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SPATIO-TEMPORAL DEEP LEARNING MODEL-AIDED SEISMIC FRAGILITY ANALYSIS OF LONG-SPAN BRIDGES CONSIDERING SPATIAL VARIABILITY OF GROUND MOTIONS

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Abstract. Structural fragility analysis plays a critical role in the assessment of infrastructures. This process commonly requires large numbers of nonlinear time history analyses via extremely time-consuming finite element simulations. Although booming deep learning (DL) techniques have been served as surrogate models to lessen computing burden, the previous DL surrogate models neglect the spatial variability of ground motions in response prediction for long-span bridges. Against this background, this paper proposes a spatio-temporal DL model for structural dynamic analysis of long-span bridges considering spatial variability of ground motions. In this model, convolution operations that can capture spatial features are integrated with gated recurrent unit (GRU) network with extraction capability of temporal features. Therefore, the spatial variability of ground motion is extracted through convolution, and the inherent temporal correlations within structural response is established via GRU. For validating the proposed spatio-temporal model, the prediction performance of this model was systematically evaluated through a case study involving a long-span cable-stayed bridge. Meanwhile, the traditional time series prediction model was used for comparison. Subsequently, the fragility analysis of bridge component was conducted, which further demonstrated the application feasibility of the proposed model for structural seismic fragility assessment. The results indicated that the proposed model could efficiently and accurately predicting the structural seismic responses and conducting fragility analysis considering spatial variability of ground motions.

1 INTRODUCTION

Driven by the growing demand for interregional connectivity in urban areas, transportation systems and lifeline infrastructure have undergone rapid development. The earthquake is a frequent natural hazard worldwide [1]. Among various infrastructure components, long-span bridges serve as key nodes within transportation networks and are particularly susceptible to seismic damage. Earthquake-induced failures of such structures may lead to partial or total collapse, causing not only substantial casualties and economic losses but also far-reaching societal disruptions [2, 3]. This underscores the urgent need for comprehensive investigations into the seismic performance of bridges to minimize structural damage and enhance safety during seismic events.

Conventional seismic analyses of bridges typically assume uniform ground motion across all supports, which is generally valid for small-span bridges. Nonetheless, this assumption is inconsistent with the actual situation for long-span and multi-point supported spatial structures such as long-span bridges. Given that the ground motions exhibit considerable spatial variability within a spatial range comparable to the length of long-span bridges. To explore the influence of these spatial effects on the seismic behavior of long-span bridges, researchers have carried out numerous numerical simulations [4, 5] and shaking table tests [6, 7]. The results indicated that it is essential to consider the spatial variability of ground motions in structural dynamic analysis and assessment for improving the seismic performance and safety of long-span bridges [8, 9, 10]. The traditional mechanics-based approaches such as finite element (FE) simulation are commonly used to conduct nonlinear time history analysis under seismic excitations. Nevertheless, such simulations are often computationally intensive and time-consuming, posing challenges for large-scale or real-time applications.

With the rapid advancement of deep learning (DL) technologies, an increasing number of researchers have investigated DL approaches as effective tools for predicting the seismic responses of bridge structures. Liao et al. [11] developed an attention-based long short-term memory (LSTM) neural network to forecast dynamic responses under previously unseen earthquake scenarios when the training data is limited. The proposed model's performance was comprehensively assessed using two types of bridges: a girder bridge and a cable-stayed bridge. Ning et al. [12] examined three distinct DL architectures, namely LSTM, WaveNet, and convolutional neural networks, to reconstruct seismic response time histories of bridges, which offers valuable insights for the community aiming to apply these models in generating accurate and efficient seismic time history predictions. Similarly, Yi et al. [13] established an enhanced DL network to analyze the random vibration behavior of bridges under a ground motion. This method was applied to forecast the seismic response of railroad cable-stayed bridges, and its reliability was thoroughly validated. Despite these advancements, the spatial variability of ground motions has rarely been considered as a part of the input in existing DL-based seismic prediction models.

Under this circumstance, a spatio-temporal DL model is proposed to conduct structural dynamic analysis of long-span bridges considering spatial variability of ground motions in this paper. In the model, convolution operations that can capture spatial features are integrated with gated recurrent unit (GRU) network with extraction capability of temporal features. Therefore, the spatial variability of ground motion is extracted through convolution, and the inherent temporal correlations within structural response is established via GRU. To validate the proposed spatio-temporal model, the dynamic responses prediction and fragility analysis of bridge component were conducted. The prediction performance of the model was systematically evaluated through a case study involving a long-span cable-stayed bridge. Meanwhile, the traditional time series prediction model was used for comparison.

2 SPATIO-TEMPORAL MODEL FOR STRUCTURAL DYNAMIC ANALYSIS

2.1 Time series prediction considering the spatial variability of ground motion

In conventional DL-based time series prediction for structural dynamics, the process typically begins with the collection of a sufficient amount of structural response data under seismic excitations.

To train a surrogate DL model that can effectively learn the intricate relationship between the ground motions and dynamic responses, these seismic excitations are then used as inputs, while the corresponding structural responses serve as outputs. Once trained, the surrogate model could accurately predict structural dynamic responses under unseen seismic earthquakes. However, the spatial variability of ground motions is not considered in traditional DL models; instead, a single seismic record time history is typically used as the sole input. For long-span bridges, the ground motions exhibit significant spatial variability, which dramatically affects the structural responses. Therefore, it is essential to incorporate this critical factor into DL-based time series prediction for structural dynamics. To address this issue, a novel spatio-temporal model is devised to capture the underlying spatial correlations of ground motions across all supports in this study. The diagram of the proposed method is illustrated in Figure 1. The multiple ground motions with spatial variability are inputted into the spatio-temporal model, various types of structural responses such as the displacement of bearings and the curvature of pylons would be simultaneously outputted in real time.

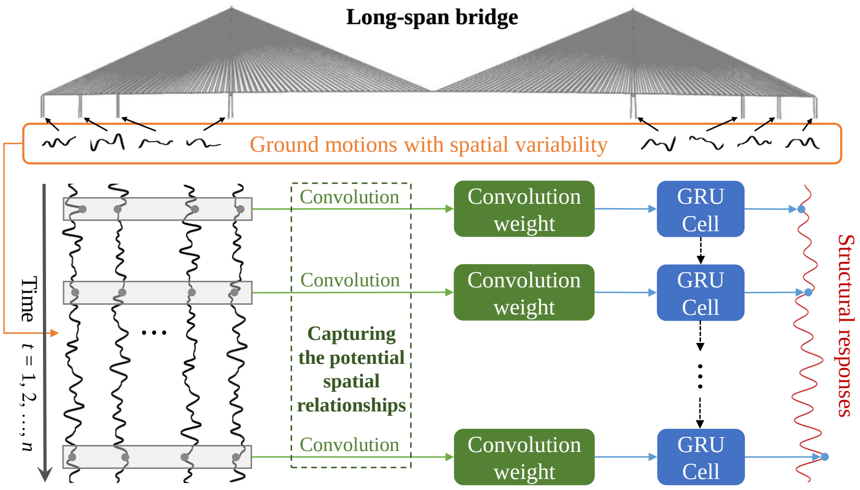


Figure 1: Diagram of the proposed method

2.2 The proposed spatio-temporal model

The essence of the proposed approach lies in extracting the spatial variability of ground motions through convolution operations and subsequently embedding these spatial features into a GRU network for time series prediction of structural responses. Inspired by the work of Shi et al. [14], this work substitutes the standard fully connections used for transitions within the GRU architecture with convolutional operations to encode spatial information from the input. Unlike typical image-based applications where spatial features are captured in two-dimensional space, the spatial variability of ground motions in this context is inherently one-dimensional. Accordingly, one-dimensional convolutional operations are adopted to accommodate the characteristic of the input data. With these modifications, the conventional GRU equations are reformulated as follows:

$$\mathbf{Z}_t = \sigma\left(\mathbf{W}_{xz} * \mathbf{X}_t + \mathbf{W}_{hz} * \mathbf{H}_{t-1} + \mathbf{b}_z\right) \tag{1}$$

$$\mathbf{R}_t = \sigma\left(\mathbf{W}_{xr} * \mathbf{X}_t + \mathbf{W}_{hr} * \mathbf{H}_{t-1} + \mathbf{b}_r\right) \tag{2}$$

$$\tilde{\mathbf{H}}_t = \tanh\left(\mathbf{W}_{xh} * \mathbf{X}_t + \mathbf{W}_{hh} * (\mathbf{R}_t \circ \mathbf{H}_{t-1}) + \mathbf{b}_h\right) \tag{3}$$

$$\mathbf{H}_t = (1 - \mathbf{Z}_t) \circ \mathbf{H}_{t-1} + \mathbf{Z}_t \circ \tilde{\mathbf{H}}_t \tag{4}$$

in which $\mathbf{Z}_t$ and $\mathbf{R}_t$ denotes the states of the update gate and reset gate at the tth time, respectively; $\tilde{\mathbf{H}}_t$ and $\mathbf{H}_t$ are the updated hidden state and hidden state at the tth time; $\mathbf{b}_z$, $\mathbf{b}_r$, and $\mathbf{b}_h$ are bias parameters; $\mathbf{W}_{xz}$, $\mathbf{W}_{hz}$, $\mathbf{W}_{xr}$, $\mathbf{W}_{hr}$, $\mathbf{W}_{xh}$ and $\mathbf{W}_{hh}$ are convolutional weight parameters; $\tanh$ denotes the hyperbolic tangent function; $\sigma()$ represents the logistic sigmoid function; $*$ denotes the convolution operator; $\circ$ represents the element-wise product of vectors.

Furthermore, it should be pointed out that an additional critical design of the proposed model is the dual-branch input structure. Specifically, the seismic excitations are fed into two independent network branches without weight sharing. These branches are designed to separately perform linear and nonlinear mappings, thus enabling the model to fully exploit the information contained in the input data. The primary distinction between the two branches is the use of the rectified linear unit (ReLU) activation function, which is applied only in the nonlinear branch. Following the individual processing, the outputs from both branches are combined using an adaptive weighting mechanism. This weight parameter β is dynamically optimized through gradient descent during model training to ensure optimal predictive performance. The final output of the model is obtained by aggregating the results of the two branches via this learnable adaptive weight:

$$\mathbf{y} = D\left[\mathbf{x}|\beta, \mathbf{w}, \mathbf{b}\right] = \beta \cdot D_L\left(\mathbf{x}|\mathbf{w}_L, \mathbf{b}_L\right) + (1-\beta) \cdot D_N\left(\mathbf{x}|\mathbf{w}_N, \mathbf{b}_N\right) \tag{5}$$

in which $\mathbf{x}$ and $\mathbf{y}$ are seismic excitations and structural responses, respectively; D_L and D_N represent the linear and nonlinear network branches, respectively; $(\mathbf{w}_L, \mathbf{b}_L)$ and $(\mathbf{w}_N, \mathbf{b}_N)$ denote model weight and bias of the linear and nonlinear network branches, respectively.

3 CASE STUDY

3.1 Description of Sutong Bridge

The Sutong Bridge in China has been extensively documented in terms of numerical modeling, making it one of the most widespread case studies in the field of long-span bridge [15, 16]. Accordingly, this study adopts the Sutong Bridge as the prototype structure. The main bridge comprises a twin-pylon double-plane full-floating system cable-stayed bridge with a main span of 1088 m. Each side span is supported by three piers, and the overall span configuration is arranged as 100+100+300+1088+300+100+100=2088 m. The pylons with a total height of 300 m adopt an inverted Y-shaped configuration and a lower crossbeam beneath the girder. The pylon columns with a hollow box-section design are built using C50 concrete. From a structural systems perspective, the bridge solely installs lateral wind-resistant bearings and longitudinal viscous dampers between the pylons and the girders, omitting vertical bearings. Conversely, vertical bearings are placed between the girder and the piers, enabling longitudinal slide while constraining lateral movement. The cables are constructed from 1770 MPa parallel wire strands.

3.2 Numerical model of Sutong Bridge

In this study, the FE model of the Sutong Bridge is composed of four primary structural components: the girders, cables, piers, and pylons. The model incorporates geometric stiffness effects induced by dead loads. To simplify the modeling processes, the bases of the pylons and piers are assumed to be rigidly fixed, thereby neglecting the influence of soil-structure interaction on the seismic behavior of the bridge [17]. The cable anchorage points are rigidly connected to the corresponding girder nodes. The bearings are modeled using Two-Node Link element with an ideal elastic-plastic constitutive relationship. The restraining behavior of longitudinal sliding bearings and transverse fixed bearings is simulated by specifying stiffness values for the elements in all three directions. The FE model includes 1033 nodes and 719 elements, as illustrated in Figure 2.

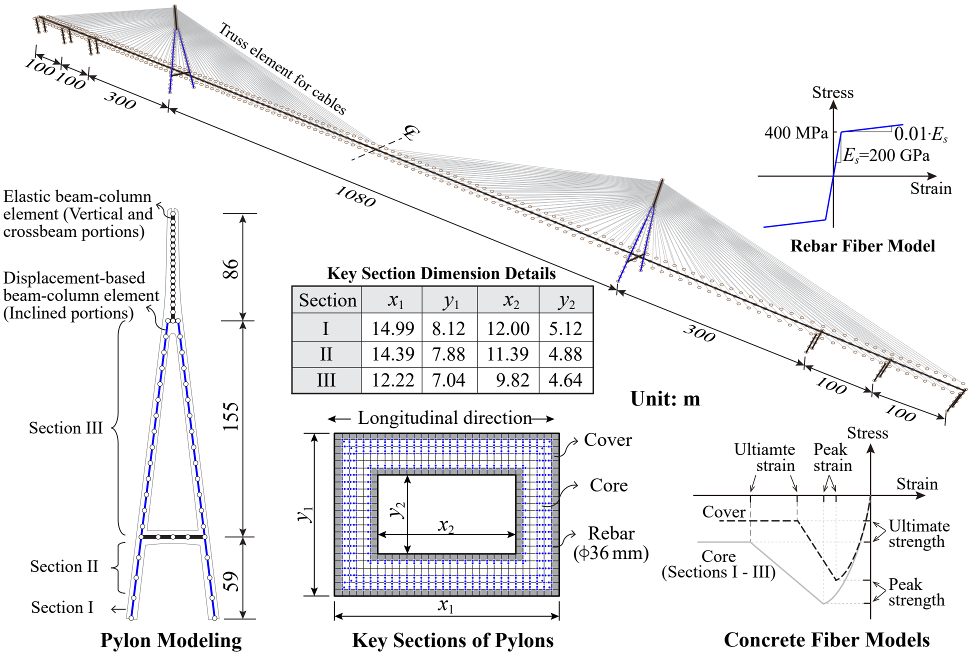


Figure 2: Finite element model of the Sutong Bridge

The girder is modeled using the Elastic Beam Column element in OpenSees, with material properties such as Young's modulus and shear modulus derived from theoretical values specified in the design documents. Given that the piers have negligible influence on the lateral seismic behavior of the pylons, they are also simulated using Elastic Beam Column elements to accelerate the computation. For the modeling of cables, the Beam With Hinges element is adopted, and the sag effect is incorporated by reducing the elastic modulus accordingly. In regions such as the cable anchorage zones and the crossbeam of the pylons, enhanced reinforcement ratios or high-strength prestressed tendons are typically used to ensure reliable force transmission. As these components are expected to remain within the elastic stage during seismic events, they are likewise modeled with Elastic Beam Column elements [17]. The lower segments of the pylon columns, situated below the bifurcation point, are simulated using displacement-based Nonlinear Beam Column elements. The fiber elements are defined with three distinct types of cross-sections, whose geometric dimensions, reinforcement layouts, and concrete configurations are illustrated in Figure 2. Accurately capturing the lateral elastoplastic behavior of the concrete pylons requires appropriate constitutive models for both steel reinforcement and concrete. The reinforcement is modeled using a bilinear kinematic hardening material, characterized by a yield strength of 400 MPa, an elastic modulus of 200 GPa, and a hardening ratio of 0.01. For the concrete, the Kent-Park model [18] is employed to simulate its nonlinear stress-strain relationship.

3.3 Random field generation of ground motion

To conduct numerical simulations for generating the training dataset of DL model, it is necessary to initially generate ground motions with spatial variability. In this study, the spatial variability of ground motions is simulated considering the comprehensive effects of wave propagation, site response, and incoherence effects. The detailed principles are omitted and are available in the reference [19]. After the seismic design intensity and other parameters are determined according to the site conditions of the Sutong Bridge, a total of 300 groups of ground motion acceleration time histories were generated at multiple excitation points using a MATLAB program for stochastic ground motion simulation. The program is primarily combined the theories about the spatial variability of ground motions with a stratified sampling approach to produce random samples of ground motion time histories with probabilistic characteristics. It should be noted that, to ensure stable results in structural dynamic analysis, displacement time histories of ground motions are generally required as load inputs when the multi-support excitation pattern is employed in OpenSees.

Subsequently, the acceleration time histories of all ground motions are transformed into displacement time histories. The 300 groups of ground motions are then transversely applied to the FE model of the Sutong Bridge to perform nonlinear time history analysis. The duration of all earthquake records is 50 s, resulting in structural responses with 5000 time steps under a sampling frequency of 100 Hz. For preliminary validation of the proposed model, only the curvature time histories of the two bridge pylons are selected as outputs in this case study. In practice, various types of structural responses can be configured as model outputs during training, enabling the model to simultaneously predict multiple responses types. Consequently, the dimensions of the ground motions and structural responses are [300, 8, 5000] and [300, 2, 5000], respectively. Finally, the entire dataset is randomly divided into 240 samples for training, 30 samples for validation, and 60 samples for testing.

3.4 Model training

The performance of DL models heavily depends on both the network architecture and the selection of hyperparameters, including the number of layers, hidden units, learning rate, dropout rate, and other configurations. In this study, the architectures and hyperparameters for all DL models are determined through a combination of trial-and-error methods and the use of the ”Optuna” software, which employs Bayesian optimization algorithms [20].

The proposed spatio-temporal model, which is referred to as ConvGRU, has two network branches. The nonlinear branch comprises a GRU layer enhanced with one-dimensional convolution operations, a dropout layer, a flatten layer, and an output layer. The GRU layer employs 100 hidden units with a convolutional kernel size of 5. A ReLU activation function is applied after the GRU layer to introduce nonlinearity. To mitigate overfitting, the dropout layer with a dropout rate of 0.3 is incorporated. Since a four-dimensional input is required in the ConvGRU model, the flatten layer should be used for dimensionality reduction prior to output. The hidden cells of the output layer correspond to the number of predicted structural responses. In contrast, the linear branch shares an identical structure with the nonlinear branch, except that no activation function is applied after the GRU layer.

To assess the performance of the proposed model, two conventional GRU-based time series prediction models are employed as a baseline for comparison. Two different input strategies are considered to evaluate the influence of the spatial variability of ground motions. In the first strategy (GRU1), only the ground motion time history at the first support point is used as input, resulting in an input shape of [300, 5000, 1]. In the second strategy (GRU2), the ground motion time histories from all eight support points are utilized as multi-feature inputs, with an input shape of [300, 5000, 8]. It should be mentioned that the GRU2 model does not explicitly learn the spatial relationships among the eight ground motions. Rather, it treats them as multiple features within the same time series. Both GRU1 and GRU2 adopt the same model architecture and hyperparameters, consisting of two GRU layers, two dropout layers, and an output layer. Each GRU layer includes 100 hidden units, followed by a ReLU activation function and a dropout layer with a dropout rate of 0.3. The number of neurons in the output layer is determined by the number of structural responses.

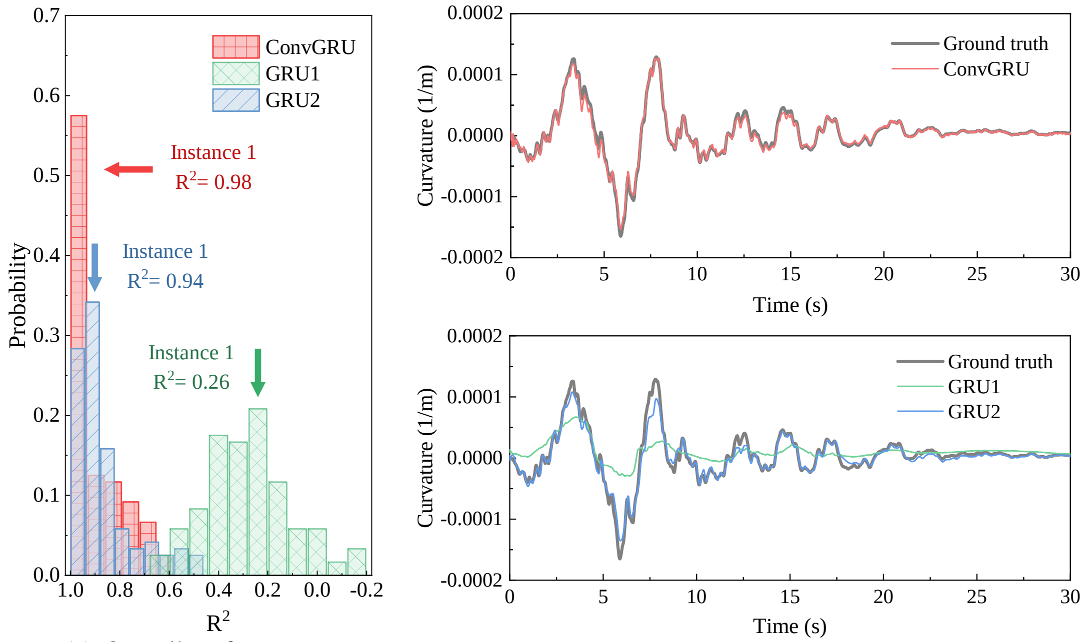
Regarding other hyperparameters, the ConvGRU, GRU1, and GRU2 models all employ the Adaptive Moment Estimation (Adam) optimizer, with an initial learning rate set to 0.001 and a decay rate of 0.0001. The batch size and maximum number of training epochs are chosen as 32 and 2000, respectively. The mean squared error (MSE) is adopted as the loss function across these networks. Prior to training, the input data are normalized to the range of [-1, 1] using the MinMaxScaler function, aiming to eliminate dimensional inconsistencies among various input features and accelerate the convergence of network optimization. All models are trained based on the Pytorch framework of the Python environment in the computer configured with a 13th Gen Intel Core i7-13700KF CPU and a NIVIDIA GeForce RTX 4070 GPU. To prevent overfitting and enhance the generalization performance, model parameters are saved based on the lowest validation loss observed during training through continuously monitoring the model's performance on the validation dataset across all epochs.

4 RESULTS AND DISCUSSION

4.1 Prediction of structural dynamic responses

To evaluate the effectiveness and accuracy of the proposed methods, the predicted results from all trained models on the test dataset are compared against the responses obtained from numerical simulations. In this work, the coefficient of determination (R^2) between the predicted and actual response series is employed as a metric to quantify the overall prediction performance [12].

Figure 3 presents the comparison results between the simulated bridge responses and the predictions for the three models. As observed in Figure 3(a), the GRU1 model exhibits the poorest performance among the three models, with the R^2 values of all test samples remaining below 0.7. This suggests that a single ground motion input fails to provide sufficient information to accurately establish the complex relationship between seismic excitations and structural responses. In contrast, the GRU2 model, which incorporates the spatial variability of ground motions during training, shows a notable enhancement in predictive accuracy, underscoring the significant influence of accounting for spatial effects in improving seismic response predictions. Furthermore, the ConvGRU model achieves superior prediction accuracy and generalization capability, demonstrating the effectiveness and robustness of the proposed approach. Specifically, for instance 1, the ConvGRU model's predictions align closely with the ground truth. While the GRU1 model can roughly capture the overall trend of the structural response, it struggles to accurately reproduce the specific response values at each time step. By contrast, the GRU2 model achieves better phase synchronization with the ground truth, it consistently underestimates the amplitudes at peak values.



(a) Overall performance

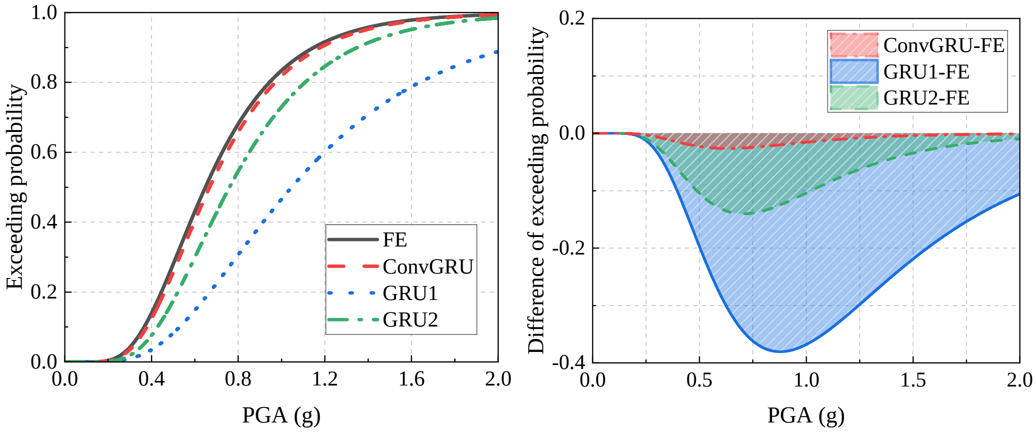
(b) Curvature time history for instance 1

Figure 3: Comparison of various DL models on prediction performance

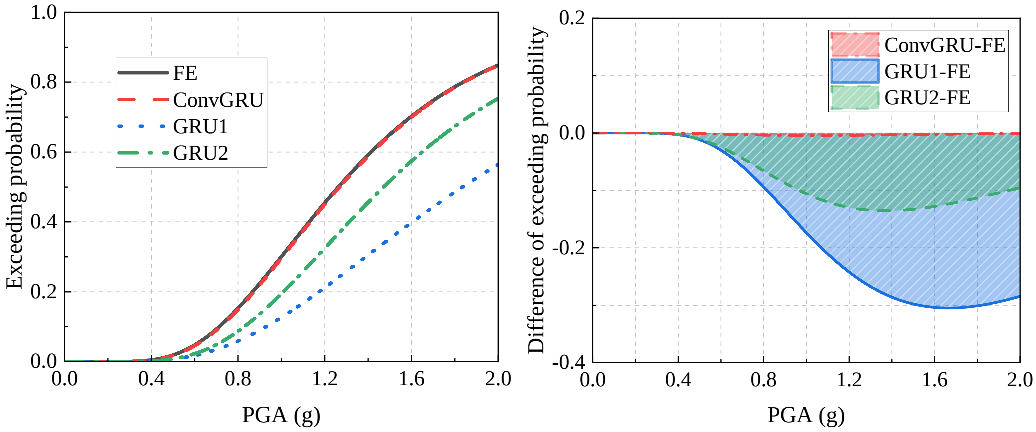
4.2 Fragility analysis

After that, the fragility analysis of pylons is performed based on diverse DL models. The pylon primarily bears axial forces and bending moments, so its damage index is represented by the curvature ductility coefficient, which is defined as the ratio of the maximum curvature to initial yield curvature under seismic loads. The thresholds for different damage states of the pylons are adopted from the quantitative description established in previous study [21].

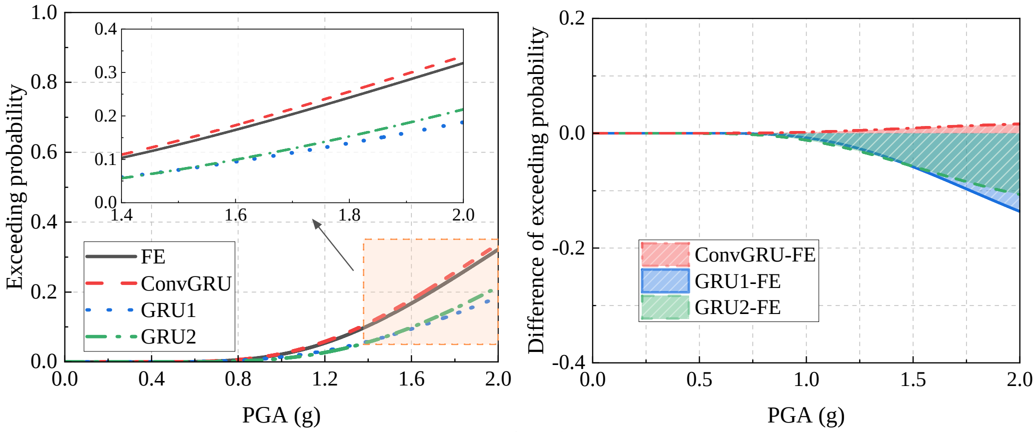
According to the demand models generated by the three models in conjunction with the predefined damage states, fragility curves are constructed and presented in Figure 4. To more intuitively illustrate the accuracy of the fragility curves based on the ConvGRU model, the discrepancies of fragility curves between the FE model and different DL models are also displayed in Figure 4. It is observed that the fragility curves generated by the ConvGRU model outperform those obtained from the GRU1 and GRU2 models, except for the complete damage condition. Since the values of exceeding probability under the complete damage condition is small, there is little difference yielded by all models. Additionally, for the extensive and complete damage states, the fragility calculated by the ConvGRU model are marginally higher than those derived from the FE simulations, introducing a desirable conservatism in practical engineering applications. Conversely, the GRU1- and GRU2-based fragility curves underestimate the probability of exceedance, causing significant risks to the structural safety. The differences of exceeding probability clearly highlight the superior predictive capability of the proposed method over GRU1 and demonstrate its notable advantage in terms of accuracy compared to GRU2. Specifically, the error of exceedance probability for the GRU1-based fragilities is almost reach up to 40%, while for the ConvGRU model, all errors remain within 3%.



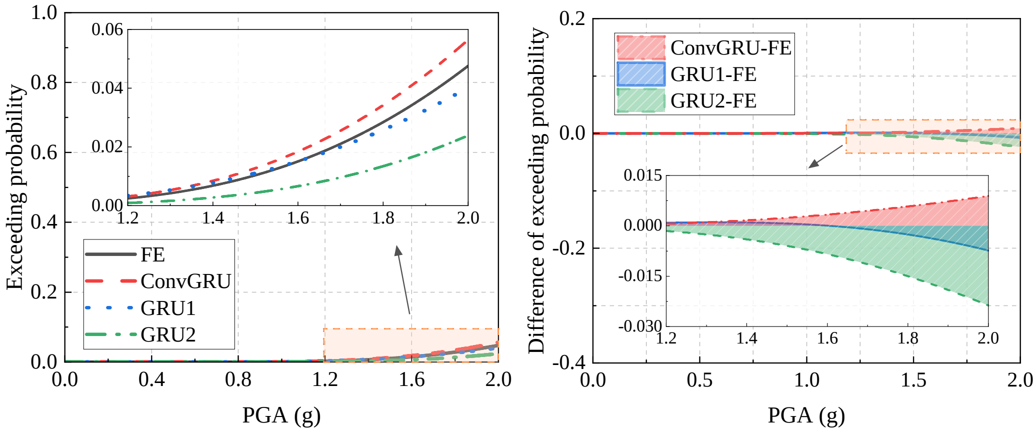
(a) Slight damage



(b) Moderate damage



(c) Extensive damage



(d) Complete damage

Figure 4: Comparison of various DL models on fragility analysis

5 CONCLUSIONS

- By incorporating the spatial variability of ground motions, the DL model achieves notable improvement in both prediction accuracy and reliability. The distribution of R^2 becomes more concentrated, with a general increase in their values. Correspondingly, in the fragility analysis, the error of exceeding probability likewise displays a pronounced decrease.

- Compared with conventional time-series prediction approaches, the proposed spatio-temporal method demonstrates remarkable advantages in both precision and robustness, highlighting its ability to capture and utilize the intrinsic spatial relationships of ground motions at different locations. Notably, for all damage states, the fragility analysis based on the proposed model maintain the errors of exceedance probability within a margin of 3%.

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