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# Structural seismic response prediction based on physics-informed neural operators

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## ABSTRACT

Accurate prediction of structural dynamic responses under earthquake excitation is key to seismic analysis but can be computationally demanding when using high-fidelity finite element analysis (FEA). Data-driven deep learning models such as Long Short-Term Memory (LSTM) networks offer enhanced computational efficiency, however it requires substantial training data and do not generalise reliably to new ground motions. To overcome these challenges, this study proposes a Physics-Informed Neural Operator (PINO) framework for structural seismic response prediction. It learns the mapping operator from ground motion series to structural response series while incorporating the governing equations of motion into the loss formulation. By training on a small set of FEA-generated samples, the model integrates both data-driven learning and physical constraints. A comparison with LSTM models trained on the same limited dataset demonstrate the proposed PINO framework achieves significantly higher accuracy and robustness when extrapolating to unseen ground motions. Results demonstrate that PINO effectively captures the underlying physical relationships between seismic excitation and structural response, enabling superior generalisation with minimal data. Moreover, the developed surrogate model can be effectively applied to predict the structural response subjected to ground motions with diverse frequency characteristics and temporal resolutions. The proposed framework offers a promising pathway toward physics-guided surrogate modelling for efficient and generalisable structural response analysis.

## 1 INTRODUCTION

Predicting structural responses under earthquake excitation is a key component for assessing structural performance and safety. Traditionally, such predictions rely on finite element analysis (FEA) methods, in which the structural equations of motion are integrated step-by-step in time to obtain response histories. While

high-fidelity numerical simulations can effectively represent complex dynamic behaviours, their computational effort is substantial, particularly for large structural systems or multi-parameter sensitivity studies. Consequently, the practical use of FEA-based time-history analysis is constrained in scenarios requiring rapid response assessment (Noor, 2025).

In recent years, data-driven machine learning models have been regarded as a promising alternative for fast structural response prediction (Liu et al., 2025). Deep neural networks can be trained using numerical simulation or experimental data to learn mappings from seismic input characteristics to structural responses. Early studies widely adopted recurrent neural networks and their variants (e.g., long short-term memory (LSTM) and gated recurrent units (GRU)) to perform rapid inference from earthquake excitation to structural response by modelling dependencies among sequential data points. Liao et al., (2023) applied an attention-enhanced LSTM to model bridge seismic responses, and Xu et al., (2022) proposed a recursive LSTM that can predict nonlinear responses of structures for arbitrary time series lengths and sampling rates. However, such sequence models are typically sensitive to training sample size and often must be constructed and trained for a specific input dimension. This dependence limits their adaptability and scalability when the sampling frequency changes or structural/seismic conditions vary. Unlike conventional deep learning approaches that learn mappings between finite-dimensional vectors, neural operators aim to learn mappings between function spaces, directly characterising the operator form between input and output functions. Representative neural-operator approaches include DeepONet (Lu et al., 2021) and the Fourier Neural Operator (FNO, Zhou et al., 2023). FNO replaces conventional convolutional or recurrent structures with global convolutions in the Fourier domain, enabling efficient capture of long-range dependencies and approximation of complex operator mappings (Li et al., 2020). Meanwhile, FNO exhibits grid-invariant properties, facilitating improved transfer and generalisation across different input resolutions, thus enhancing its applicability to multiscale spatiotemporal modelling (Kovachki et al., 2023).

It should be noted that most deep learning methods are data-driven, usually requiring substantial number of high-quality training data; their generalisation performance may degrade when operating outside the training distribution (Zhou et al., 2025). Such black-box models often lack explicit physical interpretability and cannot guarantee consistency with established physical laws, which may lead to physically implausible predictions under extrapolative conditions. To alleviate this issue, physics-informed neural networks (PINNs) embed physical priors (e.g., governing equations, boundary conditions, or conservation laws) into the learning process, typically by introducing a physics loss term into the objective function (Raissi et al., 2019). This strategy enforces physical consistency and interpretability while fitting data. PINN architectures can improve training stability and prediction accuracy under limited data or noisy observations and are more likely to preserve physical plausibility when extrapolating to unseen parameters or operating conditions, thereby reducing the risk of unreliable predictions.

This study incorporates physics constraints into FNO during training and develops a Physics-Informed Neural Operator (PINO) for structural seismic response prediction, which embeds the governing structural dynamic equations into the loss function of the neural operator, thereby improving physical consistency and generalization. Compared with a purely data-driven FNO and a conventional LSTM model, the proposed PINO achieves higher predictive accuracy and demonstrates more robust generalisation under unseen seismic excitations.

## 2 PHYSICS-CONSTRAINED PINO FRAMEWORK

### 2.1 Problem Statement in Structural Dynamics

For a multi-degree-of-freedom (MDOF) structural system subjected to seismic excitation, the equation of motion can be expressed as:

$$\mathbf{M}\ddot{\mathbf{u}}(\mathbf{t}) + \mathbf{C}\dot{\mathbf{u}}(\mathbf{t}) + \mathbf{K}\mathbf{u}(\mathbf{t}) = -\mathbf{M}\mathbf{\Gamma}\ddot{\mathbf{u}}_g(\mathbf{t}) \quad (1)$$

where  $\mathbf{u}(\mathbf{t})$ ,  $\dot{\mathbf{u}}(\mathbf{t})$  and  $\ddot{\mathbf{u}}(\mathbf{t})$  denote the displacement, velocity and acceleration response vectors, respectively;  $\mathbf{M}$ ,  $\mathbf{C}$ , and  $\mathbf{K}$  are the mass, damping and stiffness matrices;  $\ddot{\mathbf{u}}_g(\mathbf{t})$  is the ground acceleration input; and  $\mathbf{\Gamma}$  is the seismic influence coefficient vector. Typically, the above dynamic equation is solved in the time domain using explicit or implicit integration schemes to obtain response histories. As a result, computational effort can become prohibitive for long-duration excitations or parameter analysis scenarios.

From the operator-learning perspective, this dynamical system can be regarded as a nonlinear operator  $\mathcal{G}$  mapping an input function space (ground-acceleration series) to an output function space (structural dynamic response series) (Goswami et al., 2025). Considering the intrinsic differential relationships among displacement, velocity and acceleration, the displacement responses are selected as the representative output.

$$\mathbf{u}(\mathbf{t}) = \mathcal{G}(\ddot{\mathbf{u}}_g(\mathbf{t})) \quad (2)$$

To approximate the nonlinear operator  $\mathcal{G}$ , a parameterized neural operator  $\mathcal{G}_\theta$  is introduced, over the input domain of interest,  $\mathcal{G}_\theta \approx \mathcal{G}$ , where  $\theta$  denotes trainable parameters. After training, applying  $\mathcal{G}_\theta$  to a given complete ground motion time history directly yields response sequences for all degrees of freedom (DOF), thereby avoiding step-by-step time integration during inference and significantly improving prediction efficiency.

## 2.2 Theory of the Fourier Neural Operator

The FNO is an operator-learning architecture inspired by Green's function methods and the convolution theorem, designed to efficiently learn mappings between function spaces. In operator theory, solution operators for many partial differential equations can be written in the form of an integral operator, for a given input function  $v(\mathbf{x})$ :

$$(\mathcal{K}v)(\mathbf{x}) = \int_D \kappa(\mathbf{x}, \mathbf{y})v(\mathbf{y})d\mathbf{y} \quad (3)$$

where  $D$  is the domain,  $\kappa(\mathbf{x}, \mathbf{y})$  represents the integral kernel function, and  $\mathcal{K}$  signifies the mapping operator from the input function space to the output function space. FNO parameterizes the kernel integral operator via multiplicative operations in Fourier space. The operator typically takes functions defined on regular, uniformly spaced grids and outputs target fields of interest as input (e.g., time-history responses).

As illustrated in Figure 1, a typical FNO network consists of three components: a lifting layer, a series of Fourier layers, and a projection layer. The lifting layer linearly maps a low-dimensional input to a higher-dimensional feature representation (Equation 4). Each Fourier layer performs a learnable spectral filtering on truncated low-frequency modes in the Fourier domain, fuses the result with a pointwise linear transformation in the physical domain, and then applies nonlinear activation to represent complex nonlinear operators (Equation 5). The projection layer maps the high-dimensional features back to the output space, producing vectors of desired output dimension to enable parallel prediction of multi-channel response time histories (Equation 6). The update rules for the lifting, Fourier, and projection layers are defined as follows:

$$\mathbf{v}_0(\mathbf{t}) = \mathbf{P}(\mathbf{v})(\mathbf{t}) = \phi(\mathbf{W}_0\mathbf{v}(\mathbf{t}) + \mathbf{b}_0) \quad (4)$$

$$\mathbf{v}_{l+1}(\mathbf{t}) = \sigma(\mathbf{W}_l\mathbf{v}_l(\mathbf{t}) + \mathcal{F}^{-1}(\mathbf{R}_l\mathcal{F}(\mathbf{v}_l))(\mathbf{t}) + \mathbf{c}_l), \quad l = 0, 1, \dots, L-1 \quad (5)$$

$$\hat{\mathbf{u}}(\mathbf{t}) = \mathbf{Q}(\mathbf{v}_L)(\mathbf{t}) = \mathbf{W}_2\psi(\mathbf{W}_1\mathbf{v}_L(\mathbf{t}) + \mathbf{b}_1) + \mathbf{b}_2 \quad (6)$$

where  $\phi(\cdot)$ ,  $\sigma(\cdot)$ , and  $\psi(\cdot)$  denote the nonlinear activation functions;  $\mathbf{W}_0$  and  $\mathbf{b}_0$  represent the trainable parameters of the lifting layer;  $\mathbf{W}_l$ ,  $\mathbf{R}_l$ , and  $\mathbf{c}_l$  are the pointwise linear transformation weights, spectral filtering

parameters and the bias term of the  $l$ -th Fourier layer, respectively;  $\mathcal{F}(\cdot)$  and  $\mathcal{F}^{-1}(\cdot)$  denote the Fourier transform and the inverse Fourier transform; and  $\mathbf{W}_1$ ,  $\mathbf{b}_1$ ,  $\mathbf{W}_2$ , and  $\mathbf{b}_2$  signify the trainable parameters of the projection layer.

A key advantage of FNO lies in its intrinsic global receptive field. Within a single spectral transform and filtering operation, information at any time point can interact (in Fourier space) with all other time points, enabling effective capture of long-range dependencies and global fluctuation characteristics, demonstrating superior efficiency and representational capacity in characterizing long-term correlations and holistic dynamical patterns.

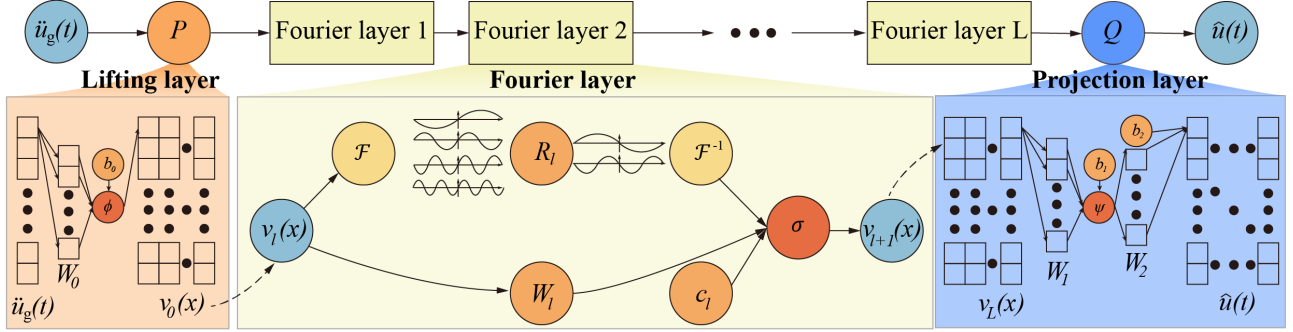


Figure 1: Schematic of the FNO architecture.

### 2.3 Physics-Integrated Loss Function

During training, a composite objective consisting of a data-fitting term and a physics-constraint term is employed to ensure both data fidelity and compliance with structural dynamics. The data-driven loss  $\mathcal{L}_{data}$  is defined as the mean squared error (MSE) between predicted and reference sequences and is normalized by the batch size  $B$ , number of DOFs  $N$ , and number of time steps  $T$ :

$$\mathcal{L}_{data} = \frac{1}{B} \sum_{i=1}^B \frac{1}{NT} \sum_{j=1}^T \|\hat{\mathbf{u}}_i(t_j) - \mathbf{u}_i(t_j)\|_2^2 \quad (7)$$

where  $\hat{\mathbf{u}}_i(\mathbf{t})$  denotes the predicted structural response for the  $i$ -th training sample and  $\mathbf{u}_i(\mathbf{t})$  denote the high-fidelity reference response obtained from FEA.

To explicitly incorporate prior physical knowledge, the structural equation of motion is further transformed into a physics-informed loss term that penalizes predictions violating dynamic behaviour. Given the relationships among acceleration, velocity, and displacement, a central-difference scheme is used to numerically approximate velocity and acceleration, which maintains second-order accuracy while mitigating instability induced by accumulated differencing errors. On this basis, the physics loss  $\mathcal{L}_{phy}$  is defined as the mean-squared norm of the residual of the equation of motion:

$$\mathcal{L}_{phy} = \frac{1}{B} \sum_{i=1}^B \frac{1}{NT} \sum_{j=1}^T \|\mathbf{M}\ddot{\hat{\mathbf{u}}}(t_j) + \mathbf{C}\dot{\hat{\mathbf{u}}}(t_j) + \mathbf{K}\hat{\mathbf{u}}(t_j) + \mathbf{M}\mathbf{f}_g(t_j)\|_2^2 \quad (8)$$

where  $\ddot{\hat{\mathbf{u}}}(t_j)$  and  $\dot{\hat{\mathbf{u}}}(t_j)$  denote the acceleration and velocity sequences obtained through central difference approximations, respectively. To simultaneously account for data fidelity and physical consistency, the total loss function is formulated as a weighted sum:

$$\mathcal{L}_{total} = \mathcal{L}_{data} + w_{phy}\mathcal{L}_{phy} \quad (9)$$

where the weighting coefficient  $w_{phy}$  is employed to regulate the intensity of the physical constraints; specifically, when  $w_{phy} = 0$ , the model reduces to a purely data-driven FNO. To effectively balance data loss and physical loss, a gradient-norm-based strategy is adopted to dynamically adjust the relative weights of the two loss components.

### 3 EXPERIMENTAL STUDY

#### 3.1 Dataset Description

To validate the proposed method, numerical experiments are conducted using a continuous girder bridge with a span arrangement of  $4 \times 40$  m as a case study. The piers are solid rectangular single-column piers with a height of 11.7 m, a longitudinal width of 1.3 m at the pier base, and a transverse width of 2.8 m. The structural layout is shown in Figure 2. The main girder uses C50 concrete, the piers use C35 concrete, and the foundations use C30 concrete; the longitudinal reinforcing steel in the piers is HRB400. The equivalent elastic stiffness of the bearings is 21,600 kN/m. In the finite element model, the girder, bearings, and piers are all simulated using elastic elements to obtain stable and accurate mass, damping and stiffness matrices. The full bridge model includes 58 nodes and 174 DOFs, incorporating horizontal and vertical translational DOFs as well as corresponding rotational DOFs. The pile-soil interaction is modelled using a six-spring model based on the  $m$ -method. Rayleigh damping is adopted in time-history analysis, with a modal damping ratio of 0.05.

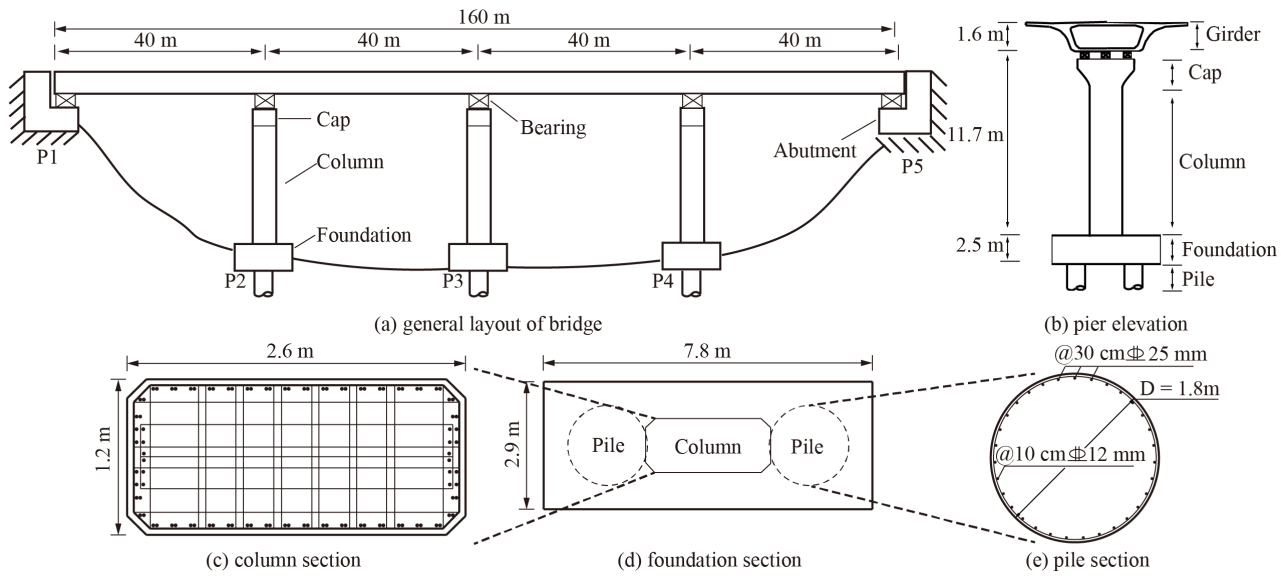


Figure 2: Structural layout and dimensions of the study bridge.

To enhance generalisation across different types of ground motions, 160 earthquake records selected by Baker et al., (2011). from the PEER ground-motion database are used as input excitations. The dataset comprises four categories of records covering different combinations of magnitude and source-to-site distance, reflecting site conditions such as hard rock and soil sites. For training and comparison, all records are standardized to a 50 s duration (via truncation or zero-padding) and resampled to a uniform time step of 0.01 s, resulting in 5000-time steps per record.

Each ground-motion record is applied to the case-study structure, and nonlinear time-history analysis is performed to compute nodal displacement response histories under different seismic inputs. Utilizing multi-process computing (with 10 processes), the construction of the seismic response database was achieved within

5 minutes. A dataset of 160 seismic-response simulations is generated, where each sample consists of an input ground-acceleration sequence and output structural displacement sequences. The dataset is randomly split into training, validation and testing subsets with a ratio of 7:2:1 for model training, hyperparameter selection, and generalisation evaluation. Since ground motion acceleration and structural displacement response differ substantially in units and magnitude, all inputs and outputs are standardized to avoid imbalance during training and to ensure consistent weighting across samples and dimensions in loss computation.

### 3.2 Model Training and Results

The proposed PINO is implemented in PyTorch and trained on a workstation equipped with an NVIDIA RTX 3060 GPU. The maximum number of training epochs is set to 100. The AdamW optimizer is employed with an initial learning rate of  $1 \times 10^{-3}$  and a weight decay of  $1 \times 10^{-5}$ . The batch size is set to 4. For quantitative and intuitive evaluation, the coefficient of determination  $R^2$  is used to assess generalisation and fitting accuracy on the test set. Figure 3 compares the average  $R^2$  for response prediction across all structural DOFs (174 in total) under different ground motions. The average  $R^2$  values of PINO on test cases exceed 0.94, indicating strong agreement between predicted response histories and high-fidelity references. Furthermore, Figure 4 presents displacement time-history comparisons at a main girder node and the top node of a middle pier. The predicted and reference responses match well in overall trends and peak characteristics, with  $R^2$  of 0.9925 and 0.9928, respectively, confirming high prediction accuracy at critical response locations.

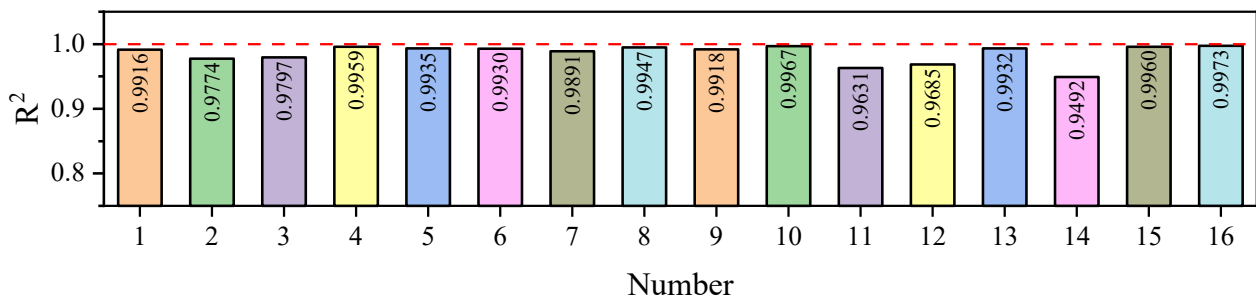


Figure 3: Average  $R^2$  values of displacement responses on the test set.

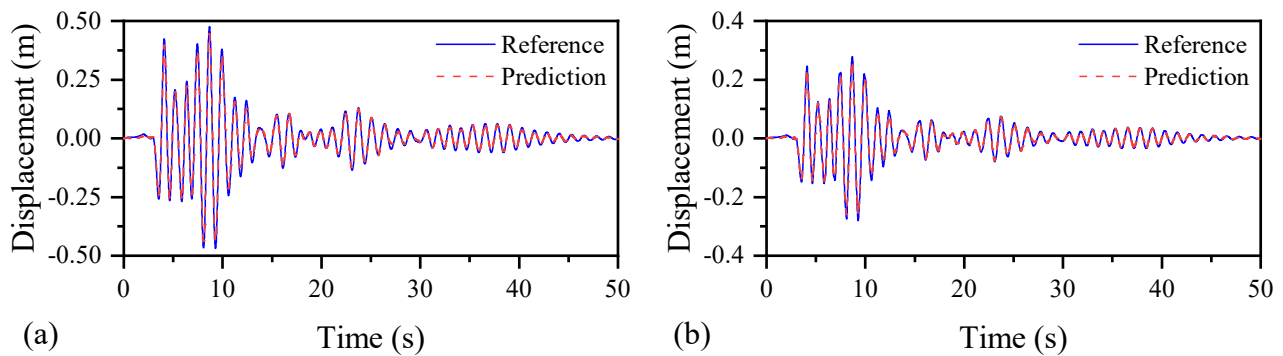


Figure 4: Comparison of predicted and reference displacement time histories at selected nodes: (a) main girder; (b) middle-pier top.

Notably, FNO exhibits the potential for zero-shot super-resolution, i.e., it can infer responses for inputs with different temporal discretization resolutions without additional retraining. To validate this property, Figure 5 compares predicted displacement time histories at the main girder node and the middle-pier top node under the same ground motion but with different sampling frequencies. Table 1 summarizes the average  $R^2$  of predicted responses under different sampling frequencies. The results show that prediction performance degrades slightly as the sampling frequency decreases but remains at a relatively high level overall. This degradation is attributed

to truncation of effective high-frequency components and possible spectral aliasing at lower sampling rates, which weakens the input signal's ability to represent high-frequency structural response features and thus affects prediction accuracy.

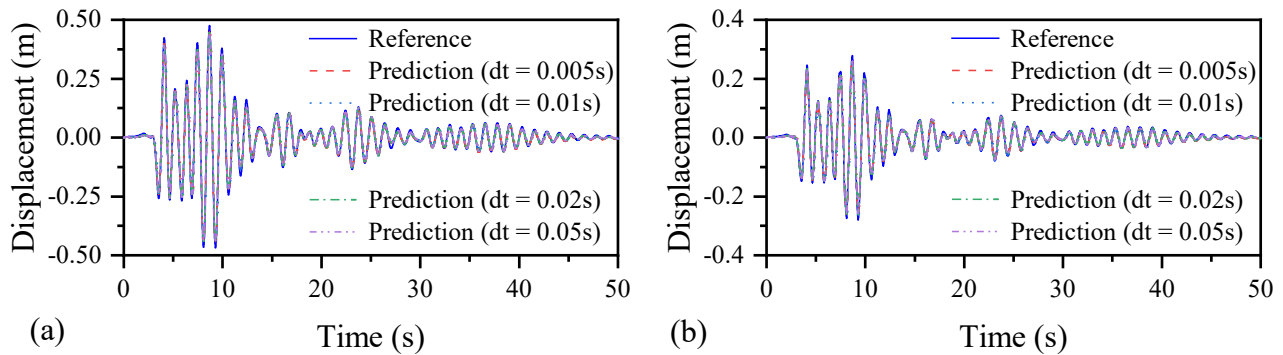


Figure 5: Comparison of node responses under earthquake excitations with varying sampling frequencies: (a) main girder; (b) middle-pier top.

Table 1: Average  $R^2$  values under different sampling frequencies.

| Sampling frequency | $R^2$  | Sampling frequency | $R^2$  |
|--------------------|--------|--------------------|--------|
| $f_s = 200$ Hz     | 0.9909 | $f_s = 50$ Hz      | 0.9865 |
| $f_s = 100$ Hz     | 0.9915 | $f_s = 20$ Hz      | 0.9653 |

### 3.3 Model Comparison

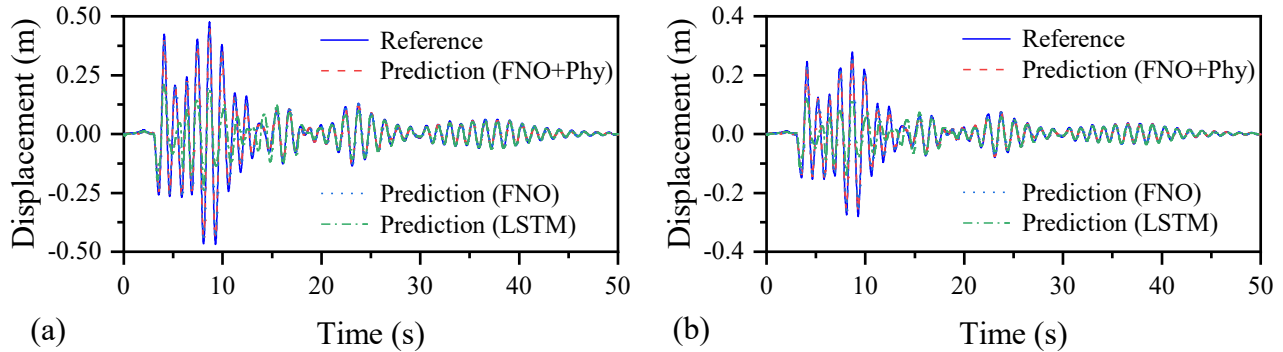
To comprehensively evaluate the predictive performance of the proposed PINO, two baseline models were considered: a standard FNO model and an LSTM model. The standard FNO shares the same network architecture and hyperparameter configuration as PINO; the primary difference is that its training objective excludes the physics-constraint term and is optimized purely by the data loss. To achieve a model complexity comparable to PINO, a 4-layer stacked LSTM is used with a hidden dimension of 64. Both baselines are trained on the same dataset as PINO under similar training procedures and the same hardware environment. Considering that sequence models often require more iterations to converge, the number of training epochs for the LSTM is set to 500.

Table 2 summarizes the  $R^2$  on the training, validation, and testing sets for all three models. Figure 6 further compares predicted displacement time histories at the main girder node and the middle-pier top node across different models. As shown in Table 2 and Figure 6, operator-learning models (FNO and PINO) significantly outperform the LSTM (test  $R^2 = 0.73$ ), while PINO achieves the highest  $R^2$  among the three (test  $R^2 = 0.98$ ). This performance gap arises because the dataset is relatively small, making it difficult for the parameter-heavy LSTM—whose learning of temporal patterns relies heavily on large data—to fully converge. In contrast, FNO leverages global convolutions in the Fourier domain to construct an inherent global receptive field, making it easier to extract overall vibration patterns between seismic input and structural response under limited samples and to improve prediction consistency across samples and DOFs, thus achieving higher and more robust accuracy. Further comparison between FNO and PINO indicates that PINO yields only a marginal improvement over FNO on the test set. This stems from the fact that the mapping from seismic input to MDOF displacement response is relatively regular and thus easier to learn under linear or weakly nonlinear dynamics. Consequently, the data-driven FNO already captures long-range dependencies and global response features

effectively, approaching a saturation level in accuracy, leaving limited room for additional gains from physics constraints.

*Table 2: Comparison of Average  $R^2$  values across different models.*

| Model | Train set | Valid set | Test set |
|-------|-----------|-----------|----------|
| LSTM  | 0.4805    | 0.7251    | 0.7316   |
| FNO   | 0.9794    | 0.9882    | 0.9853   |
| PINO  | 0.9801    | 0.9884    | 0.9857   |



*Figure 6: Comparison of node displacement time histories predicted by different algorithms: (a) main girder; (b) middle-pier top.*

Table 3 presents a comparative analysis of the computational overhead for different methods in the training and inference stages. Owing to a more prolonged convergence process (i.e., a greater number of training epochs), the training duration for the LSTM model significantly exceeds that of the other two algorithms. For the PINO model, the time consumption is slightly higher than that of the FNO algorithm because additional physics-informed loss terms must be evaluated during training. In the structural response prediction stage, the surrogate models demonstrate markedly higher computational efficiency than the FEA, with inference time amounting to only 17% of that required by FEA. It should be noted that the relatively limited FEA time observed in this study is attributable to the use of a linear elastic model. For complex nonlinear structures, the computational time of FEA increases significantly, whereas the inference time of surrogate models remains essentially constant; consequently, surrogate models are expected to exhibit even greater computational advantages.

*Table 3: Comparison of time consumption for different methods.*

| Method | Dataset preparation (s) | Training time (s) | Inference time (s / sample) |
|--------|-------------------------|-------------------|-----------------------------|
| FEA    | /                       | /                 | 15.7                        |
| LSTM   | 251.7                   | 935.7             | 2.4                         |
| FNO    | 251.7                   | 300.8             | 2.7                         |
| PINO   | 251.7                   | 394.9             | 2.7                         |

## 4 CONCLUSIONS

This study proposes a structural seismic response prediction framework based on PINO. By integrating the global mapping capability of the FNO with physics constraints derived from structural dynamic equations, the framework addresses the insufficient physical consistency often observed in traditional data-driven models. The main conclusions are summarized as follows:

(1) Operator learning models based on the FNO architecture offer substantial advantages for seismic response prediction in elastic structures. Compared to conventional sequence-based models such as LSTM networks, FNO demonstrates superior fitting accuracy and predictive robustness, particularly when training data is limited.

(2) PINO explicitly embeds physical constraints into the loss function, resulting in ensuring that predicted responses better satisfy dynamic mechanism constraints while maintaining numerical accuracy. Although physical regularization may not significantly enhance the absolute accuracy of the FNO for elastic structures, it substantially improves the physical interpretability of the prediction results.

(3) Leveraging the zero-shot super-resolution property of FNO, the model maintains cross-resolution generalisation capabilities when the sampling frequency of input ground motions varies. Without requiring additional retraining, it can accurately predict structural responses under seismic excitations of varying temporal resolutions.

## 5 ACKNOWLEDGEMENTS

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