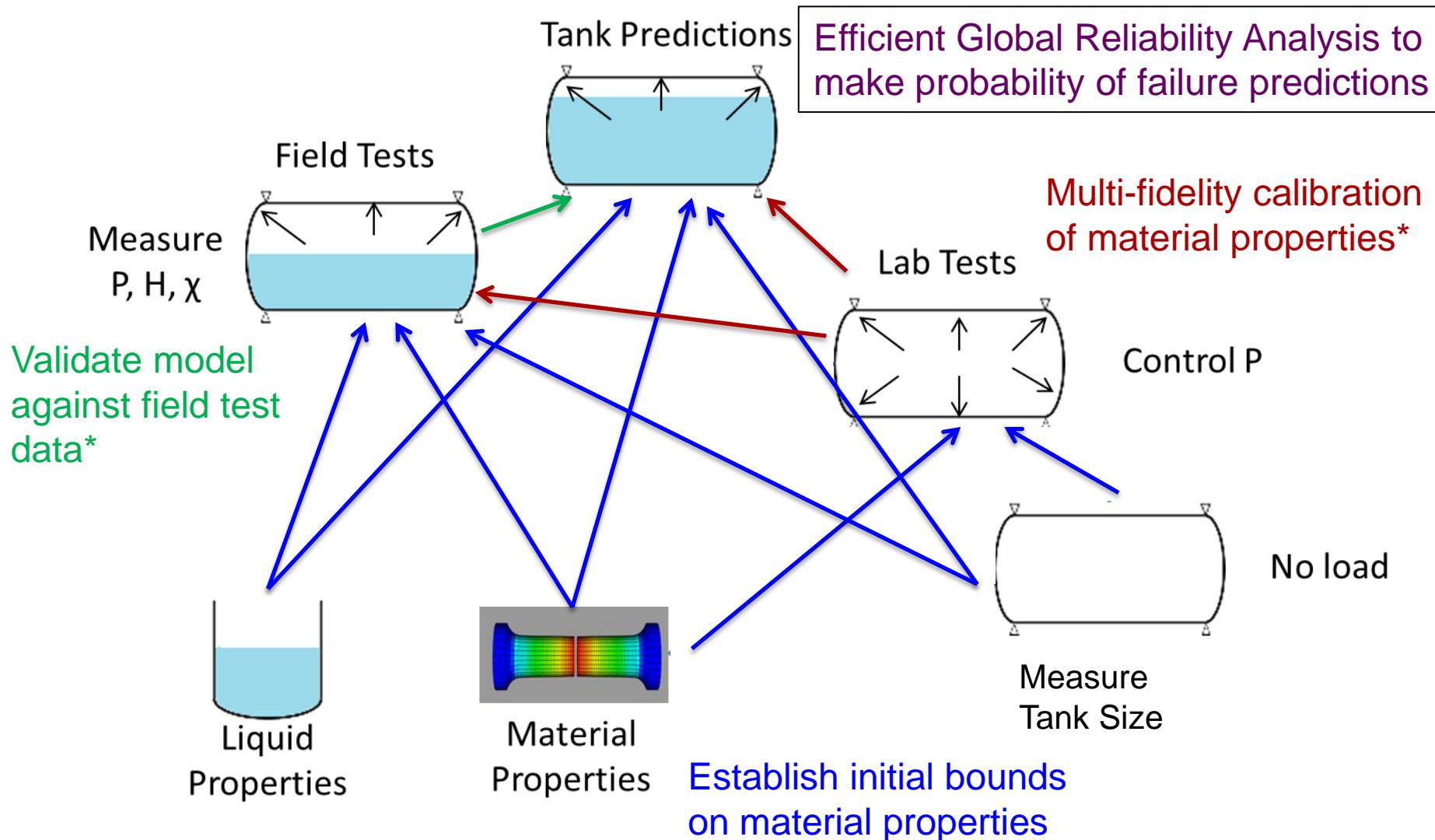


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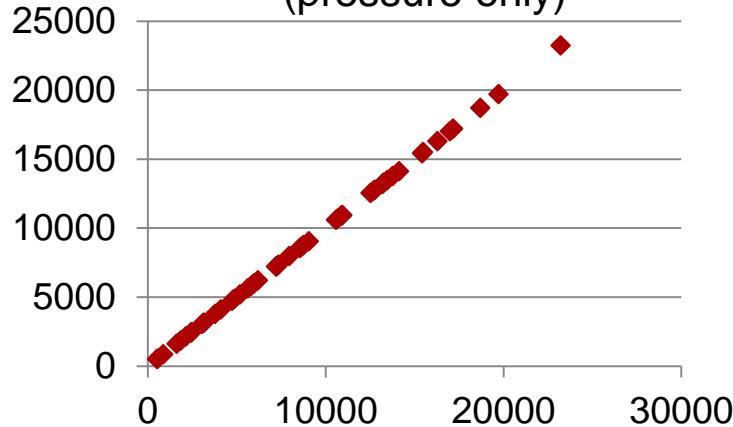
Goal is to use response surface and multi-fidelity surrogates to minimize number of simulations



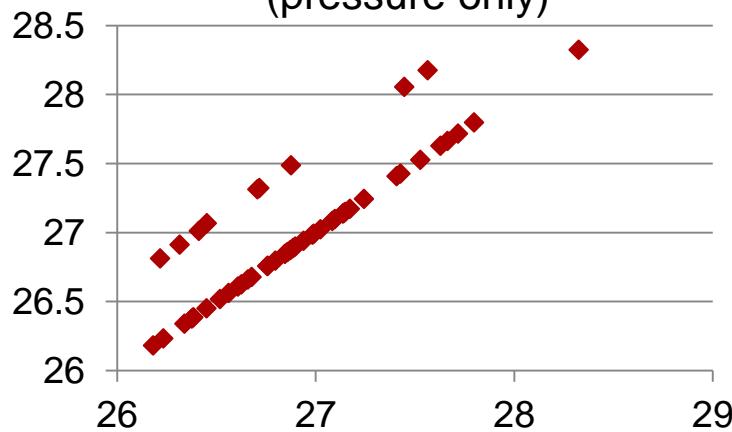
*Used polynomial chaos expansions for higher-order sensitivity analysis

Small initial LHS study established relationship between model fidelities

Mesh2 max stress vs Mesh3 max stress
(pressure only)

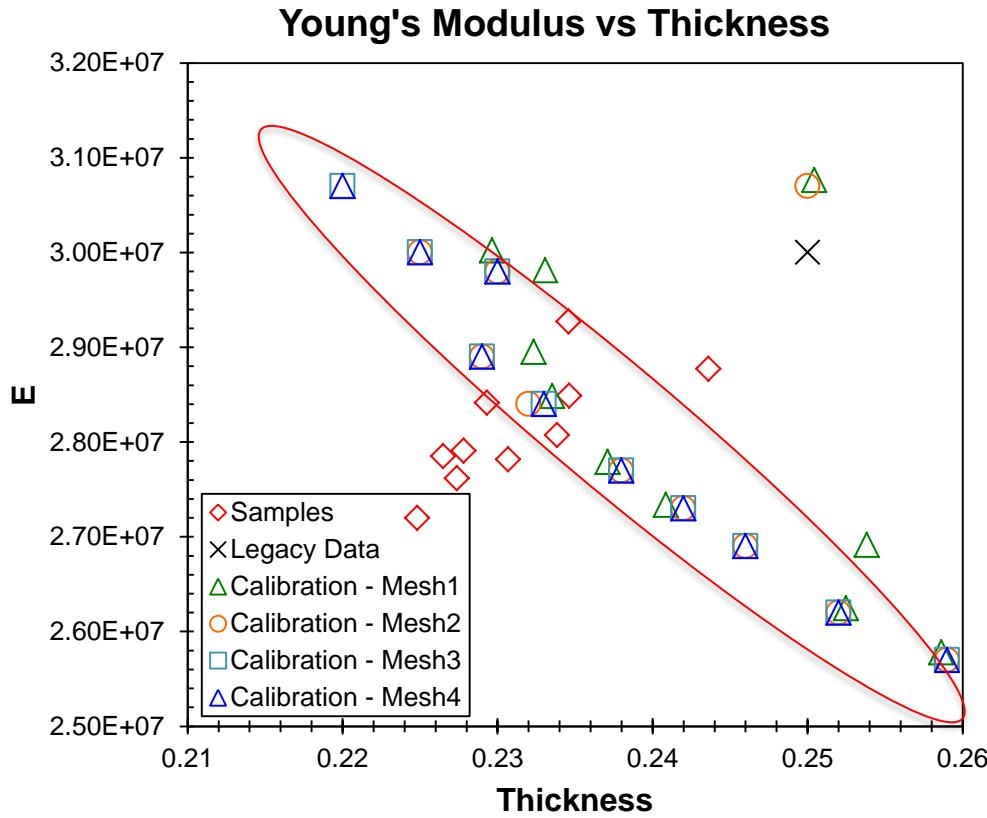


Mesh2 max stress vs Mesh3 max stress
(pressure only)



- Max stress and displacement values were consistent across fidelities
- Location of max stress varied but in a reasonably nice way
 - Most difference between Mesh2 and Mesh3
- Observations support multi-fidelity calibration approach
- Number of simulations
 - Mesh4 = 6
 - Mesh3 = 48
 - Mesh2 = 384
 - Mesh1 = 384

Calibration progressed from Mesh1 to Mesh4 – and don't forget about scale...



- Used multi-start least-squares solver
 - Calibrated Mesh1 (71 runs)
 - Fed solutions forward to calibrate Mesh2 (49 runs)
 - Then to Mesh3 (45 runs)
 - And finally Mesh4 (42 runs)
- Noticed inconsistency with material data
- Scaling parameters reduced inconsistency but converged to only one solution

Polynomial chaos expansion was used to compute higher-order sensitivities

Approximate response with Galerkin projection using global multivariate orthogonal polynomial basis functions defined over standard random variables

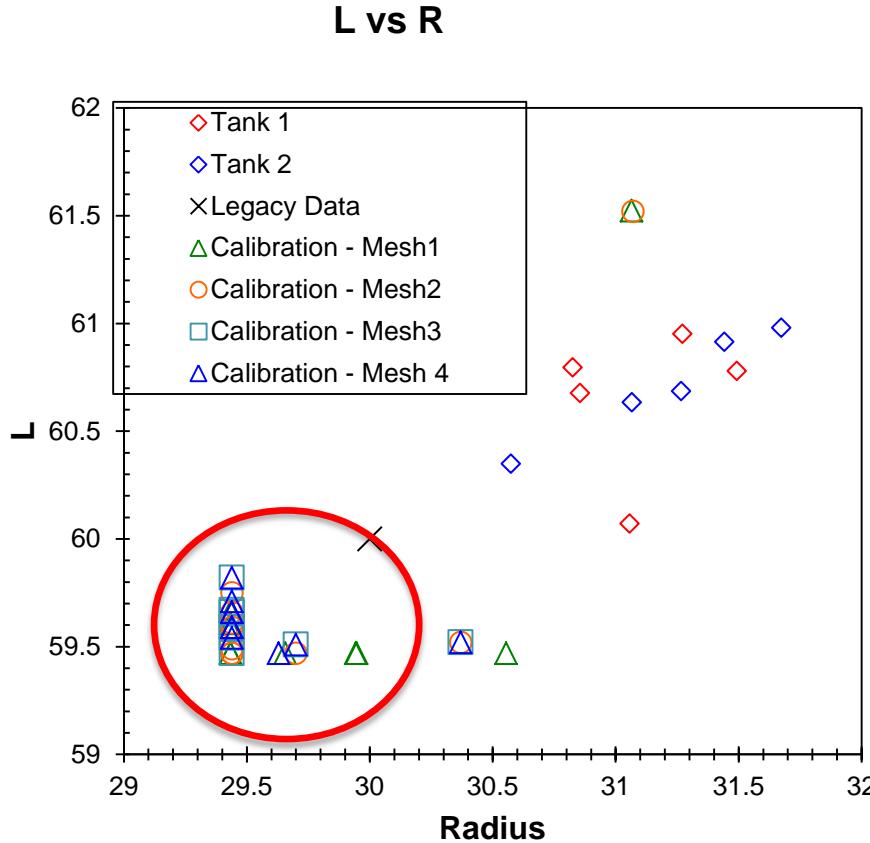
$$R = \sum_{j=0}^P \alpha_j \Psi_j(\xi)$$

$$R(\xi) \approx f(u)$$

$$\alpha_j = \frac{\langle R, \Psi_j \rangle}{\langle \Psi_j^2 \rangle} = \frac{1}{\langle \Psi_j^2 \rangle} \int_{\Omega} R \Psi_j \varrho(\xi) d\xi$$

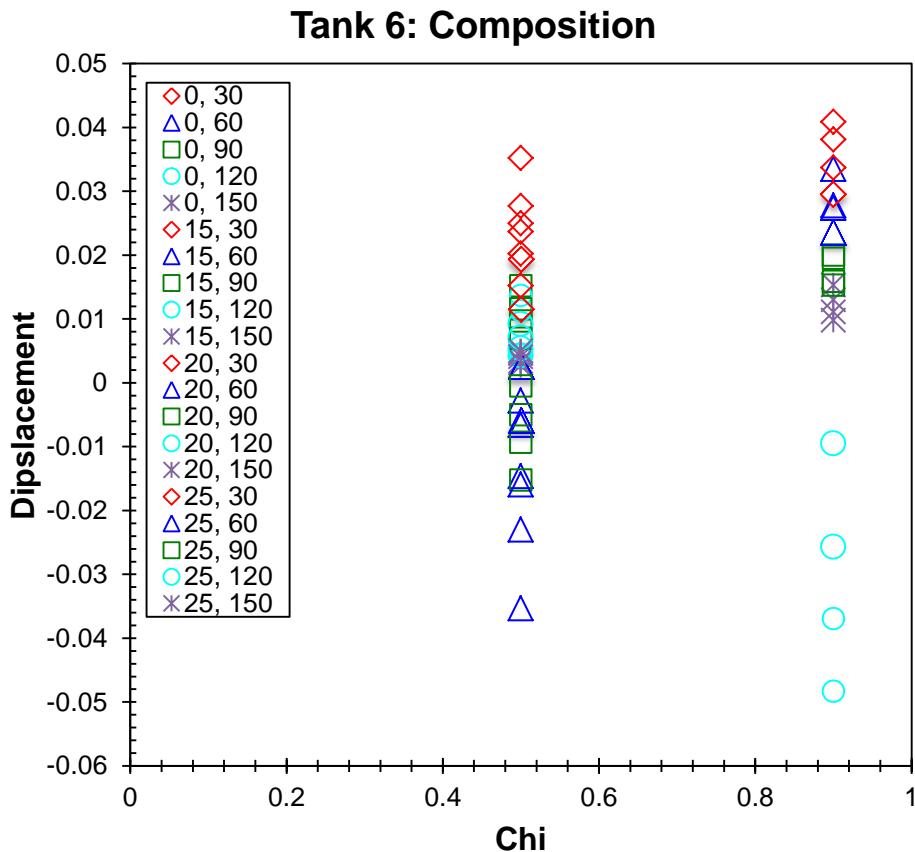
- One approximated, calculate statistics (and sensitivities) analytical, or sample the cheaper surrogate.
- Wiener-Askey Generalized PCE: optimal polynomial basis leads to exponential convergence of statistics (Normal/Hermite, Uniform/Legendre)

Higher-order sensitivities helpful in ruling out interactions of tank dimension with materials



- Noticed that calibration consistently identified smallest tank length and radius
- Sensitivities ruled out second- or third-order interactions
 - Based on polynomial chaos expansion
 - Re-used LHS samples, so no additional simulations
- Possible improvements
 - Calibrate material properties over uncertain tank dimensions
 - Split data and use part for intermediate validation

Validation activities were limited



- Data requires careful study
 - Coverage of domain
 - Confounding of effects
- Ran sensitivity study similar to that for pressure-only case
- Metric would likely emphasize bottom of tank but include all locations
- Possible improvement
 - Split data and also calibrate liquid properties
- Ran into one big issue...

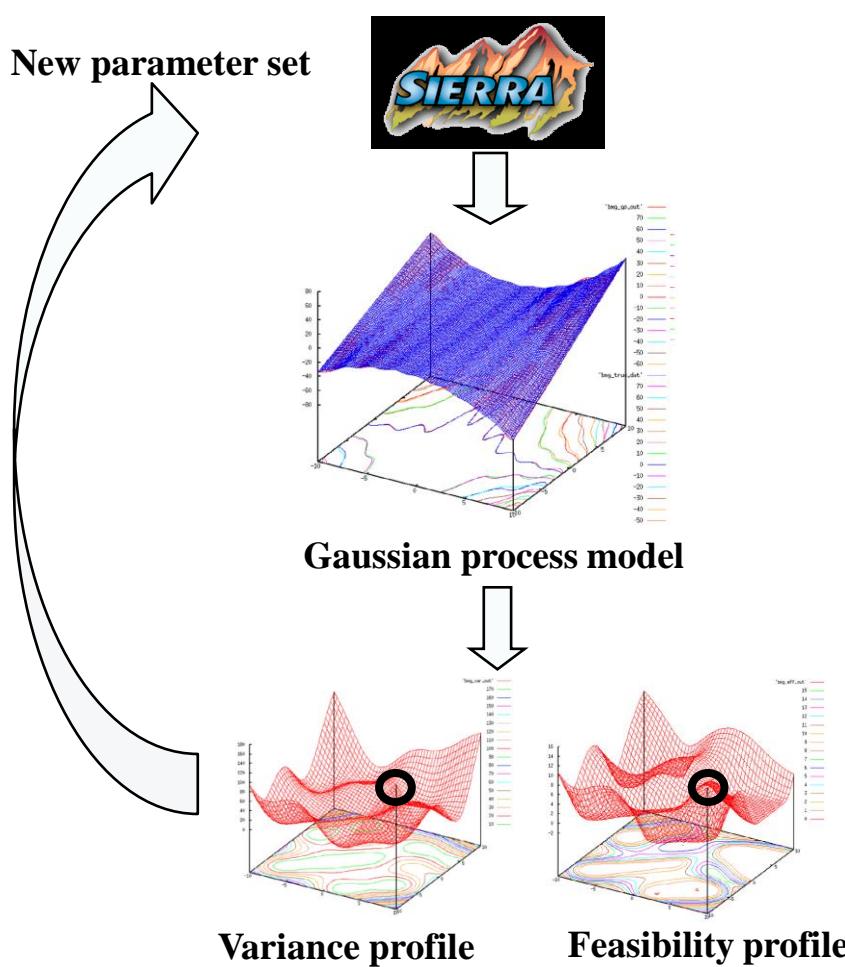
Code Verification Anyone?

When upper bound on $H > 50 \dots$

Traceback (most recent call last):

```
  File "/home/pdough/Projects/VVTankProblem/DakotaLHSLiquid_breakit//EvalTank.py", line 150, in
<module>
    main()
  File "/home/pdough/Projects/VVTankProblem/DakotaLHSLiquid_breakit//EvalTank.py", line 144, in main
    FEMTank.main(X_vec, Phi_vec, Pressure, Gamma_Chi, LiqHeight, E, Nu, Length, Radius, Thickness, meshID,
summaryFileName, dataFileName)
  File "/home/pdough/Projects/VVTankProblem/DakotaLHSLiquid_breakit/FEMTank.py", line 830, in main
    results = cylinder(X_vec_new, Phi_vec_new, Pressure_new, Gamma_new, LiqHeight_new, E_new, Nu_new,
Length_new, Radius_new, Thickness_new, M, N, ",") # don't have cylinder write any files
  File "/home/pdough/Projects/VVTankProblem/DakotaLHSLiquid_breakit/FEMTank.py", line 616, in cylinder
    results = cylEvalResults(M, N, X_vec, Phi_vec, Length, Thickness, Radius, E, Nu, Pressure, Gamma, LiqHeight)
  File "/home/pdough/Projects/VVTankProblem/DakotaLHSLiquid_breakit/FEMTank.py", line 497, in
cylEvalResults
    D_fluid_mn = cylEvalLoadCoeff_fluid_mn(Radius, gamma, LiqHeight, m, n)
  File "/home/pdough/Projects/VVTankProblem/DakotaLHSLiquid_breakit/FEMTank.py", line 440, in
cylEvalLoadCoeff_fluid_mn
    alpha = pi-acos((LiqHeight-Radius)/Radius)
ValueError: math domain error
```

Used Efficient Global Reliability Analysis (EGRA) for probability of failure estimates



- Iteratively refines Gaussian process
- Balances exploration of unknown space with refinement around threshold
- Spent too many simulations exploring

Bichon, B.J., Eldred, M.S., Swiler, L.P., Mahadevan, S., and McFarland, J.M., "Efficient Global Reliability Analysis for Nonlinear Implicit Performance Functions," *AIAA Journal*, Vol. 46, No. 10, October 2008, pp. 2459-2468.

Gaussian process is a stochastic process defined by mean and covariance functions

- Can have constant, linear, and quadratic mean trend
- Covariance function is

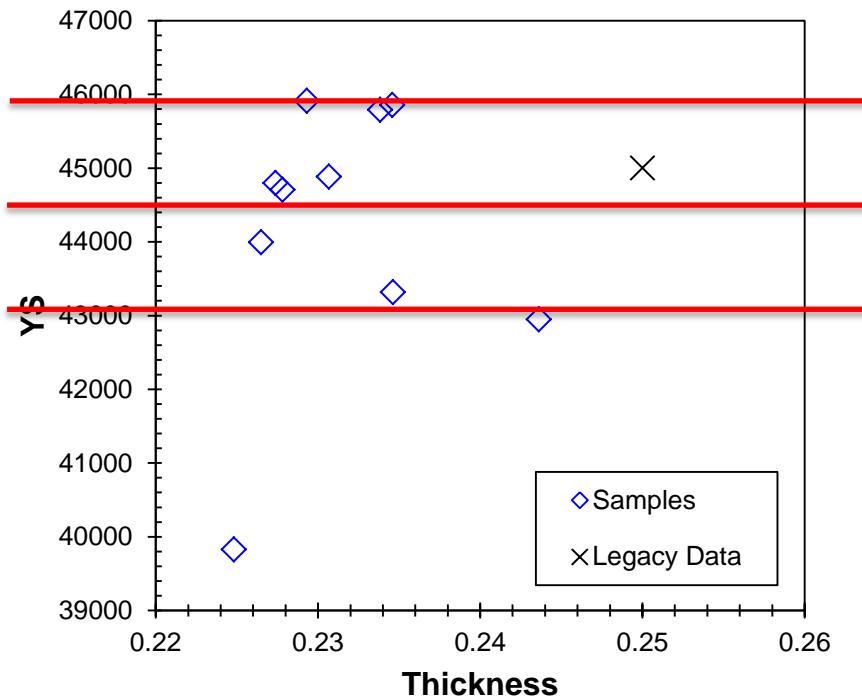
$$C_{12}(\mathbf{x}^1, \mathbf{x}^2) = \sigma^2 \exp \left\{ -\sum_{i=1}^n \rho_i^2 (\mathbf{x}_i^1 - \mathbf{x}_i^2)^2 \right\}$$

where σ and ρ_i are found by maximizing the likelihood function

$$L = \frac{-n}{2} \log(2\pi) - \frac{1}{2} \log(\det(C)) - \frac{1}{2} \mathbf{z}^T C^{-1} \mathbf{z}$$

Probability of failure at nominal test conditions came out to be 0!?!?!

YS vs Thickness



- Considered three different failure thresholds
- Also considered threshold of 20,000
 - Exceeded with probability 1
- 50 (unique) simulations using Mesh3

Do we consider the model credible enough to base a decision on?

- Geometric fidelity – not enabled by this activity
- Physics fidelity – low, by definition
- Solution verification – relationship between meshes understood
- Code verification – code crashes for some of parameter range
- Validation – insufficient time spent on it
- Uncertainty quantification – some done, incomplete for validation, no roll-up (need to include surrogate errors)

- NO, especially given limited historical experience with model
- Want to prioritize and request resources to address most pressing model and data needs