# Efficient Bayesian Inference of Miter Gates using High-Fidelity Models

Manuel A. Vega, Mukesh K. Ramancha, Joel P. Conte, Michael D. Todd

Department of Structural Engineering
Jacobs School of Engineering
University of California San Diego, La Jolla, CA 92093

**Abstract** Continuous monitoring of miter gates used in navigation locks is desirable in order to prioritize maintenance and avoid unexpected failures. Substantial economic losses to the marine cargo and associated industries are caused by the closure of these inland waterway structures. Strain gauges are often installed in many of these miter gates for data collection, and various inverse finite element techniques are used to convert the strain gauges data to damage-sensitive features. One of the damage features is the development of a contact-loss "gap" between the components (i.e. quoin blocks) that support the gate laterally, which leads to load re-distribution that can induce overload in some components of the gate. Arguably, a refined finite element model of such structure can be very computationally expensive even when using linear models. An efficient way to solve an inverse problem with time-consuming model evaluations is making use of parallel model evaluations using a Sequential Monte Carlo (SMC) algorithm and parallel solution of the finite element (FE) equations using a commercial FE software. A significant advantage of SMC algorithms is that model evaluations are independent and are able to be run in parallel. In this paper, an expensive high fidelity model of a miter gate is used to infer the gap extend given a noisy set of strain measurements.

**Keywords:** Miter Gates, Finite Element Model Updating, Inverse Problem, Model Bias , Batch Bayesian Inference, Sequential Monte Carlo.

## 1. Introduction

Navigation locks form a crucial part of inland waterways infrastructure network. Miter gates are the most common type of navigation locks in the United States (US) with other types of lock gates being sector, tainter, and vertical lift [1]. Miter gates are steel structures that allow passage of ships, boats, and watercrafts across stretches of different water levels in canals and rivers. In the US, more than half of these structural assets have surpassed their 50-year economic design life [2]. Damage to miter gates may lead to closure of a lock chamber. Two types of maintenance events (i.e., scheduled and unscheduled) apply to miter gates. Scheduled maintenance allows navigation users to adjust their activities to avoid unexpected delays and minimize their economic loss. However, unscheduled closures resulting from unexpected events such as undetected deterioration reaching a critical limit state or extreme events (e.g., barge impact) more substantially affect navigation users' economic bottom line and induce a higher cost of maintenance [3]. Estimating the condition of a miter gate and its components can help to reduce the risk in unscheduled maintenance events and prioritizing better schedule maintenance events. The U.S. Army Corps of Engineers (USACE) have established a discrete rating system to allow inspectors to rate the components of a miter gate based on condition and performance [4], which are used by decision-makers for maintenance and operations planning. However, inspections based on this rating system can vary for different inspectors because it is based on engineer judgement. Continuous structural health monitoring (SHM) of these infrastructure assets may help to reduce the uncertainty and ensure better-informed decisions that lead to safer and more reliable operations [5].

One of the consequences of deterioration in miter gates is the formation of a bearing gap that occurs between the contact blocks that interface the lock walls and the miter gate [6]. The bearing gap governs the lateral boundary conditions on the gate, and its degradation from loading, wear, corrosion, and other sources leads to changes in the stress-strain profile of the entire miter gate [7]. Experienced inspectors and lock operators have indicated the importance of knowing the condition of contact block and its role in identifying load transfer issues in the gate [2], [8]. Other analyses would have to be conducted to determine the critical gap parameters (size, location, etc.) that lead to some failure in the gate or in one of its components. Alternatively, the boundary conditions may also be obtained by inferring directly the forces that support the gate laterally [9].

Many of the miter gates owned by USACE are instrumented with strain gauges for data acquisition [10]. The relationship between the formation of the bearing gap and the stress-strain profile in the entire gate can be better understood by using a finite element (FE) model. For a SHM system, the inverse relation between the input and outputs of the FE model are desired. This inverse relation can be estimated by performing Bayesian inference that uses FE model evaluations. A Bayesian approach is desirable because it is able to quantify the risk on making decisions such as corrective maintenance of components. Many

powerful algorithms that perform Bayesian inference can be used to solve this problem [11]. However, many of these algorithms are not feasible for real-time health monitoring.

In this paper, a Bayesian Inversion of High Fidelity FE model is accomplished by using the sequential Monte Carlo (SMC) algorithm to perform Bayesian inference. This algorithm was selected due to the accuracy in its predictive capabilities and its parallelizable capabilities to perform (FE) model evaluations [12]. The paper first explains the finite element model and then describes two modelling options for the bearing gap. In the next section, Bayesian inference on miter gates are explained and results are shown for two different levels of complexity. The results show the effect of aleatory and epistemic uncertainties considered in this miter gate problem. Finally, a conclusion and further work section discusses the additional steps to be taken before deploying a SHM system in miter gates and the issues of dealing with model uncertainty.

## 2. Testbed Structure and Finite Element Modeling

In this research, the Greenup miter gate/lock located on the Ohio river is used as the testbed structure. A physics-based FE model of the gate was developed in ABAQUS software, shown in Figure 1a. This FE model has been validated using the measured strain gauge readings [2]. The Greenup gate is a brand-new gate where a negligible gap ("undamaged" condition) was assumed for validation purposes. 3D linear shells elements were used to reduce the computational cost of such a large model. Figure 1b shows the side view of a miter gate that is subjected to upstream and downstream hydrostatic forces.

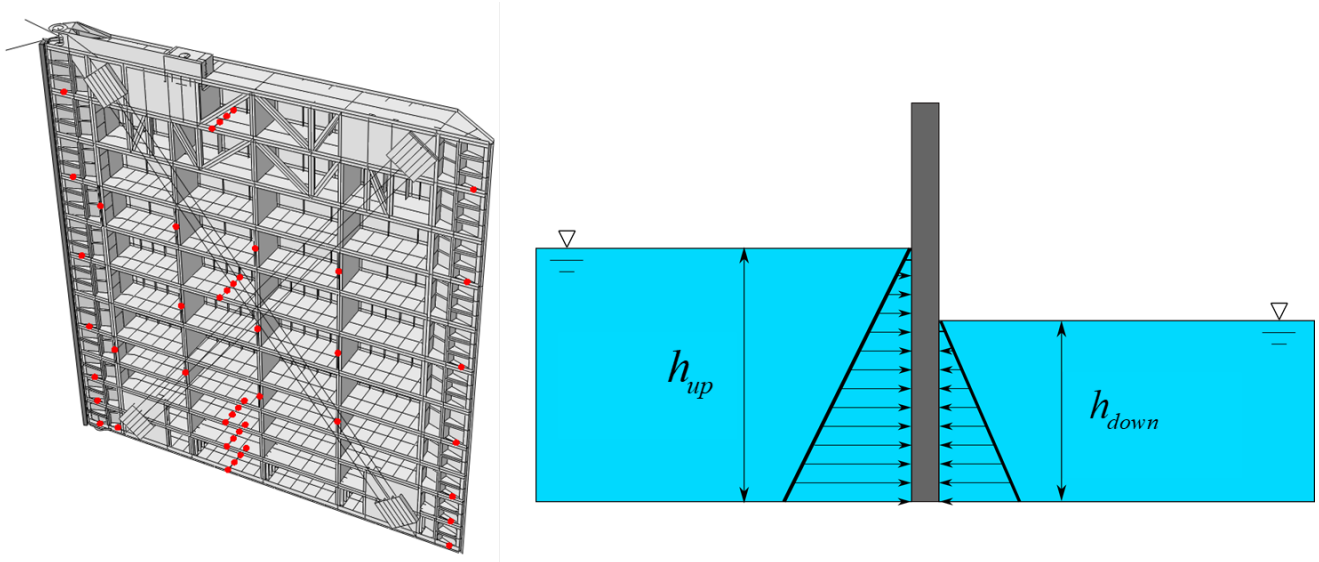


Figure 1: FE model of Greenup Gate with sensor locations and loading conditions

### 2.1 Modelling Options for Gap Formation

The gap formation between the contact (quoin) blocks control how the gate is supported laterally and consequently introduces a change in the stress/strain distribution of the entire gate, especially in the pintle area where the gate is supported by a pintle ball. For modelling purposes, the pintle ball where the gate rest is idealized as a pin support. In this paper damage is introduced by controlling the extent of the gap. In order to model the gap itself, two different modelling approaches are presented in this work:

*Option 1:* A contact-type constraint is used between the contact blocks as shown in Figure 2a, making this a computationally expensive nonlinear problem. To impose the contact constraint, the Lagrange multiplier method was employed. The strain gauge locations are far from the contact area, mostly due to physical constraints in the miter gate, but this far-field location also mitigates errors due to the method employed to enforce the contact constraint. The opposite side of the wall quoin block uses fixed boundary conditions, and symmetry boundary conditions are used at the right end (i.e., miter) of the gate to simulate the right leaf. The variables $g_l$ and $g_w$ denote the gap length and depth, respectively.

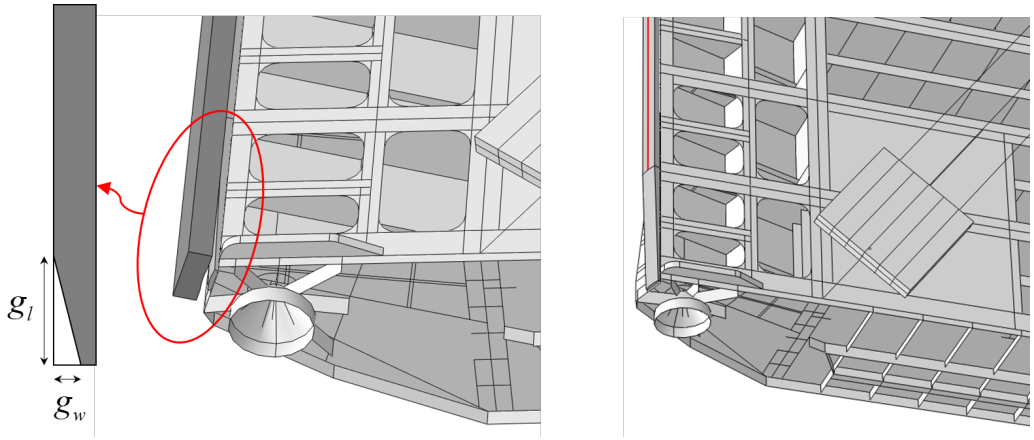


Figure 2: a) Option 1: Using contact between wall quoin block and gate quoin block, and b) Option 2: Pin boundary conditions along the gate quoin block (restrained in x and y directions) except at gap location

*Option 2:* Pin boundary conditions are used directly to support the gate quoin block instead of modelling the wall quoin block and using a contact algorithm to support the gate laterally. To model the effect of the gap formation a particular length ( $g_l$ ) of the gate quoin block is left unrestrained as shown in Figure 2b. This representation may not be as accurate as Option 1, but it is a more attractive option computationally, since it is a linear FE model.

The main difference in the physics between Option 1 and 2 is that Option 1 captures the effect of partial gap closure after the gate is subjected to hydrostatic loads. However, since the portion of the gap that closes is small under most loading scenarios, Option 2 is a reasonable alternative choice.

## 3. Estimating Gap Length in Miter Gates using Bayesian Inference

For given hydrostatic inputs and gap parameters, the FE model could be evaluated as a "forward model" to yield the resulting strain field resulting in the gate; consequently, solving an inverse problem is necessary to obtain the gap length value, $g_l$, given a set of strain measurements obtained at different locations on the miter gate. There are two general ways often used to solve an inverse problem: 1) a Bayesian approach, which computes a posterior distribution of the model parameters given prior knowledge and the data, or 2) a regularized data fitting approach, which chooses an optimal model [13] by minimizing an objective function that minimize the empirical risk (i.e. training error). In SHM, estimates of gap length (or other damage parameters) are meaningful to the decision-making process of operators and stakeholders. Therefore, the Bayesian approach is desired to obtain estimates of the gap length that can help to understand the current damage state of a miter gate. In the Bayesian approach, the posterior distribution of the model parameters (e.g. gap length) can be obtained from:

$$p\left(g_l,\sigma_{strain}\,|\,y\right)\propto p\left(y\,|\,g_l,\sigma_{strain}\right)p\left(g_l,\sigma_{strain}\right),$$

where

$$\underbrace{\mathbf{y}}_{\text{measured response}} = \underbrace{\mathbf{h}\left(g_l,\mathbf{u}\right)}_{\text{FE predicted response}} + \underbrace{\mathbf{w}}_{\substack{\text{error/}\\ \text{noise}}},$$

and where $\mathbf{y}$ represents the strain measurement at gages location, $\mathbf{u}$ represents the hydrostatic loading conditions (i.e. $h_{up}$ and $h_{down}$), and $\mathbf{w}$ is assumed to be a zero-mean uncorrelated gaussian distribution as follows:

$$\mathbf{w}\sim \mathrm{N}\left(\underbrace{\mathbf{0}}_{46\times 1},\sigma_{strain}^2\underbrace{\mathbf{I}}_{46\times 46}\right)$$

$$\boldsymbol{\theta}=\left[g_l,\sigma_{strain}\right]^T\in\sim^2.$$

The posterior distribution of the parameters is typically mathematically intractable due to the normalization term (see Eq. (1)). In this work, the computation of the posterior is accomplished by using the SMC algorithm to perform Bayesian inference.

This algorithm was selected due to the accuracy in its predictive capabilities and its parallelizable capabilities to perform (FE) model evaluations.

### 3.1 Batch Inference using SMC

Sequential Monte Carlo (SMC) or Transitional Markov chain Monte Carlo (TMCMC) methods are a class of simulation-based Bayesian inference techniques which sample from the complete joint posterior distribution of the unknown parameter vector $\boldsymbol{\theta}$. SMC methods do not impose any assumptions on the probability structure prior and the posterior; hence, these methods are applicable in very general settings. SMC methods are inherently parallelizable, therefore ideal for solving the inverse problem involving computationally-expensive FE model evaluations.

The idea of SMC is to avoid directly sampling the target PDF (posterior) but rather sample an easier-to-sample PDF and then weigh, resample, and perturb the samples to describe the target PDF. The achieve this, SMC constructs a series of intermediate PDFs, known as tempered posteriors, that start from prior distribution (easy to sample) and converge to the posterior distribution (hard to sample) as follows

$$\underbrace{p(\boldsymbol{\theta}\,|\,\mathrm{D})_j}_{\text{tempered posterior}} \propto p(\mathrm{D}\,|\,\boldsymbol{\theta})^{\beta_j} \times \underbrace{p(\boldsymbol{\theta})}_{\text{prior}} \quad j = 0,1,...,m \quad 0 = \beta_0 < \beta_1 < ... < \beta_m = 1,$$

where $\beta_j$ is the tempering parameter at stage $j$. When $\beta_j = 0$ at the initial stage ( $j = 0$), the tempered posterior $p(\boldsymbol{\theta}\,|\,\mathrm{D})_0$ is just the prior $p(\boldsymbol{\theta})$, and when $\beta_j = 1$ at the final stage ( $j = m$) the tempered posterior $p(\boldsymbol{\theta}\,|\,\mathrm{D})_m$ is the target posterior $p(\boldsymbol{\theta}\,|\,\mathrm{D})$. SMC represents the tempered posterior distribution at every stage by a set of weighted samples (also called particles). SMC approximates $j^{th}$ stage tempered posterior $p(\boldsymbol{\theta}\,|\,\mathrm{D})_j$ by weighing, resampling, and perturbing (using Markov chain Monte Carlo) the particles of $j-1^{th}$ stage tempered posterior $p(\boldsymbol{\theta}\,|\,\mathrm{D})_{j-1}$. The SMC algorithm for sampling the target posterior is shown in Table 1.

**Table 1: SMC Algorithm**

Let $N$ be the number of particle (or weighted samples) at every stage, and $ESS_j$ be the effective sample size at stage $j$

Initialize $N$, $j = 0$, $ESS_0 = N_p$, $\beta_0 = 0$

Generate $N$ samples $\left\{\boldsymbol{\theta}^i_{j=0};\ i = 1,...,N\right\}$ from the prior distribution $p(\boldsymbol{\theta})$

**while** tempering parameter $\beta_j < 1$

- increase stage number $j = j + 1$
- choose $\tilde{\beta}_j$ such that $ESS_j = 0.95 \times ESS_{j-1}$, $\beta_j = \min\left(\tilde{\beta}_j, 1\right)$
- <u>weighting</u>: $w^i_j = p\left(\mathrm{D}\,|\,\boldsymbol{\theta}^i_{j-1}\right)^{\beta_j - \beta_{j-1}}$ for $i = 1,...,N$
- <u>resampling</u>: $\tilde{\boldsymbol{\theta}}^i_j = \boldsymbol{\theta}^l_{j-1}$ with probability $w^l_j$ for $i = 1,...,N$
- <u>perturbation</u>: start an MCMC chain at $\tilde{\boldsymbol{\theta}}^i_j$ and take $N_{MCMC}$ steps with target distribution $p(\boldsymbol{\theta}\,|\,\mathrm{D})_j$ for each $i = 1,...,N$. Gather last sample of each MCMC chain to obtain $\left\{\boldsymbol{\theta}^i_j;\ i = 1,...,N\right\}$

**end**

$\left\{\boldsymbol{\theta}^i_j;\ i = 1,...,N\right\}$ are the samples of the target posterior $p(\boldsymbol{\theta}\,|\,\mathrm{D})$

## 4. Three-stage approach

Implementing a real SHM monitoring system will, arguably, involve several types of uncertainties that will affect the estimation process shown previously. One of the main sources of discrepancy between the estimation and the true model parameter values is due to model uncertainties, i.e., how the forward model (e.g. FE model) used in the inference process differs from the true physical model. To systematically tackle this problem, a 3-stage approach is used to start accounting for model uncertainties as shown in Figure 3.

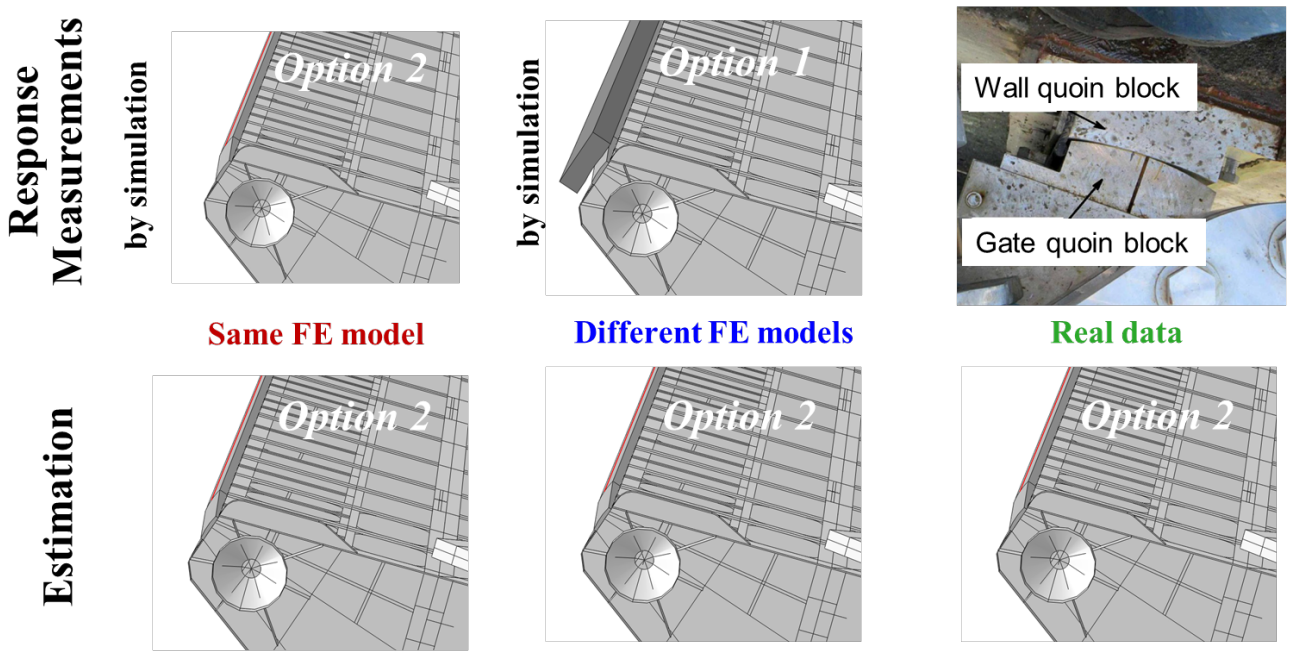


Figure 3: Systematic and progressive approach to handle various sources of uncertainties.

### 4.1 Stage 1: Same FE model

As shown in Figure 3, stage 1 uses the same FE models to represent the physical model used for estimation and the true physical model used to obtain the response measurements. Clearly, model uncertainty is not considered in this stage. As described earlier, there are two competing gap models. Option 2 is used as the FE model in this case due to its fast model evaluations. The estimation of the gap length for a specific response measurement is shown in Figure 4. The parameter $\delta$ is the estimated coefficient of variation, and $r$ is the Pearson correlation coefficient.

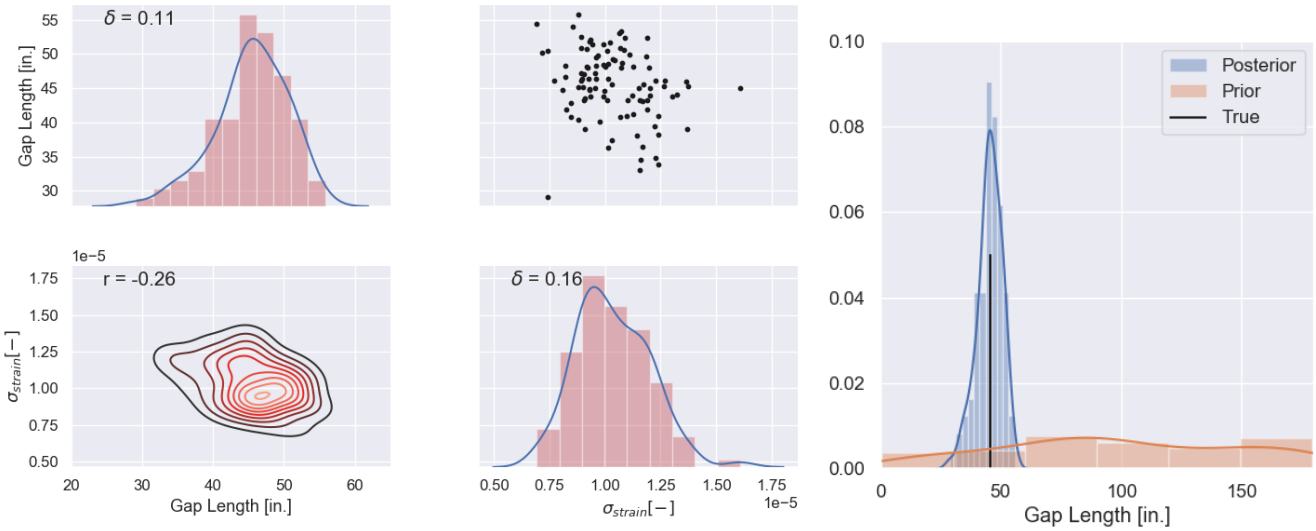


Figure 4: a) Joint posterior distribution using 100 particles, and b) prior and posterior distributions vs true value

As intended the posterior distribution covers the true value of the gap length and also the standard deviation of the (noise) error. The gap length prior distribution used for the inference follows a uniform distribution between 0 in and 180 in. These values are based on inputs from experienced lock operators.

### 4.2 Stage 2: different FE models

As shown in Figure 3, stage 2 uses different FE models to represent the physical model used for estimation (option 2) and the true physical model (option 1) used to obtain simulated response measurements. Model uncertainty is considered in this case, as the way that the gap between contacts blocks is modelled is very different between options 1 and 2. The gap depth is assumed to be 0.25 in for modelling option 1, which is used to simulate the true physical process and obtain the measurement response.

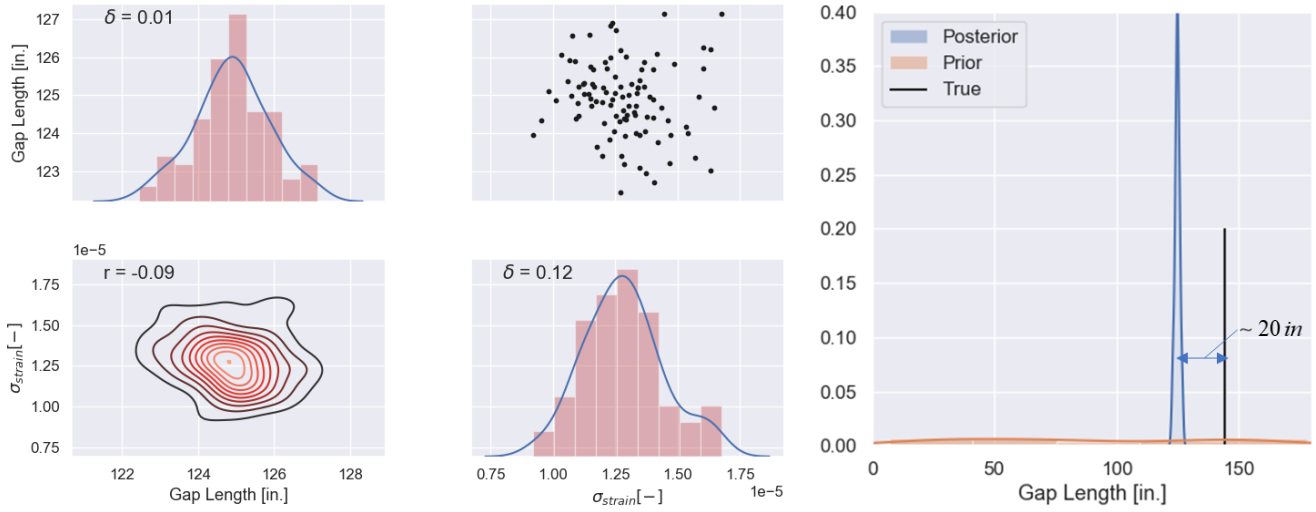


Figure 5: a) Joint posterior distributions using 100 particles, and b) prior and posterior distributions vs true value

The posterior distribution of the gap length is very confident at a gap length around 124 in, while the true simulated gap length is equal to 144 in. Therefore, for this singular case the posterior estimation is biased by ~20 in. These results are very consistent with the values obtained by Brynjarsdottir and O'Hagan [14] when two different models are used to represent the physical model used for estimation and true physical model used to obtain simulated response measurements

### 4.3 Stage 3: Real data

As shown in Figure 3, stage 3 uses real SHM data for the response measurements and a FE model to simulate the physical model used for estimation. For this step, a fully FE model should be validated at different damage levels, which in practice it is challenging to obtain. Also, additional parameters (e.g. critical crack, corrosion, uncertainty in the material, amount of prestress in the diagonals, etc.) that are strain-sensitive should be identified to improve the predictive capabilities of this problem.

## 5. Conclusions and Further Work

A miter gate gap estimation is accomplished by perform Bayesian inference using a validated high-fidelity FE model. Two different models are presented to simulate damage (formation of gap), and a comparison of their predictive capabilities is performed using a Bayesian approach. The use of the SMC algorithm in large FE models is encouraging due to its parallelizable capabilities. Often, a (surrogate) data-driven model is created to replace an expensive FE model, but this was not needed in this work. Physics-based models may be a better option for extrapolation, however, especially when limited damage data is available. Additional steps need to be taken before deploying a SHM system in miter gates specially when dealing with model uncertainty. To further improve the predictive capabilities of cases in stage 2 and 3, a bias function can be trained to learn the model uncertainty between two models as described in detail in [14]–[17]. Again, this bias function should be carefully studied/interpreted when using them for interpolation or extrapolation. Additionally, a sensitivity analysis should be studied to understand the sensitivity of the strain gages to different model parameters, as this may also lead to improved predictive capabilities.

## 6. Acknowledgements

Funding for this work was provided by the United States Army Corps of Engineers through the U.S. Army Engineer Research and Development Center Research Cooperative Agreement W912HZ-17-2-0024.

## 7. References

[1] Q. Alexander, A. Netchaev, M. Smith, C. Thurmer, and J. D. Klein, "Telemetry techniques for continuous monitoring of partially submerged large civil infrastructure," in *Sensors and Smart Structures Technologies for Civil, Mechanical, and Aerospace Systems 2018*, 2018, vol. 1059823, no. March, p. 76.

[2] S. D. Foltz, "Investigation of Mechanical Breakdowns Leading to Lock Closures," Champaign, IL, 2017.

[3] M. M. Kress *et al.*, "ERDC / CHL TR-16-8 Marine Transportation System Performance Measures Research Coastal and Hydraulics Laboratory," Vicksburg, MS, 2016.

[4] M. A. Vega, R. Madarshahian, T. B. Fillmore, and M. D. Todd, "Optimal Maintenance Decision for Deteriorating Components in Miter Gates using Markov Chain Prediction Model," in *12th International Workshop on Structural Health Monitoring*, 2019.

[5] B. A. Eick *et al.*, "Automated damage detection in miter gates of navigation locks," *Struct. Control Heal. Monit.*, vol. 25, no. 1, pp. 1–18, 2018.

[6] B. A. Eick, M. D. Smith, and T. B. Fillmore, "Feasibility of Discontinuous Quoin Blocks for USACE Miter Gates," 2019.

[7] H. Mahmoud, A. Chulahwat, and G. Riveros, "Fatigue and fracture life-cycle cost assessment of a Miter gate with multiple cracks," *Eng. Fail. Anal.*, vol. 83, no. September 2017, pp. 57–74, Jan. 2018.

[8] B. A. Eick, B. F. Treece, Zachary R., Spencer Jr., M. D. Smith, S. C. Sweeney, Q. G. Alexander, and S. D. Foltz, "Miter Gate Gap Detection Using Principal Component Analysis," 2017.

[9] M. Parno, D. O'Connor, and M. Smith, "High dimensional inference for the structural health monitoring of lock gates," pp. 1–29, Dec. 2018.

[10] U.S. Army Corps of Engineers Headquarters, "SMART GATE." [Online]. Available: https://www.erdc.usace.army.mil/Media/Fact-Sheets/Fact-Sheet-Article-View/Article/476668/smart-gate/. [Accessed: 01-Aug-2018].

[11] Y. Yang, R. Madarshahian, and M. D. Todd, "Bayesian Damage Identification Using Strain Data from Lock Gates," Springer, 2020, pp. 47–54.

[12] A. Lee, C. Yau, M. B. Giles, A. Doucet, and C. C. Holmes, "On the Utility of Graphics Cards to Perform Massively Parallel Simulation of Advanced Monte Carlo Methods," *J. Comput. Graph. Stat.*, vol. 19, no. 4, pp. 769–789, Jan. 2010.

[13] M. Vega, R. Madarshahian, and M. D. Todd, "A Neural Network Surrogate Model for Structural Health Monitoring of Miter Gates in Navigation Locks," in *37th International Modal Analysis Conference*, Orlando, Florida, 2020, pp. 93–98.

[14] J. Brynjarsdóttir and A. O'Hagan, "Learning about physical parameters: the importance of model discrepancy," *Inverse Probl.*, vol. 30, no. 11, p. 114007, Nov. 2014.

[15] M. C. Kennedy and A. O'Hagan, "Bayesian calibration of computer models," *J. R. Stat. Soc. Ser. B (Statistical Methodol.*, vol. 63, no. 3, pp. 425–464, Aug. 2001.

[16] Y. Ling, J. Mullins, and S. Mahadevan, "Calibration of multi-physics computational models using Bayesian networks," *arXiv Prepr. arXiv1206.5015*, pp. 1–38, Jun. 2012.

[17] Y. Ling, J. Mullins, and S. Mahadevan, "Selection of model discrepancy priors in Bayesian calibration," *J. Comput. Phys.*, vol. 276, pp. 665–680, Nov. 2014.