SPIE Smart Structures + NDE 2023

SPIE. SMART STRUCTURES+ NONDESTRUCTIVE EVALUATION

Gaussian process regression surrogate model for dynamic analysis to account for uncertainties in seismic loading

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Uncertainties in infrastructures

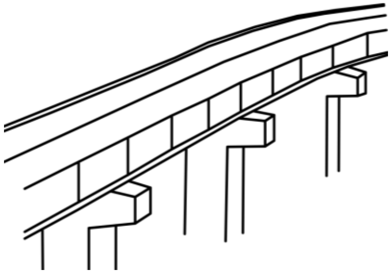
- Infrastructures such as bridges are designed for load and strength.
- However, during the service life, structures may deteriorate and suffer damage.
- This is due to the difference between design and reality. In reality, there are many uncertainties.
- A reliability analysis is required that considers uncertainties related to loads and structural strength.

(MLIT, Measures to prevent roads from aging, Aging Status)
(MLIT, Anti-aging Intiatives)

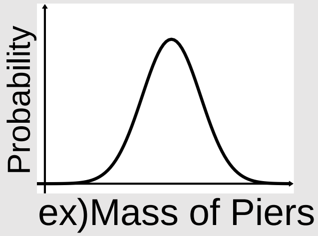
(JSCE, Steel Structure Committee)

Reliability Analysis Flow

Target



Considering Uncertainties



Reliability Analysis Flow

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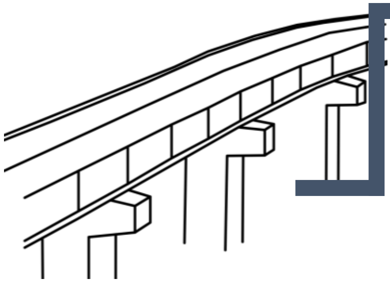
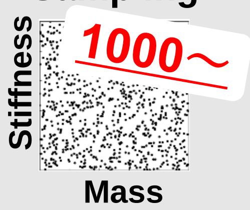
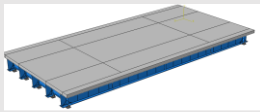


General Reliability Analysis

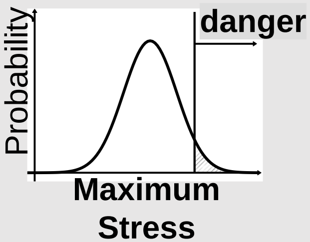
Monte Carlo Sampling



Analytical model

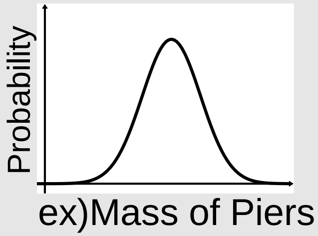


Output distribution

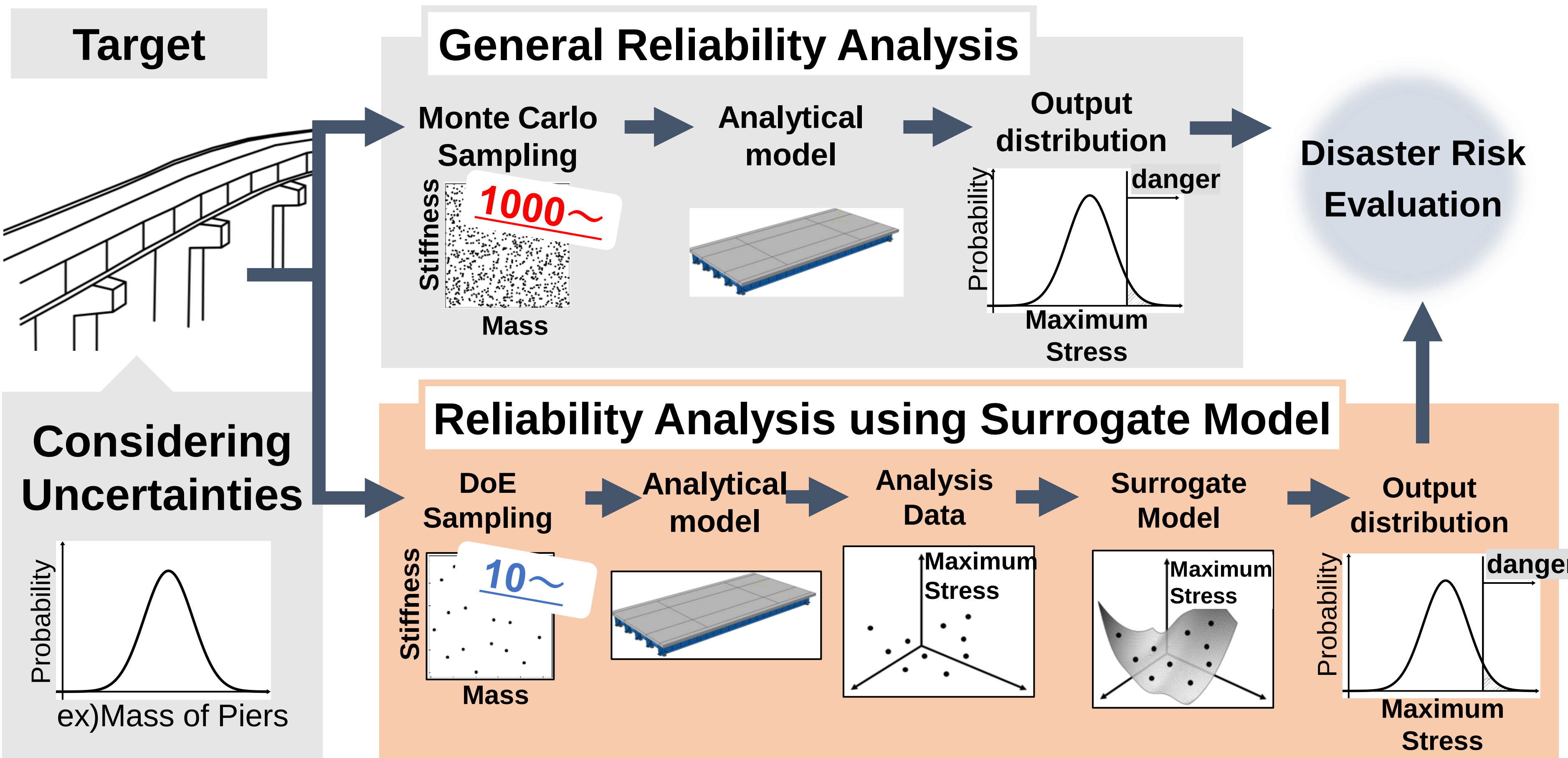


Disaster Risk Evaluation

Considering Uncertainties



Reliability Analysis Flow



Surrogate models can reduce computational cost of reliability analysis

【Previous Studies】Surrogate model for seismic response analysis

Abbiati et al. 2021

- Using parameters of artificial ground motions and structure as inputs
- Constructed surrogate model for seismic risk analysis of piping

(*Journal of Loss Prevention in the Process Industries*, Vol.72)

Cannot input actual ground motion

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Cannot input actual ground motion

Zhang et al. 2020

- Seismic waveforms are input using convolutional neural networks (CNN)
- Constructed surrogate models for seismic response analysis of buildings

(*Engineering Structures*, Vol.206)

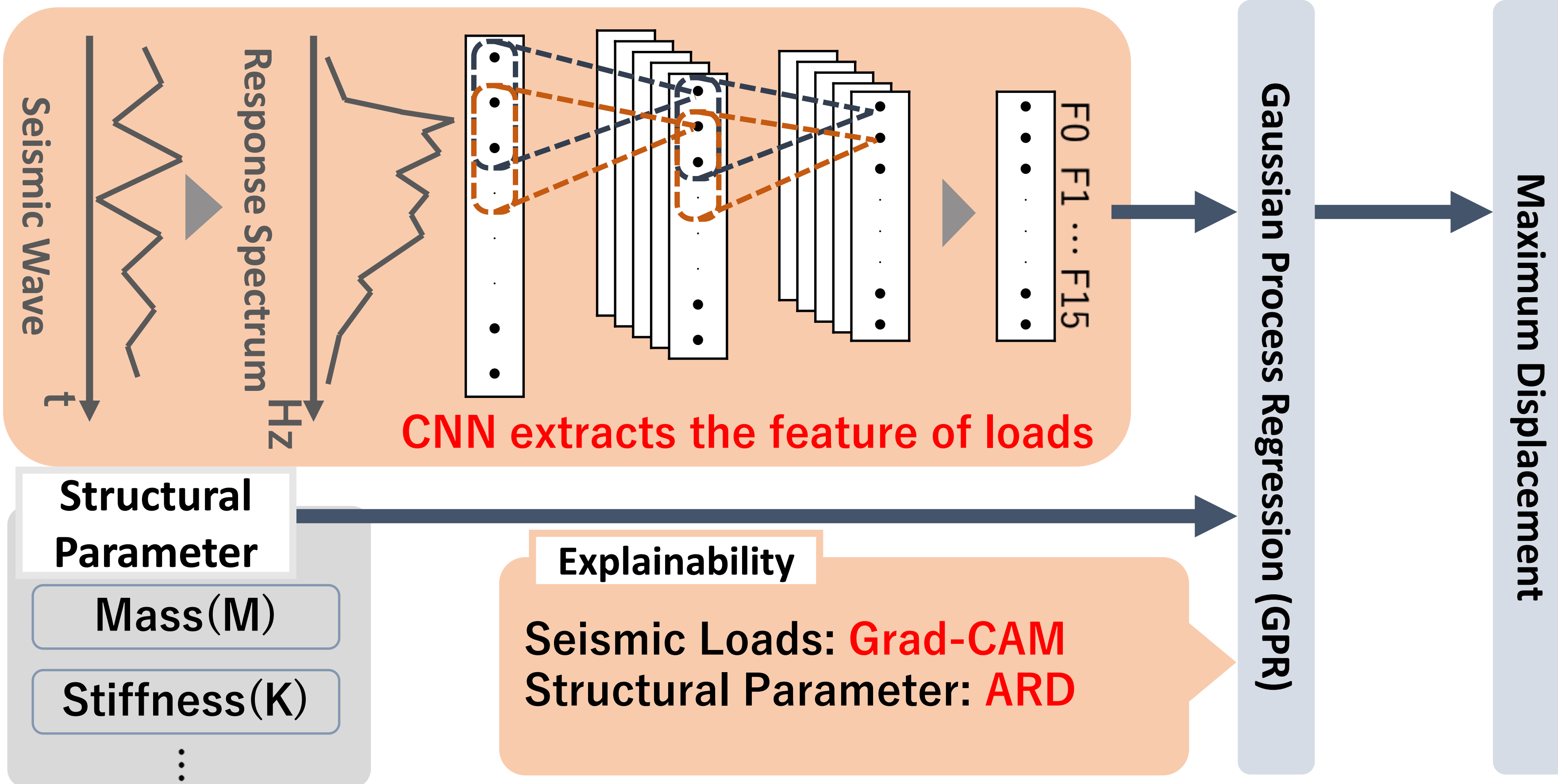
- **Not consider structural uncertainty**
- **Unclear why the result is obtained**

Issue

- **Considers both actual ground motion and structural parameters**
- **Be able to explain why the predicted results are obtained (Explainability)**

【Objective】Deep kernel learning surrogate model

Feature extraction of seismic loads



Constructing explainable deep kernel learning surrogate model with CNN and GPR to reduce computational costs on seismic risk analysis

Gaussian Process Regression (GPR) with ARD Kernel

GPR

- **Nonparametric**
- **Non-linear regression**

$$y = f(\mathbf{x})$$

$$f \sim GP(\mathbf{0}, k(\mathbf{x}, \mathbf{x}'))$$

$$\mathbf{y} \sim \mathcal{N}(0, \mathbf{K})$$

$\mathbf{x}$: input vector

$\mathbf{y}$: output vector

k : kernel function

$\mathbf{K}$: kernel matrix

Kernel Matrix

$$K_{\mathrm{nm}} = k(\mathbf{x}_{\mathrm{n}}, \mathbf{x}_{\mathrm{m}})$$

K_{nm} : elements of kernel matrix

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ARD Kernel Function

ARD ： Automatic Relevance Determination

Matern5/2 kernel

$$k(\mathbf{r}) = \sigma\left(1 + \sqrt{5}\sum_{i=1}^{D}\frac{r_{\mathrm{i}}}{l_{\mathrm{i}}} + \frac{5}{3}\sum_{i=1}^{D}\frac{r_{\mathrm{i}}^{2}}{l_{\mathrm{i}}^{2}}\right)\exp\left(-\sqrt{5}\sum_{i=1}^{D}\frac{r_{\mathrm{i}}}{l_{\mathrm{i}}}\right)$$

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Length Scale (l_i)

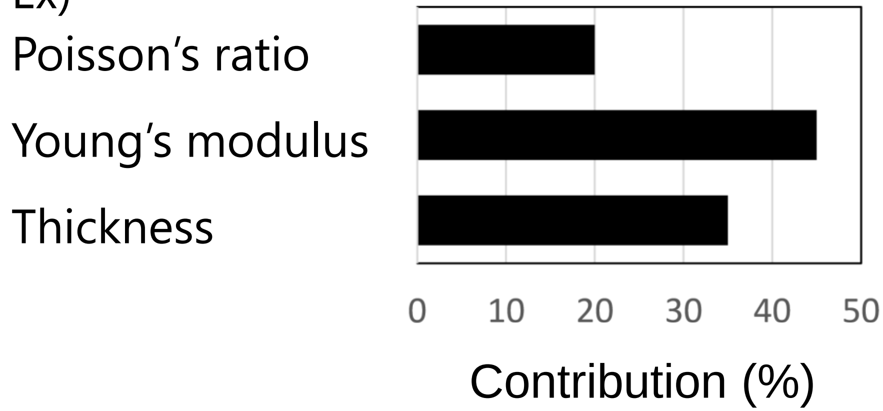
Represents the contribution

of each input variable to the output

ARD Kernel

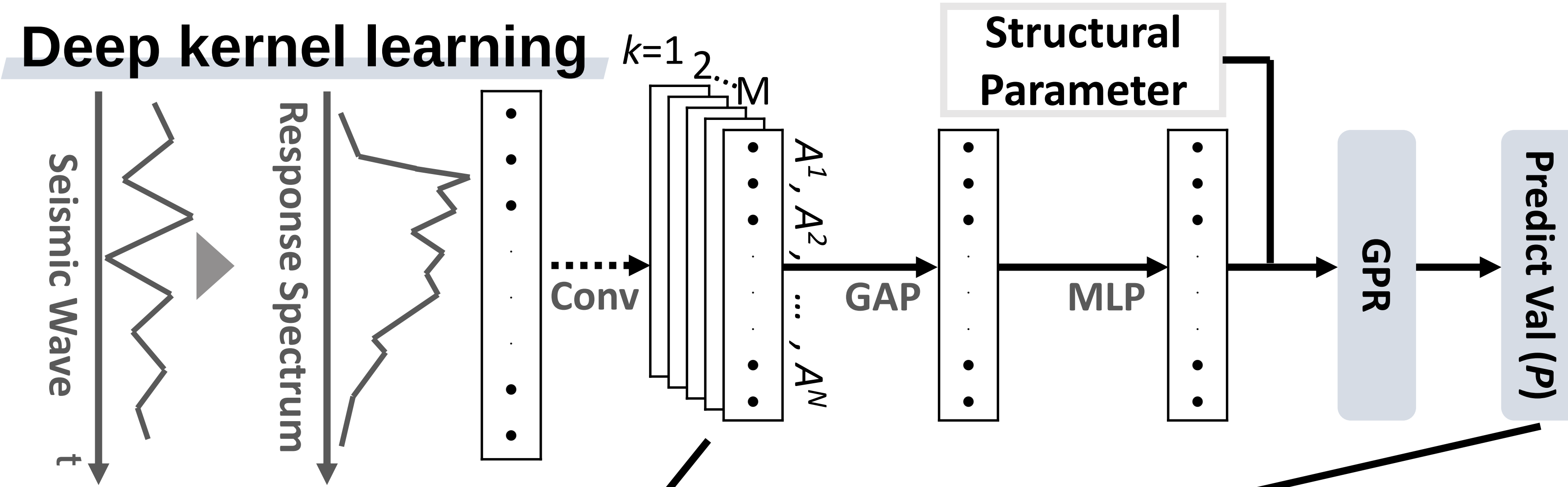
Estimate the contribution of input parameters

Ex)



Grad-CAM for contribution of seismic loads

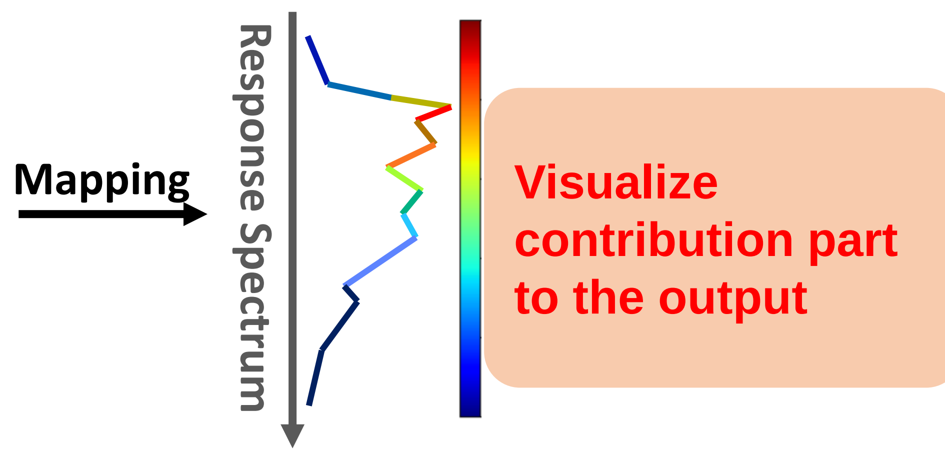
Deep kernel learning



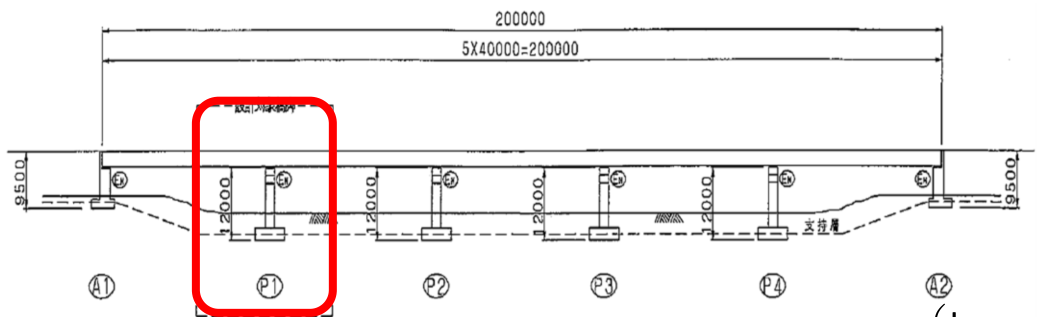
Grad-CAM

$$\alpha_k = \frac{1}{N}\sum_i^N \frac{\partial P}{\partial A_i^k}$$

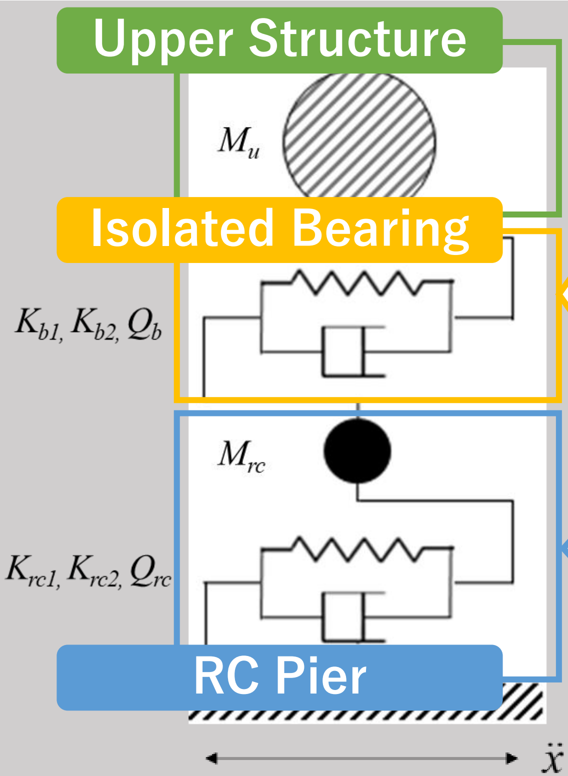
$$L_{\text{Grad-CAM}} = ReLU\left(\sum_k^M \alpha_k A^k\right)$$



Analytical model of an isolated RC pier

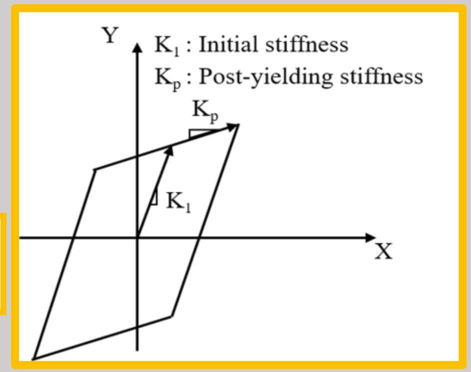


(Japan Road Association, 1997)

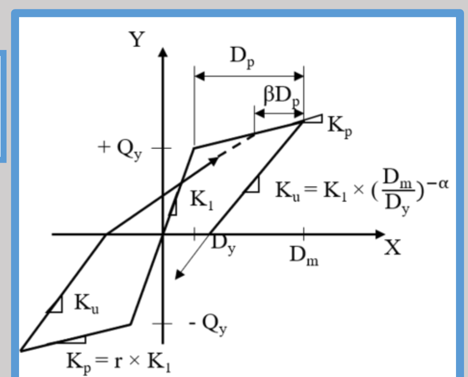


2DOF model of Isolated RC Pier

Bilinear Model



Takeda Model



Analysis Parameters

Integration：

- Newmark - β
- Newton Raphson

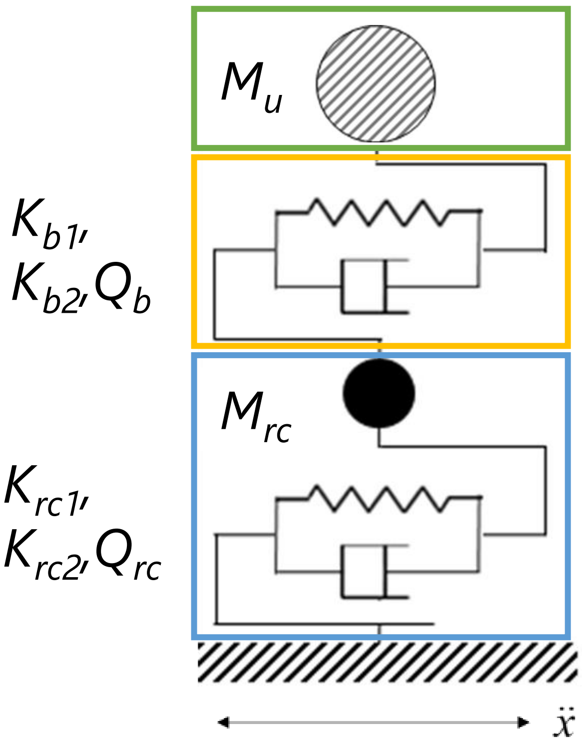
Time Increment： 0.001s

Rayleigh damping

Damping Ratio：

- 2% for pier
- 0% for bearing

Uncertainty parameter setting



Parameters		Nominal	Uncertainty
Superstructure	Weight (*Mu*)	604,000 kg	Uniform Distribution ± 10 %
Seismic Isolation Bearing	Primary stiffness (*Kb1*)	40,023.2 kN/m	
	Secondary stiffness (*Kb2*)	6,154.4 kN/m	
	Yield load (*Qb*)	1,117.2 kN	
RC Pier	Weight (*Mrc*)	346,300 kg	
	Primary stiffness (*Krc1*)	110,000 kN/m	
	Secondary stiffness (*Krc2*)	8,250 kN/m	
	Yield load (Qrc)	3,399 kN	

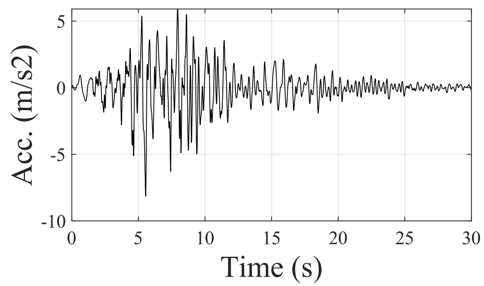
（Reference: Japan Road Association, 1997）

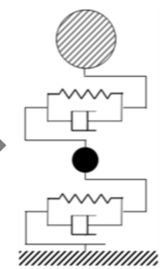
Reliability Analysis Overview and Input/Output

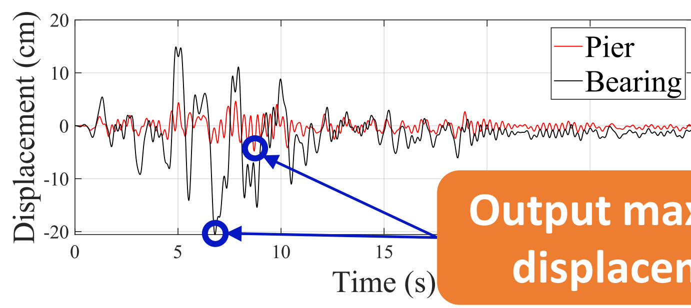
Uncertain Parameters → **Seismic Response Analysis** → **Maximum Displacement (Pier and Bearing)**

8 structural parameters
20 waves uncertainty

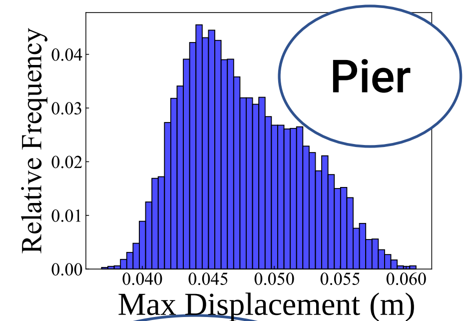
- *JMA KOBE (1996)*
- *Tsurui-nishi (2003)*
- *Tsurui-higashi (2003)*
- *Taiki (2003)*
- *Tokamachi (2004)*
- *Ojiya (2004)*
- *Nagaoka (2004)*
- *Ichinoseki-nishi(2008)*
- *Otsu (2016)*
- *Oguni (2016)*

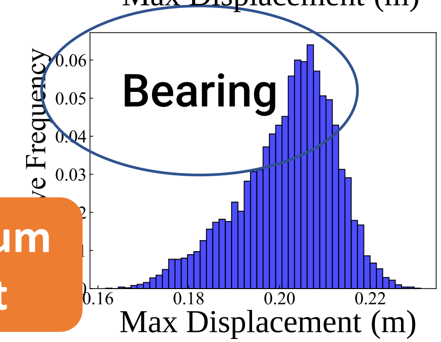






Output maximum displacement





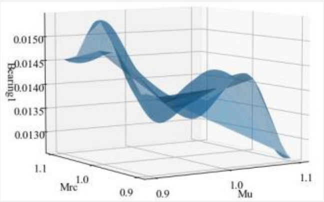
Surrogate model inputs and outputs

Inputs

Structural Parameter

Response Spectrum

→ **Surrogate Model** →



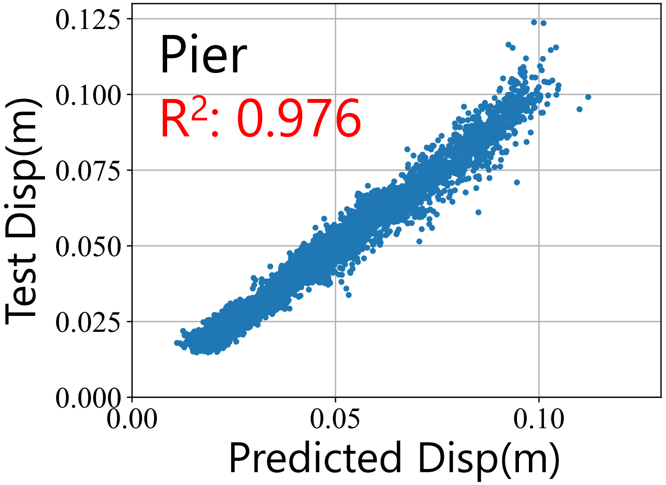
Outputs

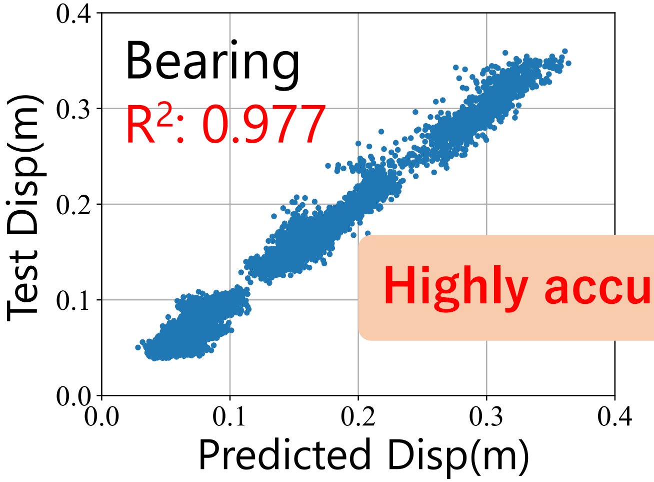
Maximum Displacements of Pier and Bearing

【Result】Predict Maximum Displacement

Predicts by surrogate model

Train data：300　Test data(from analysis)：10000





Highly accurate predictions.

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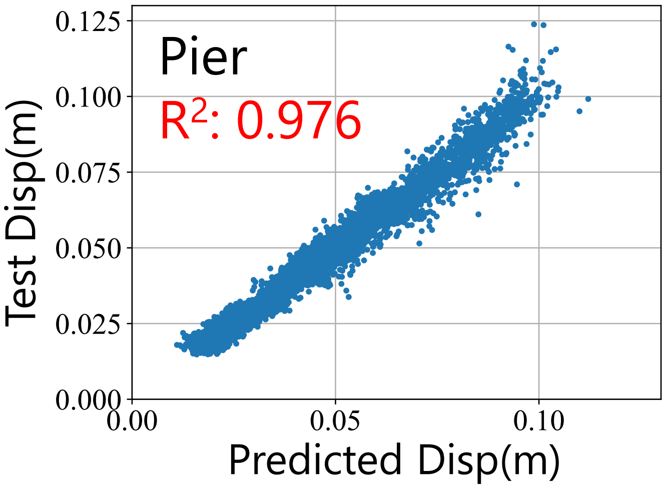
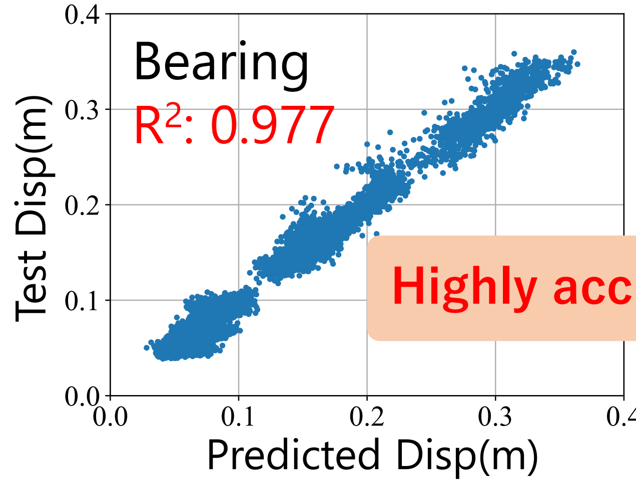
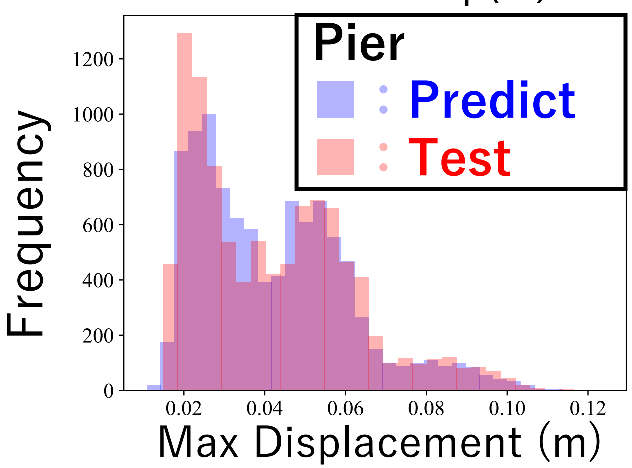
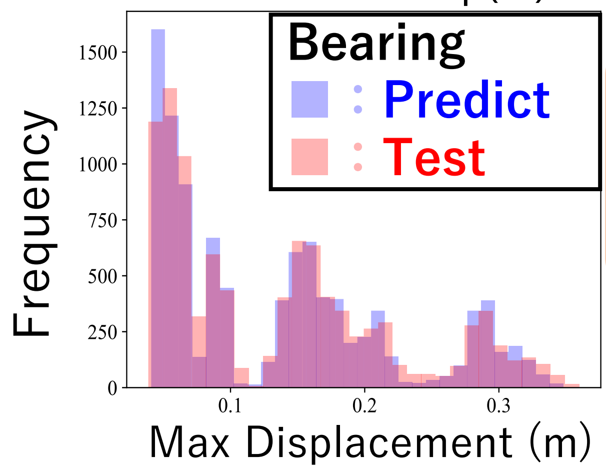




Highly accurate predictions.





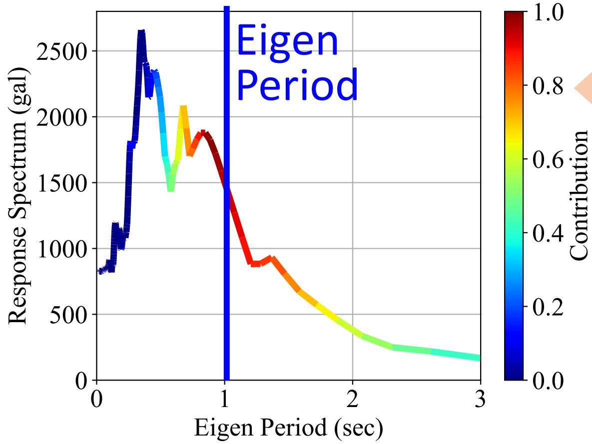
Max displacement distribution is predictable.

Surrogate models can predict with high accuracies

【Result】Estimated Contribution

Estimated Contribution to Pier's Max Disp

Train num：300　Test (from analysis) num：10000



High
Acceptability

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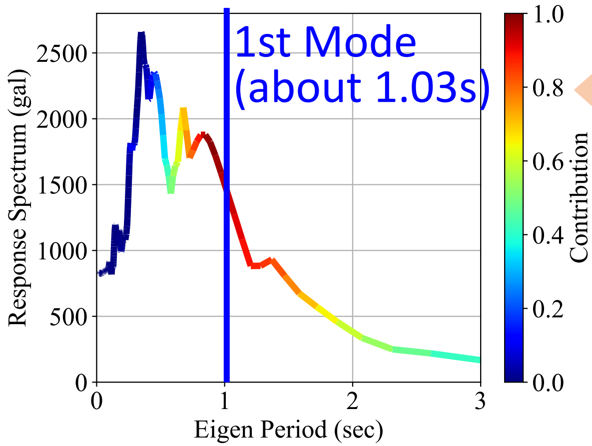
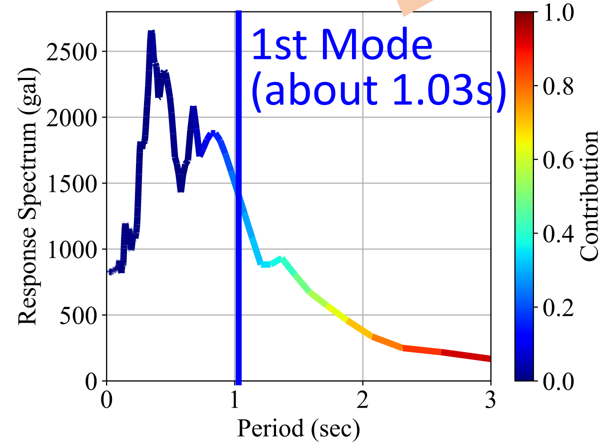


High Acceptability

Low Acceptability



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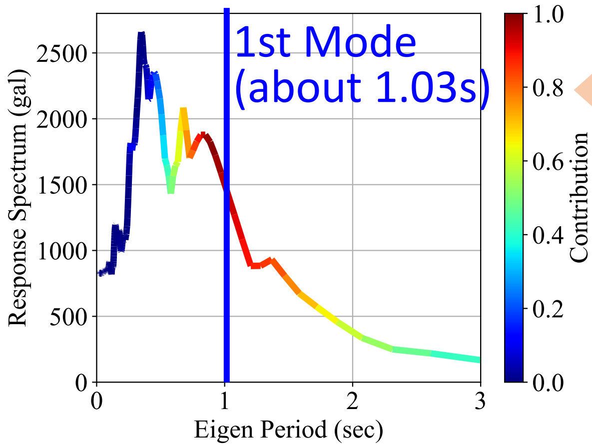

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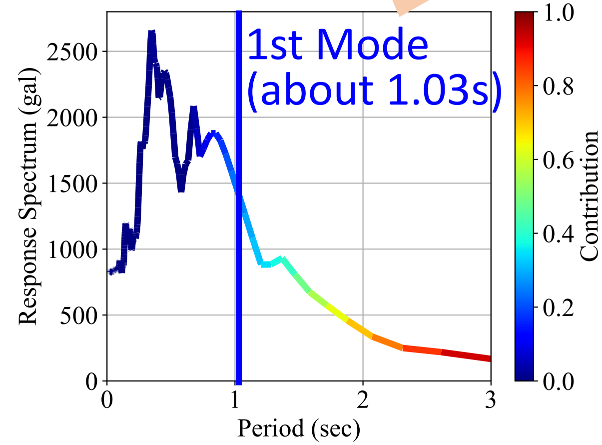

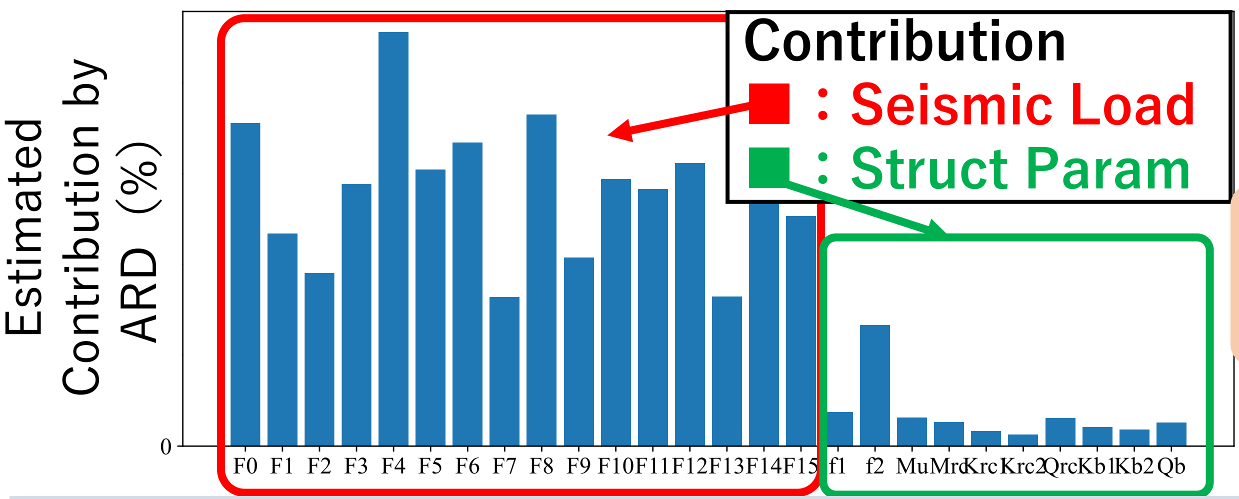

Large contribution from seismic loads

Contributions of seismic loads and structural parameters can be estimated

Conclusion and Future Works

Conclusion

- A surrogate model for seismic response analysis using deep kernel learning was constructed.
- Seismic load features were extracted by CNN.
- The contributions of seismic loads were estimated by Grad-CAM and structural parameters by ARD.
- The constructed surrogate model exceeded 0.97 in the R2 index, and the predicted distribution was qualitatively consistent with the test data.
- In some cases, the Grad-CAM showed a larger contribution close to the natural period, while in other cases it did not.
- The ARD-estimated contributions were in agreement with the engineering findings as well, with the external forces having a larger contribution.

Future Work

- Combined with adaptive sampling, which preferentially samples points that have a significant impact on the performance of the surrogate model, the computational cost could be further reduced

Thank you for listening.

Acknowledgement

This study was supported by the JST FOREST Program, Japan