Data-Driven Probabilistic Parameter Estimation and Reliability Prediction for Nonlinear Structures

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Content

I. Research Background and Significance

II. Data-Driven Parameter Estimation for Probabilistic Models of Nonlinear Structures

III. Effects of Multi-Source Uncertainty on Parameter Estimation

IV. Shaking-Table Validation Using a Steel-Concrete Composite Bridge Tower

I. Research Background and Significance

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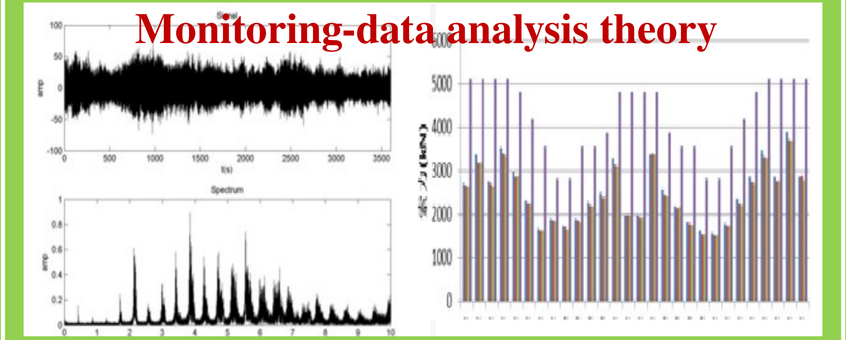
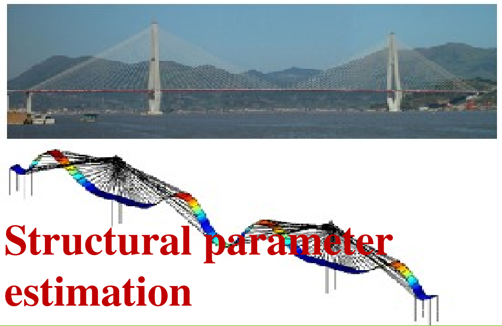
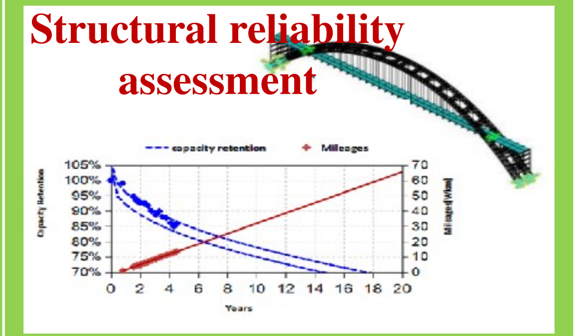
The safe service of major engineering structures under long-term and hazard loads is becoming increasingly critical.

Civil engineering structures → (Early service stage) → Essentially intact → (Mid-service stage) → Minor damage → (Late service stage) → Severe damage or collapse

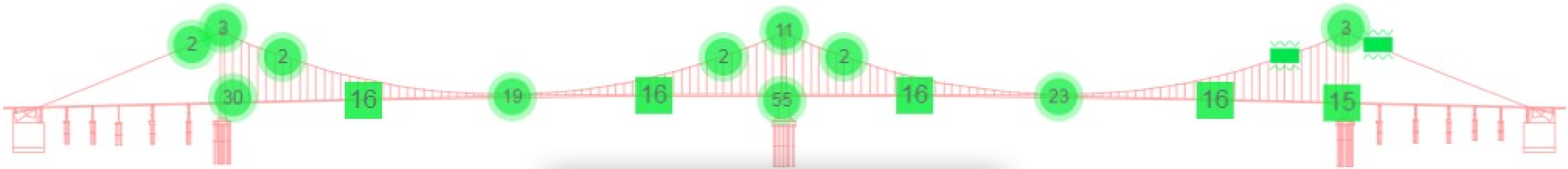
Civil structures under long-term loading are essentially time-varying and nonlinear structural systems.







I. Research Background and



Wuhu Yangtze River Second Highway Bridge

The 1,622 m main bridge is a five-span, separated-steel-box-girder cable-stayed bridge with split-column towers and four cable planes. It adopts a fully floating system; the tower height is 262.48 m.

Ma'anshan Yangtze River Highway Bridge - Left-Channel Suspension Bridge

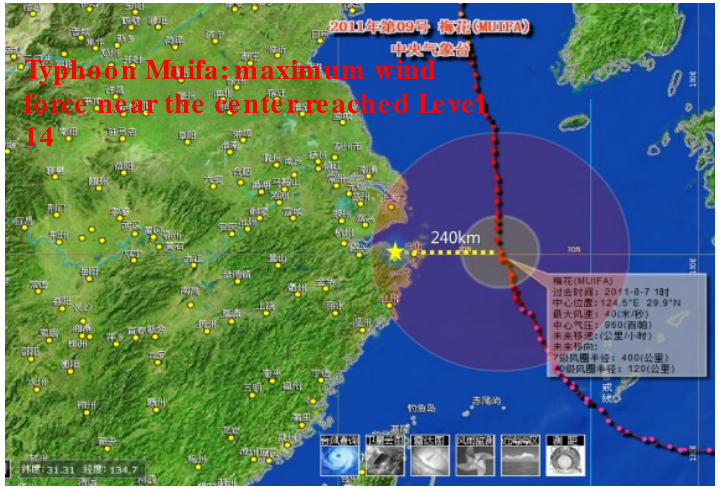
The left-channel main bridge adopts a three-tower, two-span suspension scheme with a span arrangement of (360+2*1080+360) m. The middle tower uses a non-floating structural system and a steel-concrete composite tower.

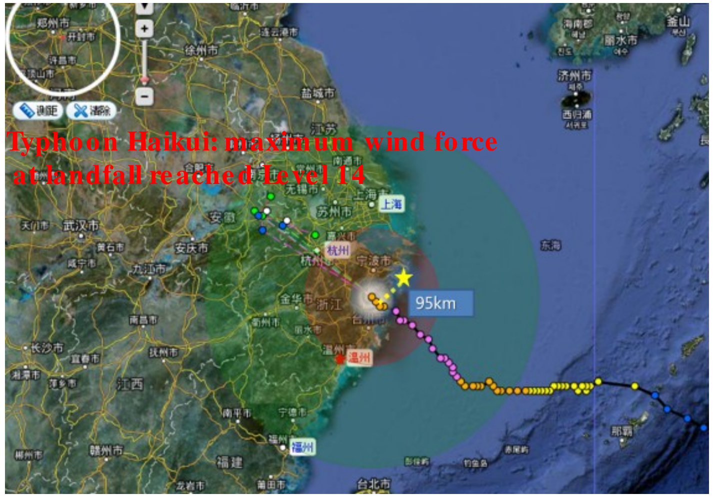
Wangdong Yangtze River Highway Bridge

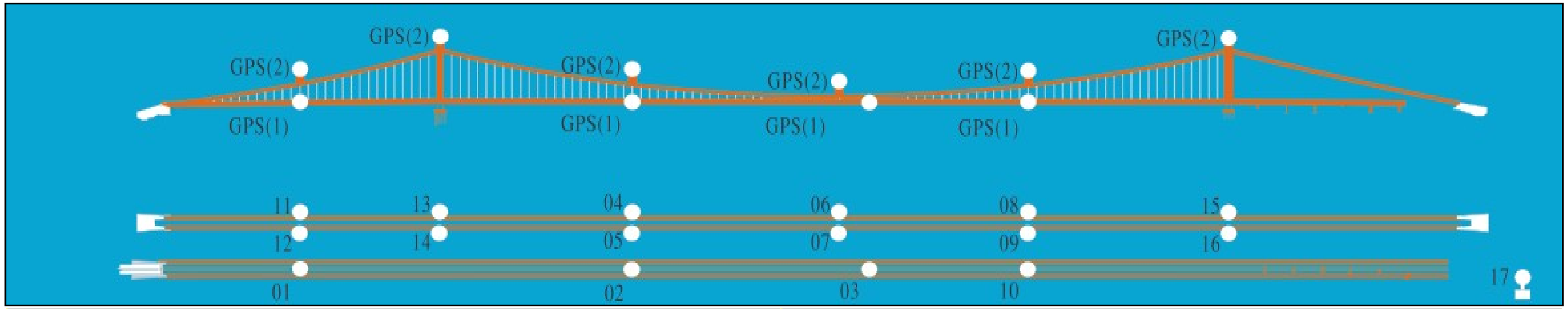
The most convenient Yangtze River crossing on National Expressway G35. The 1,250 m main bridge is a two-tower, double-cable-plane, semi-floating cable-stayed bridge with a 638 m main span and a span arrangement of (78+228+638+228+78) m.

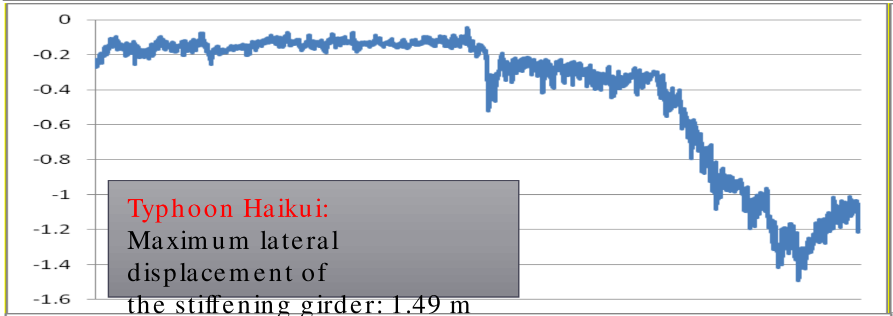
***The Implementation Plan for Building Structural Health Monitoring Systems for Long-Span Highway Bridges* states clearly that the construction of structural health monitoring systems for long-span bridges is an important measure for promoting the high-quality development of bridges, an essential component of new infrastructure development, a key means of ensuring the safety and durability of long-span bridges, and an important approach to improving scientific bridge maintenance and management.**

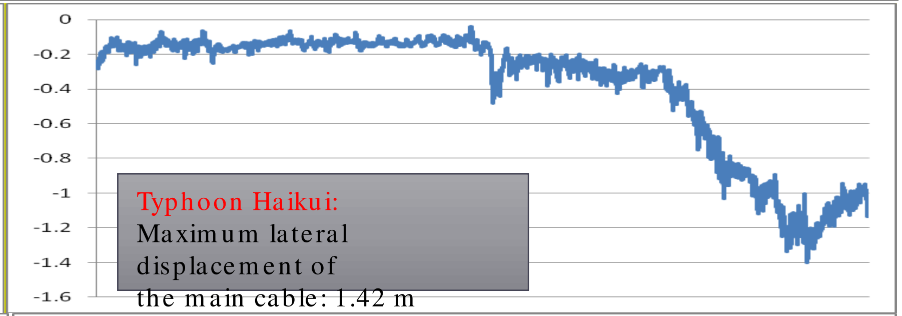
I. Research Background and Significance

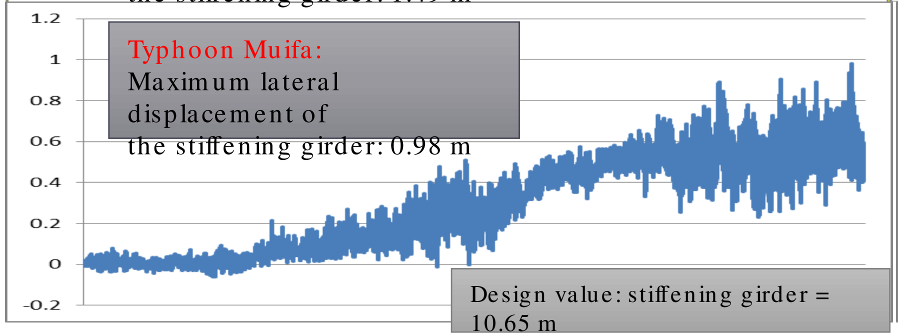


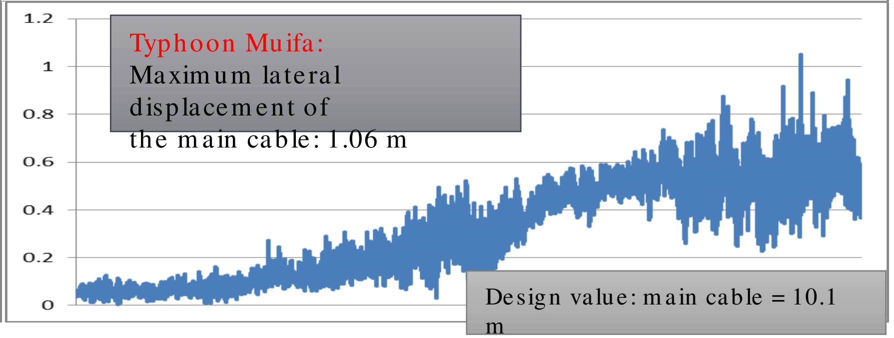










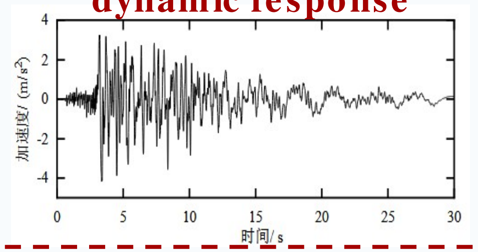


Key challenges remain in both theory and practice, including reliable structural sensing, accurate and credible measured data, the gap between data mining and engineering applications, and the unclear evolution of structural performance

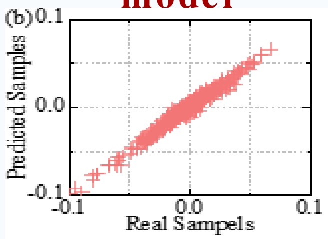
I. Research Background and Significance

Data-driven parameter estimation for probabilistic models of nonlinear bridge structures

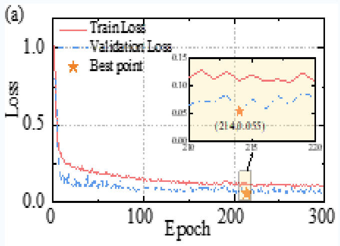
Data-driven structural dynamic response



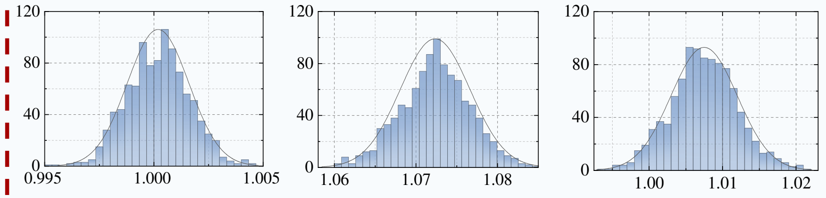
GPR surrogate model



GAN



Probabilistic model parameter estimation



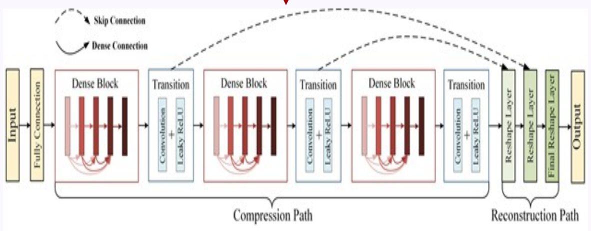
Effects of multi-source uncertainty on probabilistic model parameter estimation

Computational uncertainty

Sampling method

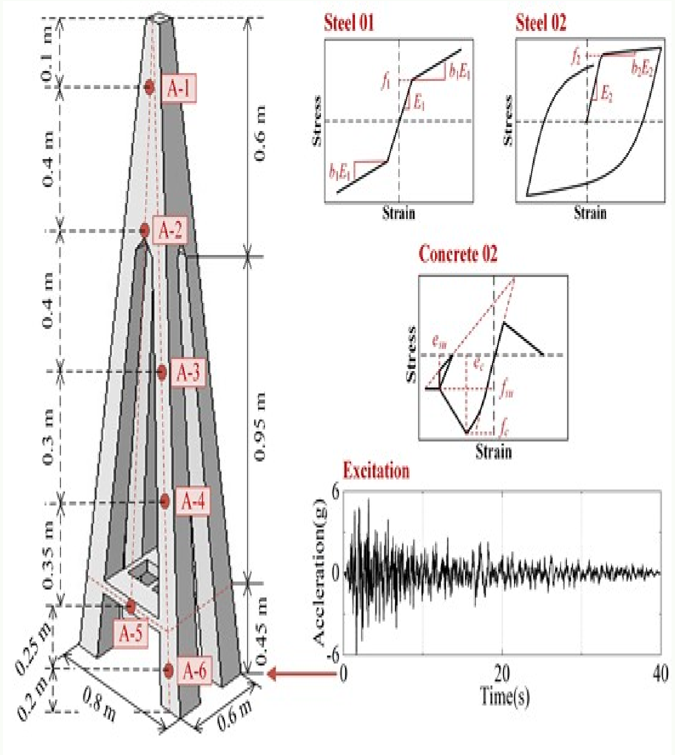
Sample size

Model uncertainty



Measurement uncertainty

Shaking-table validation using a steel-concrete composite bridge tower



II. Data-Driven Parameter Estimation for Probabilistic Models of Nonlinear Bridge Structures

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Existing Issues

Accurate structural parameter estimation under SHM, reliability analysis, and risk assessment, and directly affects response prediction and safety evaluation. Traditional approaches rely on high-fidelity physical models and extensive measured data, leading to high computational cost and limited performance for high-dimensional, nonlinear, and complex structural systems.

GPR-GAN-Based Parameter Estimation for Probabilistic Models of Nonlinear Bridge Structures

Proposed Solution

Gaussian Process Regression (GPR)

Replaces costly finite-element analysis with an efficient parameter-to-response surrogate.

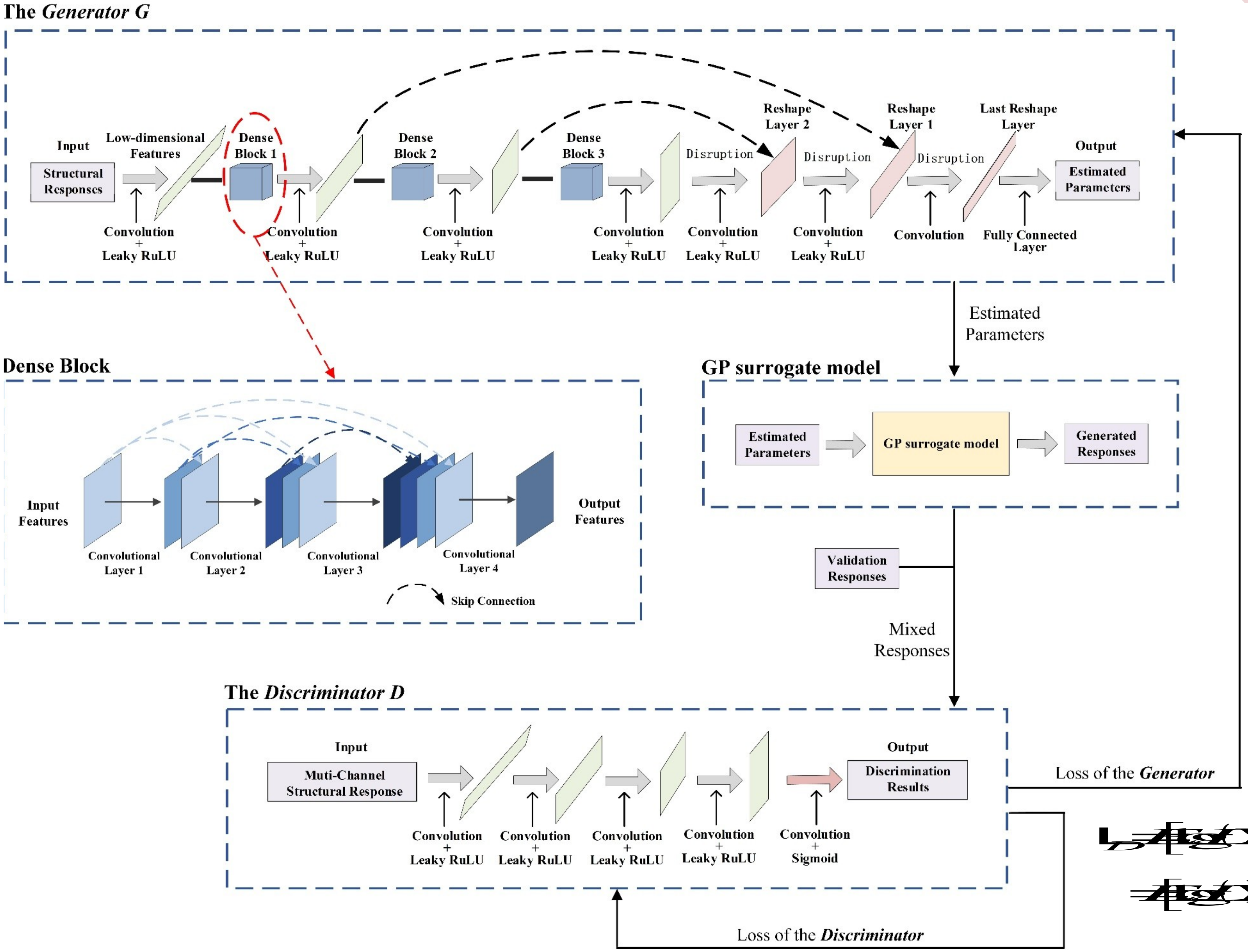
Generative Adversarial Network (GAN)

Enables rapid response-to-parameter inversion by learning structural parameter distributions.

GPR-GAN probabilistic model parameter-estimation method

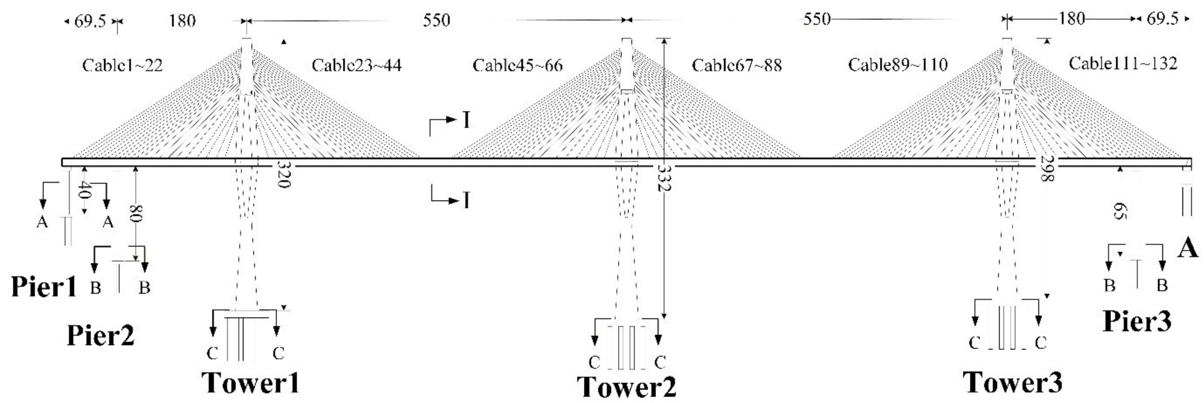
GPR-GAN integrates a GPR-based forward surrogate into an improved GAN framework, combining generative representation with efficient response prediction to achieve accurate parameter estimation for complex nonlinear structures.

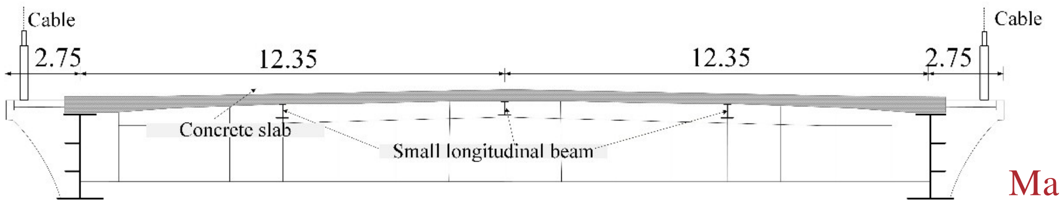
GPR-GAN Model Architecture



II. Data-Driven Parameter Estimation for Probabilistic Models of Nonlinear Structures

Example: Probabilistic Model Parameter Estimation for a Three-Tower Cable-Stayed Bridge



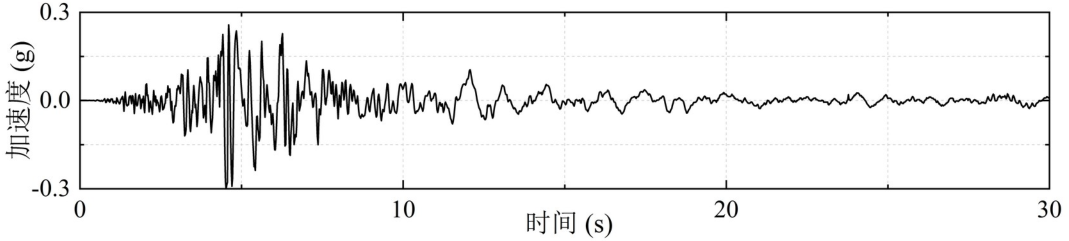


Main-girder section

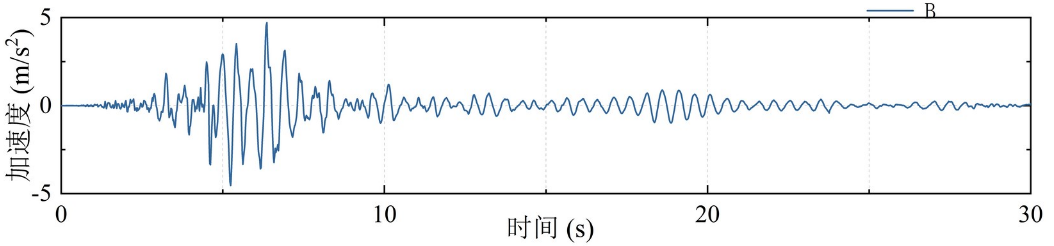
Structural Parameters of the Three-Tower Cable-Stayed Bridge

Material Element	Structural parameters	Theoretical value	Variation range
Tower	f_s^{tower}	500 MPa	[350.0, 650.0] MPa
	E_c^{tower}	200 GPa	[140, 260] GPa
	f_c^{tower}	50.0 MPa	[35.0, 65.0] MPa
Beam	E_c^{beam}	35.5 GPa	[24.85, 46.15] GPa
	E_s^{beam}	200 GPa	[140, 260] GPa
	G_s^{beam}	77.0 GPa	[53.9, 100.1] GPa

The cable-stayed bridge has 249.5 m side spans, a 550 m main span, and a total length of 1,599 m. It is supported by main towers 3-5, auxiliary piers 2 and 6, transition pier 1, and abutment 7. The main girder is a steel-concrete composite system with a 30.2 m deck width. Two I-shaped steel longitudinal girders spaced 24.7 m apart form the primary frame; web and flange thicknesses are 20 mm and 16 mm. Steel crossbeams and secondary longitudinal girders are connected with high-strength friction bolts, and the concrete deck slab is

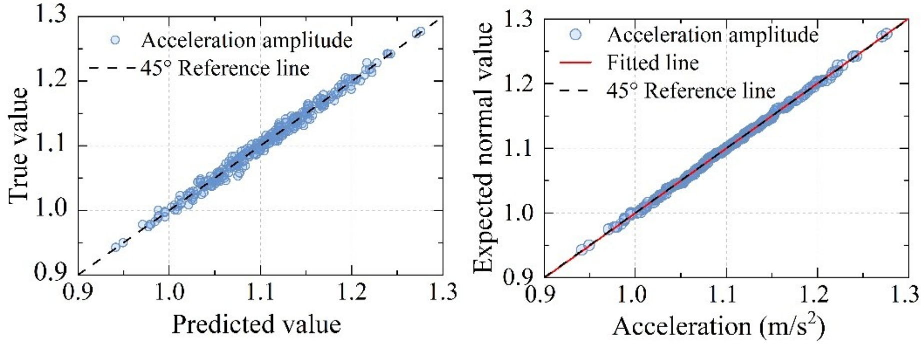


Northridge earthquake loading time history (PGA=0.3g)

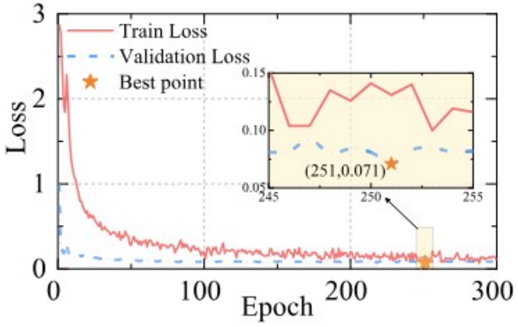


Acceleration response at the top of the middle tower

II. Data-Driven Parameter Estimation for Probabilistic Models of Nonlinear



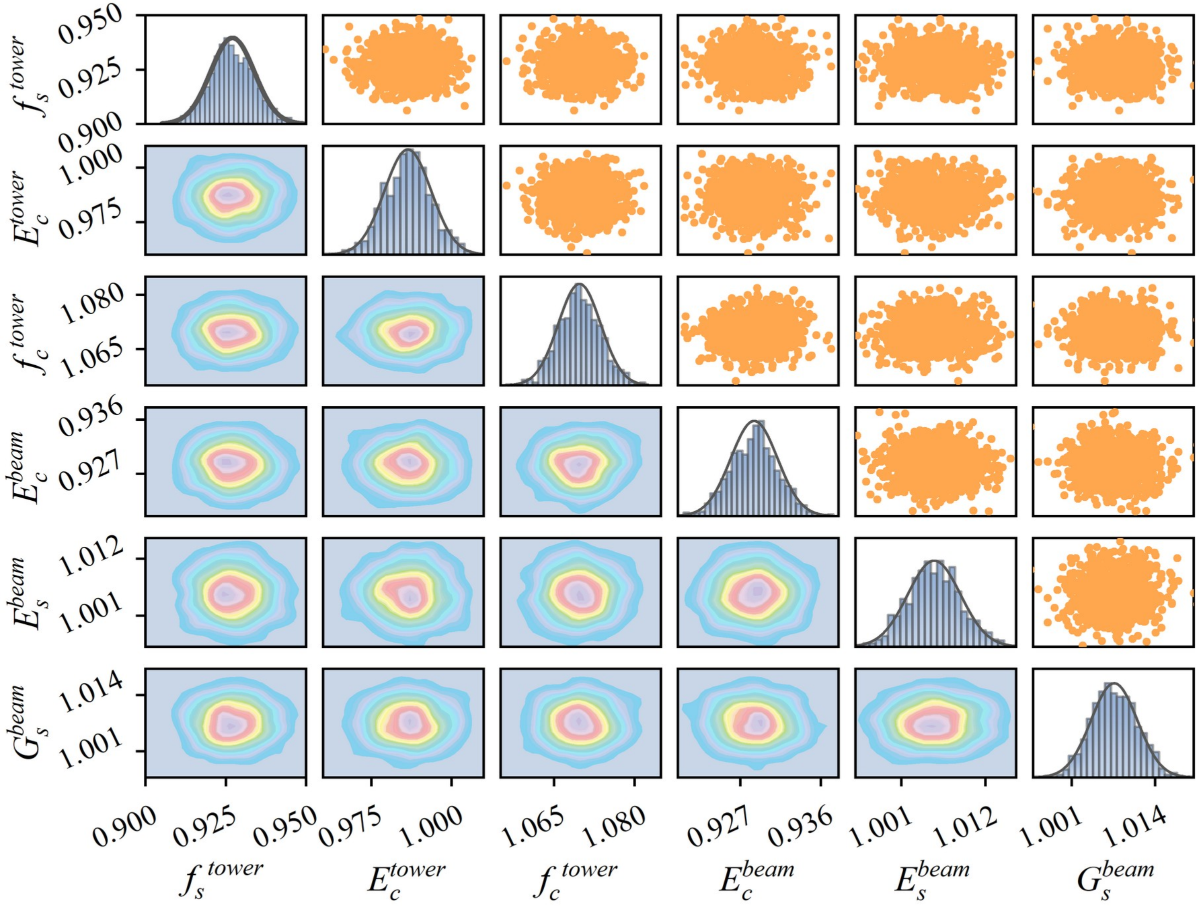
GPR model prediction results

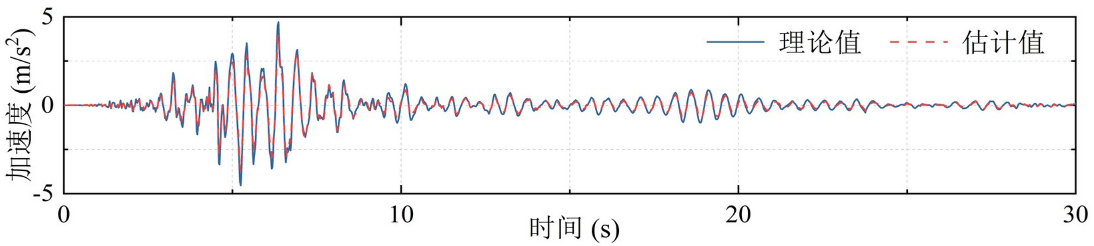


Generator loss curve

Parameter-estimation results for

Parameter	Bias(θ)	NRMSE(θ)	CV(θ)
f_s^{tower}	0.927	7.32%	0.73%
E_c^{tower}	0.989	1.54%	0.74%
f_c^{tower}	1.069	6.98%	0.37%
E_c^{beam}	0.929	7.15%	0.28%
E_s^{beam}	1.005	0.63%	0.34%
G_s^{beam}	1.007	0.84%	0.36%





Comparison of acceleration responses at the middle-tower top

III. Effects of Multi-Source Uncertainty on Parameter Estimation

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Existing Issues

many finite-element model calls, which creates high computational cost and makes it difficult to build large, well-covered training datasets.

•Simplifications and approximations in physical or mathematical models introduce model error. During parameter estimation, this error can create systematic bias and reduce accuracy and reliability.

•Measurement noise contaminates response data, amplifies uncertainty in parameter estimation, and widens confidence intervals.

Proposed Solution

Multi-source uncertainty

Computational uncertainty

•Effect of training-sample size on parameter estimation;

•Effect of sampling strategy on parameter estimation.

Model uncertainty

•DenseNet model-error surrogate;

•GPR-DN-GAN considering model error.

Observation uncertainty

•Effect of noise intensity on parameter estimation;

•Sensitivity analysis of noise types;

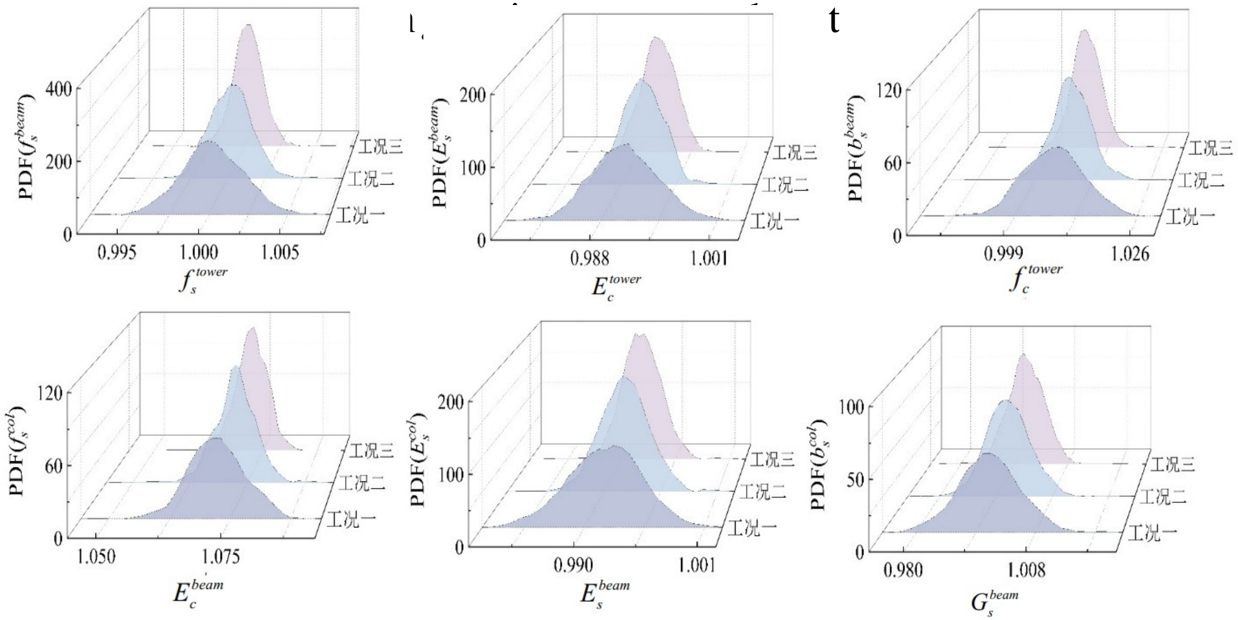
•Hierarchical noise-robust strategy.

III. Effects of Multi-Source Uncertainty on Parameter

Influence of Sample Size on Parameter Estimation

Number of sampling points

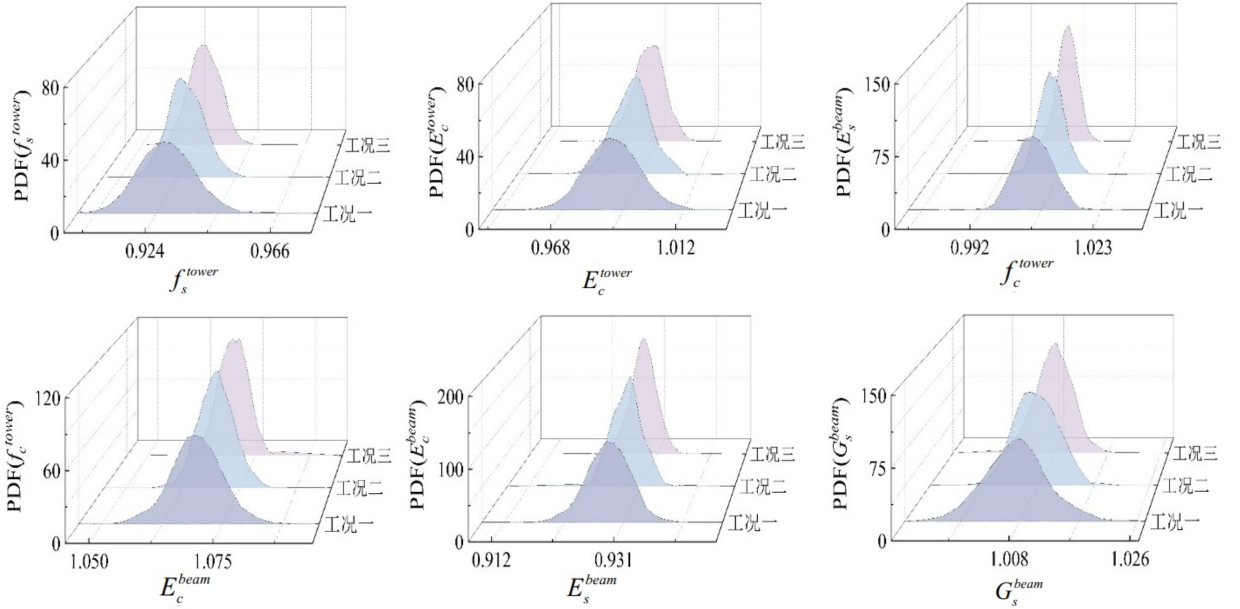
To study the effect of sampling-point number on estimation accuracy and computational time, 64 (Case 1), 256 (Case 2), and 1024 (Case 3) acceleration-



The results show that GPR-GAN can still capture the nonlinear information and distributional features embedded in structural parameters and responses with fewer sampling points. However, increasing the number of sampling points is necessary and effective for improving estimation accuracy and reducing

Number of sample groups

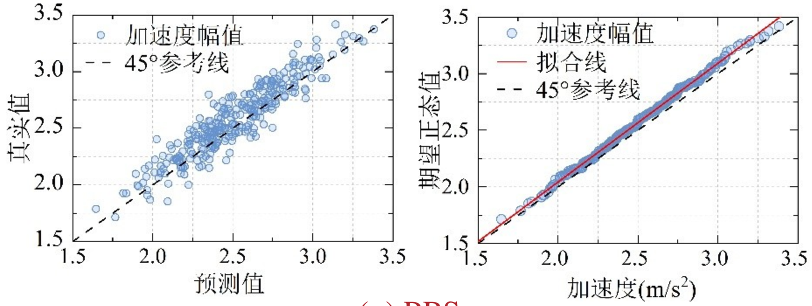
GPR-GAN is trained using 100 (Case 1), 300 (Case 2), and 500 (Case 3) sample groups, with each acceleration-response sample containing 256 sampling



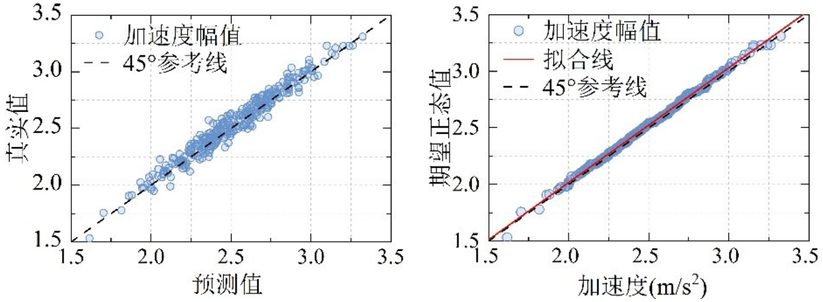
Increasing sample size improves prediction accuracy and stability, but also increases computational burden. A reasonable sample-group size improves training stability and model generalization while reducing cost under the required estimation accuracy.

Effect of sampling strategy on probabilistic model parameter estimation

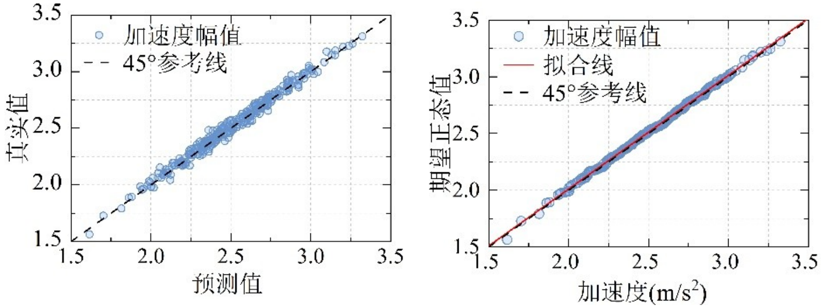
Three hundred samples are generated in the parameter space using PRS (Case 1), LHS (Case 2), and Sobol sequence sampling (Case 3), respectively. To isolate the influence of each method and ensure independent analysis, GPR-GAN and its embedded GPR model are trained with samples generated by the same sampling strategy.



(a) PRS

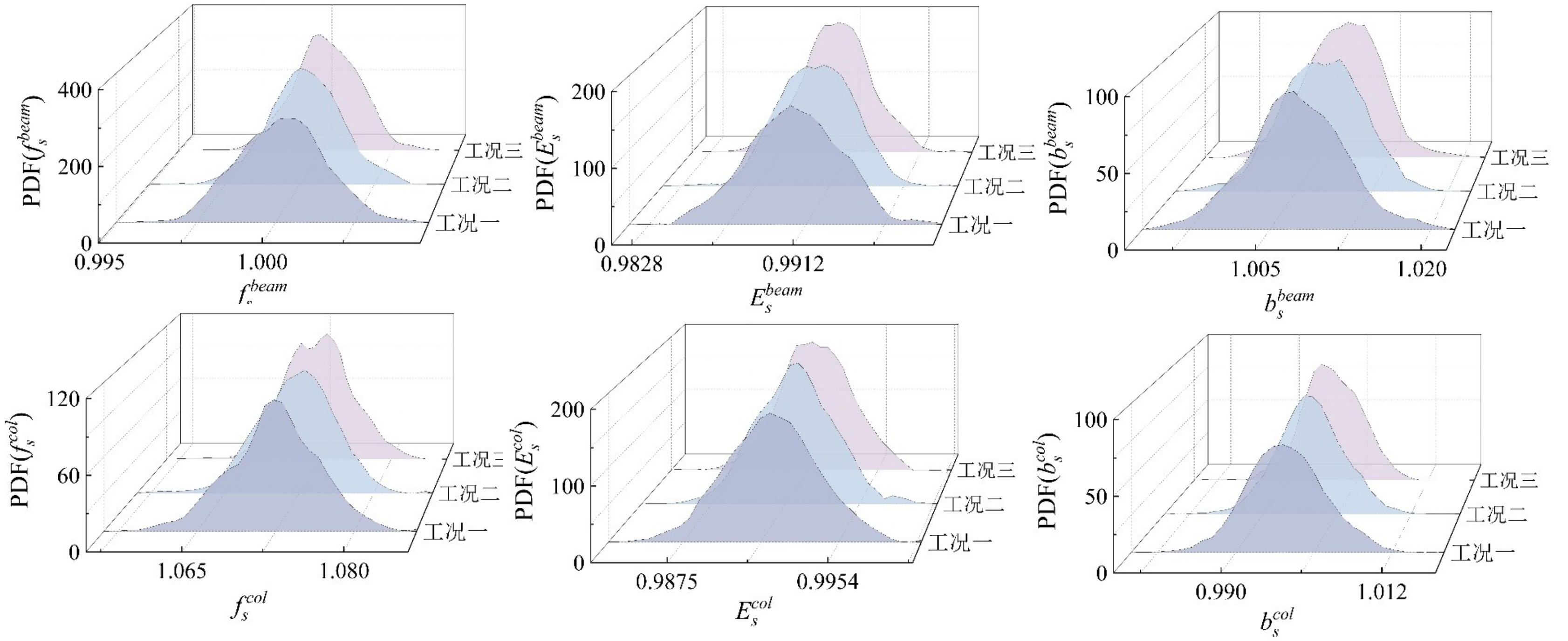


(b) LHS

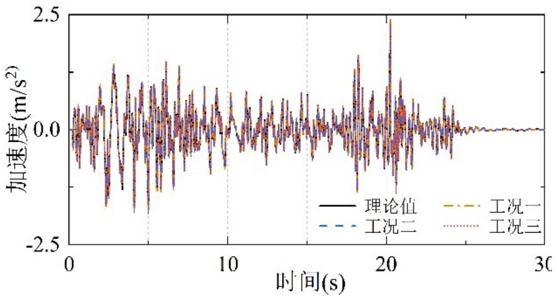


(c) Sobol sequence sampling

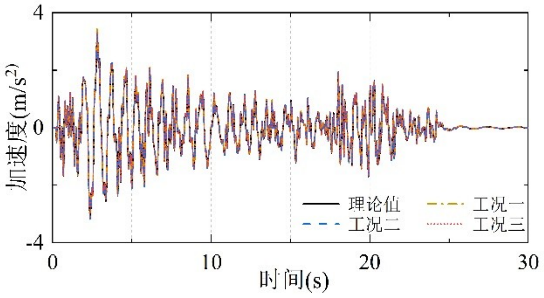
GPR prediction results under different sampling strategies



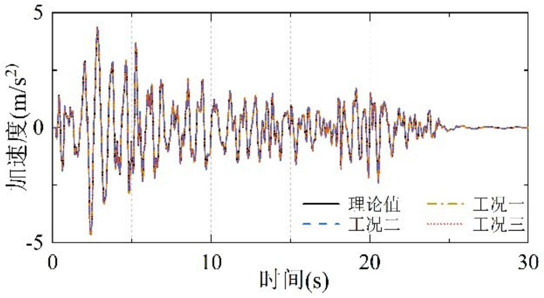
Parameter-sample histograms under different sampling strategies



A-1



A-2



A-3

Comparison of acceleration responses under different sampling

III. Effects of Multi-Source Uncertainty on Probabilistic Model Parameter Estimation

Parameter classification

Design variables x
- Initial conditions — Initial temperature, etc.
- Boundary conditions — Fabrication parameters, etc.

Structural parameters θ
- Physical parameters — Material properties, etc.
- Tuning parameters — Multiplicative factors, etc.
- Specific parameters — User-defined parameters, etc.

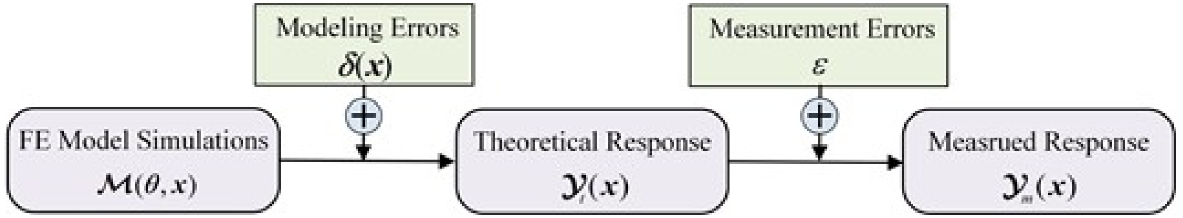
Representation of model error

Because a numerical model is a simplified and discretized representation of the real structure, unavoidable response discrepancies remain even when the structural parameters θ are precisely determined. Model error is introduced to distinguish this systematic bias between numerical predictions and the real structure.

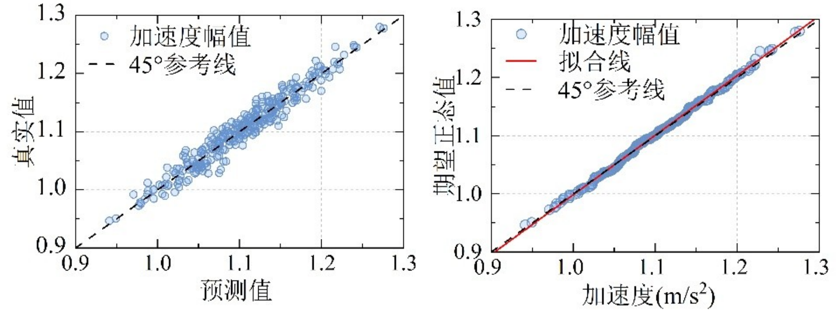
$$\underbrace{y_{\mathrm{r}}}_{\text{True response}} = \underbrace{m(x,\theta)}_{\text{Numerical model response}} + \underbrace{\delta(x)}_{\text{Model error}}$$

When measurement noise is considered, the equation can be further expressed as:

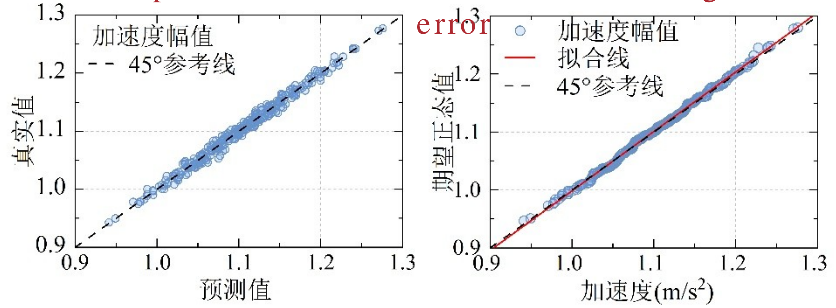
$$y_{\mathrm{m}} = m(x,\theta) + \delta(x) + \underbrace{\varepsilon}_{\text{Measurement noise}}$$



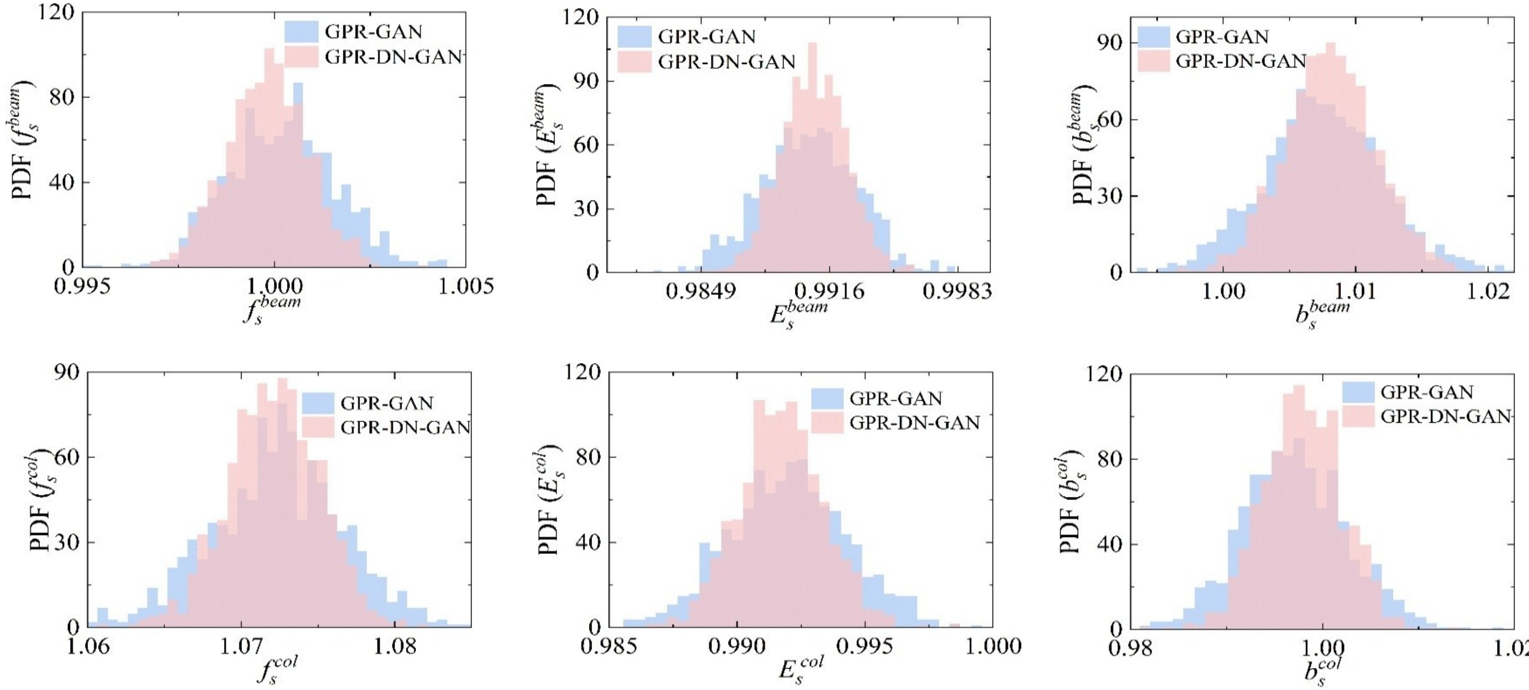
Relationship among model prediction, true value, and measured



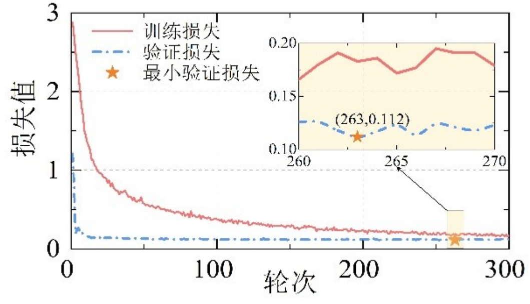
GPR prediction results without considering model error



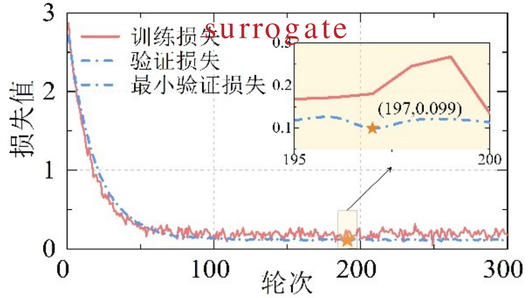
GPR prediction results considering model error



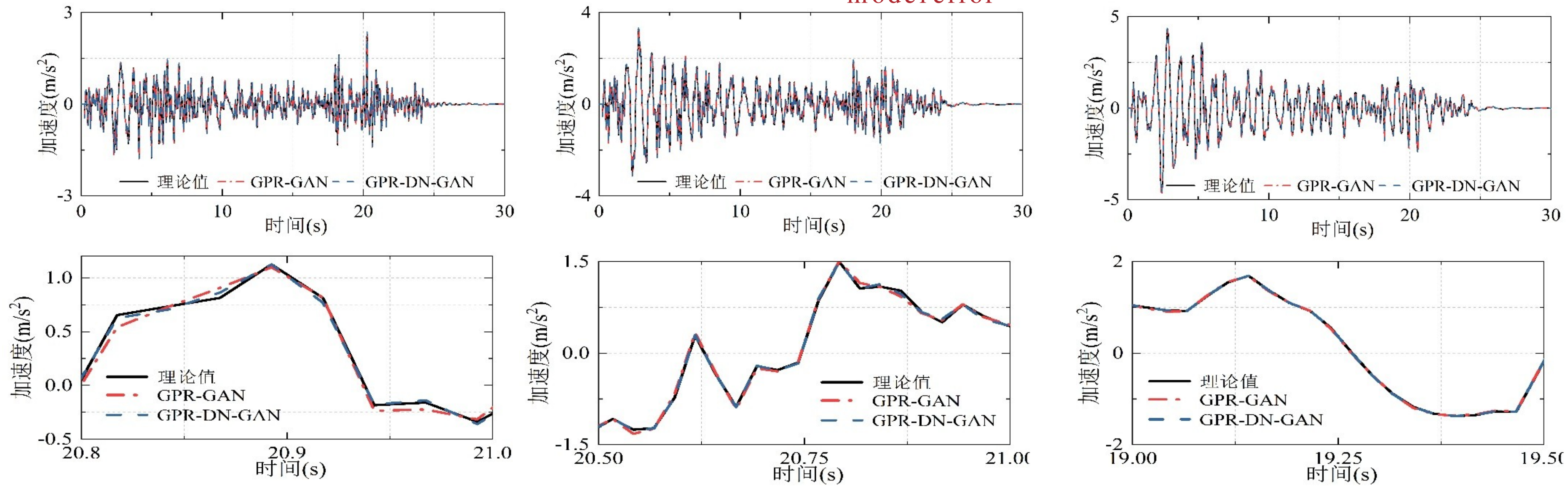
Parameter-sample histograms for the three-tower cable-stayed bridge considering model error



Loss curve of the model-error surrogate



Generator loss curve of GPR-DN-GAN



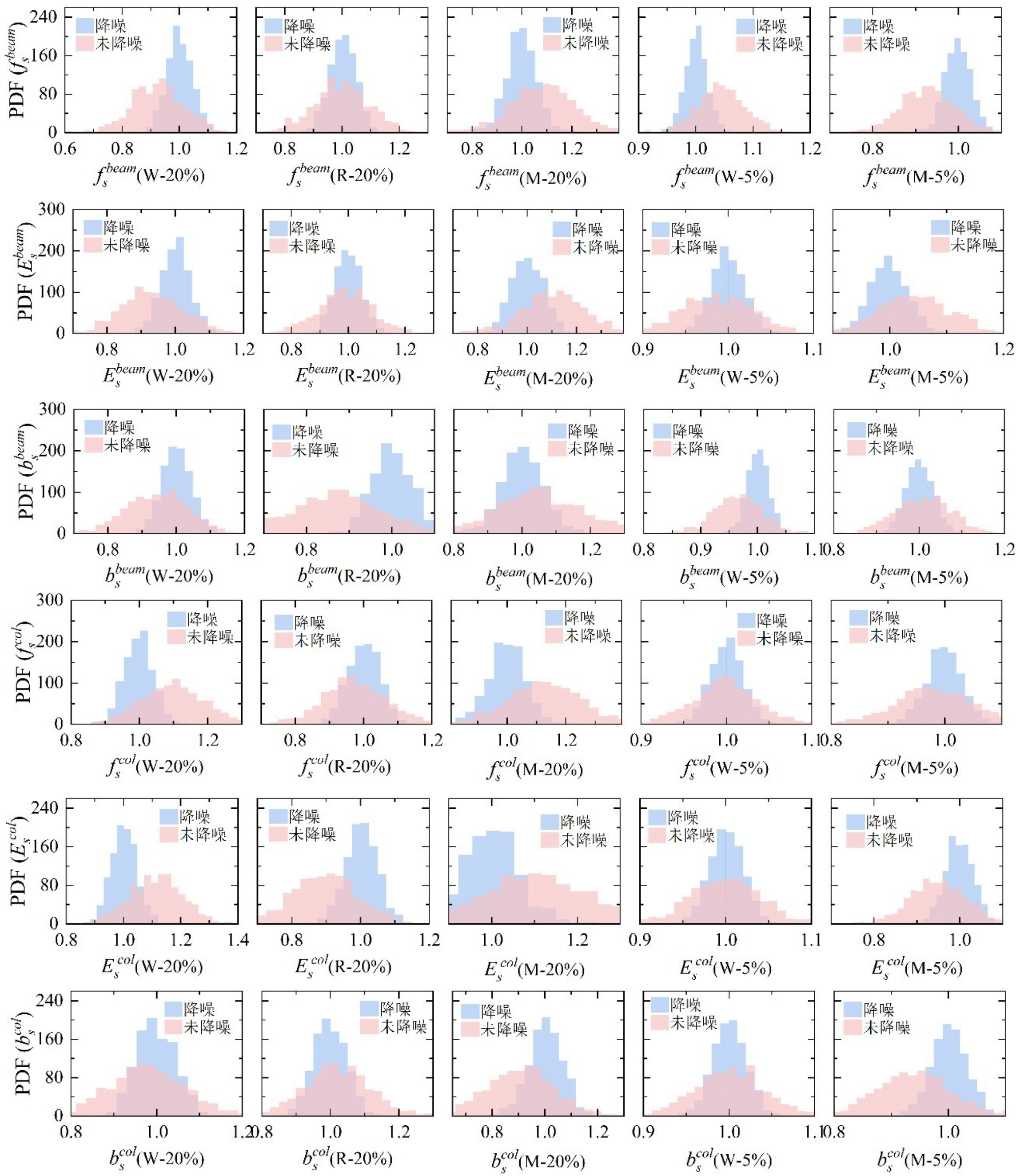
Comparison of acceleration responses at the middle-tower top considering model error

III. Effects of Multi-Source Uncertainty on Parameter Estimation

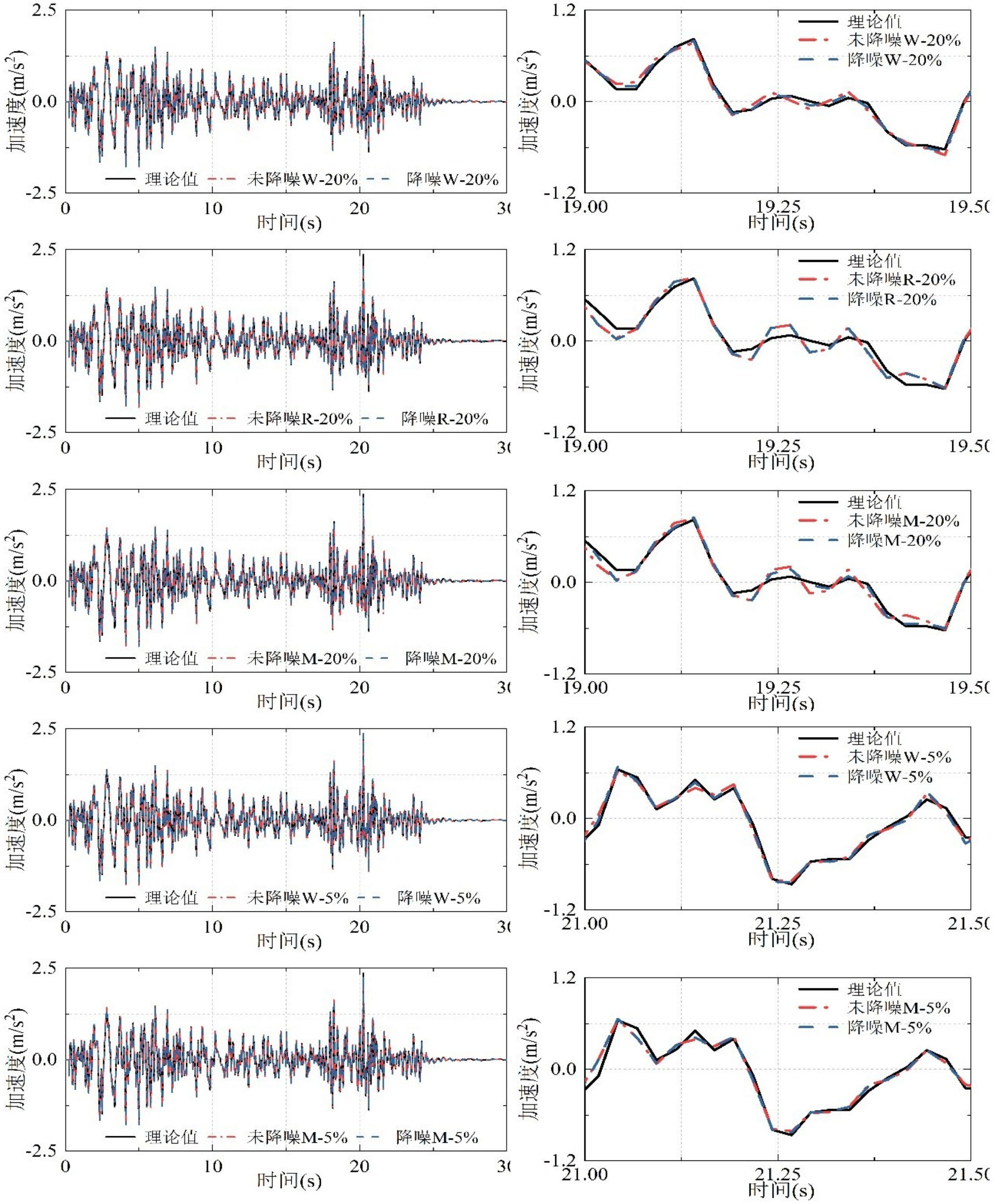
Influence of Measurement Uncertainty on Parameter Estimation

Measurement uncertainty mainly appears as noise interference in dynamic structural response measurements. Beyond sensor thermal noise and analog-circuit electronic noise, it may include environmental disturbances, data-acquisition baseline shifts, temperature-humidity effects, synchronization errors, and drift errors. These errors propagate through structural responses into parameter estimation, potentially causing systematic bias, increased uncertainty, convergence failure, or overfitting, thereby reducing model generalization.

Noise type	Engineering background
Gaussian white noise	Thermal and electronic noise in accelerometers, velocity sensors, strain gauges, and other electrical measurement devices
Pink noise	Widely present in changing environmental backgrounds, wind loading, and long-term foundation settlement
Red noise	Can simulate low-frequency nonstationary processes such as sensor zero drift and data-acquisition baseline variation
Impulse noise	Usually caused by rapid transients from electromagnetic interference, sensor jumps, or sampling-synchronization failures



Structural-parameter sample histograms for the three-tower cable-

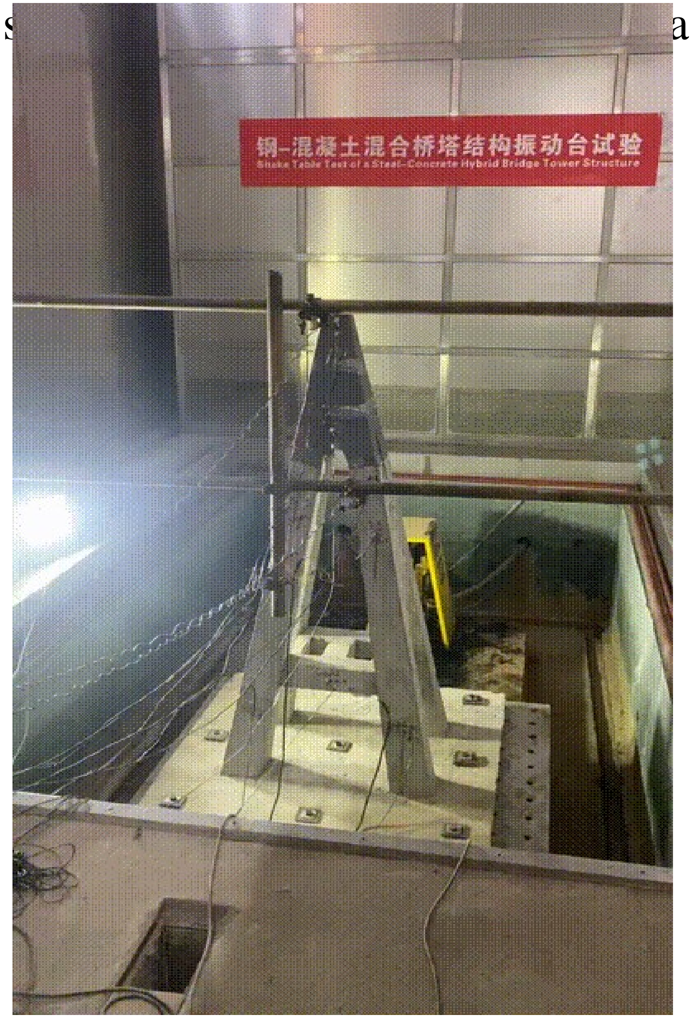


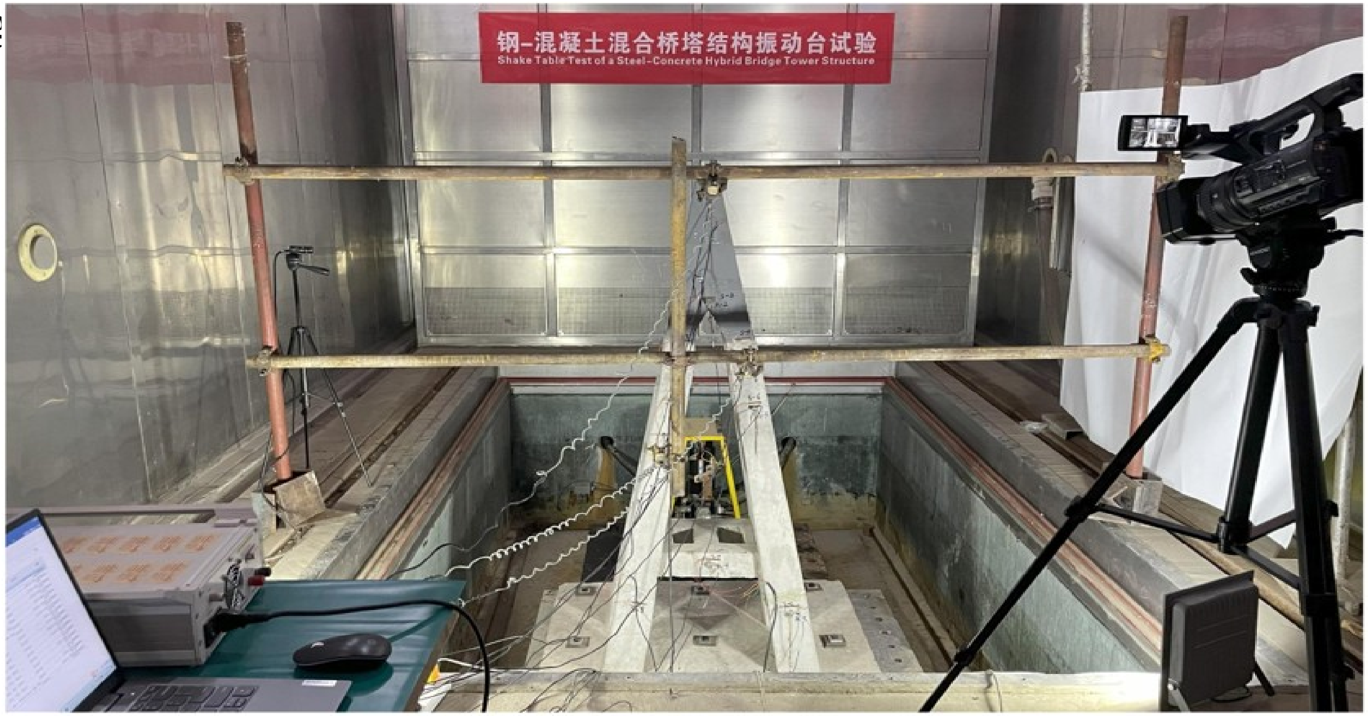
Comparison of acceleration responses at the middle-tower top

IV. Shaking-Table Validation Using a Steel-Concrete Composite Bridge Tower

IV. Shaking-Table Test of a Steel-Concrete Composite Bridge Tower

The bridge-tower test model is scaled according to similarity theory with a scale ratio of 1:172. The 2.0 m model consists of an upper steel tower column and a lower reinforced-concrete tower column. The 0.6 m upper column uses Q420qD high-strength steel to simulate the steel anchor-box region for cable anchorage in the prototype; the 1.4 m lower column is reinforced concrete with C60 concrete, corres aring





Test Structure of the Steel-Concrete Composite Bridge Tower

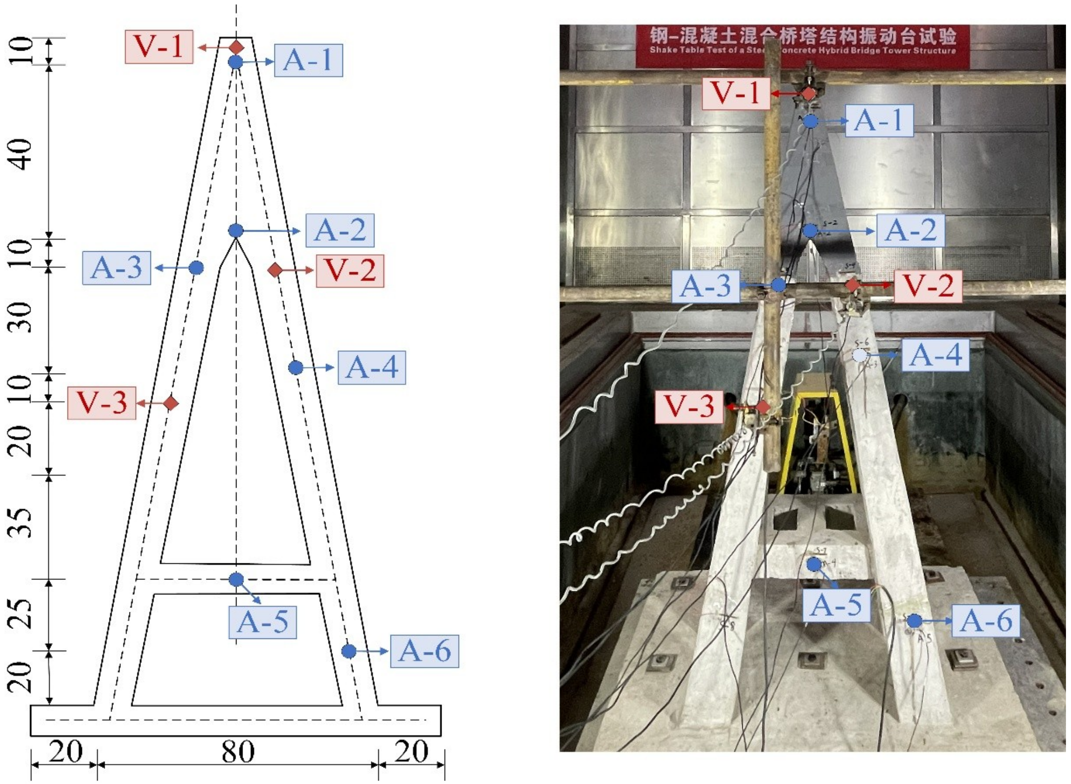
Material Parameters of the Steel-Concrete Composite

Material	Elastic modulus（Pa）	Poisson's Ratio	Density（kg/m3）
C60	3.67×10^{10}	0.167	2500
Q420qD	2.1×10^{11}	0.3	7820

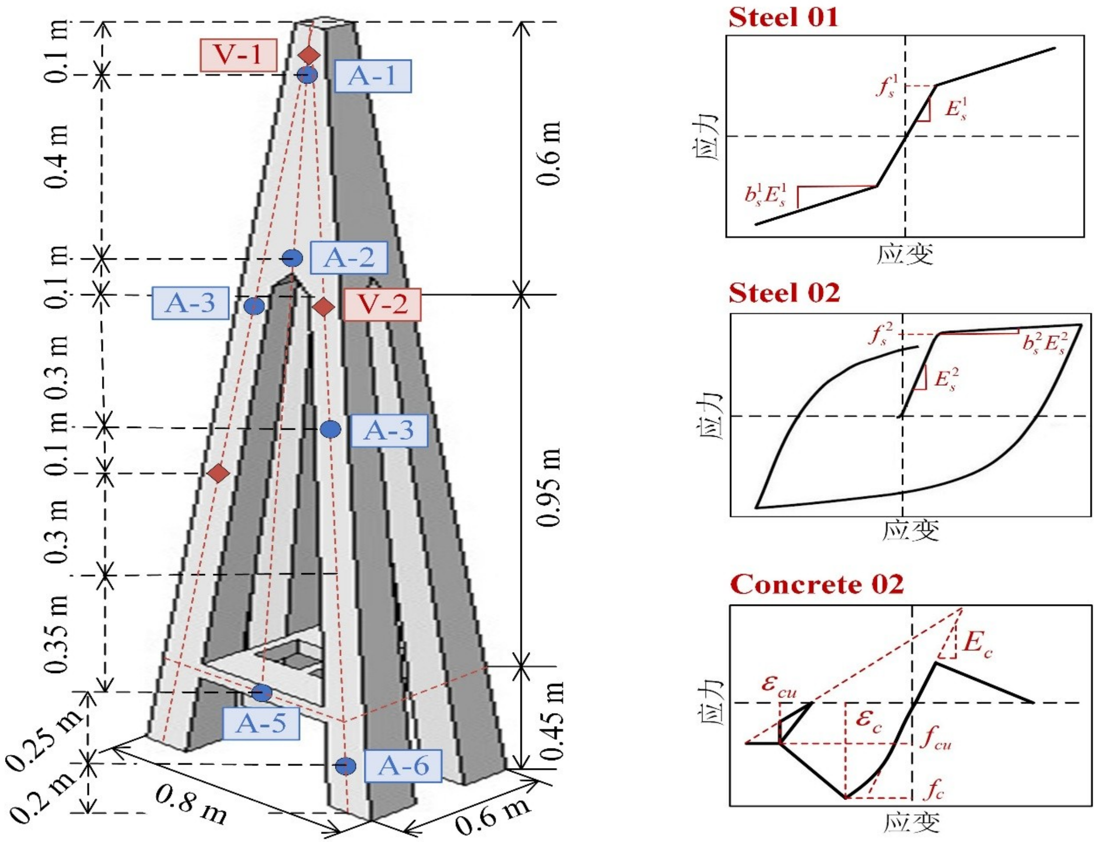
IV. Shaking-Table Test of a Steel-Concrete Composite Bridge Tower

Six unidirectional acceleration sensors (A1-A6) are installed on the test structure. Three displacement transducers (V1-V3) are placed at the tower top, the steel-concrete transition segment, and the mid-tower position to record horizontal displacement.

The nonlinear finite-element model of the steel-concrete composite bridge tower is developed in OpenSees using the geometry and material parameters of the scaled shaking-table model.

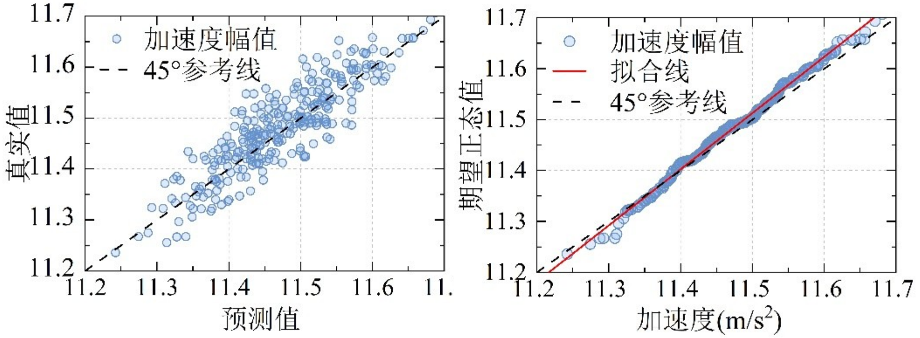


Measurement-point layout

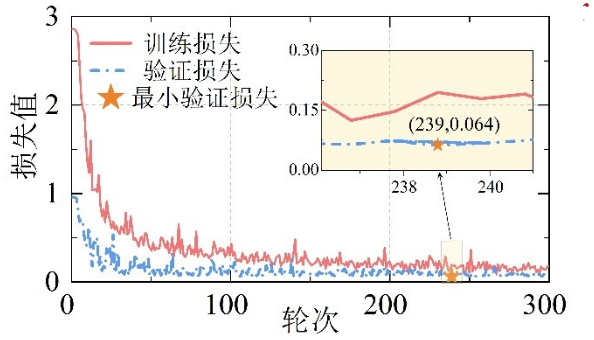


Bridge-tower finite-element model and nonlinear material constitutive relationships

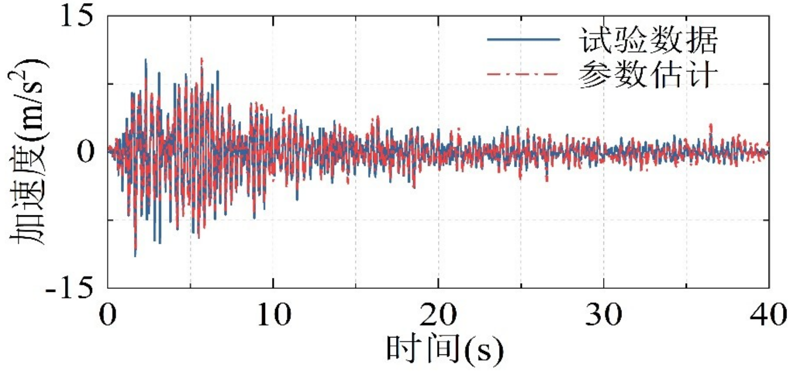
GPR-GAN-Based Probabilistic Model Parameter Estimation for a Steel-Concrete Composite Bridge Tower



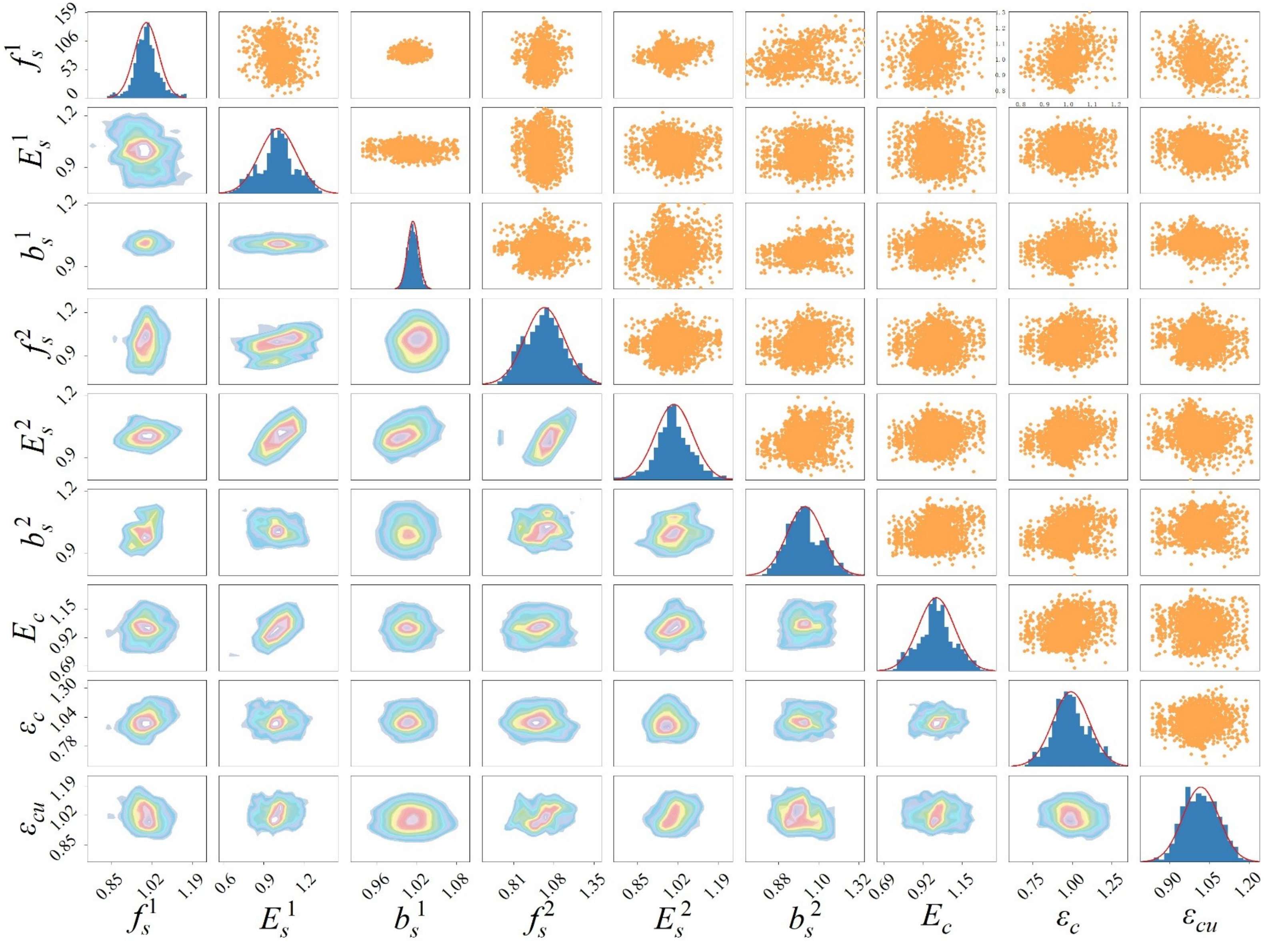
GPR prediction results for the steel-



Generator loss curve for the steel-



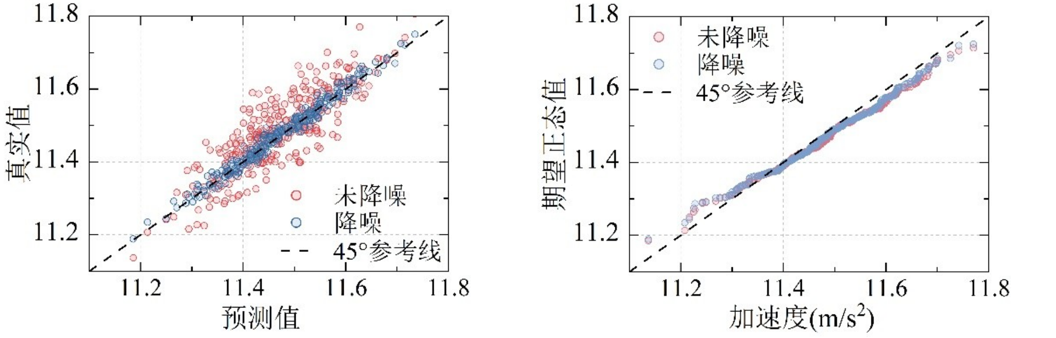
Comparison of acceleration responses of the steel-concrete



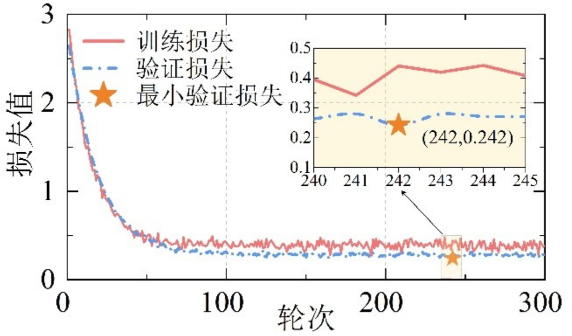
Parameter-estimation sample histograms for the steel-concrete composite bridge towe

IV. Shaking-Table Test of a Steel-Concrete Composite Bridge Tower

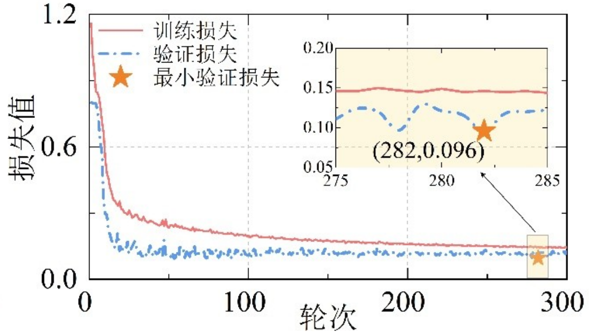
Parameter Estimation for the Steel-Concrete Composite Bridge Tower Considering Model Uncertainty



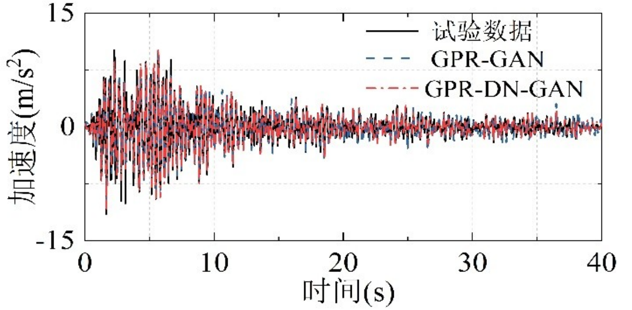
Prediction-accuracy comparison of the GPR surrogate for the steel-concrete composite bridge tower



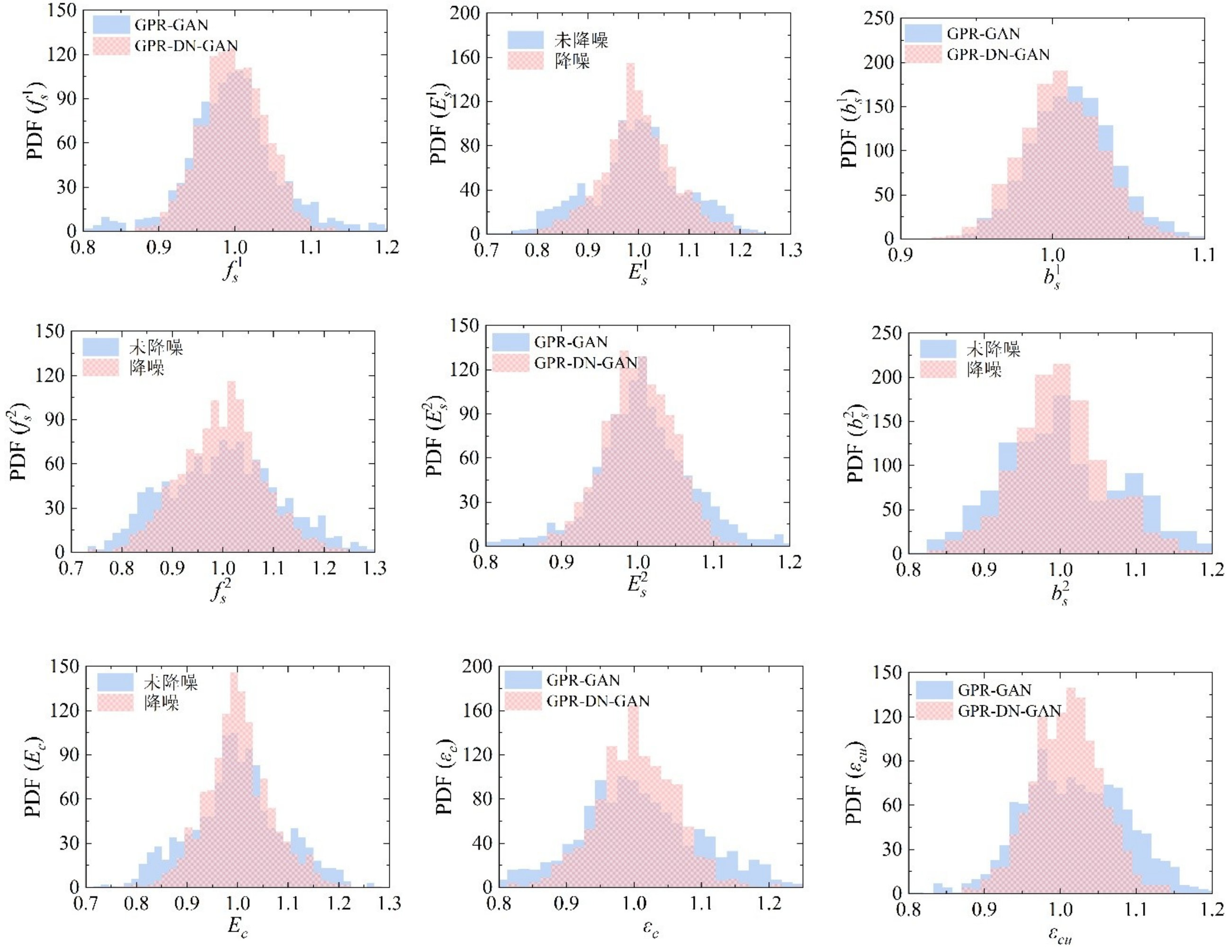
Loss curve of the model-error surrogate



Generator loss curve



Acceleration-response comparison with the noise-



Structural-parameter sample histograms considering model error

The response error decreases from 14.10% in the baseline case to

Thank you for your attention.