Computer model calibration as a method of selecting material properties for design of a wind turbine blade

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1 Introduction

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2 Gaussian processes and computer calibration

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2.1 Gaussian processes

Blah

2.2 Gaussian process regression

Blah

2.3 Gaussian processes in computer model calibration

Blah

3 The emulator

Blah

3.1 Wind turbine blade simulator

Blah

3.2 Mathematical basis for the emulator

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3.3 Design

Blah

3.4 Covariance parameters

Blah

3.4.1 Finding covariance parameters via MCMC

Blah

3.4.2 Grid optimization

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3.4.3 Gradient method

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3.5 Normalization of inputs and standardization of outputs

Blah

3.6 Computational difficulties

Blah

3.6.1 Likelihoods

Blah

3.6.2 Ill-conditioned covariance matrices

Blah

4 MCMC using the emulator

Blah

4.1 MCMC methods

Blah

4.2 The model

Blah

4.2.1 Desired observation variance

	Heteroskedastic, constant	Homoskedastic, constant	Heteroskedastic, prior	Homoskedastic, prior
Deflection	0.749	0.729	0.659	0.709
Rotation	0.0904	0.0865	0.0773	0.0843
Cost	276.16	236.11	350.80	233.95

Table 1: Comparison of model outputs, where the desired data outputs are assumed to be either homoskedastic or heteroskedastic, with either a specified constant variance or a $1/\sigma^2$ prior.

4.2.2 Full model and likelihood

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4.2.3 Computational difficulties

Blah

4.3 Boundary constraints

Blah

4.3.1 Convergence difficulties

Blah

4.3.2 The Metropolis-Hastings algorithm

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4.3.3 Implementation of the Metropolis-Hastings algorithm

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4.4 Which data to desire?

Blah

4.4.1 Motivations behind the choice of desired data

Blah

4.4.2 Differing results

Desired data d	σ^2_{defl}	σ^2_{rot}	σ^2_{cost}	$\mu_{v\|d}$	$\mu_{h\|d}$	$\sigma^2_{v\|d}$	$\sigma^2_{h\|d}$
$(0, 0, 0)$	375.45	277.69	2.62	0.215	$4.01 \cdot 10^{-2}$	$4.41 \cdot 10^{-2}$	$1.92 \cdot 10^{-3}$
$(0.65, 0.077, 96)$	16.74	15.25	$4.62 \cdot 10^{-7}$	$1.09 \cdot 10^{-3}$	$3.36 \cdot 10^{-4}$	$1.02 \cdot 10^{-5}$	$9.97 \cdot 10^{-6}$

Table 2: Comparison of results for two different (low) values of d. Values listed are, respectively, the posterior means for the observation variance of each model output, posterior means for volume fraction (v) and thickness (h), and posterior variance of volume fraction and thickness.

4.5 Exponentially distributed desired data

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4.5.1 Motivation

Blah

4.5.2 Implementation and results

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4.6 Identifiability issues

Blah

5 Future work

Blah

5.1 Alternative means of handling cost

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5.1.1 Removing cost from the model

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5.1.2 Alternative priors for controlling cost

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5.2 Building a desired data response surface

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5.3 Implementing Hamiltonian Monte Carlo

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5.3.1 Hamiltonian Monte Carlo

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5.3.2 Benefits

Blah

5.4 Model discrepancy

Blah

6 Conclusion

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