A Hybrid Surrogate Modeling Method for Corrosion Morphology Prediction Under Non-Stationary Dynamic Loading

GUOFENG QIAN, DAVID NAJERA-FLORES, ZHEN HU and MICHAEL D. TODD

ABSTRACT

The loads on the structures or components are more often fluctuating stochastically over time and exhibit non-stationary statistical behaviors. The goal of this research is to predict the corrosion growth of large civil infrastructure using multi-scale simulations with the consideration of time-dependent stochastic loads along with other sources of uncertainty. A stochastic process modeling method is first employed to model the stochasticity of the load conditions based on real-world data. A multi-scale simulation model is then constructed to predict the corrosion morphology evoluation over time subject to dynamic loads. The model consists of a mesoscale phase-field simulation and a macroscale structural analysis model. The required high computational effort of the multi-scale simulation model makes it unsuitable for probabilistic analysis purposes, which requires the execution of the model thousands of times. This research proposes a hybrid surrogate modeling to substitute the original multi-scale simulation model. The hybrid surrogate model consists of a deep neural network-based autoencoder for dimension reduction and a Gaussian process regression-based model for forecasting and uncertainty quantification. A navigational lock miter gate case study is employed to demonstrate the efficacy of the proposed method.

INTRODUCTION

Pitting corrosion under stress is a prevalent form of degradation observed in civil infrastructure [1]. Accurately forecasting the pitting corrosion evolution over time is crucial for maintenance planning and optimization of life-cycle costs for structures where corrosion-induced consequences are significant. The forecasting of damage limit states is typically conducted through either data-driven methods, physics based approaches, or a combination of both [2, 3]. In the case of large civil infrastructure such as the miter gates analyzed in this study, data pertaining to the degradation caused by pitting corrosion is generally not available. Therefore, physics-based corrosion damage prediction employing high-fidelity computer simulations offers a promising approach to overcome this challenge.

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Operational and environmental loading have a significant impact on the long-term evolution of corrosion in structures [4]. To model the growth of pitting corrosion while accounting for these factors, various computational methods have been proposed, including the finite volume method (FVM), cellular automata (CA) techniques, peridynamic (PD) formulations, and phase-field (PF) models [5–8]. The phase-field method is advantageous because it allows for the incorporation of mechanical stress into the electrochemical equations to simulate the growth of corrosion under stress conditions [9]. However, all the studies are limited to the influence from the static mechanical load. While the load keeps varying in the real world. For long-term degradation processes like corrosion, the influence of the changing load should be considered.

The phase-field models used for simulating corrosion are typically based on solving a system of coupled partial differential equations that describe the evolution of various physical quantities, such as the chemical potential, concentration, and stress, over time and space. These equations are highly nonlinear and are coupled with each other, making their numerical solution computationally expensive. Additionally, corrosion problems often involve complex geometries and boundary conditions, which further increase the computational cost of the simulations. Motivated by overcoming the computational challenge of using high-fidelity computer simulations for probabilistic corrosion analysis, this paper proposes a hybrid surrogate modeling method that combines a neural network-based autoencoder with Gaussian process regression surrogate model.

STOCHASTIC LOAD CONDITION MODELING

The structure of interest in this paper is the Greenup miter gate located in Kentucky, USA. The water elevation on both sides of the Greenup dam is monitored every fifteen minutes by the United States Geological Survey [10]. In order to model the water levels, the water level monitoring data is decomposed into the trend, seasonality, and noise [11] with moving average. However, the monitoring data show almost no regular seasonal pattern in the series as Figure 1 shows. Thus, the water level time series data is decomposed mainly into the trend and noise two parts.

After that, the water level is modeled as a second-order stochastic process using the Karhunen–Loeve expansion method as below [12]

$$h\left(t\right) = \mu\left(t\right) + \sigma\left(t\right) \sum_{i=1}^{N} \sqrt{\lambda_i\left(t\right)}\xi_i \eta_i\left(t\right), \tag{1}$$

in which $\mu\left(t\right)$ is the mean of the process and is the trend component from the decomposition; $\sigma\left(t\right)$ is the standard deviation calculated from noise component; $\lambda_i\left(t\right)$ and $\eta_i\left(t\right)$ are the eigenvalues and the associated eigenvectors obtained from eigendecomposition of the autocorrelation matrix obtained with the noise component and the correlation function is shown in Figure 1; ξ_i is a set of uncorrelated standard Gaussian random variables.

Based on the stochastic modeling of the water level, different realizations of water level time series data can be generated with the KL expansion.

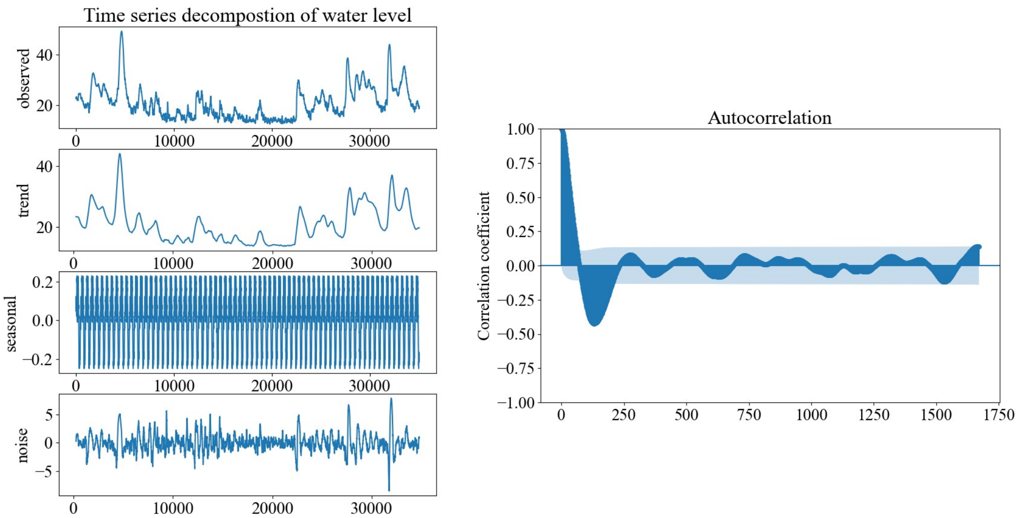

Figure 1. Time series decomposition for water level monitoring data (left) and autocorrelation plot of noise component (right)

MACROSCALE STRUCTURAL ANALYSIS

To simulate the stress response of the structure under varying water levels, a high-fidelity linear finite element model of a large infrastructure, the Greenup miter gate, is utilized. This finite element model, as shown on the left side in Figure 2 has been validated in the previous study [13]. The structure is discretized with 64919 shell elements. The model is capable of simulating the structure behavior under different water elevations on both sides.

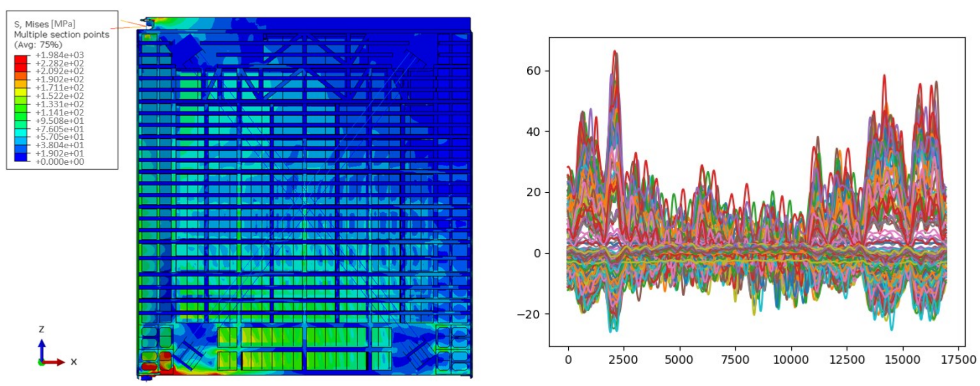

Figure 2. Miter gate finite element model (left) and the stress values of locations selected (right)

The stress distribution is complex in such large infrastructures. However, a limited number of stress responses can be simulated in the corrosion model due to computational cost. Therefore, two hundred locations within different average stress ranges are selected to represent the stress response on the entire structure. Specifically, the stress responses under one hundred time-series realizations of KL-expansion water levels are simulated and averaged over different realizations and time series. Positions on the gate are then grouped by different stress ranges for the selection. The right side plot on Figure 2 shows the stress value of the locations selected.

MESOSCALE PHASE-FIELD CORROSION SIMULATION

The phase-field method has been broadly applied for physics-based corrosion simulation [14–16]. The phase-field method has demonstrated both competence and flexibility in simulating the evolution of corrosion [15]. In the phase-field method, the phase transition is characterized using a continuous variable ξ instead of a discrete phase transition. Multiple partial differential equations (PDEs) are coupled together to describe the phase change, taking into account ionic concentration and diffusion. Additionally, the impact of mechanical stress on the generalized chemical potential can also be incorporated into the phase-field model, which is then coupled with other PDEs [9].

The mechanical stress term μ_{me} is coupled into the reaction equation in the activation overpotential term η_a

$$\eta_a = \Delta\phi - \frac{\mu_{M^{n+}} + n\mu_e - \mu_M + \mu_{me}}{nF}, \tag{2}$$

where $\mu_{M^{n+}}$, μ_e and μ_M are the activities of components, and $\Delta\phi$ is the interfacial potential difference. The reaction equation for the phase transition can be then written as the following

$$\frac{\partial \xi}{\partial t} = -L_\sigma \left(g'(\xi) - \kappa \nabla^2 \xi \right) - L_\eta h'(\xi) \left(\exp \frac{(1-\alpha)\eta_a}{RT} - \bar{c}_+ \exp \frac{-\alpha n F_r \eta_a}{RT} \right). \tag{3}$$

In the above equation, L_σ represents interfacial mobility, while L_η represents the reaction coefficient, which can be calibrated using experimental data. R denotes the molar gas constant, T denotes temperature, and F_r represents Faraday's constant. A comprehensive derivation of this equation can be found in [9].

The authors applied this technique to a two-dimensional plate with dynamic normal stress and shear stress being applied on one side of the plate, resulting in the growth of pitting corrosion from the top center region. The dynamic stress is generated from the miter gate simulation described above. The results are shown in Figure 3. The corrosion evolution shows different growth speeds, directions, and shapes. This result is interesting as the dynamic load actually has a significant influence on the corrosion process.

A HYBRID SURROGATE MODELING FOR CORROSION MORPHOLOGY PREDICTION

The overall architecture of the surrogate model is shown in Figure 4. As the time-dependent prediction of high-dimensional features demands a considerable amount of training data, the prediction is conducted in the latent space after reducing the dimension.

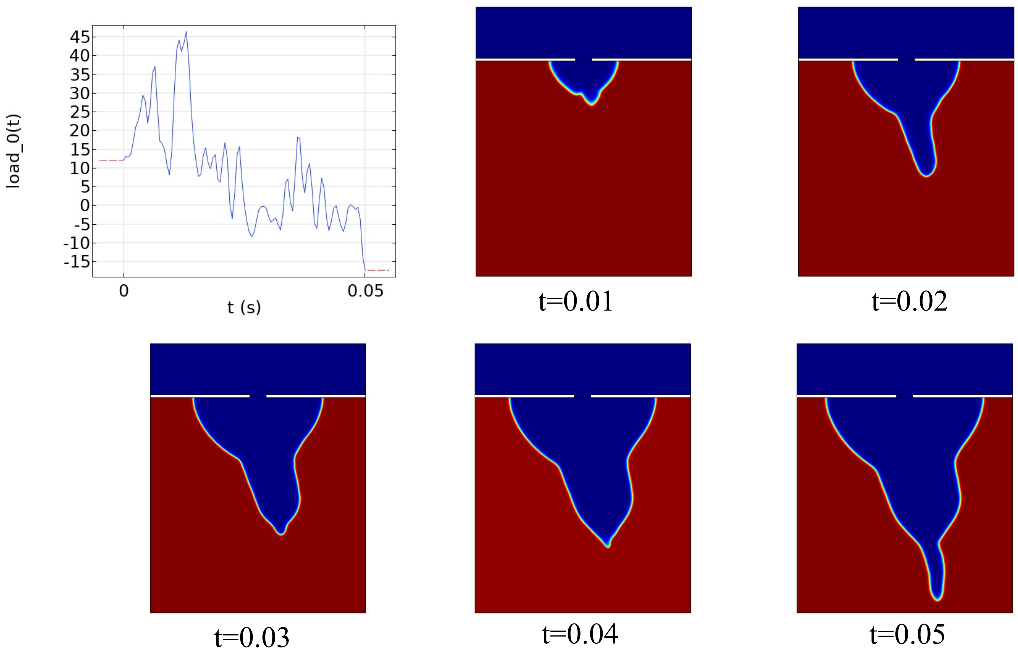

Figure 3. Corrosion simulation result and mechanical dynamic load

In order to reduce the dimension of the pit shape data from thousands to six dimensions in the latent space, a convolutional neural network (CNN) autoencoder is utilized.

In order to predict the time-dependent behavior at any given time step, a GP-based nonlinear autoregressive network with exogenous inputs (NARX) is constructed. The GP model generates the corrosion shapes for the next time step based on the dynamic load and environmental factors, $\theta = [\boldsymbol{\sigma_{xx}}, \boldsymbol{\tau_{xy}}, L_\eta, D^e]$, which represent the dynamic normal stress, dynamic shear stress, reaction constant, and diffusion coefficient. Subsequently, the GP-NARX model is responsible for recursively predicting the corrosion shapes for the subsequent time step based on the shapes from the previous ten-time steps in conjunction with θ. Ultimately, the low-dimensional features in the latent space for the next step are transformed back to the image space utilizing the aforementioned CNN-Autoencoder structure.

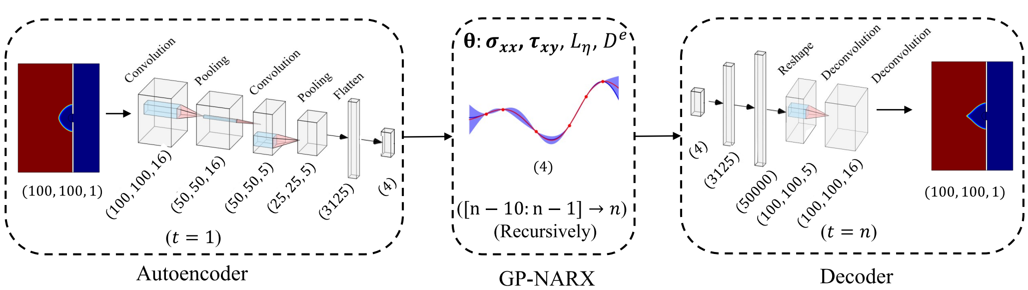

Figure 4. The architecture of the surrogate model

RESULTS AND DISCUSSION

In this section, we present the prediction results for two different cases, where the simulation results are considered as the ground truth. The true value corresponds to the simulation results, whereas the GP mean represents the mean value of our surrogate model prediction. Additionally, the 5 and 95 percentiles results depict the distribution and uncertainties in the prediction. Figure 5 shows the prediction result for a relatively low stress level case. The mean prediction is accurate, except for the boundary area. The 5 and 95 percentiles are also close to the mean, indicating low prediction uncertainty for this case. Thus, the model is confident about the prediction results.

The prediction results for a case with a relatively high stress level are presented in Figure 6. In this case, the prediction is not as accurate as in the previous case, with the corrosion boundary being blurry. The detailed curve change during the evolution is also not captured by the current surrogate model. The 5th and 95th percentiles show a large range, which indicates that the model is not confident about its prediction and that the prediction uncertainty is significant. While the mean prediction is not as accurate in this case, the true value still falls within the range of the 5th and 95th percentiles.

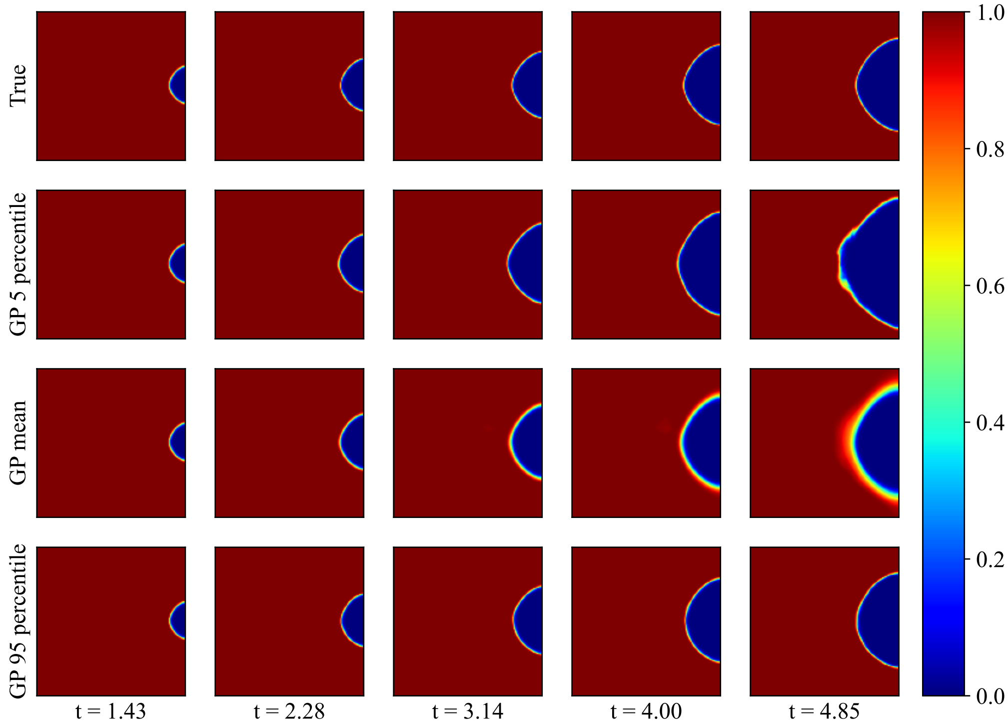

Figure 5. Surrogate prediction for low stress level case

CONCLUSIONS

The hybrid surrogate model (CNN-GP-NARX) proposed in this study has the capability of accurately predicting the corrosion evolution under dynamic mechanical stress on a structure. This method significantly reduces the computational cost and enables

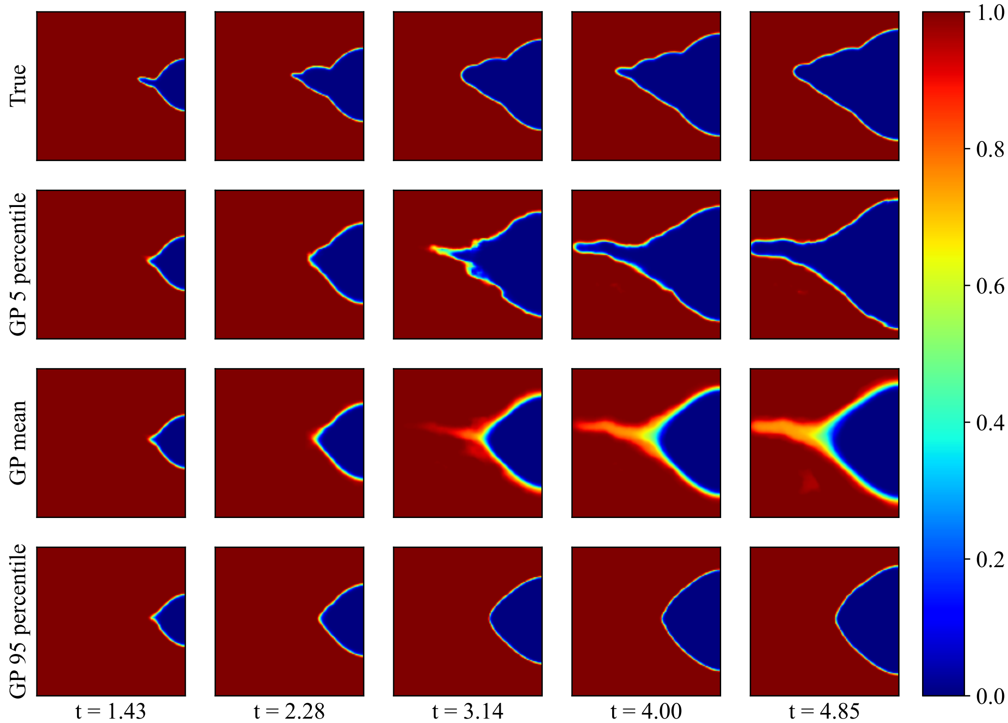

Figure 6. Surrogate prediction for high stress level case

faster and more efficient predictive assessments. Additionally, the model is capable of accurately capturing the material boundary or interface in the corrosion process. The model's ability to capture the prediction uncertainty is also noteworthy, making it useful in considering other sources of uncertainty in future studies. Overall, the hybrid surrogate model has shown great promise as a robust and efficient tool for predicting pitting corrosion growth in civil infrastructure.

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