Bayesian Neural Networks vs. Model Updating for Inference of Miter Gate Damage

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ABSTRACT

Miter gates are critical components of inland waterways and their failure can have significant consequences. These gates must fully contact a wall or stress concentrations develop, leading to cracking and failure. To detect gaps in the contact, we compare two inference methods: Bayesian model updating using the transitional Markov chain Monte Carlo (TMCMC) method and neural network-based Bayesian inference. TMCMC is a widely used method, but inference is computationally expensive. In contrast, neural network-based Bayesian inference trains a neural network upfront and infers damage parameters using the computationally efficient neural network, dramatically reducing runtime as more datasets are gathered and parameters are updated. Through a case study data gathered at a specific miter gate, both methods are compared on their performance inferring boundary condition degradation using vision-based displacement data. Results show that neural network-based Bayesian inference achieves similar accuracy to TMCMC updating with a significant reduction in computational costs from hours to seconds. These computational advantages may aid in online and edge applications at miter gates and other civil structures. With regular updates of miter gate bearing contact damage, decision-makers can more effectively maintain miter gates.

INTRODUCTION

Inland waterways are critical for the transportation of billions of dollars in goods annually. For instance, the Markland lock on the Ohio River saw 65.5 million tons in shipped goods in 2014. Closure of this lock, or others like it, would result in significant economic consequences – an estimated $1.3 billion in additional annually transportation costs [1]. A primary cause of these disruptive closures is the need for miter gate repairs and maintenance. Currently, assessing the structural health of these gates relies heavily on visual inspection, but a significant portion of the gate remains submerged, hindering thorough evaluation. Consequently, locks must be closed periodically, typically every few years, to allow for a complete inspection. To minimize these costly and disruptive closures, structural health monitoring (SHM) offers a promising alternative. SHM systems use regular sensor measurements to track the condition of the gates, enabling data-driven decisions about maintenance needs.

Figure 1 illustrates the downstream Barkley miter gate and its key components. Miter gates, like the one shown, are essential for controlling water levels within lock chambers, enabling vessels to navigate differing elevations. The gate consists of two leaves that meet in the center of the chamber at the miter, forming a watertight seal when closed. Each leaf incorporates steel blocks running vertically along both the quoin (the end that engages with the lock wall) and the miter ends; these blocks serve as the primary contact surfaces when the gate is acting as a dam.

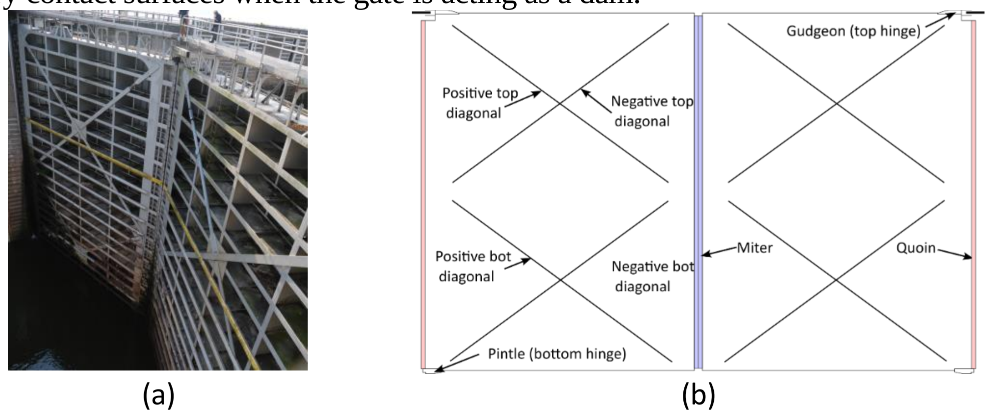


Figure 1. Identification of components for downstream Barkley miter gate: (a) View from lock wall and (b) elevation view.

During a lockage that starts from a full chamber, the gates are closed. Hydrostatic pressure forces the leaves together, the miter contact blocks together, and the quoin contact blocks against the wall. When the chamber is empty, its water level is equal to the downstream water level, eliminating the unbalanced hydrostatic forces on the gate. In this state, the miter and quoin contact areas are no longer under significant load, and the gate primarily supports its own weight. Consequently, the two main load cases considered are (1) a filled chamber and (2) an empty chamber.

Recent advances have explored the use of computer vision, RGB images and optical flow techniques [3], for miter gate SHM. The optical flow technique finds structural displacements in the image plane. Wang et al. [4] estimated 2D displacement of an in-situ miter gate from optical flow, but results suffered from camera motion obscuring structural motion. Model updating both connects vision-based displacements to the structural state of miter gates and can address the camera ego motion. A common approach to interpreting SHM data and updating structural models is Bayesian model updating (BMU), often implemented with Markov-Chain Monte Carlo (MCMC) [5] methods. While the Transitional Markov chain Monte Carlo (TMCMC) [6] method offers improvements, Fillmore et al. [7] showed that the TMCMC technique remains a significant computational burden for SHM of miter gates. To address these limitations, recent research has investigated neural network-based Bayesian inference (NNBI) [8] [9], which offers the potential for faster parameter estimation. These methods require a computationally intensive off-line training phase, but subsequent predictions are significantly faster, potentially reducing online and long-term SHM costs.

This work investigates the application of NNBI for estimating miter gate parameters from vision-based displacement data and compares its performance to TMCMC methods. Results demonstrate the NNBI achieves similar accuracy to TMCMC model updating with a substantial reduction in computational time, offering a promising path towards more efficient and cost-effective SHM of critical water infrastructure.

METHODOLOGY

We collected vision-based displacement measurements $\boldsymbol{d}$, similar as outlined in [7]. The forward model outputs synthetic measurements $\widehat{\boldsymbol{d}}$ based on a set of parameters to be updated. Given the thin-plate construction of miter gate skins, shell elements are used in the FE model. Mesh verification studies [11] have demonstrated reasonable behavior with 2-inch elements. The FE model incorporates typical miter gate boundary conditions as thoroughly described by Eick et al. [12]. To simplify the analysis while capturing essential behavior, the miter contact described above and in Figure 1 was modeled using a set of rollers preventing out-of-plane movement, and the quoin contact was modeled using a set of pins.

The parameters are chosen based on their relevance to structural behavior and magnitude of the response of the gate to them. If the contact interfaces along the quoin contact blocks are lost (see **Error! Reference source not found.**), stress concentrations cause a redistribution of stresses under load case (1), which accelerates fatigue damage accumulation. Therefore, monitoring for loss of contact along the quoin and miter contact surfaces holds value to decision-makers. At the Barkley miter gate, there are concerns about the quoin contact interface based on inspection. However, direct measurement of quoin contact degradation is not possible under load case (1) due to lack of access from the top of the lock wall. This research helps to confirm whether the boundary conditions are in fact degraded along the quoin under load case (1).

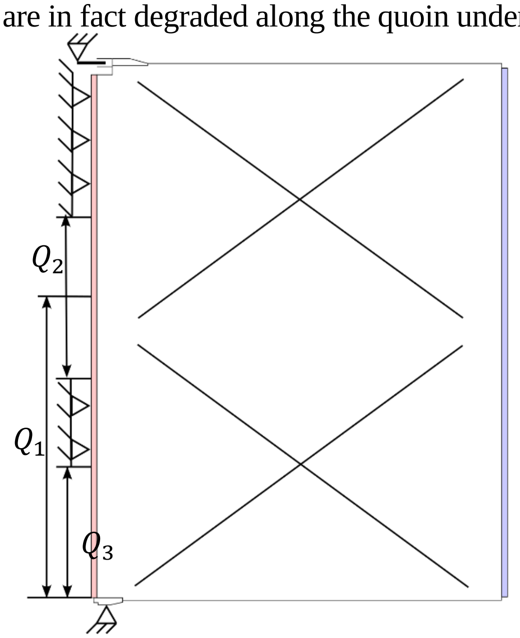


Figure 2. Parameterized boundary conditions (under load case (1)) for Barkley downstream miter gate.

Neural-network based Bayesian inference and TMCMC

This research compares the TMCMC method with NNBI. The Bayesian formulation takes prior (previous belief about parameters) and likelihood (probability of sensor measurements) distributions of the model parameters $\boldsymbol{\theta}$, and outputs the posterior distribution of these parameters, thereby inferring the most likely model parameter values. The posterior probability density function $p\big(\boldsymbol{\theta}|\boldsymbol{d}, M(\boldsymbol{\theta})\big)$ is given by Bayes' theorem as [13]

$$p\big(\boldsymbol{\theta}|\boldsymbol{d}, M(\boldsymbol{\theta})\big) = c^{-1}\mathcal{L}(\boldsymbol{d}|\boldsymbol{\theta}, M(\boldsymbol{\theta}))p\big(\boldsymbol{\theta}|M(\boldsymbol{\theta})\big), \tag{1}$$

where c^{-1} is a scaling factor that ensures the integral of the posterior PDF over the whole domain sums to 1, $\mathcal{L}(\boldsymbol{d}|\boldsymbol{\theta}, M(\boldsymbol{\theta})) = p(\boldsymbol{d}|\boldsymbol{\theta}, M(\boldsymbol{\theta}))$ is the likelihood function that returns the goodness-of-fit of the synthetic measurements given some parameter realization, and $p\big(\boldsymbol{\theta}|M(\boldsymbol{\theta})\big)$ is the prior PDF of the parameters. For more details on the scaling factor, log-likelihood implementation, and the TMCMC implementation, refer to [7].

The BayesFlow invertible neural network implemented in Python [14] is utilized for NNBI in this research. BayesFlow consists of a summary neural network to reduce dimensionality of observation data, a latent distribution to sample from during inference, an invertible neural network that takes the reduced dimensionality observation data and the samples drawn and outputs the approximate posterior. The BayesFlow workflow [14] is illustrated in Figure 3.

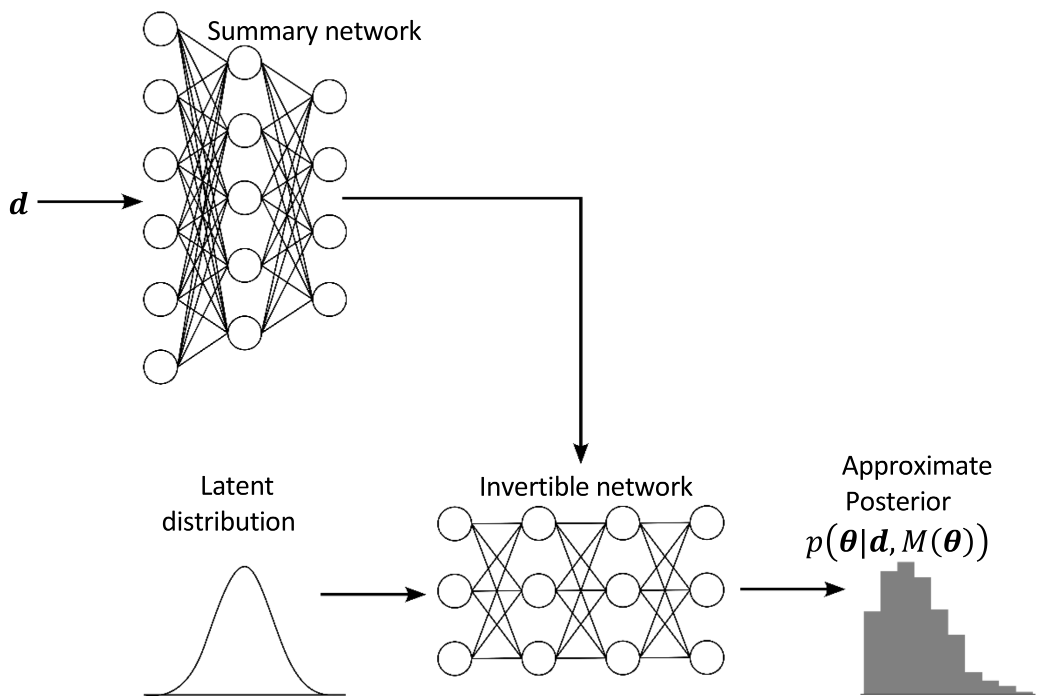


Figure 3. BayesFlow workflow for inference of Barkley downstream miter gate parameters.

The summary network in this application consists of 3 dense 1D layers with 270 nodes in the first layer corresponding the vision-based displacements with relu activation, 135 nodes in the second layer with relu extraction, and 52 nodes in the final layer with elu extraction. Therefore, the dimension is reduces from 270 to 52 and sent to the invertible network. The invertible network has 12 layers of affine coupling blocks and outputs the approximate posterior.

Training data was generated by the FE model in a preprocessing step 60,000 samples sampled from uniform parameter distributions in the range $\Delta T \in [-0.002,0.002], T_{NB} \in [0,8], T_{NT} \in [0,8], T_{PB} \in [0,15], T_{PT} \in [0,15], Q_1 \in$

$[240,1056], Q_2 \in [0,360], Q_3 \in [0,240], M_1 \in [240,1056], M_2 \in [0,360], M_3 \in [0,240], \Phi_x \in [-0.02,0.02], \Phi_y \in [-0.02,0.02], \Phi_z \in [-0.02,0.02]\}$.

RESULTS

Two series of training were performed of 200,000 epochs each, with the losses plotted in Figure 4.

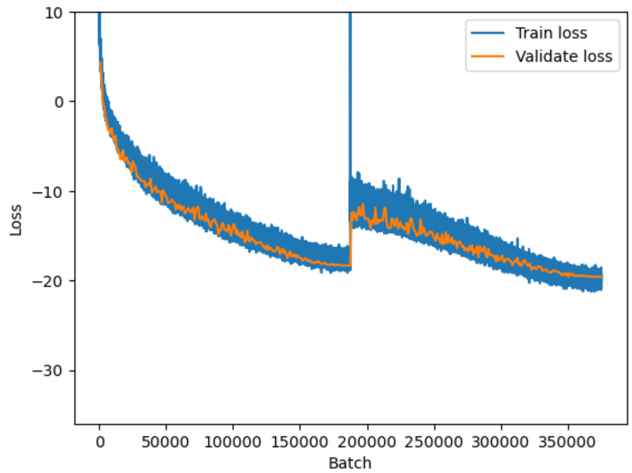


Figure 4. NNBI training (blue) and test (orange) set convergence.

Reference FE model parameter values and predicted parameter values are plotted as x and y values respectively in Figure 5. The scatter plot reflects the accuracy of the predicted parameter values. As the scatter plot falls more along the line $x = y$, then the predictions are more accurate, which is measured using the coefficient of determination R^2.

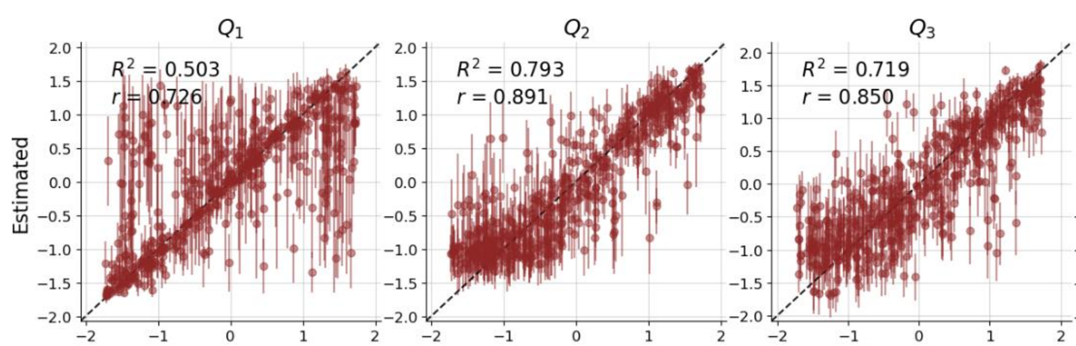
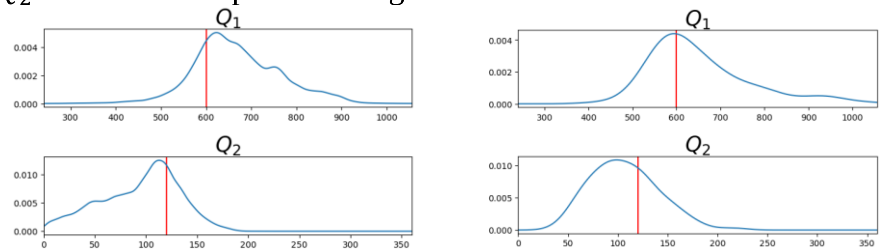


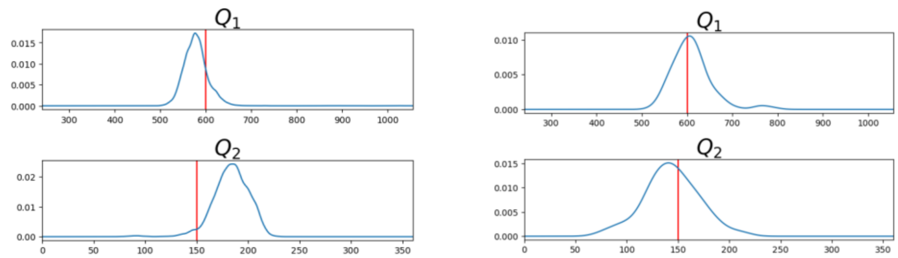
Figure 5. Ground truth vs estimates of scaled parameters from NNBI.

It is observed that camera parameters, thermal expansion, bottom miter gap, and positive top diagonal tension are accurately estimated with $R^2 > 0.98$. In contrast, the negative bottom diagonal tension is inaccurately estimated with $R^2 < 0$; as discussed in [7], the bottom diagonal tensions are inaccurately estimated because few POI's are at the bottom of the gate. An interesting effect apparent in upper quoin gap length Q_2 and upper miter gap length M_2 is that for the smallest values, less than the scaled -1 value, estimates are inaccurate. As discussed in [7], these inaccuracies reflect the physical behavior of the gate. As the gaps get small enough, they change the displacements of the gate very little. Therefore vision-based displacements are insensitive to changes in gap length below a certain threshold.

Producing plots of ground truth vs estimates of scaled parameters from TMCMC would allow direct comparison with accuracy of NNBI results. However, TMCMC predictions take too long to produce such a plot. Rather, the sensitivity of each algorithm to small Q_2 is used for comparison in Figure 6.



(a) TMCMC, true $Q_2 = 120\ in.$ (b) NNBI, true $Q_2 = 120\ in.$



(c) TMCMC, true $Q_2 = 150\ in.$ (d) NNBI, true $Q_2 = 150\ in.$

Figure 6. Comparison of predicted TMCMC and NNBI distributions. The vertical red line is the true value.

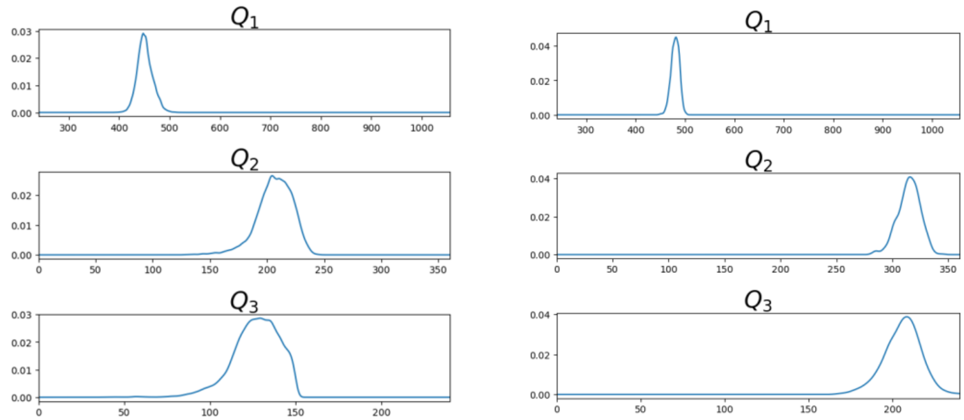
The NNBI predictions are more accurate than the TMCMC results, with predicted Q_2 relative error between the mean and true value, as shown in Table 1.

Table 1. Predicted Q_2 relative errors for TMCMC and NNBI methods

True Q_2(in.)	TMCMC relative error	NNBI relative error
125	21.3%	10.9%
150	22.2%	3.58%

These accuracy results indicate that NNBI infers boundary condition degradation capably using vision-based displacements, improving upon TMCMC relative errors significantly.

Inferring model parameters using NNBI takes only 0.055 s for online inference (about 12 hours for off-line training) while TMCMC takes 10,800 s. Since about 20 minutes is required to cycle between load cases (1) and (2) and obtain the necessary vision-based measurements, real-time monitoring in this context requires inference run times less than 1200 seconds. The NNBI predictions easily meet this time requirement, indicating the promising potential of neural network-based inference in performing online structural health monitoring. The TMCMC and NNBI parameter results based on real world measurements $\boldsymbol{d}$ are shown in Figure 7.



(a) TMCMC predictions (b) NNBI predictions

Figure 7. TMCMC and NNBI parameter predictions. The mean for $T_{NT} = -0.767$ and $M_3 = -55.7$.

Both methods predict similar values for $H, T_{NT}, T_{PB}, T_{PT}, Q_1, M_3, \phi_x, \phi_y$, and ϕ_z. Both methods have high uncertainty for T_{NB}, NNBI predicts Q_2 about 100 inches longer than TMCMC, NNBI predicts Q_3 about 75 inches longer, and NNBI predicts a 150 in. miter gap about 300 in. higher. Ultimately, large contact gaps are predicted by both methods and indicate that maintenance programs should investigate further.

CONCLUSION

This research successfully applied a neural network-based Bayesian inference method to accurately and efficiently detect boundary condition degradation for the downstream Barkley miter gate using vision-based displacement measurements. For synthetic data, the NNBI method was shown to have higher accuracy than the TMCMC method. The real-world results confirmed significant degradation along the quoin, providing critical information to support timely maintenance decisions. By significantly reducing computation time compared to TMCMC, NNBI paves the way for practical, real-time structural health monitoring by enabling damage prognosis, edge computing, and opening new avenues for advance SHM techniques.

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