Chapter 5
Degradation Model Correction of Miter Gates Through Synthesis of Hybrid Modeling with Recursive Bayesian State Estimation

Zhao Zhao, Yichao Zeng, Michael D. Todd, and Zhen Hu

Abstract Modeling the degradation behavior of miter gates is of importance for risk-informed maintenance decision-making. Due to the complicated nature of the damage mechanisms and the lack of understanding them clearly, degradation models are usually developed based on simplifications and assumptions. As a result, these models may not accurately represent the true degradation behavior. To improve the accuracy of empirical degradation models of miter gates and ensure reliable failure prognostics, this paper proposes a novel degradation model correction framework by integrating hybrid modeling techniques with recursive Bayesian state estimation. The proposed work consists of two phases: the offline training phase and the online updating phase. During the offline training phase, the unknown model bias term is modeled as a random noise with uncertain standard deviation. Synthetic data are then generated using a physical model based on prior knowledge of the uncertain model parameters and model bias. The synthetic data is utilized to train a conditional Invertible Neural Network (an inference network). In the online updating phase, the trained inference network is used to obtain posterior samples. Meanwhile, the Gaussian mixture model and dual particle filter techniques are utilized to recursively update posterior samples, thereby improving the estimation accuracy. Subsequently, model bias is inversely estimated using the degradation model, which uses the updated model parameters and the gap length from the inference model. Finally, a regression model is utilized to correct the biases inherent in the simplified degradation model. Results of a case study show that the proposed framework can effectively improve the accuracy of the degradation model for failure prognostics of miter gates.

Keywords Degradation model · Miter gates · Model Uncertainty · Parameter Uncertainty

Introduction

Miter gates are key components in inland waterway lock systems to enable the smooth transit of barges and ships [1–3]. Despite their critical role, a significant number of these gates have surpassed their intended design lifespan of 50 years, leading to an urgent need for effective repair and maintenance strategies. Thus, it is imperative to understand the deterioration mechanism of miter gates [4, 5]. Although a simplified degradation model for miter gates has been developed to describe the gap growth based on abstracted inspection data in recent years [6], its prediction error is inevitable because of many inherent assumptions and simplifications.

To improve the accuracy and reliability of the degradation model and further better predict failure conditions, this study presents a hybrid modeling technique with recursive Bayesian state estimation, comprehensively accounting for both parameter and model uncertainties.

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Proposed Method

The whole technical route of the proposed method is shown in Fig. 1, which consists of three main steps [7]. In the first step, we generate synthetic data based on prior knowledge of model parameters and bias through a simplified degradation model. We assume that model bias is affected by gap length, which is incorporated into the formula for measuring unobservable gap lengths. Additionally, the prior is constrained to preserve the model's physical meaning. By applying the two-level degradation model, we can generate synthetic strain data for specified model parameters, gap lengths, and biases. Thus, the training dataset is structured with gap length, model bias, and model parameters as inputs, and strain data as outputs. After that, we focus on the offline training for a likelihood-free inference model. The training datasets are first processed through a specially designed summary network. Then, an inference network, such as a conditional Invertible Neural Network (cINN), is used to perform joint training for inference. Following that, in Step 2, posterior samples of gap length and model parameters are generated by plugging new observations into the trained summary network and cINN. To further refine these posterior samples, two techniques, including a Gaussian Mixture Model (GMM) and Dual Particle Filtering, are employed for recursive sample updates over a long-term monitoring period. Based on the recursive updating of the posterior distributions of gap length and model parameters, a numerical procedure is developed to estimate the bias of the degradation model. In Step 3, two regression models, including a Gaussian process regression (GPR) model and a polynomial regression (PR) model, are employed to capture the relationship between gap length and model bias. Finally, the predictive accuracy of degradation curves is improved by utilizing the updated model parameters and the model bias identified through the GPR model or the PR model. More details of the method can be found in Ref. [7].

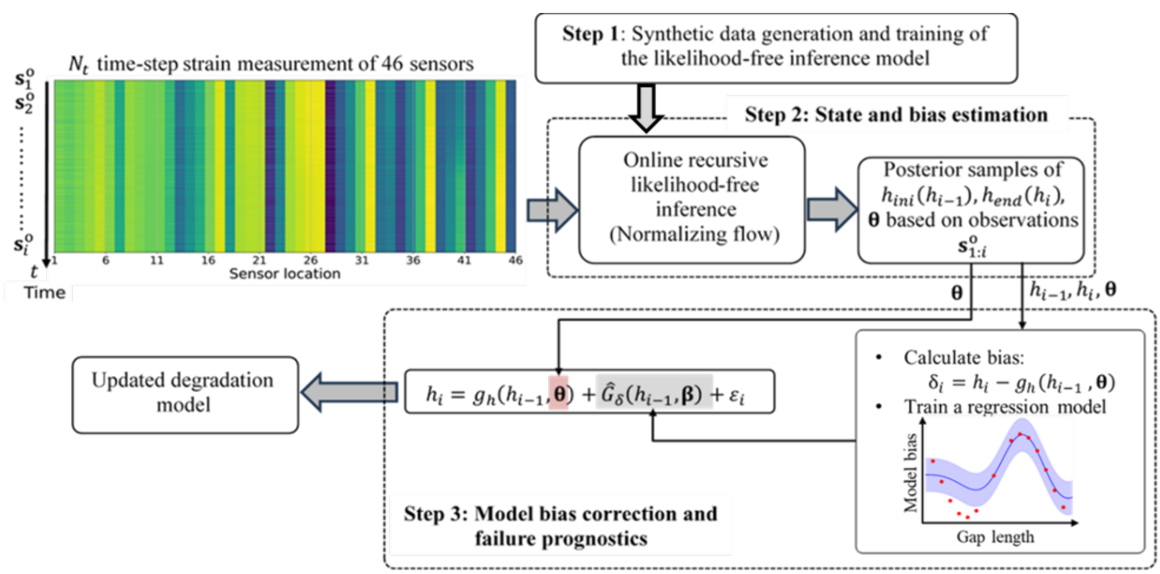


Fig. 1 Schematic diagram of the proposed methodology [7].

Application To A Miter Gate

To assess the effectiveness of the proposed model, synthetic strain measurements are initially generated using model parameters from a true degradation model. While the true degradation model is considered unknown, our proposed method aims to infer the true parameters and model bias for given strain data. We then evaluate the accuracy of failure prognostics, such as predicting the remaining useful life (RUL), by comparing the performance of the updated degradation model against that of the original simplified degradation model.

Fig. 2 presents a comparison of gap length predictions, which accounts for model bias using respectively GPR model and PR model, against predictions made without considering model bias [7]. The prognostic outcomes for gap length obtained from both the GPR and PR models exhibit a high degree of accuracy and closely follow the true degradation curve, outperforming the original model that ignores model bias.

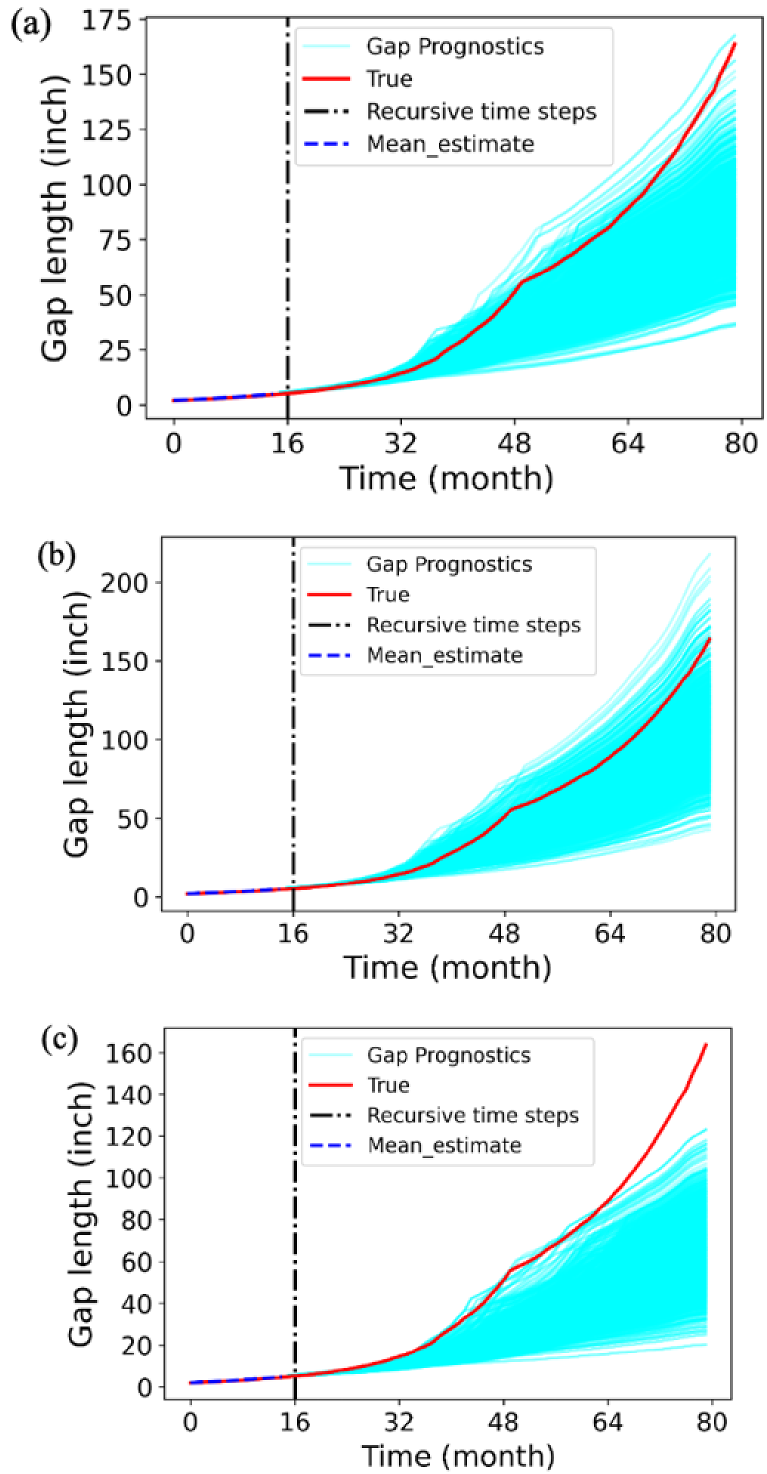
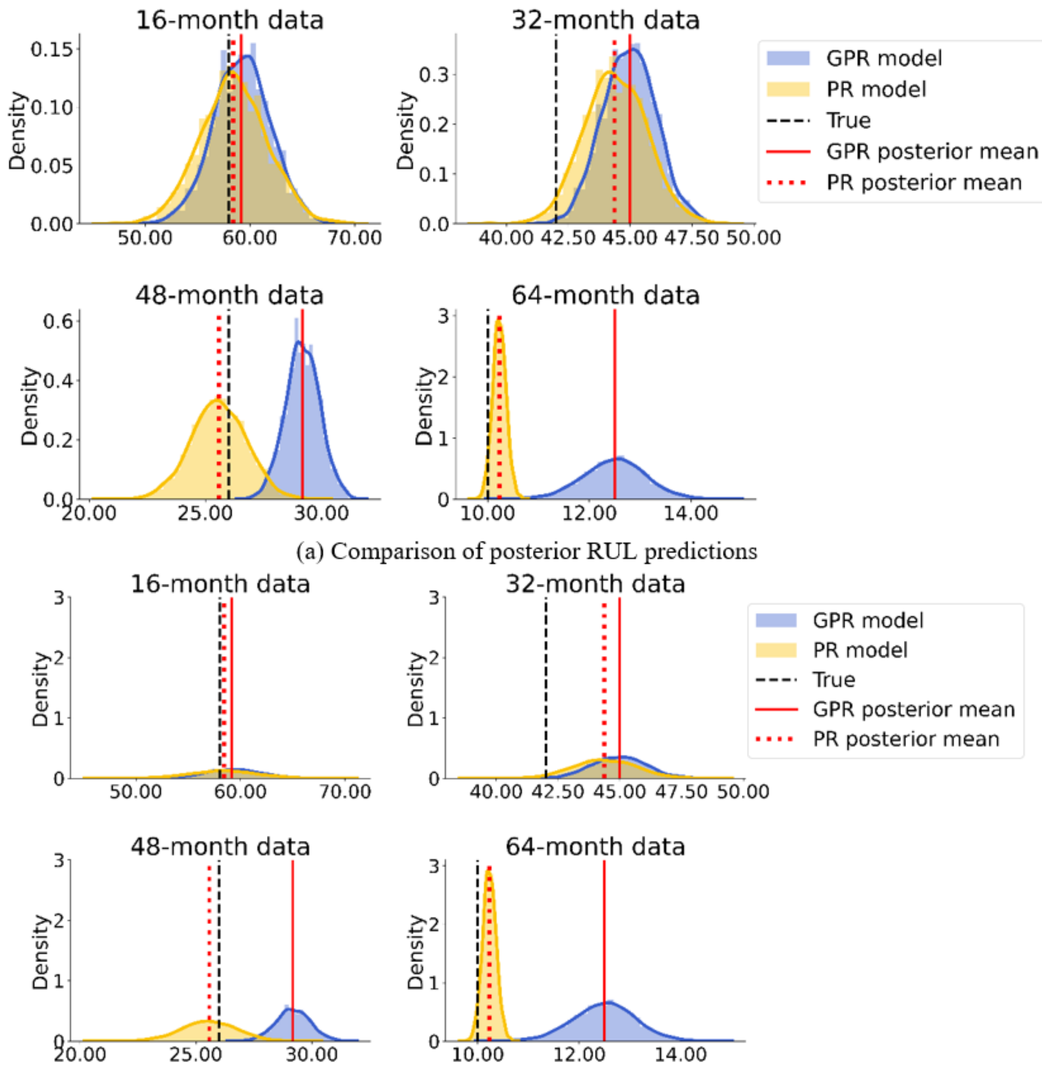


Fig. 2 Prediction of degradation curves by 16-month data: (a) GPR model prediction; (b) PR model prediction; (c) prediction without model bias [7].

Fig. 3 presents the density distributions of RUL estimates using both GPR and PR models across four different data durations (16-month, 32-month, 48-month, and 64-month). Across all scenarios, the estimates of the PR model consistently align more closely with the true RUL compared to that of the GPR model. This consistent performance highlights the PR model's overall superior accuracy and reliability in RUL estimation compared to the GPR model.



(a) Comparison of posterior RUL predictions

(b) Comparison of posterior RUL predictions

Fig. 3 Estimated posterior distribution of RUL [7].

Conclusion

This study proposes an innovative method for degradation models correction through a hybrid modeling with recursive Bayesian state estimation. The primary objective is to simultaneously account for model parameter uncertainty and model bias and improve the accuracy of model predictions and failure prognostics, specifically for miter gate degradation models. The proposed method has two phases: an offline training phase and an online recursive updating phase. During the offline training phase, synthetic data is generated to jointly train a summary network and a cINN model. In the online recursive updating phase, the gap length, bias parameter, and degradation model parameters are estimated by the trained cINN based on measured strain data. The model updating process is implemented recursively to refine the posterior samples of the model parameters. This refinement is achieved through the application of dual particle filtering in conjunction with a GMM to enhance the accuracy of the estimations. The model bias is inversely estimated by the gap length estimated from the cINN model and recursively updated model parameters. A GPR model and a PR model are used to establish the relation between gap length and model bias. The failure prognostics (e.g., prediction of degradation curves and RUL estimate) is improved by the updated model parameters and model bias captured by the GPR and PR models. The proposed method is applied to a miter gate structure and the results show that the proposed approach significantly outperforms a simplified degradation model that ignores model bias, which highlights the importance of accounting for model bias in degradation models.

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