Damage Diagnostics of Miter Gates Using Domain Adaptation and Normalizing Flow-Based Likelihood-Free Inference

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Abstract

Miter gates are vital civil infrastructure components in inland waterway transportation networks. To provide risk-informed insights for decisions related to repair and maintenance, sensors have been installed on some miter gates for monitoring. Despite the monitoring system's ability in collecting a large volume of monitoring data, accurately diagnosing damage state in such large structures remains challenging due to the lack of labeled monitoring data, since these structures are designed with high reliability and for a long operation life. This paper addresses this challenge by proposing a damage diagnostics approach for miter gates based on domain adaptation. The proposed approach consists of two main modules. In the first module, Cycle-Consistent generative adversarial network (CycleGAN) is employed to map monitoring data of a miter gate of interest and other similar yet different miter gates into the same analysis domain. Subsequently, a normalizing flow-based likelihood-free inference model is constructed within this common domain using data from source miter gates whose damage states are labeled from historical inspections. The trained normalizing flow model is then used to predict the damage state of the target miter gate based on the translated monitoring data. A case study is presented to demonstrate the effectiveness of the proposed method. The results indicate that the proposed method in general can accurately estimate the damage state of the target miter gate in the presence of uncertainty.

1. Introduction

Navigational locks in inland waterway are infrastructure that allows ship and barge traffic to move through different water elevations. One critical component in navigational locks is a miter gate, which seals the chamber during a locking operation. Many miter gates have been in service for over their 50-year design life, raising safety and reliability concerns (Foltz, 2017). Therefore, routine structural evaluations are crucial for early fault detection and timely intervention. Traditionally, the inspection requires expensive and labor-intensive dewatering process for trained inspectors to get access to different components. Additionally, these inspection results are often inconsistent due to inevitable human bias from inspectors (Eick et al., 2018a; Wang, Huang, & Du, 2010; Vega, Hu, Fillmore, Smith, & Todd, 2021). Recently, structural health monitoring (SHM) have increasingly gained attention as tools for reducing human-inspection effort in assessing structural integrity (Estes, Frangopol, & Foltz, 2004; Nemani, Thelen, Hu, & Daining, 2023; Eick et al., 2018b). It is crucial for life-cycle management of structures but needs careful design and implementation to maximize its benefits (Vistasp M. Karbhari, 2009).

The current SHM methods for damage diagnostics can be broadly categorized into three groups, namely (1) data-driven approaches; (2) physics-based approaches; and (3) hybrid approaches that combines physics-based method with data-driven approaches. For instance, one of the most common used physics-based methods is Bayesian inference method which leverages computational simulations and Bayesian techniques to solve inverse problems (Thelen et al., 2022). Recently, several Bayesian-based SHM approaches have been developed for detecting damage in inland waterway infrastructure like miter gates (Ramancha, Vega, Conte, Todd, & Hu, 2022; Levine, Golecki, Gomez, Eick, & Spencer, 2023; Qian, Zeng, Hu, & Todd, 2024; Qian, Wu, Hu, & Todd, 0). While Bayesian inference is a powerful tool for damage diagnostics in SHM, its effectiveness can be compromised by the quality or availability of monitoring data for a specific miter gate in question (Zeng, Zeng, Todd, & Hu, 2024b, 2024a). Moreover, the accuracy of diagnostics based on Bayesian inference is highly dependent on the accuracy of the simulation model (Hu, Hu, & Hu, 2024). Uncertainty sources in physics-based simulations, stemming from model simplifications, assumptions, or incomplete understanding, can result in biased or incorrect damage estimations. In contrast, data-driven approaches are much more flexible and rely on fewer assumptions, making them very widely used in data-rich applications. Therefore, data-driven methods can help overcome the limitations of physics-based methods, particularly for damage modes that are not physically well-understood (Thelen et al., 2022).

A major challenge in applying data-driven SHM methods to miter gates is that data-driven methods usually need labeled monitoring data from different damage status. Such labeled monitoring data is unavailable in practice for many gates. Although some gates are instrumented with various monitoring sensors, desired data from different damage status still might not existed given small size of miter gate population. However, valuable inspection data from similar yet different miter gates can be leveraged to alleviate or overcome the data scarcity for data-driven damage diagnostic approach. Existing research includes population-based SHM (PBSHM), which leverages data from groups of similar structures to estimate the damage condition of the specific structure (Bull et al., 2021; Gosliga, Gardner, Bull, Dervilis, & Worden, 2021; Gardner, Bull, Gosliga, Dervilis, & Worden, 2021). PBSHM performs domain adaptation (DA) with transfer learning to adapt measurements from unfamiliar structure to measurements from familiar structures (Whalen & Mueller, 2022; Huang et al., 2022; Venkateswara & Panchanathan, 2020). DA is especially useful when a miter gate with an unknown damage state, leading to limited or no labeled data. Several studies employing deep convolutional neural networks (Li & He, 2020; Chen, Wang, Wu, Deng, & Wang, 2023) and Generative Adversarial Networks (Kwak & Lee, 2023) for DA. However, quantifying uncertainty in damage diagnostics using DA remains challenging.

This paper proposes a damage diagnostics framework for miter gates. This framework overcomes the data scarcity by DA and quantifies the uncertainties with normalizing flow-based likelihood-free inference. The proposed method comprises two modules: the first module converts observations from both target and source miter gates into a common domain through domain adaptation; the second module constructs a probabilistic model to determine the damage state of the target miter gate, utilizing known damage states from the source miter gates. The main contributions of this paper can be summarized as follows:

- This paper pioneers the combination of domain adaptation techniques with a conditional invertible neural network to enable damage diagnostics with quantified uncertainty.
- The framework employs a domain adaptation method, Cycle-Consistent GAN (CycleGAN), which effectively translates information of both source and target miter gates into a unified domain.
- The proposed framework is demonstrated and compared using a practical application example of miter gate structural systems.

The remainder of this paper is organized as follows: Sec. 2 provides an overview of miter gates and the challenges associated with damage diagnostics. Sec. 3 outlines the proposed framework. Sec. 4 presents a case study along with a discussion of the results. Finally, Sec. 5 concludes the paper.

2. DAMAGE DIAGNOSTICS OF MITER GATES

2.1. Miter gates in inland waterway lock systems

A navigation lock is a crucial component of the inland waterway transportation network, facilitating the passage of ships, boats, and other watercraft across river elevation changes. In the United States, the miter gate, illustrated in Fig. 1, is an essential element of these navigation locks. The potential failure of miter gates can lead to the unexpected closure of a lock chamber, resulting in significant economic losses. Therefore, it is imperative to detect damage early in these structures and timely perform necessary maintenance.

Figure 1. Miter gates in inland waterway lock systems

2.2. Challenges in damage diagnostics of miter gates

One common type of damage in miter gates is the formulation of ”gap” between the contact blocks that interface the lock walls and the miter gate, as illustrated in Fig. 2. This gap can lead to a redistribution of stress within the gate structure, creating high-stress zones that may exceed acceptable limits and potentially cause failure. These gaps are often underwater and not easily observed. Although some miter gates managed by the USACE are equipped with strain gauges for data collection, most sensor monitoring data are unlabeled, posing significant challenges for effective damage detection.

In this paper, we propose a domain adaptation method for damage diagnostics in miter gates by leveraging monitoring data from similar yet different miter gates with known damage labels. The historical labeled monitoring data from these miter gates will be used to inform the damage estimation of a miter gate of interest, whose damage status is unknown. Details of the proposed method are provided in the next section.

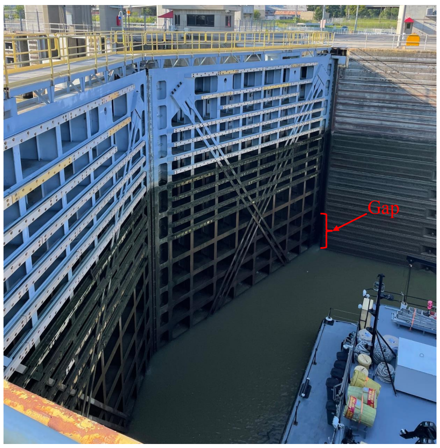

Figure 2. Illustration of "gap" on miter gate structures

3. PROPOSED METHOD

In this section, we first provide an overview of the proposed framework. Following that, we will introduce the domain adaptation methods and probabilistic damage inference techniques employed in this study in detail.

3.1. Overview

Fig. 3 presents an overview of the proposed framework. The fundamental concept is to utilize inspection and monitoring data from similar (in a nominal design sense), though different, miter gates to create an approach for estimating the damage state of a target miter gate using data-driven approaches. As illustrated in this figure, the proposed framework consists two main modules, which are outlined as follows:

1. **Domain adaptation based on CycleGAN**: This module is dedicated to translating observations from both the target and source gates into a unified domain. This process is crucial for establishing a relationship between the damage state of the target miter gate and the inspection and measurement data from the source miter gates.
2. **Probabilistic damage inference using normalizing flow after domain adaptation**: This module involves constructing a model to infer the damage state of the target miter gate based on observation data, utilizing the labeled damage states of the source miter gates within the translated domain.

In the following subsections, we provide a detailed explanation of each of these modules.

3.2. Domain adaptation based on CycleGAN

CycleGAN, introduced by Zhu *et al.*, addresses unpaired image-to-image translation challenges by transforming images from one style to another, such as horses to zebras or summer to winter scenes. This method effectively learns relationships between different unpaired domains (Zhu, Park, Isola, & Efros, 2017). Fig. 4 shows the CycleGAN architecture used for domain adaptation of monitoring data from the source miter gates and the target miter gate of interest.

A crucial feature of CycleGAN is its cycle consistency loss, which ensures that an image can be translated to the other domain and back to the original domain, retaining its content and structure. Therefore, its architecture includes two main components: two generator networks and two discriminator networks. Each generator-discriminator pair facilitates image translation between two domains: Domain A: D_A (source miter gate) and Domain B: D_B (target miter gate). The first generator, $\mathcal{F}_{X\to Y}$ $(x \in X)$, translates monitoring data from source miter gates to the target miter gate as (Zhu et al., 2017)

$$\begin{aligned}\mathcal{F}_{X\to Y}(x) = \mathrm{Conv}_{\text{out}} \circ\sigma \circ \mathrm{Norm} \circ \mathrm{Conv}_n \\ \circ\sigma \circ \mathrm{Norm} \circ \cdots \circ \mathrm{Conv}_1(x),\end{aligned} \tag{1}$$

where "$\circ$" represents function composition, which indicates that each layer in the network is applied sequentially, with the output of one layer becoming the input to the next layer. Conv_i represents convolution layers, σ represents activation functions, "Norm" represents normalization layers. Similarly, the second generator, $\mathcal{F}_{Y\to X}$, translates monitoring data from the target domain (i.e., target miter gate) to the source domain (i.e., source miter gates).

The next part consists of two discriminators, $\mathcal{P}_Y\left(y'\right)$ and $\mathcal{P}_X\left(x'\right)$. Those discriminators have the ability to distinguish between real and translated monitoring data in their respective domains. In this paper, PatchGAN discriminators are utilized to evaluate smaller patches of the monitoring data rather than assessing the entire datasets as "real" or "fake" globally (Demir & Unal, 2018). PatchGAN is designed to focus on local image structures, making it effective for tasks that require preserving texture and detail, such as image-to-image translation in this miter gate scenario (Demir & Unal, 2018).

The loss functions in CycleGAN are essential for facilitating effective monitoring data translation between two unpaired domains. The loss components include adversarial losses, cycle consistency loss, and identity loss. For the generator $\mathcal{F}_{X\to Y}(\cdot)$ and discriminator $\mathcal{P}_Y(\cdot)$, the adversarial loss

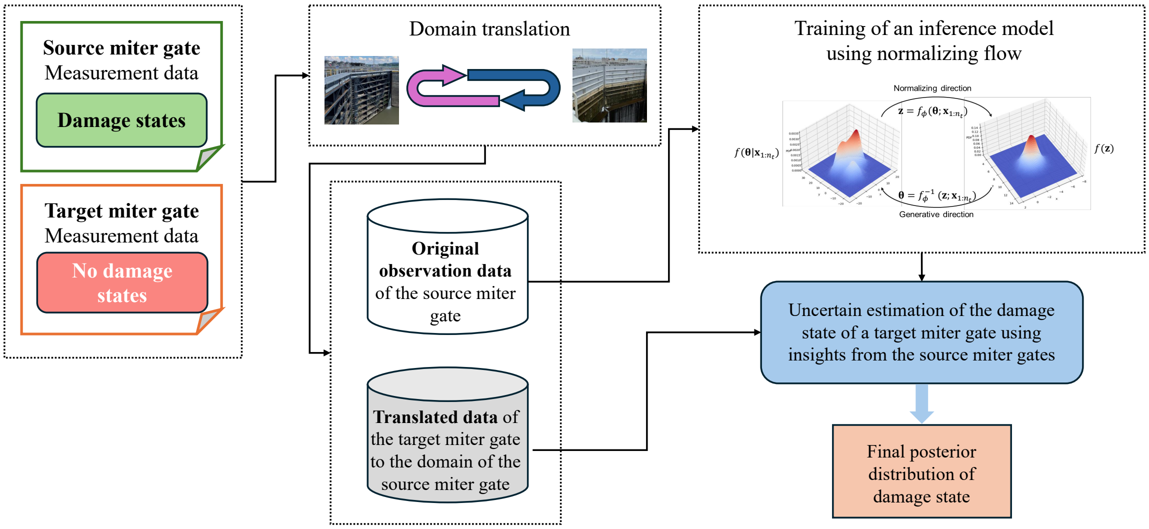

Figure 3. Overview of the proposed framework

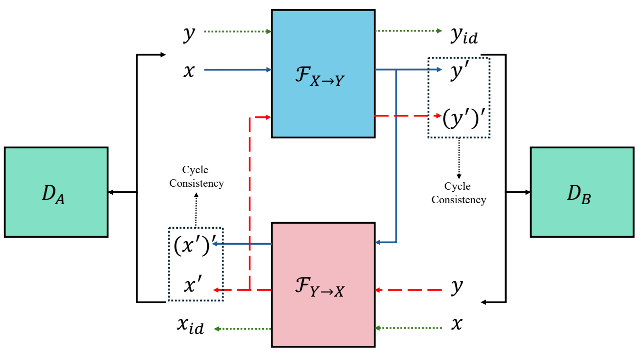

Figure 4. The structure of CycleGAN

is given by (Zhu et al., 2017)

$$\mathcal{L}_{\text{adv}}\left(\mathcal{F}_{X\to Y}, \mathcal{P}_Y, X, Y\right) = \mathbb{E}_{y\sim Y}\left[\frac{1}{N^2}\sum_{i,j}\log \mathcal{P}_Y(y)_{i,j}\right] + \mathbb{E}_{x\sim X}\left[\frac{1}{N^2}\sum_{i,j}\log\left(1-\mathcal{P}_Y\left(\mathcal{F}_{X\to Y}(x)\right)_{i,j}\right)\right], \tag{2}$$

where N is the number of data in the dataset, $\mathbb{E}[\cdot]$ stands for expectation operation, the first term maximizes the probability for real monitoring data $y \in Y$ and the second term minimizes the probability for the generated data $\mathcal{F}_{X\to Y}(x)$ to be identified as fake by $\mathcal{P}_Y$. Similarly, we have $\mathcal{L}_{\text{adv}}\left(\mathcal{F}_{Y\to X}, \mathcal{P}_X, Y, X\right)$.

The second part is the cycle consistency loss, which is given by

$$\begin{aligned}&\mathcal{L}_{\text{cyc}}\left(\mathcal{F}_{X\to Y}, \mathcal{F}_{Y\to X}\right)\\ &= \mathbb{E}_{x\sim X}\left[\left\|\mathcal{F}_{Y\to X}\left(\mathcal{F}_{X\to Y}(x)\right) - x\right\|_1\right]\\ &+ \mathbb{E}_{y\sim Y}\left[\left\|\mathcal{F}_{X\to Y}\left(\mathcal{F}_{Y\to X}(y)\right) - y\right\|_1\right],\end{aligned} \tag{3}$$

where this term ensures $x \to y \to x$ and $y \to x \to y$ mappings approximate the original monitoring data.

The last part is the identity loss and is given by

$$\begin{aligned}\mathcal{L}_{\text{identity}}\left(\mathcal{F}_{X\to Y}, \mathcal{F}_{Y\to X}\right) = \mathbb{E}_{y\sim Y}\left[\left\|\mathcal{F}_{X\to Y}(y) - y\right\|_1\right]\\ + \mathbb{E}_{x\sim X}\left[\left\|\mathcal{F}_{Y\to X}(x) - x\right\|_1\right],\end{aligned} \tag{4}$$

where this term maintains identity mappings when $y \in Y$ or $x \in X$ are passed to their own domain generators.

Therefore, the total loss is expressed as:

$$\mathcal{L} = \mathcal{L}_{\text{adv}} + \lambda_{\text{cyc}}\mathcal{L}_{\text{cyc}} + \lambda_{\text{identity}}\mathcal{L}_{\text{identity}}, \tag{5}$$

in which λ_{cyc} and $\lambda_{\text{identity}}$ are weighting factors for cycle consistency and identity losses, respectively.

The objective is to find optimal generators and discriminators by solving a minimax optimization problem that balances the adversarial, cycle consistency, and identity losses. We can express this as

$$\mathcal{F}^*_{X\to Y}, \mathcal{F}^*_{Y\to X} = \arg\min_{\mathcal{F}_{X\to Y}, \mathcal{F}_{Y\to X}}\max_{\mathcal{P}_X, \mathcal{P}_Y}\mathcal{L}. \tag{6}$$

Let the monitoring data of the source miter gates be $\mathbf{x}_{1:n_t} \in X$ and the damage state be $\boldsymbol{\theta}$, that of the target miter gate be $\mathbf{y}_{1:n_t} \in Y$, after the training of the CycleGAN model, we can map monitoring data of the target miter gate to that of the source miter gates as

$$\hat{\mathbf{x}}_{sy,1:n_t} \approx \mathcal{F}_{Y\to X}(\mathbf{y}_{1:n_t}), \tag{7}$$

where $\hat{\mathbf{x}}_{sy,1:n_t}$ represents the equivalent synthetic monitoring data for the source miter gates, which corresponds to the actual monitoring data of the target miter gate.

3.3. Probabilistic damage inference using normalizing flow after domain adaptation

As described in Sec. 3.1, after mapping the monitoring data $\mathbf{y}_{1:n_t}$ of the target miter gate to the source miter gates, we construct a damage inference model using data of the source miter gates. The damage inference model is then employed to predict the damage state of the target miter gate based on its synthetic monitoring data $\hat{\mathbf{x}}_{sy,1:n_t}$ in the source domain after domain adaptation.

In this section, normalizing flow is used to approximates the damage posterior distribution $p(\boldsymbol{\theta}|\mathbf{x}_{1:n_t})$ using a parameterized approximate posterior distribution $p_\phi(\boldsymbol{\theta}|\mathbf{x}_{1:n_t})$ as accurately as possible:

$$p(\boldsymbol{\theta}|\mathbf{x}_{1:n_t}) \approx p_\phi(\boldsymbol{\theta}|\mathbf{x}_{1:n_t}). \tag{8}$$

This approximation is achieved by starting with a underlying standard normal distribution $f(\mathbf{z})$ and applying a series of bijective transformations. As shown in Fig. 5, there are two types of flow transformation, namely generative direction and normalizing direction. In the former, the underlying standard normal variables $\mathbf{z}$ are mapped to the target variables $\boldsymbol{\theta}$, i.e., $\boldsymbol{\theta} = f_\phi^{-1}(\mathbf{z};\mathbf{x}_{1:n_t})$. This allow us to generate the samples of $\boldsymbol{\theta}$ from the posterior distribution $p(\boldsymbol{\theta}|\mathbf{x}_{1:n_t})$ by sampling $\mathbf{z}$ from $f(\mathbf{z})$. In the latter, the target variables $\boldsymbol{\theta}$ are mapped back to the underlying standard normal variables, i.e., $\mathbf{z} = f_\phi(\boldsymbol{\theta};\mathbf{x}_{1:n_t})$. f_ϕ and f_ϕ^{-1} are a pair of invertible functions.

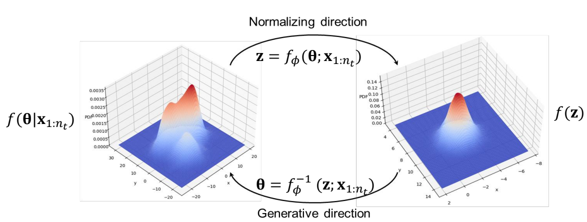

Figure 5. Illustration of Normalizing Flows

In practice, f_ϕ and f_ϕ^{-1} are often intractable since the target posterior distribution $p(\boldsymbol{\theta}|\mathbf{x}_{1:n_t})$ is highly irregular and strongly non-Gaussian. An alternative way is to learning the invertible mapping relationship by training conditional invertible neural networks (cINN) based on data. As illustrated in Fig. 6, the basic building block of cINN is the affine coupling block. Each block consists of two complementary affine coupling layers that split the input vector into two halves. Then, the split inputs are transformed into inputs of the next block by an affine function. Also, the inverse direction operation can also be easily implemented by an affine function. By stacking multiple blocks together, cINN can approximate f_ϕ and f_ϕ^{-1} well (Zeng, Zeng, et al., 2024b, 2024a).

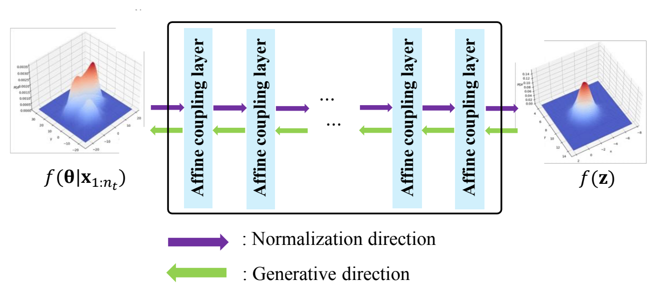

Figure 6. Illustration of conditional invertible neural network (cINN)

According to the probability density transformation law, the approximate posterior $p_\phi(\boldsymbol{\theta}|\mathbf{x}_{1:n_t})$ can be re-parameterized in terms of f_ϕ as follows:

$$p_\phi(\boldsymbol{\theta}|\mathbf{x}_{1:n_t}) = p(\mathbf{z} = f_\phi(\boldsymbol{\theta};\mathbf{x}_{1:n_t}))\left|\det\left(\frac{\partial f_\phi(\boldsymbol{\theta};\mathbf{x}_{1:n_t})}{\partial\boldsymbol{\theta}}\right)\right|. \tag{9}$$

During the training of cINN, one is desirable to minimize the Kullback-Leibler (KL) divergence between the target posterior distribution $p(\boldsymbol{\theta}|\mathbf{x}_{1:n_t})$ and the approximate one $p_\phi(\boldsymbol{\theta}|\mathbf{x}_{1:n_t})$ as (Radev, Mertens, Voss, Ardizzone, & Köthe, 2020)

$$\begin{aligned}\hat{\phi} &= \arg\min \mathbb{E}_{\mathbf{x}_{1:n_t}\sim p(\mathbf{x}_{1:n_t})}[\mathbb{KL}(p(\boldsymbol{\theta}|\mathbf{x}_{1:n_t})||p_\phi(\boldsymbol{\theta}|\mathbf{x}_{1:n_t}))] \\ &= \arg\max \int\int \log p_\phi(\boldsymbol{\theta}|\mathbf{x}_{1:n_t})p(\boldsymbol{\theta}|\mathbf{x}_{1:nt})d\boldsymbol{\theta}d\mathbf{x}_{1:n_t}.\end{aligned} \tag{10}$$

By substituting Eq. (9) into Eq. (10), we have:

$$\begin{aligned}\hat{\phi} = \arg\max \int\int &\{\log p(\mathbf{z}) + \log|\det J_{f_\phi}|\} \\ &\times p(\boldsymbol{\theta}|\mathbf{x}_{1:nt})d\boldsymbol{\theta}d\mathbf{x}_{1:n_t},\end{aligned} \tag{11}$$

where $\partial f_\phi(\boldsymbol{\theta};\mathbf{x}_{1:n_t})/\partial\boldsymbol{\theta}$ is abbreviated as J_{f_ϕ}.

For a batch of M simulated data $\{(\boldsymbol{\theta}^{(j)},\mathbf{x}_{1:n_t}^{(j)})\}_{j=1}^{M}$ from the source miter gates, Eq. (11) can be computed by means of Monte Carlo simulation (MCS) as (Radev et al., 2020)

$$\hat{\phi} = \arg\max_\phi \frac{1}{M}\sum_{j=1}^{M}\log p(f_\phi(\boldsymbol{\theta}^{(j)};\mathbf{x}_{1:n_t}^{(j)})) + \log|\det J_{f_\phi}^{(j)}| \tag{12}$$

Since $\log p(z) \propto -\frac{1}{2}||z||_2^2$ for Gaussian distribution, Eq. (12) can be rewritten as:

$$\hat{\phi} = \arg\min_{\phi} \mathcal{L}(\phi), \tag{13}$$

with

$$\mathcal{L}(\phi) = \frac{1}{M}\sum_{j=1}^{M} \frac{||f_\phi(\theta^{(j)}; \mathbf{x}_{1:n_t}^{(j)})||_2^2}{2} - \log|\det J_{f_\phi}^{(j)}|. \tag{14}$$

where $\mathcal{L}(\cdot)$ is the loss function which can be minimized with any stochastic gradient descent method.

Denoting the resulting normalizing flow model after training as $\mathcal{H}(\cdot)$, it can be used to obtain the posterior samples of the damage state θ of the target miter gate as

$$\hat{\theta}^{(i)} \approx \mathcal{H}(\mathcal{F}_{Y\rightarrow X}(\mathbf{y}_{1:n_t}), \boldsymbol{z}^{(i)}), \forall i = 1, \cdots, N_{\text{MCS}}, \tag{15}$$

where $\boldsymbol{z}^{(i)}$ is the i-th MCS sample of the multivariate Gaussian distribution $f(\mathbf{z})$.

4. CASE STUDY

4.1. Problem description

To demonstrate the feasibility of the proposed framework, we tested it on a scenario involving two different yet similar miter gates. Fig. 7 shows the two miter gates, one located upstream and the other downstream within the same water basin. Although these two miter gates share inherent similarities due to their similar operational conditions and structures, they also exhibit differences in their detailed structural designs.

Figure 7. Illustration of source and target miter gates on a river.

In this paper, the data for the two miter gates are hypothetically generated by simulating the reality and modifying the operational conditions and structural responses of a miter gate previously studied in our research (Vega et al., 2021; Ramancha et al., 2022). It is assumed that each miter gate has eight strain gauges. Using surrogate models constructed based on finite element simulations, we generate 200 sets of strain observations for the source miter gates, and 180 sets of strain observations for the target miter gate with unknown damage states. Each set of strain observations consists of eight strain gauges over twenty time steps (i.e., n_t= 20). The damage states (i.e., gap length) corresponding to the source miter gates are different and are available from historical inspections. Their counterparts of the target miter gate are unknown and are to be estimated (Zeng, Zhao, Qian, Todd, & Hu, 2024).

4.2. Domain adaptation using CycleGAN

CycleGAN is utilized to perform domain adaptation on the data from the target miter gate, leveraging the data from the source miter gates. The preprocessing for the CycleGAN model includes several key steps:

1. Sort the data by the highest strain response values.
2. Normalize the data to constrain its range.
3. Convert the data into image format, with dimensions representing time steps and sensor indices.

This image-formatted data is then used to train the CycleGAN, ensuring it accurately learns the relationships between the source and target domains. Once the CycleGAN is trained, we evaluate its performance by visualizing the translation through scatter plots of sensor data from the source domain versus the target domain, both before and after applying the CycleGAN. Figure 8 compares the strain data from sensors on both the source and target miter gates, highlighting significantly different distributions for the same sensors across these different structures. Figure 9 illustrates a comparison between strain data from sensors on source miter gates and translated strain data from sensors on target miter gates after domain adapatation. The figure demonstrates that the synthetic source data, generated from the target miter gate using CycleGAN, closely aligns with actual observations from the source miter gates. This indicates that the CycleGAN has successfully adapted the target miter gate data to match the characteristics of the source miter gate data.

4.3. Damage inference after domain adaptation

After mapping the observations of the source and target miter gates into the same domain using CycleGAN (see Figs. 8 and 9), as discussed in Sec. 3.3, we proceed to train a normalizing flow model with the cINN method. This training is based on the observations of the source miter gates and their corresponding damage labels. Subsequently, we employ the trained normalizing flow model to perform likelihood-free inference for the target miter gate and thereby estimating its damage state under uncertainty. Figure 10 presents the comparison between the prior and posterior distributions of the gap length for five different scenarios. As depicted in this figure, the proposed approach in general provides accurate estimates of the true damage state of the targe miter gate. However, in scenario 3, a bias is observed between the estimated

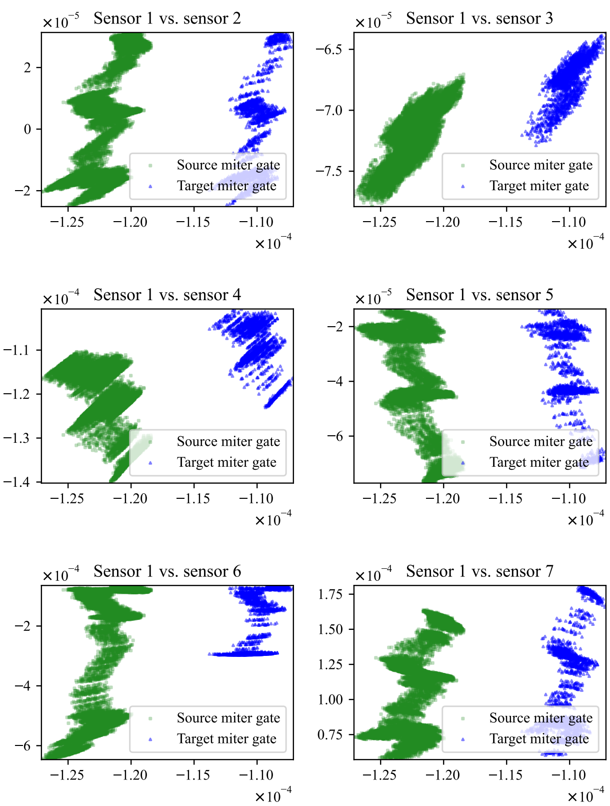

Figure 8. Scatter plot comparison of measurement data between the source and target miter gates

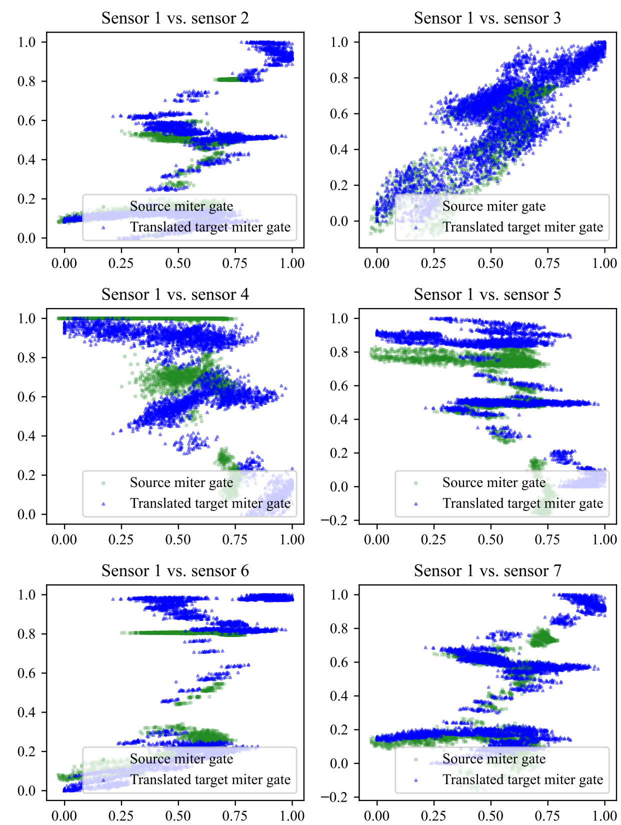

Figure 9. Scatter plot comparison of measurement data between the source and target miter gates after domain adaptation using CycleGAN

posterior distribution and the true damage state. Following that, Fig. 11 compares the estimated damage state (measured as gap length) to the actual damage state across 180 cases, covering all possible damage regimes. In the figure, the red line represents the true damage state, while the blue error bars indicate the estimated damage state, with a four-sigma uncertainty interval. Consistent with the results presented in Fig. 10, the results indicate that the proposed damage inference method—utilizing normalizing flow and domain adaptation with CycleGAN—can accurately estimate the damage state of the target miter gate, despite the lack of labeled monitoring data for the gate.

5. CONCLUSION

This paper presents a novel damage diagnostics approach for miter gates with unlabeled monitoring data. In order to infer the unknown damage state of a gate, we first employ a domain adaptation approach based on CycleGAN, which maps the monitoring data from the target miter gate to data from source miter gates. Subsequently, by leveraging the mapped data, we propose a probabilistic inference method based on normalizing flow to efficiently estimate the damage state in the presence of uncertainty. A case study demonstrates the efficacy of the proposed method.

This paper focuses on mainly damage diagnostics through information fusion between two miter gates using domain adaptation approach which is a data-driven approach. The integration of this purely data-driven approach with a physics-based damage inference method is worth studying. Such an integration has been explored in our other work in Ref. (Zeng, Zhao, et al., 2024).

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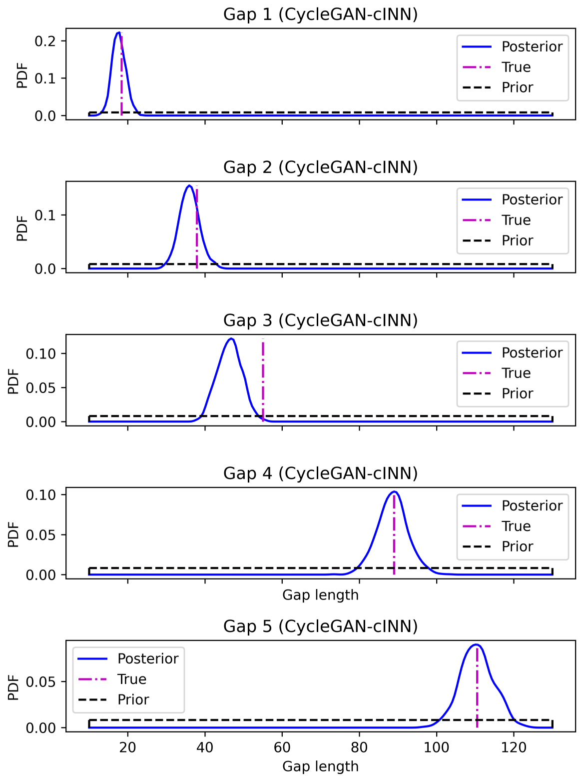

Figure 10. Posterior distribution of gap length obtained using cINN and CycleGAN-based domain adaptation

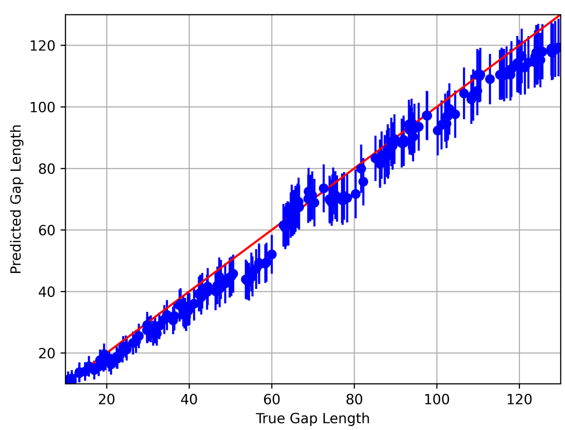

Figure 11. Errorbar plot of the posterior distribution of different gap length estimates (CycleGAN-based domain adaptation)

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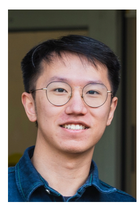
BIOGRAPHIES



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