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

**Title:** Computer model calibration as a method for design, with an application to wind turbine blades

**Abstract:** Computer simulations have become a common means of studying phenomena for which it is difficult to acquire data through direct physical experimentation. Often these computer models contain unknown inputs, called calibration inputs, the values of which must be estimated for successful simulation. The value of a calibration input may be estimated, for example, by combining observations of the simulator output with real-world experimental data. Previous explorations of computer model calibration have approached calibration as a matter of bringing a computer model into agreement with physical reality. 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. We illustrate this technique using a finite element simulation of wind turbine blade performance. We create a Gaussian process emulator of the finite element output and use Markov chain Monte Carlo sampling to calibrate the parameters of the emulator. Whereas in traditional model calibration, the result of calibration would be to discover the settings that allow a simulation to approximate reality, here the result of calibration is to discover settings that allow the simulation to approximate the desired performance outcome.

1. Overview of NSF-DEMS project goals
2. Background and conceptual underpinnings
   1. Explanation of Gaussian processes
   2. Explanation of Gaussian process regression
   3. Background on the use of Gaussian processes for computer model calibration
3. The emulator
   1. Description of the finite element model to be emulated
   2. Mathematical basis for the emulator (formulae for trained mean and covariance functions)
   3. Design used to sample the simulator
   4. Covariance parameters for the emulator and how they were selected
      1. Computational difficulties (and how they complicate the use of MCMC here)
      2. Using a grid optimization framework: advantages and disadvantages
      3. Gradient descent method: explanation and advantages
   5. Normalization of the emulator inputs, and standardization of the outputs
   6. Computational difficulties and solutions
      1. Use of log-likelihoods
      2. Use of covariance matrix nuggets
4. The MCMC routine and results
   1. Background on MCMC
   2. Choice of priors and resulting posterior likelihood
      1. Selection of observation variance prior
         1. Setting constant observation variance at 2 s.d.’s positive
         2. Setting constant homoskedastic observation variance
         3. Setting prior on homoskedastic observation variance
         4. Setting prior on heteroskedastic observation variance
      2. Full model description and likelihood
      3. Computational difficulties and solutions
         1. Log-likelihoods
         2. Parallelization of multiple chains
   3. Elimination of boundary constraints: why and how
      1. Problems with ignoring boundary constraints
      2. Metropolis-Hastings algorithm background
      3. Implementation of M-H algorithm
   4. Choice of desired data
      1. Motivations driving the choice of desired data
      2. Results of selecting different values of desired data
   5. Taking the desired data to be exponentially rather than normally distributed
      1. Motivation
      2. Implementation and results
   6. Issues arising from the non-identifiability of volume fraction, thickness when cost is relaxed
5. Future work
   1. Alternative means of handling cost
      1. Removing cost from the model
      2. Placing a prior on VF, thickness as a means of controlling cost
   2. Creation of a response surface of model output at posterior means given desired data
   3. Implementation of Hamiltonian Monte Carlo technique
      1. Background on HMC
      2. Implementation and expected benefits
   4. Inclusion of discrepancy function
6. Conclusion: discussion of the role of computer model validation as a potential methodology for design