PROBABILISTIC PARAMETER ESTIMATION OF NONLINEAR BRIDGE STRUCTURES UNDER MULTI-SOURCE UNCERTAINTIES USING A GPR-GAN FRAMEWORK

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Extended Abstract

Accurate parameter estimation is essential for structural health monitoring, model updating, and seismic performance assessment of bridge structures. For nonlinear bridge components subjected to strong dynamic excitation, key mechanical parameters related to stiffness, damping, hysteretic behavior, and damage evolution are difficult to identify directly from measured responses. Conventional deterministic model updating methods usually provide a single optimal parameter set, but they cannot adequately characterize the uncertainty induced by limited simulations, model simplification, and measurement noise. These uncertainty sources may interact with each other in practical monitoring and experimental testing, leading to biased or unstable parameter estimates. Therefore, an efficient probabilistic parameter estimation method is required to integrate numerical simulations, measured responses, and uncertainty quantification.

In this study, a Gaussian process regression–generative adversarial network framework, termed GPR-GAN, is introduced for probabilistic parameter estimation of nonlinear bridge structures under multi-source uncertainties. Gaussian process regression is first used to construct a surrogate model that maps uncertain structural parameters to dynamic response features, thereby replacing repeated nonlinear finite element simulations. Based on the response–parameter database generated by the surrogate-assisted numerical model, a generative adversarial network is then trained to learn the inverse mapping from structural responses to uncertain parameters. The generator produces candidate parameter samples conditioned on measured or simulated responses, while the discriminator regularizes the generated

samples by distinguishing them from physically admissible parameter samples. Through adversarial learning, response reconstruction, and parameter consistency constraints, the GPR-GAN framework estimates probabilistic parameter distributions rather than a single deterministic solution.

The influence of multi-source uncertainties on the proposed framework is further investigated. Computational uncertainty is examined by analyzing the effects of training sample size and sampling strategy on surrogate accuracy and parameter estimation stability. Measurement uncertainty is studied by introducing different noise types, mixed noise conditions, and noise intensity levels into structural response data, so as to reveal how contaminated measurements affect estimation bias, response reconstruction error, and parameter dispersion. Model uncertainty is considered by explicitly representing the discrepancy between the numerical model and the reference structural response. To reduce the influence of systematic model-induced bias, a DenseNet-based model discrepancy surrogate is incorporated into the GPR-GAN framework to form an extended GPR-DN-GAN model, enabling parameter estimation while accounting for model discrepancy.

The proposed framework is validated using nonlinear bridge-related structural systems, including a three-tower cable-stayed bridge and a shaking table test of a steel–concrete composite bridge tower. For each case, uncertain structural parameters are sampled within physically reasonable ranges to construct the simulation database. The GPR surrogate is trained to approximate the forward relationship between structural parameters and seismic response features, and the GAN estimator is used to infer parameter distributions from response observations. The estimated parameter samples are then propagated through the forward model to reconstruct dynamic responses, providing a direct assessment of whether the inferred probabilistic parameters can reproduce the observed nonlinear behavior.

The results of the study indicate that the GPR-GAN framework can effectively estimate the probabilistic characteristics of key structural parameters under limited samples and nonlinear dynamic responses. The uncertainty analysis shows that sample size, sampling strategy, measurement noise, and model discrepancy affect parameter estimation in different ways. Measurement noise mainly increases the dispersion and bias of estimated parameters, whereas model uncertainty may introduce systematic response deviation if not explicitly considered. After introducing the DenseNet-based model discrepancy surrogate, the reconstructed responses show improved

agreement with the reference responses, indicating that model discrepancy representation can reduce the risk of compensating modeling errors through biased structural parameters.

The main contribution of this study lies in the development of a GPR-GAN-based probabilistic parameter estimation framework for nonlinear bridge structures under multi-source uncertainties. By integrating surrogate modeling, generative inverse estimation, uncertainty influence analysis, and model discrepancy representation, the proposed framework provides an efficient tool for extracting structural parameter information from dynamic response data. The study offers a feasible route for data-model-driven structural health monitoring, nonlinear model updating, and seismic performance assessment of bridge structures.

Keywords: *bridge structures; structural health monitoring; probabilistic parameter estimation; GPR-GAN; multi-source uncertainty.*