Pitting Corrosion Model Updating Using Experimental Data

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ABSTRACT

Both physics-based (deterministic) and statistical models are widely used in structural health monitoring (SHM) research due to their ability to predict damage progression, particularly in scenarios with limited data availability. However, while all parameters in statistical models and certain parameters in physics-based models cannot be directly measured, updating these parameters using measurement data is essential for ensuring accuracy. This study presents a novel approach to updating a hybrid corrosion model using accelerated corrosion experimental data combined with an amortized likelihood-free Bayesian inference method. In the proposed framework, pit numbers and dimensions developed after different corrosion time durations are first measured using a high-precision laser scanner. Two reaction coefficients and two statistical parameters, which are not directly measurable, are selected for updating in the hybrid simulation. A summary network and a conditional invertible inference network are jointly trained on extensive simulation data to learn the mapping between observed data and model parameters. The trained network is then utilized to infer the posterior distribution of the model parameters based on experimental measurements. The results demonstrate that the proposed conditional invertible neural network-based inference method can effectively and efficiently update the hybrid model, enhancing parameter estimation for complex damage mechanisms such as corrosion. Additionally, a key advantage of this approach is its computational efficiency, as it can perform inference within seconds—significantly faster than other likelihood-free inference methods. This capability makes it particularly suitable for real-time SHM applications, improving both accuracy and practicality in damage assessment.

INTRODUCTION

Pitting corrosion represents a critical threat to civil infrastructure, primarily because

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localized corrosion pits often remain undetected until structural integrity is compromised [1, 2]. Previous research has explored various corrosion modeling approaches, including empirical equation-based models [3–5], purely statistical models [6, 7], and physics-based models for individual pit evolution [8–11]. However, integrated models combining statistical and physics-based methods for comprehensive modeling of multiple pit evolution remain scarce.

Bayesian model updating techniques are extensively used to reduce uncertainties in model predictions. Nevertheless, traditional Bayesian approaches require explicit likelihood functions, which become intractable in hybrid models integrating partial differential equations with stochastic processes. Consequently, likelihood-free inference methods, such as Approximate Bayesian Computation (ABC) [12], become essential.

Another significant challenge is the availability of detailed corrosion data. Given that corrosion can take decades to evolve, comprehensive datasets documenting temporal corrosion progression are extremely limited. Furthermore, recorded maintenance interventions or repairs are often missing from these datasets, reducing their utility for effective model updating [13].

This study addresses these challenges by proposing a hybrid corrosion modeling framework combining a physics-based single-pit evolution model with a statistical pit initiation model. Accelerated corrosion experiments were conducted to generate high-quality datasets. Utilizing these experimental results, the proposed framework employs likelihood-free inference for effective Bayesian model updating. Results demonstrate the model's ability to be robustly updated using experimental data, significantly enhancing its predictive accuracy and reliability.

THE HYBRID PITTING CORROSION MODELING

The pitting corrosion model developed in this study comprises two complementary parts, as depicted on the left side of Fig.1: (1) a multi-physics phase-field simulation of single pit evolution, and (2) a statistical model describing pit initiation times. The pit evolution component couples multiple partial differential equations, including the Butler-Volmer equation, diffusion equation, Poisson equation, and mechanical equilibrium equation [11], thereby enabling the simulation of stress effects on corrosion. Mechanical loading is intentionally excluded from this study to isolate the influence of key non-measurable parameters. The physics-based single-pit evolution model offers several advantages over purely data-driven approaches: it requires fewer data points, is robust against limited data scenarios due to its physics-based foundation, and inherently propagates uncertainties from various sources into the final predictions when data are scarce.

The initiation component employs a statistical approach because pit initiation exhibits significant stochastic variability and the underlying mechanisms remain an active research area [14,15]. Due to limited knowledge about the precise distribution governing initiation times, the Beta distribution was chosen for its flexibility in modeling diverse initiation probability density functions. By integrating both simulation components, this hybrid model effectively simulates the initiation and subsequent evolution of multiple pits over time.

Four primary parameters were identified for updating through experimental measurements due to their inherent non-measurability: two environmental parameters from the pit evolution model—θ_1 (reaction constant describing electrochemical reactions) and θ_2 (diffusion coefficient)—and two shape parameters from the initiation model—λ and β.

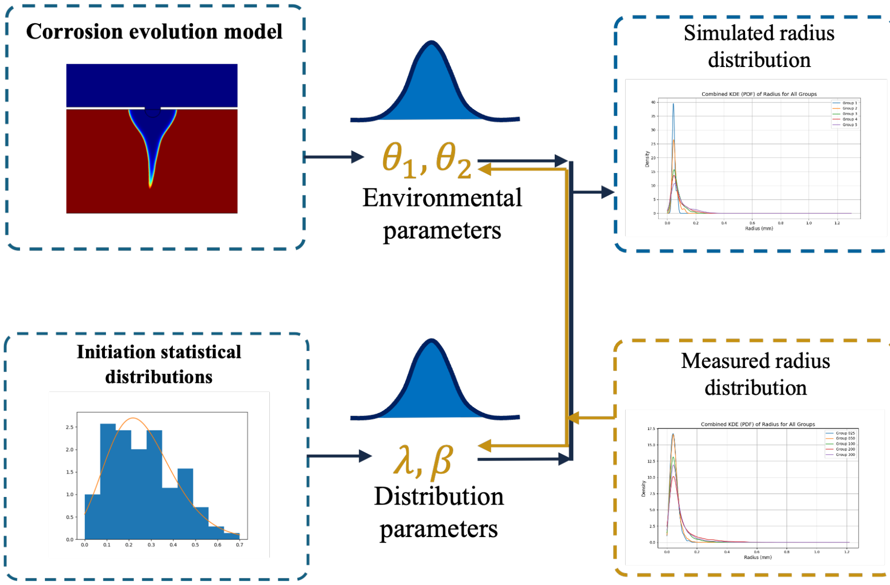


Figure 1. The framework of the model updating.

THE EXPERIMENT SETUP AND MEASUREMENTS

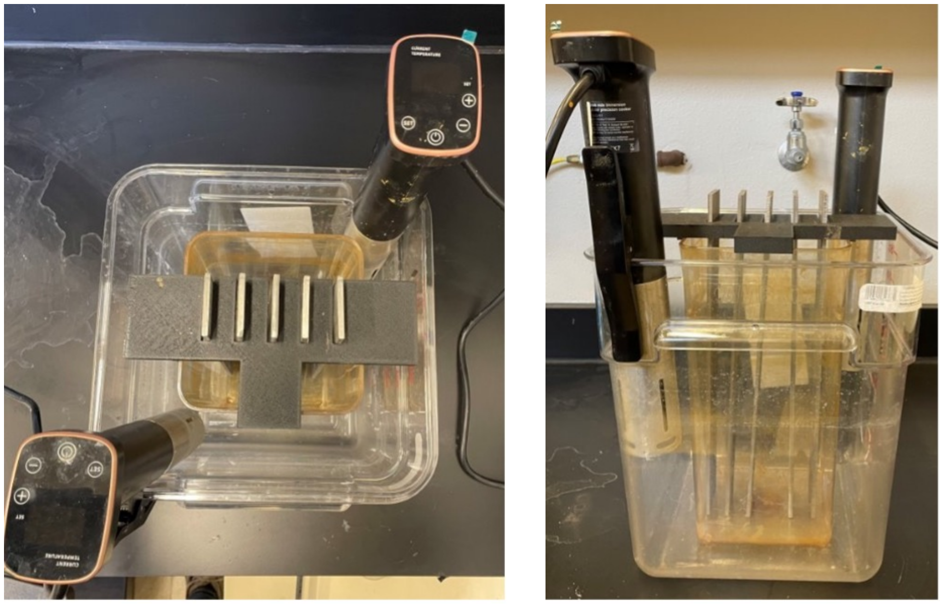
Accelerated Unloaded Pitting Corrosion Experiment

This study modifies and expands on the experimental methods originally developed by Muehler et al [16]. The specimens tested were AISI 304 stainless steel (50.8 mm × 342.9 mm × 4.7625 mm, purchased from Metals Depot), which were sanded until shiny and washed with DI water. These samples were placed in a solution of iron (III) chloride ($FeCl_3$, purchased from Sigma-Aldrich) with a ratio of 8.11 g $FeCl_3$ for every 100 ml of deionized (DI) water. This solution was heated to 50°C and added to a corrosion resistant container, as shown in Figure 2. This container was then placed in a heated water bath to maintain the temperature of the corrosive solution. The steel specimens were corroded for different time durations until being removed and thoroughly washed with DI water.

Pit Morphology Measurement

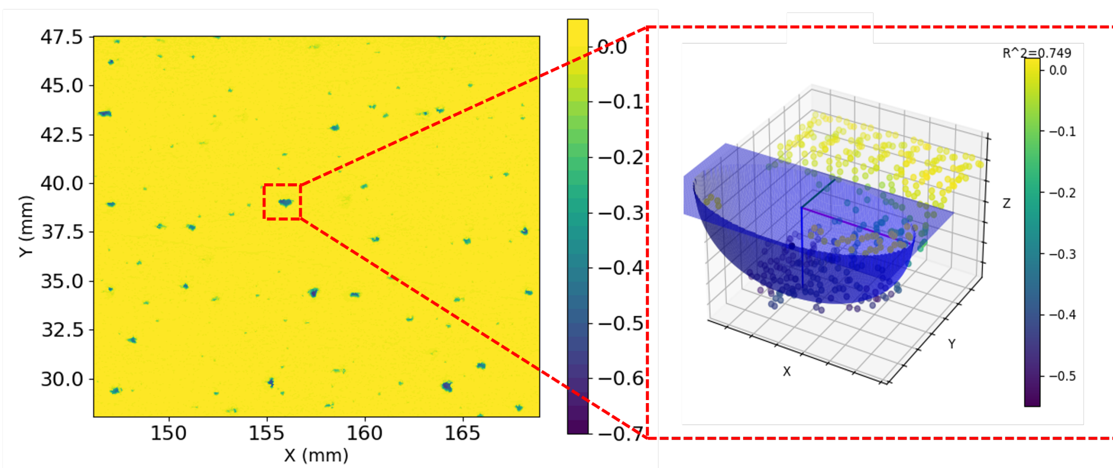
To measure the morphologies of the generated pits on the steel specimens, an LSM4-2 laser distance scanner attached to a Micro-Vu Vertex 312UC system was employed. A region of 30 × 45 mm2 in the center of the specimen was inspected with the laser scanner, where discrete points were measured at even intervals over the surface at a resolution of 4 microns.

A list of 3D points for each specimen was then processed to extract the location and geometry of pits. First, the points were normalized to the average surface, as shown in Figure 2a. Next, points representing a pit were assembled based on the slope of the surface, which were fitted to a half ellipsoid function (Figure 2b). Based on the ellipsoid function, pit depth and surface opening area could be calculated.



(a) (b)

Figure 2. Accelerated pitting corrosion experimental setup from (a) top view and (b) side view.



(a) (b)

Figure 3. (a) An example color contour plot of adjusted laser scan data obtained from a specimen after 3 hours of corrosion time, and (b) a 3D view of a pit with its corresponding ellipsoid fit..

LIKELIHOOD-FREE MODEL UPDATING WITH CONDITIONAL INVERTIBLE NEURAL NETWORK

A likelihood-free inference approach is necessary for updating the complex corrosion model employed in this study, as traditional likelihood-based Bayesian methods become intractable when dealing with models governed by coupled partial differential equations. Among likelihood-free methods, classical approximate Bayesian computation (ABC) has previously been applied to physics-based corrosion modeling [17]; however, ABC remains computationally intensive due to its inherently inefficient accept-reject sampling procedure. Moreover, ABC relies on a subjectively determined threshold to accept or reject a sample. If the threshold is not selected properly, it may lead to sub-optimal inference results. To overcome these limitations, we leverage recent advances in deep learning—in particular, conditional invertible neural networks (cINNs)—to perform amortized Bayesian inference, thereby significantly reducing computational costs during inference. Although similar techniques have been explored in bioengineering contexts [18], their application to pitting corrosion modeling remains largely unexplored [19].

The proposed inference framework, illustrated in Fig. 4, comprises two primary components: a summary network and an inference network. The summary network processes noisy observations W of varying lengths to generate a low-dimensional representation, W^s, which conditions the invertible inference network. Specifically, the cINN framework integrates Bayesian inference principles with deep learning via a normalizing flow architecture, enabling the transformation of complex posterior distributions into simpler, tractable Gaussian forms. This design allows for efficient posterior estimation even in high-dimensional parameter spaces. Moreover, the scalability and flexibility of normalizing flows make them particularly well-suited for capturing the intricate, non-Gaussian posteriors often encountered in physics-based corrosion modeling.

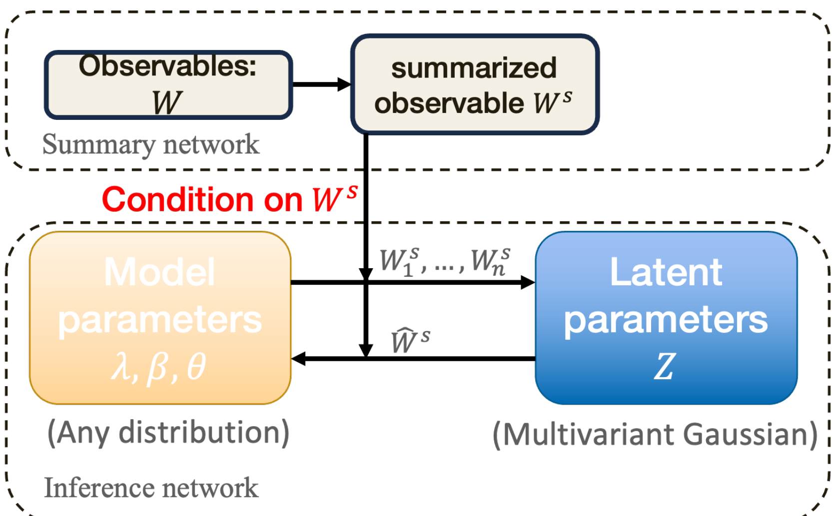


Figure 4. The workflow of the invertible neural network for model updating.

MODEL UPDATING RESULTS

The observation data from the first four time steps are used to inform the model, while the fifth time step serves as the reference for evaluating the prediction results after model updating. The pit width distribution is selected as the feature for comparison between the measurements and simulations.

The posterior distributions of the four key parameters are shown in Fig. 5, where Parameters 1 to 4 correspond to λ, β, θ_1, and θ_2, respectively. The posterior distributions for λ, β, and θ_1 display clear single peaks within the prior ranges, indicating that these parameters can be effectively updated using the proposed approach. In contrast, the posterior distribution for θ_2 remains broad without a well-defined peak. This observation suggests that the model is relatively insensitive to θ_2. A plausible explanation is that, under accelerated corrosion conditions, the kinetics governed by the corrosive solution (represented by θ_1) dominate the system behavior, whereas the influence of the diffusion process (characterized by θ_2) is comparatively less significant.

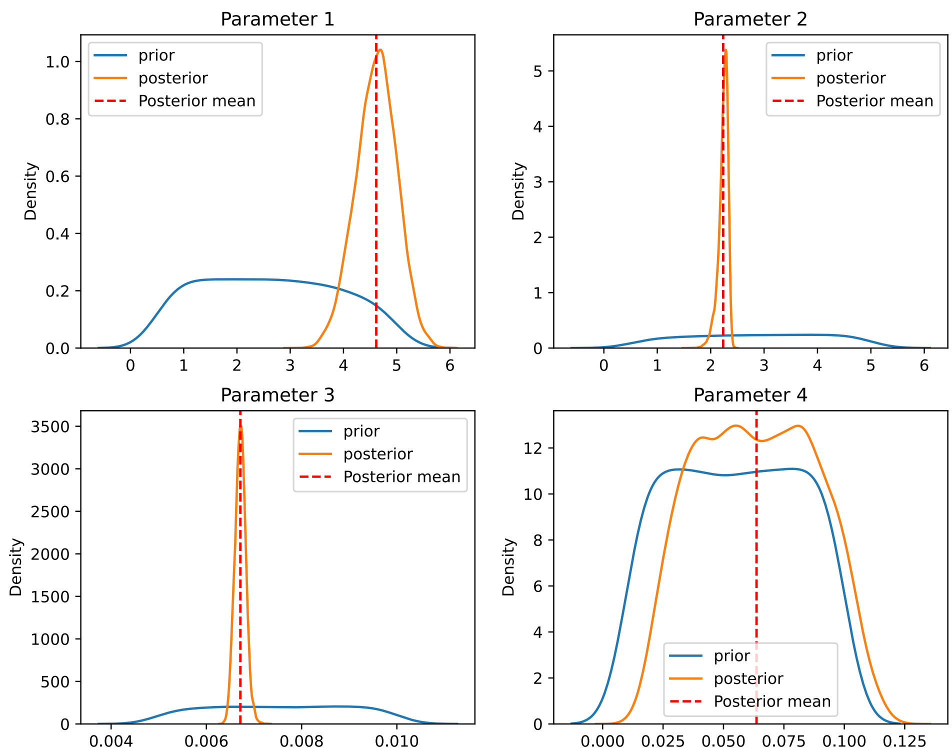


Figure 5. Posterior probability density functions (PDFs) of the four key parameters.

After obtaining the posterior distributions of the four parameters, the updated model is used to predict the pit width distribution at the fifth time step. The predicted distribution is compared with the corresponding measurements in Fig. 6. The results show that the predictions based on the updated model are more concentrated around the measured values compared to those based on the prior (i.e., the uncalibrated model), demonstrating the improved predictive capability achieved through model updating.

CONCLUDING REMARKS

This study presents a hybrid pitting corrosion model updated through accelerated corrosion experiments and a cINN-based likelihood-free inference method. The integration of experimental measurements with a hybrid simulation framework enables accurate

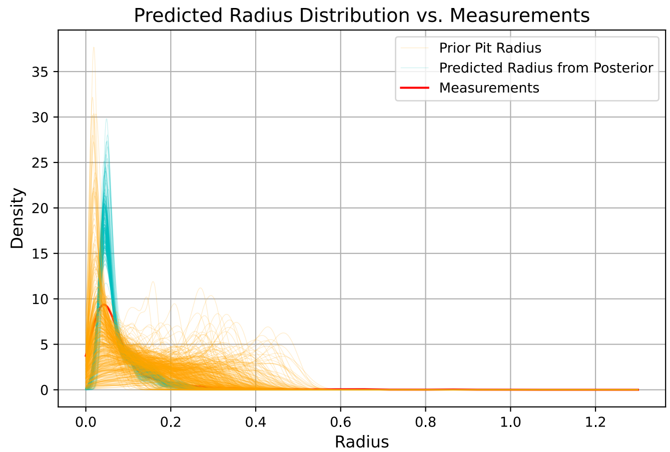


Figure 6. The prediction results using posterior distribution of the parameters.

posterior estimation of key non-measurable parameters, significantly improving predictive performance. The results show strong agreement between updated model predictions and independent measurements, demonstrating that the proposed approach offers a fast, accurate, and practical solution for real-time SHM of complex corrosion processes.

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