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Seismic Fragility Analysis of Curved Rocking Bridges using Active Learning

An Enhanced Approach based on Active Learning

Xueqi Zhong, Jianzhong Li, Feiyu Liao, Chiyu Jiao, Xu Chen*

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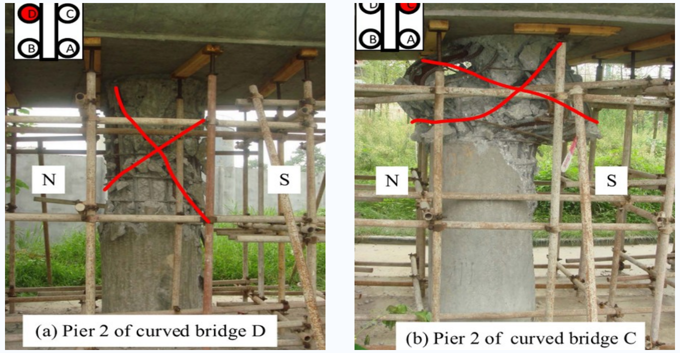
Presentation Content

CONTENTS

Curved Bridges: Application & Seismic Risks

- **Application:** Fit complex terrain; widely applied.
- **Challenge:** Bending-torsion coupling → high risk.
- **Case:** Wenchuan EQ failure shows urgency.

Huilan Overpass Failure Scenario
(Wenchuan Earthquake)



(a) Pier 2 of curved bridge D

(b) Pier 2 of curved bridge C

Rocking Piers for Seismic Resilience

- **Advantage:** Self-centering; small residual displacement.
- **Research Gap:** Focus on straight bridges; curved ones under-studied.
- **Aim:** Investigate curvature-rocking coupling.

Seismic risk of curved bridges is prominent; improving resilience is urgent.

1. Research Motivation & Objectives

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Traditional fragility analysis struggles to balance multi-dimensional uncertainty and computational efficiency.

Model Oversimplification: Ignores multi-dimensional ground motion intensity couplings.

Structural Complexity: Curved rocking bridges are controlled by many structural/material factors

Limitations of Traditional Analysis

- **Oversimplification:** Ignores ground motion couplings.
- **Multi-Variable:** Needs multiple performance indices.

Solution & Research Objectives

- **Efficient Methods:** Surrogate + active learning.
- **Core Objective:** Efficient curved bridge framework.

2. Research Methodology - Framework

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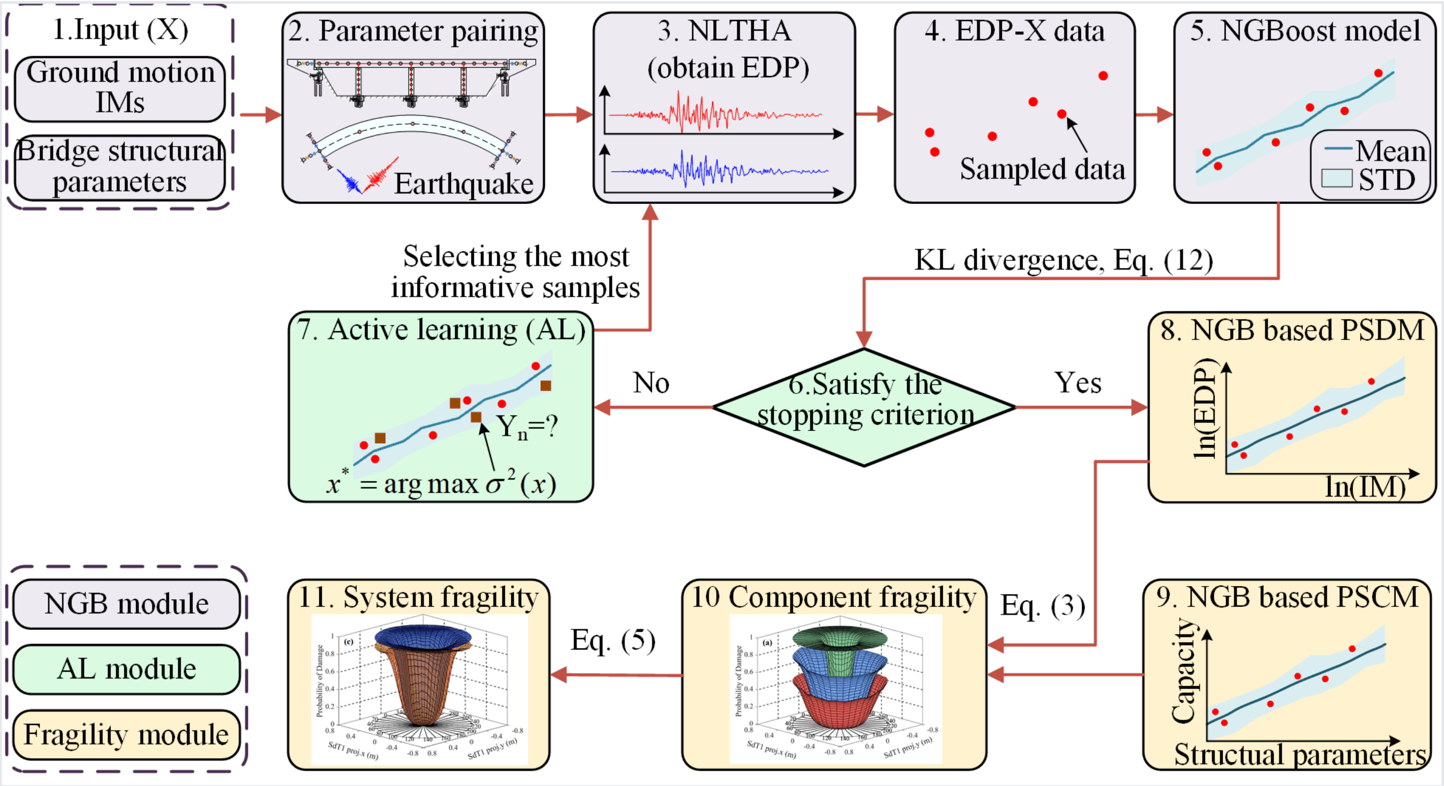

Core Modules

1. NGB Module:

Predicts seismic responses & EDP statistics.

2. AL Module:

Samples data to boost efficiency.

3. Fragility Module:

Computes fragility surface.

Workflow

Multi-parameter Sampling → **Time History** Analysis → **ML Training** Active Loop → **Fragility** Analysis

Multivariate Fragility: Integrating incidence angle & structural variables

Traditional Fragility Definition

Probability of structural response exceeding damage threshold

$$P_f = \mathrm{P}[\, D > C \mid \mathrm{IM} \,]$$

***D*:** Seismic demand (e.g., displacement)
***C*:** Component capacity (e.g., strength)
IM: Intensity Measure (e.g., peak ground acceleration)

Multivariate Fragility

Explicitly incorporating incidence angle and structural variables

$$P_f = \mathrm{P}[\, D(\mathrm{IM}, S, \theta) > \mathrm{C}(S) \mid \mathrm{IM}, \theta \,]$$

***S*:** Variables of structural dimensions and material properties
***θ*:** Ground motion incidence angle

2.Methodology: NGB & Active Learning

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NGB Surrogate Model: Quantifying Prediction Uncertainty

- **Core:** Learns to predict both the mean and variance, quantifying uncertainty.
- **Principle:** Iteratively optimizes the negative log-likelihood, balancing accuracy and robustness.

Active Learning: Achieving Target Accuracy with Minimum Samples

- **Strategy:** Selects samples with the highest variance for NLTHA (Nonlinear Time History Analysis) to reduce uncertainty.
- **Convergence:** The model is considered converged when the KL divergence is below a threshold.

Method Application Process

Step 1: Build the NGB model
Train with initial samples, output mean and variance, identify high-uncertainty regions.

Step 2: Active learning loop
Select high-variance samples for NLTHA, iteratively update the model.

Step 3: Convergence termination
When KL divergence meets the standard, output the high-precision model.

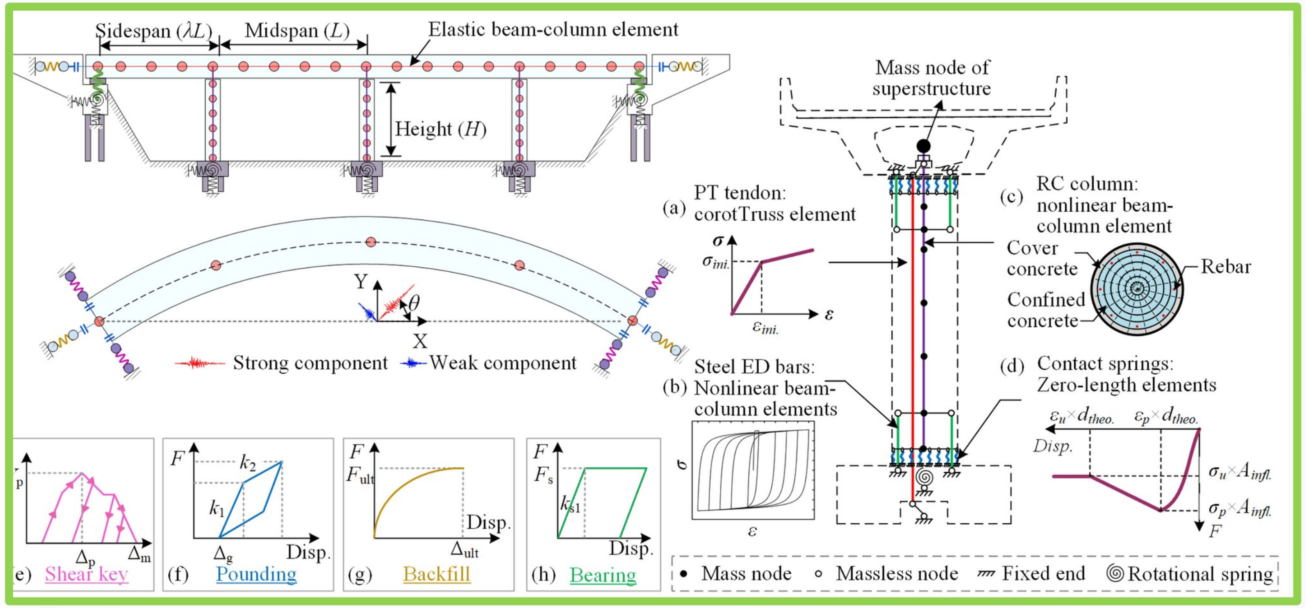
3. Case Study: Curved Rocking Bridge

Bridge Overview

A four-span continuous concrete box-girder curved bridge, serving as the benchmark model for this study.

Finite Element Model (OpenSees)

- **Superstructure:** Simulated with elastic beam elements to reflect stiffness characteristics.
- **Rocking Piers:** Simulated with fiber beam elements for RC columns; 'CorotTruss' for prestressing tendons; nonlinear beam elements for energy-dissipating rebars; zero-length contact springs for the rocking interface.
- **Other Components:** Shear keys, bearings, abutments, and pounding effects are all simulated with refined nonlinear models.



Benchmark Curved Rocking Bridge

High-precision nonlinear seismic model.

3. Case Study: Structural Uncertainty

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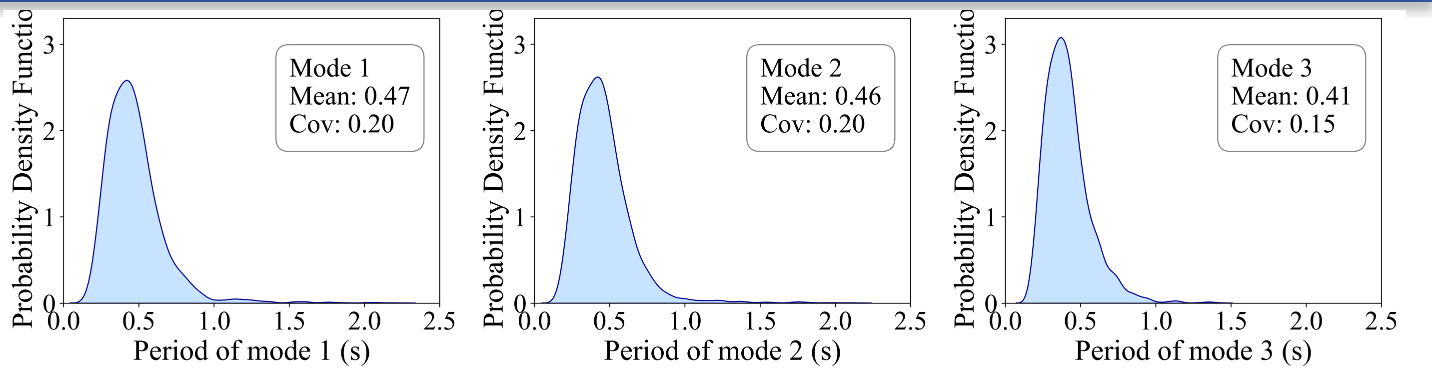
Uncertainty parameters

Source: 13 variables (geo, mat, load)
Distribution: Norm, Lognorm, Uniform
Sample: LHS (2000 samples)



No.	Variable	Distribution	Mean	Deviation	Min	Max	Refer.
Superstructure							
1	Span length, L (m)	Normal	41.15	10.67	22.86	70.1	[39]
2	Side-to-main span ratio, λ	Normal	0.75	0.2	0.4	1	[44]
3	Radius, R (m)	Normal	150	45	30	300	/
Rocking pier							
4	Height, H (m)	Lognormal	7.13	1.15	5.18	9.75	[39]
5	Diameter, D (m)	Lognormal	2	0.4	1.6	2.4	[45]
6	PT axial load ratio, α (%)	Uniform	12.5	/	5	20	[46,47]
7	PT area ratio, γ (%)	Uniform	0.6	/	0.2	1	[48,49]
8	ED bar area, β (%)	Uniform	1	/	0	2	[43,50]
9	ED bar yield strength, f_{ed} (MPa)	Lognormal	400	40	340	460	[51]
10	Concrete strength, f_c (MPa)	Normal	31.37	3.86	22.75	39.09	[52]
Other parameters							
11	Mass factor, m_f	Uniform	1.05	0.06	0.95	1.15	[52]
12	Damping ratio, ξ	Normal	0.45	0.0125	0.02	0.07	[52]
13	Earthquake incidence angle, θ (°)	Uniform	180	/	0	360	/

Uncertainty causes wide dispersion in modal periods

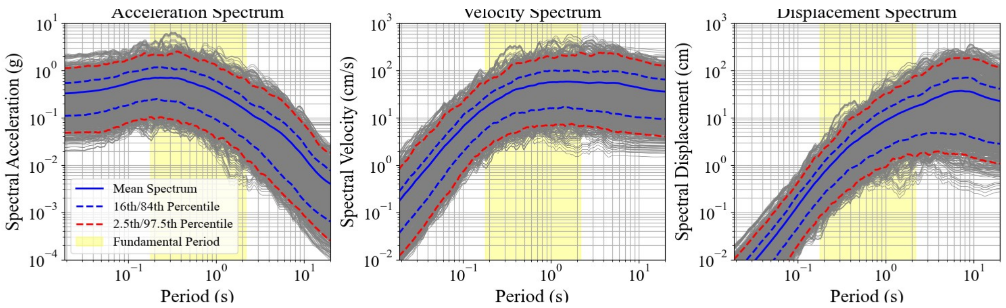
3. Case Study: Ground Motion Selection

A high-quality dataset is the foundation of machine learning model performance.

This study constructed a dataset of 2000 samples, combining statistical analysis of bridge dynamic properties and scientific scaling of ground motions to cover real engineering scenarios.

1. GM Record Selection & Scaling

- 240 ground motion records were selected and randomly scaled to generate 2000 records.
- Response spectra cover bridge periods.



Response Spectra of Ground Motions

2. Intensity Measures (IMs)

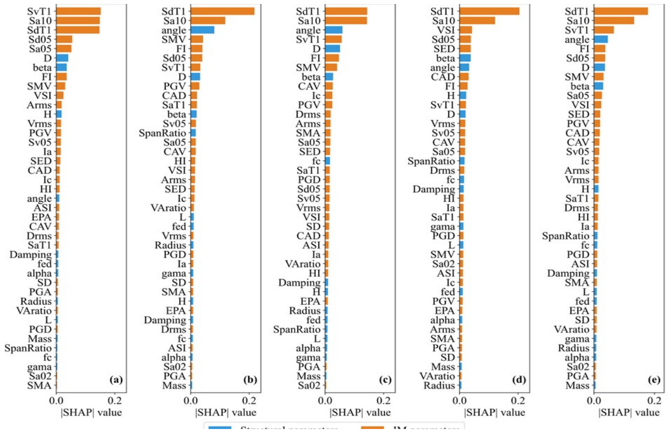
28 candidate IMs were selected

No.	IM (unit)	Name
1	PGA (g)	Peak Acc.
2	SMA (g)	Sustained Acc.
3	CAV (cm/s)	Cum. Vel.
4	A_rms (g)	RMS Acc.

Optimal input features selected via SHAP importance & correlation filtering

SHAP Importance

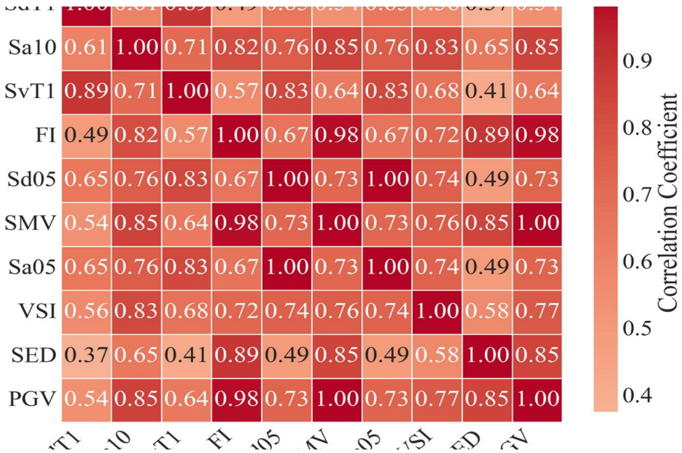
Purpose: Quantify 41 params’ contribution.
Finding:
- IMs are more important than structural parameters.
- $S_{d\text{-}T1}$ is the primary feature;



SHAP Importance
$S_{d\text{-}T1}$ dominates all 41 params.

Correlation Filtering

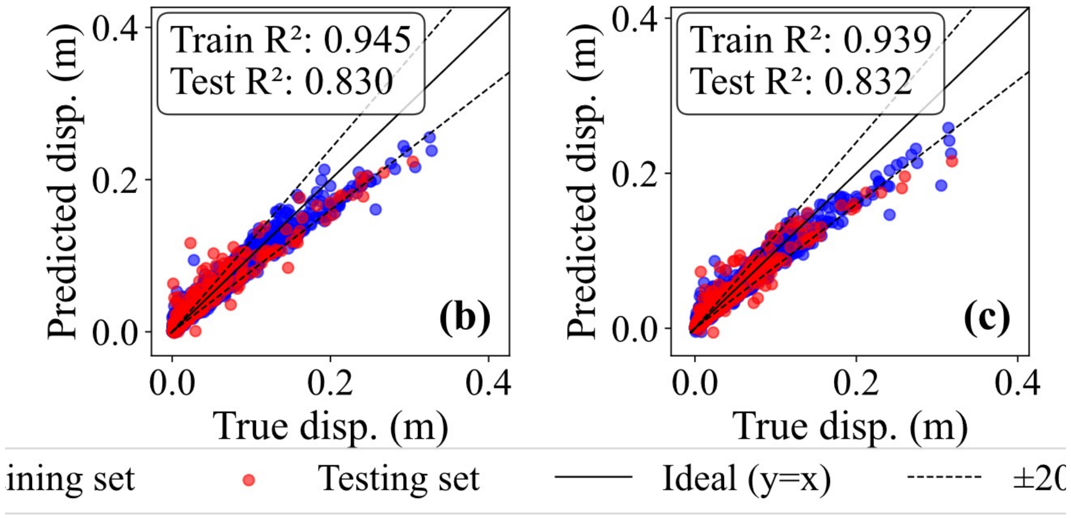
Purpose: Select non-redundant params.
Result: $S_{d\text{-}T1}$ & FI: low correlation, high complement.



Correlation Matrix
Filter low-correlation, high-imp indicators.

Performance Evaluation of the Surrogate Model for Probabilistic Seismic Demand:

- **Model Construction:** An NGB model was used, taking 8 key structural parameters and 2 IMs as input, and outputting 4 EDPs.
- **Evaluation Metrics:** R^2 was used to evaluate goodness of fit, and RMSE to measure deviation.
- **Key Conclusion:** R^2 values are all > 0.83, and most points lie within a ±20% error range, satisfying engineering accuracy requirements.



Observed vs. predicted responses: high accuracy.

Conclusion: The NGB surrogate model based on selected features can predict seismic responses with high precision, serving as an efficient tool to replace numerical simulations for seismic assessment.

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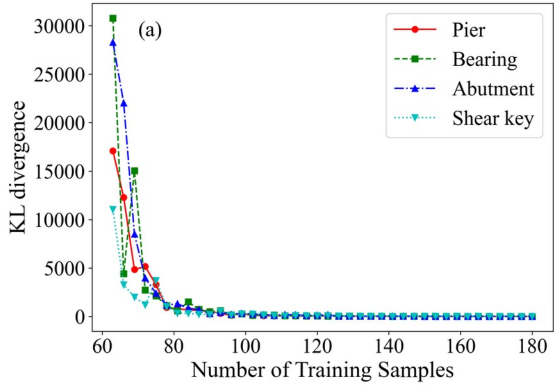
AL-NGB Algorithm Convergence Process and Performance Evaluation:

01. AL-NGB Convergence Analysis

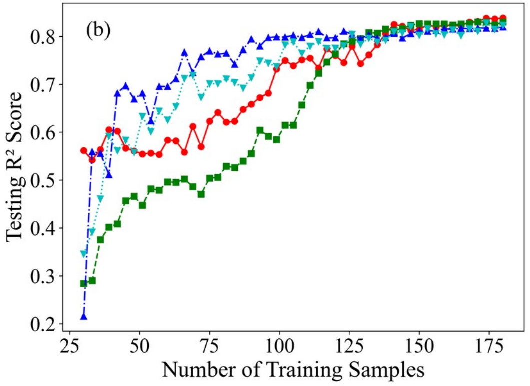
- KL divergence stabilizes when the sample size reaches 100+;
- R^2 stabilizes at 0.8 when the sample size is 120+.

02. Model Performance & Efficiency

150 samples (10% data) match accuracy of full dataset.

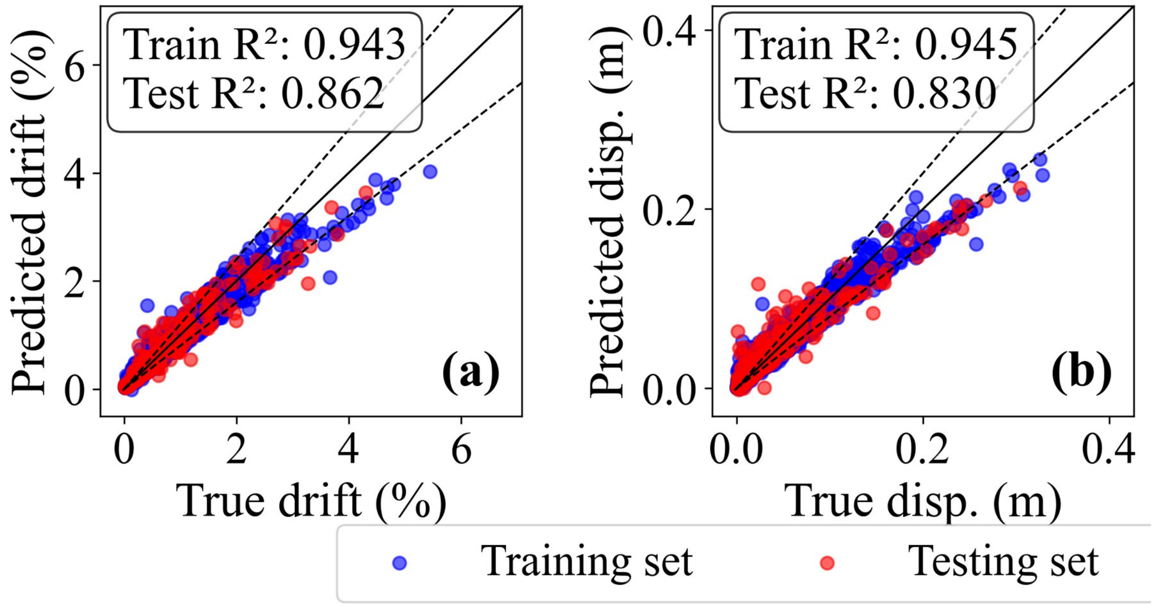


KL Divergence



R² Value

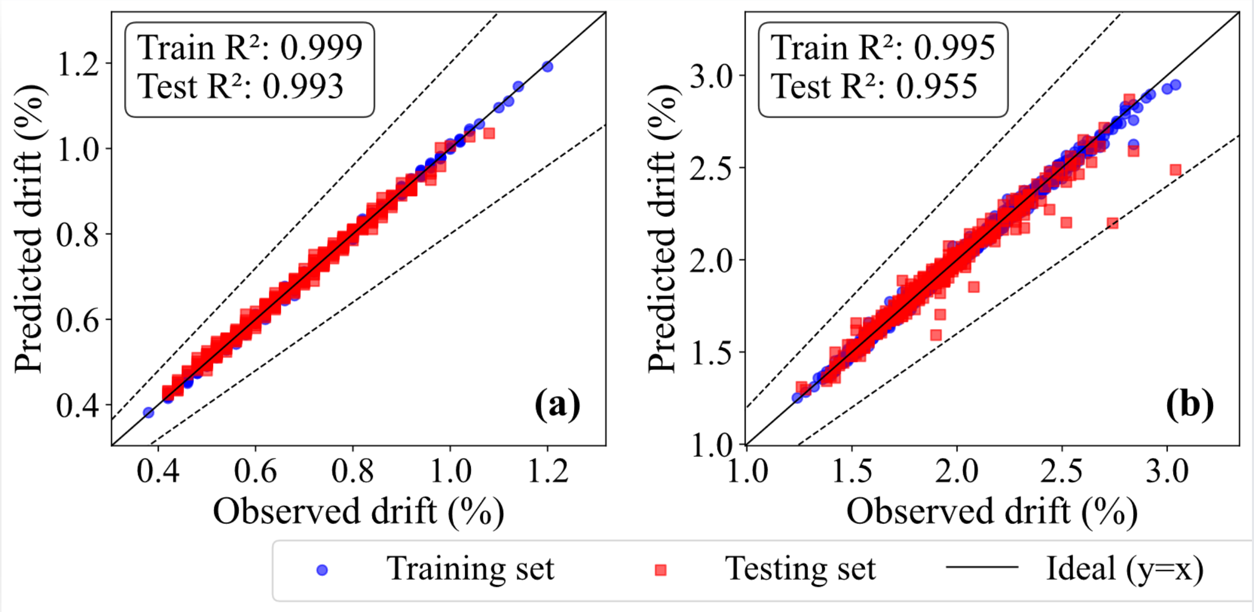
Performance vs. Sample Size



Probabilistic Seismic Capacity Models (PSCM) for Components:

PSCM Modeling & Validation for Rocking Piers

- **Damage States:** Three levels of quantified damage states were defined, with clear damage thresholds.
- **Modeling Logic:** Based on Pushover analysis of 2000 models, an NGB model was trained.
- **Accuracy:** The prediction goodness of fit **$R^2 > 0.95$**, which is accurate and reliable.



Damage Limits for Other Components

The damage limit states for bearings, abutments, etc., were determined, summarizing their mean and standard deviation.

Validation of Pier Capacity Model

Data points follow perfect prediction line (high accuracy).

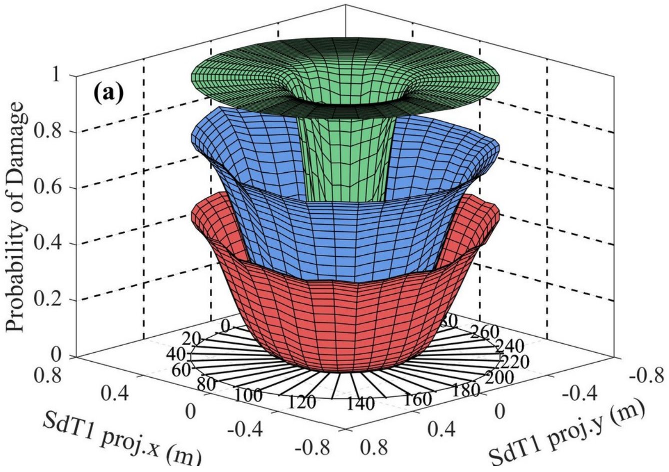
5. Fragility Analysis: Ground Motion Angle Effects

Analysis Objective: To quantify the influence of different ground motion incidence angles (θ) on the fragility of key components of the curved rocking bridge.

Sensitivity Analysis:

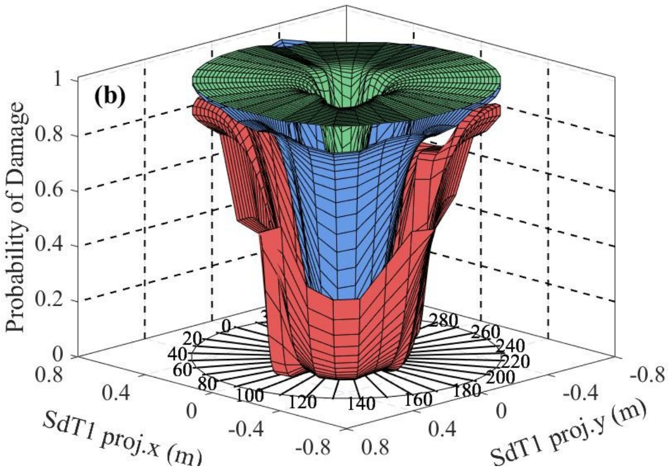
- **Piers:** Damage probability is not sensitive to the angle (the fragility surface is centrally symmetric).
- **Bearings / Shear Keys:** Fragility shows an asymmetric distribution and strongly depends on θ.

Core Conclusion: Ignoring the incidence angle will significantly underestimate the structural risk.



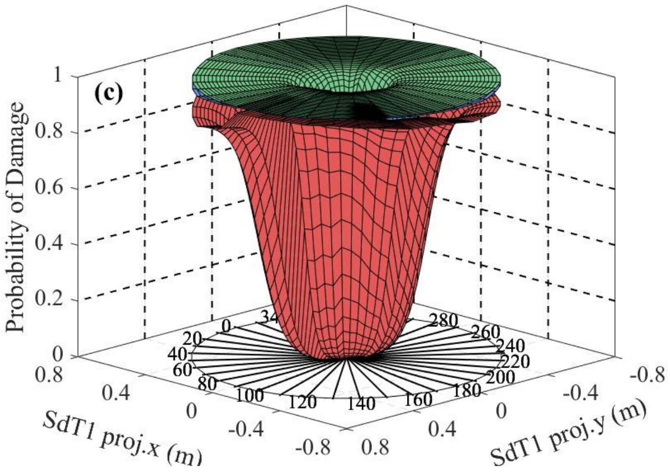
Piers Fragility

(Angle Insensitive)



Bearings Fragility

(Angle Sensitive)

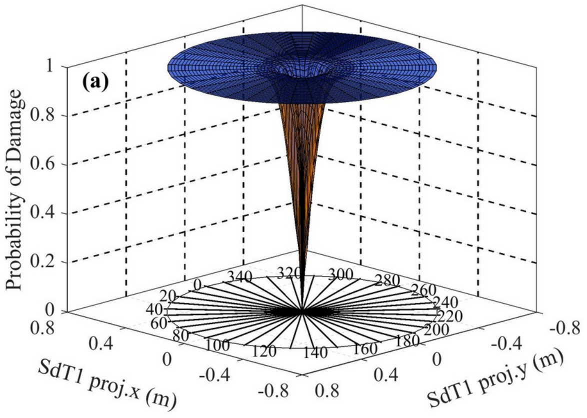


Shear Keys Fragility

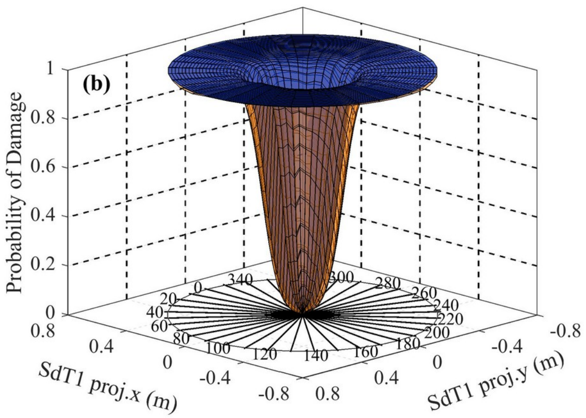
(Angle Sensitive)

5. Fragility Analysis Considering Ground Motion Angle

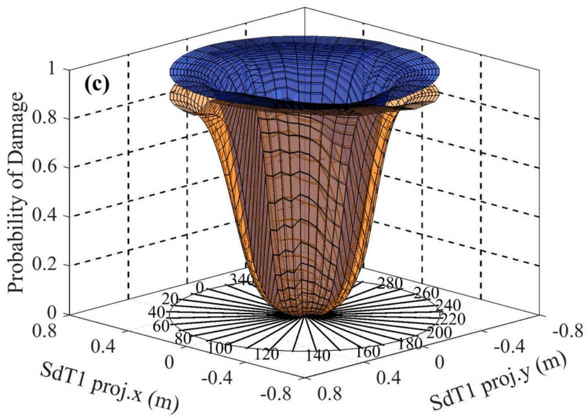
Bridge System Fragility Analysis



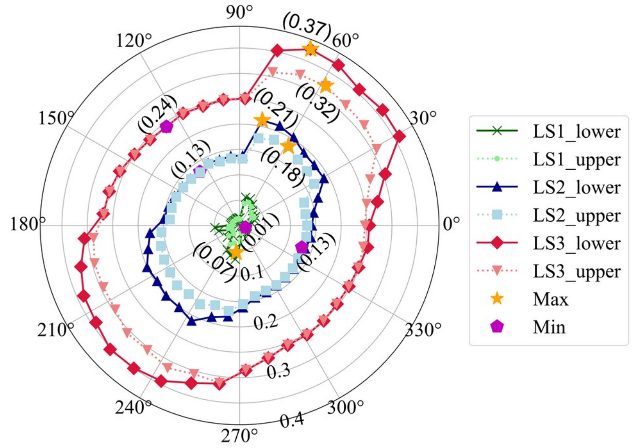
Damage State 1



Damage State 2



Damage State 3



Avg. Sd-T1 vs Angle

Fragility: Weakest Link

System fragility is controlled by the weakest component (e.g., shear keys).

Direction Matters

Specific directions ('most unfavorable') increase failure probability.

Underestimation

Ignoring directionality severely underestimates true fragility.

6. Conclusions and Future Work

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Efficient Surrogate Model

The established NGB surrogate model enables fast and accurate prediction of the multivariate seismic demand and component capacity of curved rocking bridges.

Key Influencing Factors

Identified '$S_{\text{d-T1}}$' and 'FI' as the optimal intensity measures; the ground motion incidence angle significantly affects the fragility of key components.

System Fragility Analysis

System fragility depends on the performance of key components and is highly sensitive to the ground motion incidence angle. Seismic design needs to strengthen key components.

Efficiency of Active Learning

Verified the high efficiency of the active learning framework, achieving prediction accuracy comparable to the full-data model with only about 10% of the training samples.

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Thank You for Your Attention!

Please feel free to discuss and provide guidance.

Xueqi Zhong, Associate Professor
College of Transportation and Civil Engineering
Fujian Agriculture and Forestry University
Tel： 185 5879 7993