Computer model calibration for design, with an application to wind turbine blades

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Computer experiments

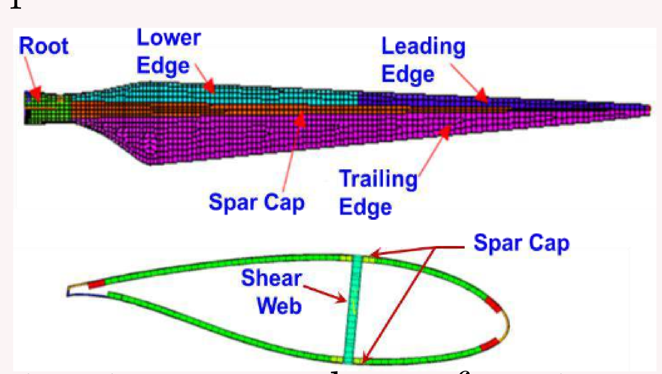
Researchers increasingly look to computer experiments to investigate phenomena where physical experimentation is difficult or impossible[6, 7].

Computer model calibration

- Computer models may include unknown inputs (calibration inputs) that must be estimated[4].
- Calibration input is often estimated by combining simulator output with field data.
- Calibration is ordinarily thought of as bringing a computer model into agreement with reality.

Finite element smulator

We rely on a finite element simulator of the blade cost and performance.



- Calibration inputs: volume fraction, thickness of blade material. Control input: temperature.
- Outputs are tip deflection, rotation, and cost; the design goal is to minimize these.
- Model utilizes `ANSYS` simulation software; computation cost is too high for use in MCMC.

References

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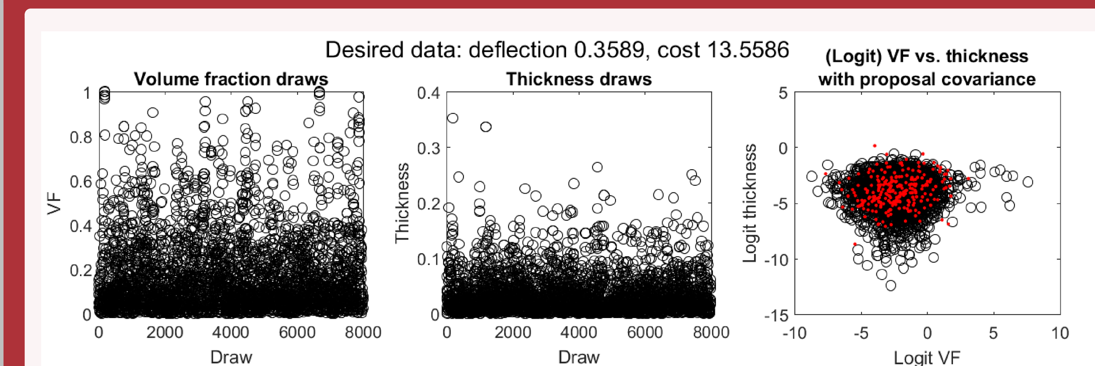
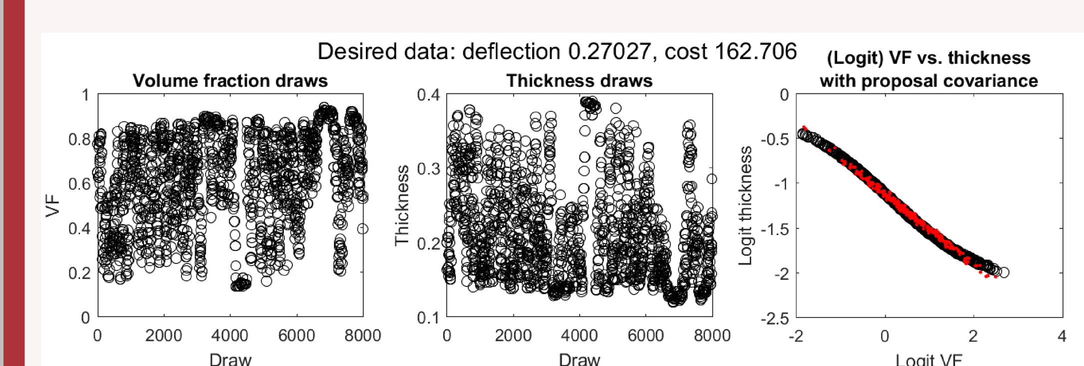
Central idea

Previous explorations of computer model calibration have approached calibration as a matter of bringing a computer model into agreement with physical reality[1, 4, 3, 8]. **In the present work, we consider computer model calibration as a method for design.** Under this framework, we calibrate a computer model not using physical experimental data, but rather using "desired data" which describes the performance one hopes to achieve in the simulated system.

Results





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MCMC imp

- Calibrate volume fracti
desired data. Set a unif
- Each iteration of the M
for x_3, x_4, and the obse
- Where $\mathbf{y}$ is the desired
$\Sigma_{\mathcal{D}} = \mathrm{Var}(\mathcal{D})$, the likeli

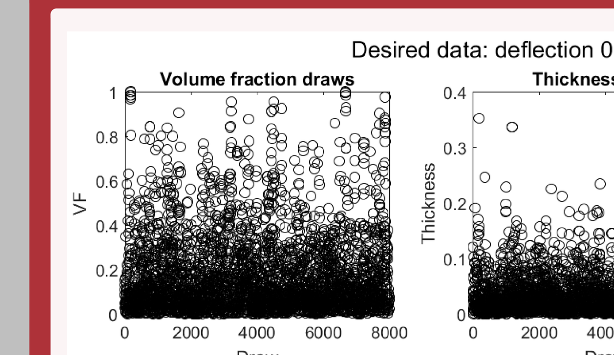
$L(\mathcal{D}|x_3,x_4,\lambda,\boldsymbol{\beta},\Sigma_{\mathcal{D}}) = |$

hence[8] the full posteri

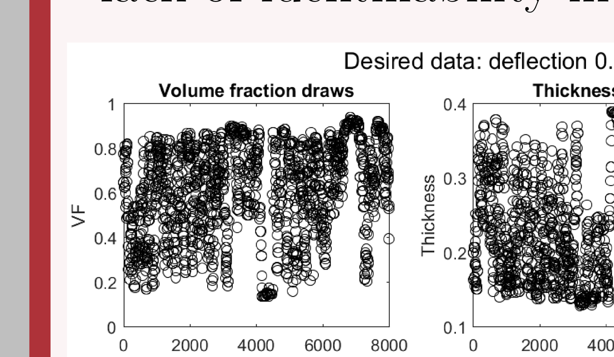
$$\pi(x_3, x_4, \sigma_d^2, \sigma_r^2, \sigma_c^2)$$

- Eliminate boundary co
$\tau_j = \log(\sigma_j^2)$ for $i = 3,$
- We use the Metropolis-
we set normal proposal
$\tau_j^{(n)}|\tau_j^{(n-1)}$, $\forall i \forall j$.
- In burn-in, the proposa
using the sample covari
achieving optimal accep

Resu



- Posterior means are ser
desired data. Therefore
consider a surface over
- Where desired output i
ambitious, the MCMC
lack of identifiability in



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