## NONPARAMETRIC FUNCTIONAL CALIBRATION OF COMPUTER MODELS

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## Supplementary Material

Here the reader may find additional material, including the full conditional distributions for implementing the proposed model and supplementary figures.

## S1 Full Conditional Distributions for the Proposed Model

Under the reparameterized version of Model (2.4) we have the following full conditional distributions needed for a Gibbs sampling algorithm:

$$\pi(\boldsymbol{\theta}_{1}^{(\mathbf{x})} \mid \xi, \nu, \lambda_{\theta}, \lambda_{y}, \mathbf{y}) \propto \exp\left\{-\frac{\lambda_{y}}{2}(\mathbf{y} - \boldsymbol{\eta}(\boldsymbol{\theta}_{1}^{(\mathbf{x})}, \exp\{-e^{\xi}\}))^{T}(\mathbf{y} - \boldsymbol{\eta}(\boldsymbol{\theta}_{1}^{(\mathbf{x})}, \exp\{-e^{\xi}\}))\right\}$$

$$\times \exp\left\{-\frac{\lambda_{\theta}}{2}(\mathbf{g}(\boldsymbol{\theta}_{1}^{(\mathbf{x})}) - \mu_{\theta}\mathbf{1})^{T}\mathbf{R}_{\nu}^{-1}(\mathbf{g}(\boldsymbol{\theta}_{1}^{(\mathbf{x})}) - \mu_{\theta}\mathbf{1})\right\}$$

$$\pi(\xi \mid \boldsymbol{\theta}_{1}^{(\mathbf{x})}, \lambda_{y}, \mathbf{y}) \propto \exp\left\{-\frac{\lambda_{y}}{2}(\mathbf{y} - \boldsymbol{\eta}(\boldsymbol{\theta}_{1}^{(\mathbf{x})}, \exp\{-e^{\xi}\}))^{T}(\mathbf{y} - \boldsymbol{\eta}(\boldsymbol{\theta}_{1}^{(\mathbf{x})}, \exp\{-e^{\xi}\})) + \xi - e^{\xi}\right\}$$

$$\lambda_{y} \mid \boldsymbol{\theta}_{1}^{(\mathbf{x})}, \xi, \mathbf{y} \sim \operatorname{Ga}\left(a_{y} + \frac{N}{2}, \ b_{y} + \frac{1}{2}(\mathbf{y} - \boldsymbol{\eta}(\boldsymbol{\theta}_{1}^{(\mathbf{x})}, \exp\{-e^{\xi}\}))^{T}(\mathbf{y} - \boldsymbol{\eta}(\boldsymbol{\theta}_{1}^{(\mathbf{x})}, \exp\{-e^{\xi}\}))\right)$$

$$\lambda_{\theta} \mid \boldsymbol{\theta}_{1}^{(\mathbf{x})}, \nu \sim \operatorname{Ga}\left(a_{\theta} + \frac{N}{2}, \ b_{\theta} + \frac{1}{2}(\mathbf{g}(\boldsymbol{\theta}_{1}^{(\mathbf{x})}) - \mu_{\theta}\mathbf{1})^{T}\mathbf{R}_{\nu}^{-1}(\mathbf{g}(\boldsymbol{\theta}_{1}^{(\mathbf{x})}) - \mu_{\theta}\mathbf{1})\right)$$

$$\pi(\nu \mid \boldsymbol{\theta}_{1}^{(\mathbf{x})}, \lambda_{\theta}) \propto |\mathbf{R}_{\nu}|^{-1/2}\exp\left\{-\frac{\lambda_{\theta}}{2}(\mathbf{g}(\boldsymbol{\theta}_{1}^{(\mathbf{x})}) - \mu_{\theta}\mathbf{1})^{T}\mathbf{R}_{\nu}^{-1}(\mathbf{g}(\boldsymbol{\theta}_{1}^{(\mathbf{x})}) - \mu_{\theta}\mathbf{1}) + \nu - e^{\nu}\right\}$$

$$\times (1 - \exp\{-e^{\nu}\})^{b_{\theta}-1}.$$
(S1.1)

## S2 Supplementary Tables and Figures



Figure 1: Smoothed approximate posterior distributions of  $c_2$ ,  $\beta_0^U$ , and  $\beta_1^U$  (first three panels from the left) when replacing the GP prior with  $\theta_1(x) = \beta_0 + \beta_1 \sqrt{x}$ . The far right panel plots realizations of the estimating curves (grey lines) based on draws of  $\beta_0^U$  and  $\beta_1^U$  from their posterior, along with the true function for reference (heavy black line).



Figure 2: Posterior predictions at holdout settings with approximate 95% error bars under (a)  $\theta_1(x)$  constrained at  $x_1$  and  $x_N$ , (b)  $\theta_2$  constrained between tight prior bounds, (c)  $\theta_1(x) = \beta_0 + \beta_1 \sqrt{x}$ , and (d)  $\theta_1$  assumed constant.

Table 1: Root mean squared predictive error (RMSPE) at the holdout settings for each link function.



Figure 3: Posterior sample paths of  $c_1(\cdot)$  obtained from using the logit, probit, c-log-log, and identity link functions with the simulated data example. The tick marks at the bottom indicate the settings for the training data.



Figure 4: Trace plots of sampled values of the calibration parameters  $c_2$ ,  $c_1(x_{10})$ , and  $c_1(x_{15})$  for three different chains (with different initial values) under vague priors for both  $c_1(\cdot)$  and  $c_2$ .



Figure 5: Sample paths of  $c_1(\cdot)$  obtained from combining the three chains in Figure 4. The tick marks at the bottom indicate the settings for the training data.



Figure 6: Histograms of sample statistics calculated from 2,000 replicated datasets from the posterior predictive distribution:  $T_1$  = sample mean (left panel),  $T_2$  = sample variance (middle panel),  $T_3 = \sum_{i=1}^{N} x_i y_i$  (right panel). The dark vertical lines are at the observed statistics from the field data.



Figure 7: Posterior predictions of maximum stress from the glide VPSC model with approximate 95% error bounds at the observed experimental settings.