Title
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111Equation Chapter 1 Section 1Model Uncertainty Quantification and Updating of a Boundary Condition Model of a Miter Gate Using Strain Measurements

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ABSTRACT
This paper presents a model uncertainty quantification and updating approach for a boundary condition model of a miter gate. A boundary condition model is used as the forward model to predict the boundary load condition of a miter gate for a given gap length. The boundary force prediction is then employed as inputs to a strain analysis model that predicts the strain response of the gate. Due to model simplifications, the boundary condition model may not accurately represent the true physics. By following the Kennedy and O'Hagan (KOH) framework under a Bayesian scheme, this paper corrects the unobservable boundary condition model using the strain measurements by simultaneously estimating the gap length and quantifying the model uncertainty. Results show that the proposed approach can effectively estimate the unknown gap length and improve the prediction of both the boundary condition model and strain response model.

Keywords: Miter Gates, Boundary Condition Model, Model Calibration, Uncertainty Quantification, Model Updating

Introduction
The US Army Corps of Engineers (USACE) maintains 236 miter gates at 191 sites [1]. One of the most common failures of miter gate is the deterioration of quoin block due to the rolling contact between supporting wall and miter gate, leading to the loss of contact, i.e. gap. Unexpected closure of miter gates will happen when high-stress area where boundary force exceeds the limit states emerges as the gap length increases. Early gap prediction is required before gap length is too large to maintain normal operation of miter gates. Even through models have been developed to predict the boundary forces along quoin block by using a contact model or by simplifying the contact as a pin boundary condition, these models may not accurately predict the boundary load condition due to model assumptions and simplifications. In addition, the unknown gap length of quoin block further complicates the boundary load condition analysis. In this work, we are going to implement Bayesian calibration to identify the gap length and correct the boundary condition model. Since true boundary force is distributed and unobservable, we construct a multi-level model for miter gate and use strain measurements for Bayesian calibration.

Multi-level simulation models
A high-fidelity ABAQUS finite element simulation model was developed for stress analysis and boundary contact analysis as shown in Fig. 1 [3], in which the distributed boundary forces at normal and tangential directions can be respectively obtained for a given gap length. Based on finite element model, a reduced-order model of strain analysis was developed for prediction of strain gauges using static condensation method [4] with the distributed boundary force as input. Even though both the boundary contact analysis model and strain analysis model share the same finite element model, the analyses are performed in a multi-level manner. As shown in Fig. 2, boundary condition model, g_{BC}^{m}, is called unobservable model since the distributed boundary force $\mathbf{F}_{BC}(\mathbf{x}, \mathbf{d}_u)$ is unobservable, whereas the strain analysis model, g_o^m, is called observable model because strain gauge data $\mathbf{y}_o(\mathbf{x}, \mathbf{d}_o)$ can be measured. Furthermore, the unobservable distributed boundary force may be one of inputs of prediction model, such as the fatigue analysis model. In Fig. 2, $\mathbf{x}$ are upstream and downstream water levels governing the hydrostatic load on the gates, θ^* is the unknown true gap length since gap is underwater in practice. $\mathbf{d}_u$, $\mathbf{d}_o$ and $\mathbf{d}_p$ are respectively the spatial coordinates in the different model responses.

Modularized Bayesian calibration of multi-level model

The underlying true unobservable boundary force can be modeled by

$$\mathbf{F}_{BC}^{true}(\mathbf{x},\mathbf{d}_u)=\begin{cases}\rho g_{BC}^{m}(\mathbf{x},\mathbf{d}_u,\theta_l^*)+\boldsymbol{\delta}_{BC}(\mathbf{x},\mathbf{d}_u), \text{ if } \mathbf{d}_u \geq \theta_l^* \\ 0, \text{ otherwise}\end{cases}. \quad (2)$$

22* MERGEFORMAT ()

where N_u is the number of spatial coordinates $\mathbf{d}_u$, $\boldsymbol{\delta}_{BC}(\mathbf{x},\mathbf{d}_u)$ represent the model discrepancy of g_{BC}^{m} due to the model assumptions or simplifications, ρ is an unknown regression coefficient. Since unobservable distributed response $\mathbf{F}_{BC}^{true}(\mathbf{x},\mathbf{d}_u)\in \mathbb{R}^{2N_u\times 1}$ cannot be obtained in practice to calibrate g_{BC}^{m}, we employed the strain measurements given below

$$\mathbf{y}_o^{e}(\mathbf{x},\mathbf{d}_o)=\mathbf{y}_o^{true}(\mathbf{x},\mathbf{d}_o)+\boldsymbol{\varepsilon}(\mathbf{d}_o)=g_o^{m}(\mathbf{x},\mathbf{d}_o,\theta_l^*,\mathbf{F}_{BC}^{true}(\mathbf{x},\mathbf{d}_u))+\boldsymbol{\varepsilon}(\mathbf{d}_o).$$

33* MERGEFORMAT ()

where $\boldsymbol{\varepsilon}(\mathbf{d}_o)=[\varepsilon(\mathbf{d}_{o,1}),\ldots,\varepsilon(\mathbf{d}_{o,N_o})]^T$ are the measurement errors of strain data $\{\mathbf{x}^e, \mathbf{y}_o^e\}$, N_o is the number of $\mathbf{d}_o$.

The modularized Bayesian scheme [5-6] is adopted. In Module 1, reduced-order model is constructed for g_{BC}^{m} and g_o^{m} using Lagrange multiplier method and static condensation method respectively [4]. Module 2 estimates $\hat{\rho}$ and construct surrogate model $\hat{\boldsymbol{\delta}}_{BC}(\mathbf{x},\mathbf{d}_u,\boldsymbol{\omega}^*)$ based on the strain observations $\{\mathbf{x}^e, \mathbf{y}_o^e\}$, where $\boldsymbol{\omega}^*$ are the hyper-parameters of the constructed discrepancy surrogate model. Module 3 updates the posterior distribution of θ_l (i.e. $f_{\Theta_l}(\theta_l \mid \mathbf{y}_o^e, \mathbf{x}^e, \boldsymbol{\omega}^*, \rho^*)$) by Bayesian inference scheme. In Module 4, the distributed boundary force after calibration and correction is predicted as

$$\hat{\mathbf{F}}_{BC}(\mathbf{x},\mathbf{d}_u)\mid \mathbf{y}_o^e,\mathbf{x}^e,\boldsymbol{\omega}^*,\rho^* = \int_{\theta_l}\rho^* g_{BC}(\mathbf{x},\mathbf{d}_u,\theta_l) f_{\Theta_l}(\theta_l \mid \mathbf{y}_o^e,\mathbf{x}^e,\boldsymbol{\omega}^*,\rho^*)d\theta_l+\hat{\boldsymbol{\delta}}_{BC}(\mathbf{x},\mathbf{d}_u,\boldsymbol{\omega}^*)\in \mathbb{R}^{2N_u\times 1}.$$

44* MERGEFORMAT ()

and the corrected strain response prediction is obtained in similar manner like Eq. (3).

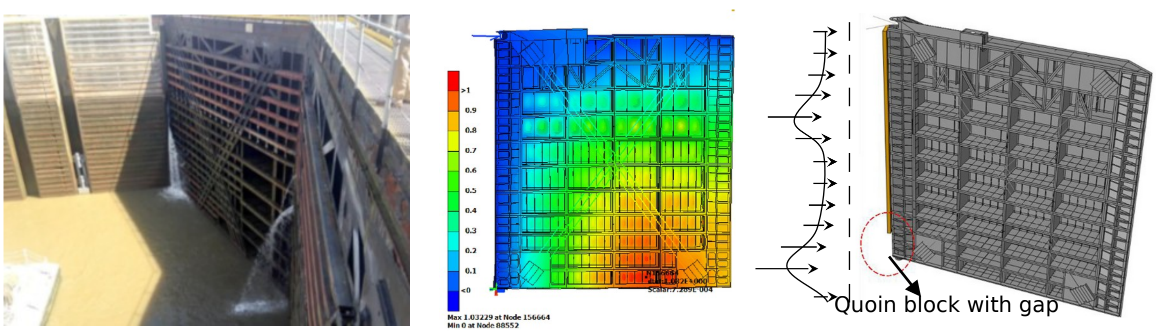

Fig. 1 Miter gate and finite element model (Left: Miter gate; Middle: stress analysis; Right: contact force analysis)

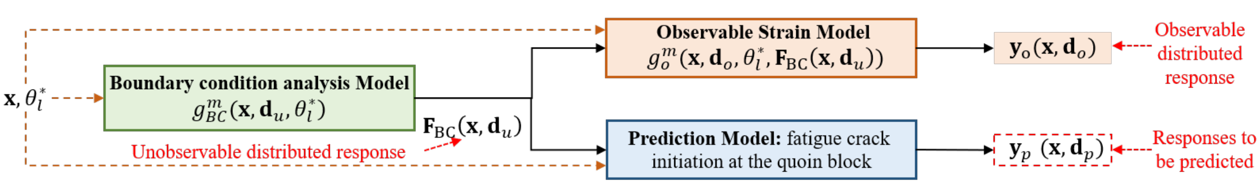

Fig. 2 Multi-level analysis model of miter gate

Results

For the purpose of demonstrating and verifying the proposed method, we assume the boundary force discrepancy functions as

$$\boldsymbol{\delta}_N(\mathbf{x},\mathbf{d}_u)=3(x_{up}-x_{down})[(762-\mathbf{d}_u)/1200]^3, \text{ if } \mathbf{d}_u \geq \theta_l^*.$$

55* MERGEFORMAT ()

$$\boldsymbol{\delta}_T(\mathbf{x},\mathbf{d}_u)=[(x_{up}-x_{down})/100]^2 \sin(\mathbf{d}_u/240), \text{ if } \mathbf{d}_u \geq \theta_l^*.$$

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where both $\boldsymbol{\delta}_N(\mathbf{x},\mathbf{d}_u)$ and $\boldsymbol{\delta}_T(\mathbf{x},\mathbf{d}_u)$ will equal to zero if $\mathbf{d}_u<\theta_l^*$, $\boldsymbol{\delta}_N(\mathbf{x},\mathbf{d}_u)$ and $\boldsymbol{\delta}_T(\mathbf{x},\mathbf{d}_u)$ are the discrepancy of normal and tangential boundary force respectively. $\mathbf{x}=[x_{up}, x_{down}]$ denote the upstream and downstream water levels varying over

[24, 744] inches, $\mathbf{d}_H$ denote the height coordinates along the quoin block whose height is equal to 762 inches (i.e. $\mathbf{d}_H \in [0, 762]$), θ_l^* represents the true gap length, which is assumed to be 150 inches for illustration. Building upon the boundary condition model, assumed discrepancy functions and gap length, 500 strain data are synthesized by Eq. (2) with $\rho=0.8$, and each group of data have 7 strain responses collected through the strain gauges in Fig. 1. The standard deviation of strain measurement error is assumed to be $\sigma_\varepsilon=1$. After that, θ_l^*, $\boldsymbol{\delta}_N(\mathbf{x}, \mathbf{d}_H)$, $\boldsymbol{\delta}_T(\mathbf{x}, \mathbf{d}_H)$, and ρ are assumed to be unknown while performing Bayesian calibration. A non-informative uniform distribution $\theta_l \sim \mathrm{Unif}(135, 165)$ inches is assumed to be the prior distribution of θ_l.

The regression coefficient is estimated to be 0.83, and the maximum a posterior estimation of θ_l is equal to 149 inches, which is very close to the assumed true θ_l^*. Fig. 3 shows the normal force prediction after correction. Fig. 3(a) and (b) respectively compare the normal force discrepancy and total normal force prediction at a certain water level (upstream level: 426 inches; downstream level: 120 inches). Fig. 3(c) shows an error surface by fixing downstream water level at 120 inches. The results show that Bayesian calibration improves the prediction accuracy of boundary force analysis model. Moreover, Fig. 4 depicts the comparison of strain response prediction errors at the seven sensor locations of 50 different input settings by respectively fixing downstream and upstream levels. It indicates that the prediction accuracy of observable strain model can also be improved dramatically after calibration and correction of unobservable boundary condition model.

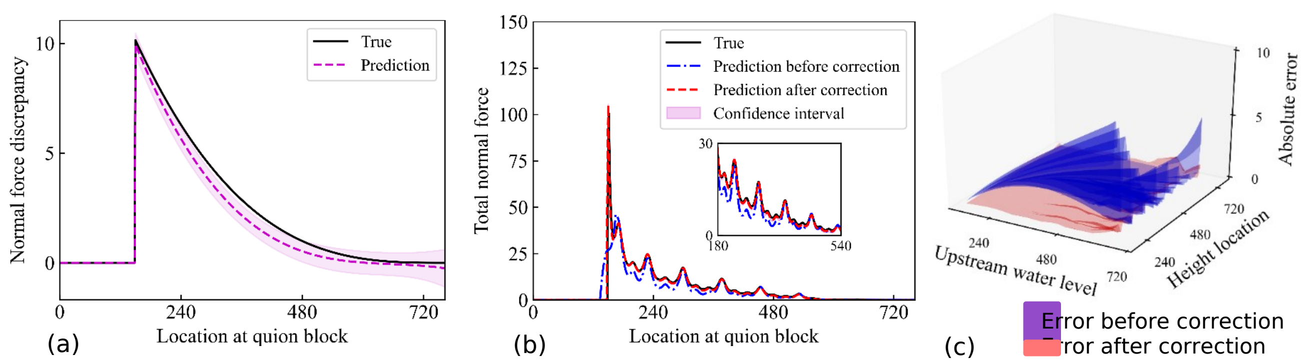

Fig. 3 Normal force prediction after correction: (a) normal force discrepancy reconstruction and (b) total normal force prediction at a certain water level, as well as (c) normal force prediction errors by fixing downstream water level at 120 inches

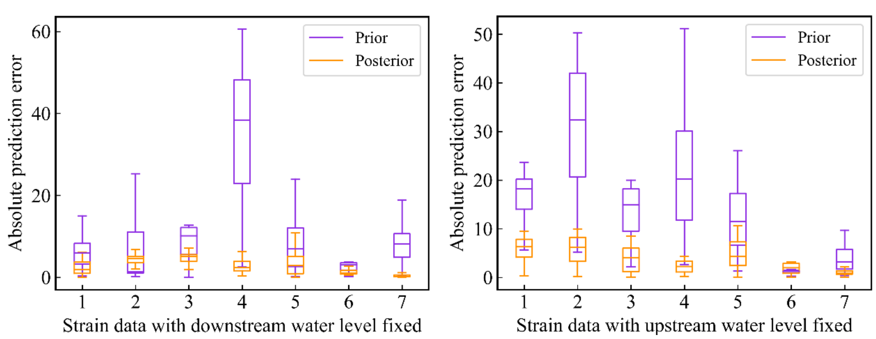

Fig. 4 Prediction errors of seven strain responses with downstream water level or upstream water level fixed

Conclusions

This work proposed a modularized Bayesian calibration method for multi-level simulation model of miter gate, where the observable strain measurements are employed to tackle the challenge of correcting the unobservable model with distributed boundary force response. Results show the prediction accuracies of both unobservable and observable models are improved.

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