

Research on innovative hybrid analysis method for structural seismic response based on neural network restoring force model

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ABSTRACT Quasi-static testing is the primary seismic research method employed. The method proposed in this study utilizes the neural network (NN) algorithm for restoring force identification to extend the hysteretic performance of nonlinear complex components obtained from quasi-static tests shared or performed at a lower cost to the time history analysis of the seismic response of the entire structure. This approach enables accurate analysis of the seismic performance of the structure under real earthquake ground motions at a relatively low experimental costs. At the level of restoring force model recognition, the eight-path hysteresis model recognition theory and the corresponding complete set of input and output variables in the NN algorithm are proposed. The NN restoring force model was established using input and output parameters that characterize hysteresis state features, with a two-hidden-layer NN architecture. The case study results indicate that the prediction results of the NN restoring force model align well with the target values when trained on samples obtained under both seismic and quasi-static loading conditions. At the level of the nonlinear dynamic analysis of structures, the hybrid analysis method of structural seismic response based on NN restoring force model is proposed. In this method, the potentially severe nonlinear and elastic parts of the structure are divided into several NN substructures and principal numerical substructure, respectively. The pseudo-static test data of nonlinear regions were used to train the proposed NN restoring force model to identify the restoring force of NN substructures in the same region under time-history dynamic analysis. The platform was built to complete the data interaction between several NN substructures and principal numerical substructures, and a precise integration method was used to program the dynamic equation solving module, gradually completing dynamic response analysis of the entire structure. A multi-degree-of-freedom nonlinear frame case study indicate that the proposed method has good accuracy and can effectively analyze the structural nonlinear seismic response.

KEYWORDS restoring force model, neural network algorithm, module programming, hybrid analysis method, nonlinear dynamic analysis

1 Introduction

Engineering structures often exhibit extensive dynamic responses under strong earthquakes. The structural seismic performance design requires accurate and

efficient analysis methods. The dynamic response of the entire structure is usually controlled by the inelastic behavior of the key components or regions, and the accuracy of the nonlinear restoring force model of these key components is the main factor affecting the accuracy of the dynamic response analysis [1]. To improve the

accuracy and efficiency of structural seismic analysis, it is of great practical significance and application value to investigate the identification method of the restoring force model of the key components with serious nonlinearity and establish a high-precision and high-efficiency dynamic response analysis method for the entire structure.

Currently, commonly used constitutive models are provided in the form of empirical or fitting formulas based on certain assumptions [2,3]. Some key nonlinear factors (such as the post-cracking characteristics of concrete and the stress hysteresis effect of reinforced components after earthquakes) are difficult to fully and accurately consider in numerical constitutive models [4]. Additionally, with the proliferation of new materials and structural forms, traditional methods can no longer fully meet the demands of technological advancement. The key reasons are: on one hand, constructing reasonable and accurate nonlinear constitutive equations is extremely difficult and time-consuming, causing research to lag behind practical engineering applications. On the other hand, detailed and complex constitutive models place higher demands on the robustness and efficiency of numerical implementation algorithms [5]. The generalized constitutive model includes the relationship between the stress and strain at the material level and that between the restoring force and displacement at the component level [1]. Given that the nonlinear restoring force model at the component level is difficult to identify accurately, the pseudo-dynamic test uses the computer to solve the dynamic equation of the structure and directly obtains the resilience from the test [6]. Considering that only some key components of the actual structure enter a nonlinear failure state under earthquake, whereas most of the other structures or components maintain the elastic state [7]. Nakashima and Takai [8] proposed substructure technology and applied it to a pseudo-dynamic test. The substructure pseudo-dynamic test method divides the structure into two parts: the experimental and numerical substructures. Synchronous loading tests were performed on the test substructure, and data interaction was carried out with the numerical substructure through network data transmission to complete the dynamic response analysis of the entire structure [9,10]. Accordingly, several open-source hybrid simulation frameworks, such as OpenFresco [11] and UI-SimCor [12], have been widely used. However, this method is usually limited by the number of experimental substructures, laboratory conditions and scale for complex structures and is faced with nonlinear control, time delay, and compensation of actuators [13,14].

In recent years, the rapid development of deep neural network (NN) models has provided new technological means for applied research in multiple fields of structural engineering [15–17], including multi-level computational

analysis of materials [18–20], components [21–23], and systems [24,25], as well as the fields of engineering operation and maintenance [26–28]. Given the difficulties and costs associated with obtaining accurate constitutive or hysteretic models, NN models, with their exceptional performance and ability to approximate complex nonlinear relationships, can theoretically serve as surrogate models for hysteretic responses [29–31]. Scholars in this field have established data-driven constitutive surrogate models to learn and derive the constitutive relationships of novel materials. These models include the shear constitutive model [32], soil constitutive model [33,34] and rate-dependent material constitutive model [35], all of which are capable of capturing complex material behavior using stress and strain data from experiments or simulations. The same approach can also be used to identify the hysteretic behavior of the structural components. For the component-level restoring force model, Kim et al. [36,37] developed a comprehensive NN model to predict the complex hysteretic behavior of beam-column connections under cyclic loading. Yun et al. [38] recognized the hysteretic model of steel frame connections based on the NN algorithm, and the numerical simulation results showed that the NN algorithm can identify the stiffness degradation of the hysteretic curve and contraction of the hysteretic loop. Gu et al. [21] proposed a deep ensemble learning-driven method combining long short-term memory and explicit hysteresis models to extract structural behavior features and predict key parameters, achieving improved generalization and accuracy compared to traditional data-driven approaches. Wang et al. [39] proposed the DeepSNA framework, an end-to-end deep learning method for structural nonlinear analysis, validated on steel plate shear walls. Horton et al. [40] utilized forward-feed NNs to predict the parameters of the modified Ibarra-Krawinkler model for reduced beam section connections, achieving high accuracy in modeling cyclic hysteresis behavior. Additionally, Xu et al. [41] proposed the novel training strategy for identifying hysteretic behavior.

The above research findings demonstrate that the NN restoring force identification method provides a new approach, in addition to numerical simulation and substructure test loading, which can learn and predict the hysteretic behavior. This identification method holds significant application value for components whose constitutive or hysteretic models are unknown or difficult to explicitly express through functional relationships. However, the above studies rarely focus on the integration between the identification of local component hysteretic behavior and the computation of the entire structure, and most deep NN models are trained and predicted based on large amounts of finite element simulation data. Given that current seismic research still

primarily relies on pseudo-static tests, this study aims to use hysteresis data obtained from pseudo-static tests of components to train the developed NN model and to establish an interface between local component identification and overall structural analysis, thereby extending the low-cycle test results of local component to the dynamic analysis of the entire structure.

This study develops an NN restoring force model with new input variables and establishes a method of structural dynamic response analysis, referring to the concept of substructure test. At the level of restoring force model recognition, the eight-path hysteresis model recognition theory and the corresponding complete set of input and output variables in the NN model are proposed. At the structural analysis level, a hybrid seismic response analysis method based on the NN restoring force model is proposed. In this method, the potentially severe nonlinear region and the elastic region of the complete structure are divided into several NN substructures and principal numerical substructure, respectively. The hysteretic behavior of NN substructure is identified by trained NN restoring force model, and the restoring force of numerical substructure is directly obtained according to elastic constitutive relation. The data interaction platform between each substructure is constructed, and the dynamic differential equation is solved step by step under the closed-loop calculation to realize the analysis and calculation of the dynamic response of the entire structure. Current seismic research primarily relies on pseudo-static tests. The proposed method uses the NN algorithm to identify the restoring force and extends the hysteretic behavior research results of component obtained from the pseudo-static test to the dynamic

response analysis of entire structure. Therefore, the method can analyze the seismic performance of the structure under real ground motion with the local pseudo-static test shared or conducted at a lower cost.

2 Establishment of neural network restoring force model

2.1 Input and output variables of neural network restoring force model

In a nonlinear hysteretic model, the displacement and restoring force of the structure do not exhibit a linear mapping, requiring sufficient variables to characterize the state of the structural restoring force. Yun et al. [42] proposed the six-path hysteresis theory, which divides the hysteresis loop into typical path regions from path 1 to path 6. These regions represent the states of forward loading, forward unloading I, forward unloading II, reverse loading, reverse unloading I, and reverse unloading II under displacement control, respectively. The internal variable $\Delta\eta_n$ and ξ_n were introduced to imply the direction for next time along the equilibrium path. The definitions of $\Delta\eta_n$ and ξ_n are shown in Eq. (1). The mapping of the hysteresis curve regions can be achieved through the symbolic combination of the input variable set $[\Delta\eta_n, \xi_n, x_n]$, as shown in Fig. 1(a).

$$\begin{cases} \xi_n = R_{n-1}x_{n-1}, \\ \Delta\eta_n = R_{n-1}\Delta x_n = R_{n-1}(x_n - x_{n-1}), \end{cases} \quad (1)$$

where x_{n-1} and x_n are the displacements at steps $n-1$

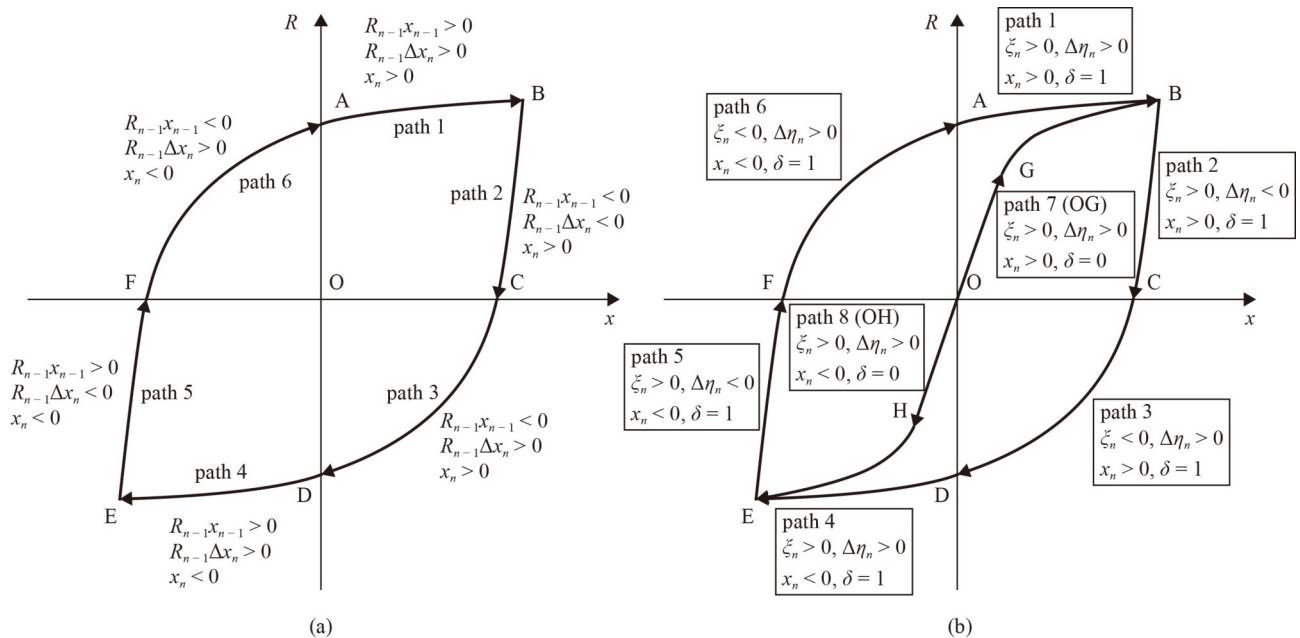


Fig. 1 Modes of the hysteretic behavior: (a) six-path modes of the hysteretic behavior; (b) eight-path modes of the hysteretic behavior.

and n , respectively, and R_{n-1} is the restoring force at step $n-1$.

The study proposed an eight-path hysteresis model by adding positive and negative linear loading segments, namely paths 7(OG) and 8(OH) (Fig. 1(b)), on the basis of the six-path hysteresis model [42]. The internal variable δ is introduced into the input variable group to represent the elastic-plastic state of the structure. When the maximum turning point displacement x_{history} of the loading process of is within the elastic limit displacement x_{elastic} range, the component is considered to be in the elastic state and $\delta = 0$. x_{history} beyond this range indicates that the component has entered an elastic-plastic state and $\delta = 1$. Therefore, variable δ is defined by Eq. (2):

$$\delta = \begin{cases} 0, & x_{\text{history}} \in [-x_{\text{elastic}}, x_{\text{elastic}}], \\ 1, & x_{\text{history}} \notin [-x_{\text{elastic}}, x_{\text{elastic}}]. \end{cases} \quad (2)$$

The input variable set $[\Delta\eta_n, \xi_n, x_n, \delta]$ can cover all eight paths on the hysteresis curve. And the corresponding variable combinations of each loading path, as shown in Table 1. Because variable δ is introduced, its definition depends on the maximum displacement x_{history} of the loading process of the structure. Therefore, $[x_{\text{history}}, R_{\text{history}}]$ was selected as an additional variable to measure the impact of the loading process on the plastic development of the components. Considering that the positive and negative loadings have no symmetry during the actual time history loading, the maximum displacement response $x_{\text{history}+}$ and $x_{\text{history}-}$ and the maximum force response $R_{\text{history}+}$ and $R_{\text{history}-}$ in the positive and negative loading processes are included in the input variable group. Finally, the variable E_{n-1} describing hysteretic energy dissipation is added and defined by Eq. (3). Thus, the input variable group of 11 variables used in this model is determined by Eq. (4):

$$E_{n-1} = \frac{1}{2}(R_{n-1} + R_{n-2})(x_{n-1} - x_{n-2}). \quad (3)$$

$$\text{INPUT} = [x_n, \Delta\eta_n, \xi_n, \delta, x_{\text{history}+}, x_{\text{history}-}, R_{\text{history}+}, R_{\text{history}-}, E_{n-1}, x_{n-1}, R_{n-1}]. \quad (4)$$

The output variable of the proposed NN restoring force model is the restoring force R_n , as shown in Eq. (5):

$$\text{OUPUT} = [R_n]. \quad (5)$$

2.2 The structural parameters of back propagation (BP) neural network

The BP NN is a type of multilayer feedforward NN trained according to the error backpropagation algorithm [43]. The basic algorithm of the BP NN consists of two stages: signal forward and error BP. The training data are input from the input layer, undergoes nonlinear transformations in the hidden layers, and then propagates forward along the connection path to finally reach the output layer. When the output layer cannot obtain the expected output, the network enters the process of error backpropagation. The output errors are propagated in the reverse order and are distributed among each unit in every layer. The errors obtained from each unit in every layer are used as the basis for adjusting the weights and thresholds of each unit. By repeatedly adjusting the weights and thresholds, the error can be minimized within the tolerance limit along the gradient direction.

Figure 2 shows the multilayer NNs with d input neurons, l output neurons, and q hidden neurons. Where the threshold of the j th neuron in the output layer is denoted by θ_j and the threshold of the h th neuron in the hidden layer is denoted by γ_h . The connection weight between the i th neuron in the input layer and the h th neuron in the hidden layer is v_{ih} , and the connection weight between the h th neuron in the hidden layer and the j th neuron in the output layer is w_{hj} . The input received by the h th neuron in the hidden layer is denoted as

Table 1 Variable combinations of each path in the eight-path hysteresis model

Path name	Loaded state	Path location	Signs of input variable				Signs of output variable
			ξ_n	$\Delta\eta_n$	x_n	δ	R_n
Path 1	elastoplastic forward loading	AB	+	+	+	1	+
Path 2	elastoplastic forward unloading I	BC	+	−	+	1	+
Path 3	elastoplastic forward unloading II	CD	−	+	+	1	−
Path 4	elastoplastic reverse loading	DE	+	+	−	1	−
Path 5	elastoplastic reverse unloading I	EF	+	−	−	1	−
Path 6	elastoplastic reverse unloading II	FA	−	+	−	1	+
Path 7	elastic forward loading	OG	+	+	+	0	+
	elastoplastic forward loading	GB	+	+	+	1	+
Path 8	elastic reverse loading	OH	+	+	−	0	−
	elastoplastic reverse loading	HE	+	+	−	1	−

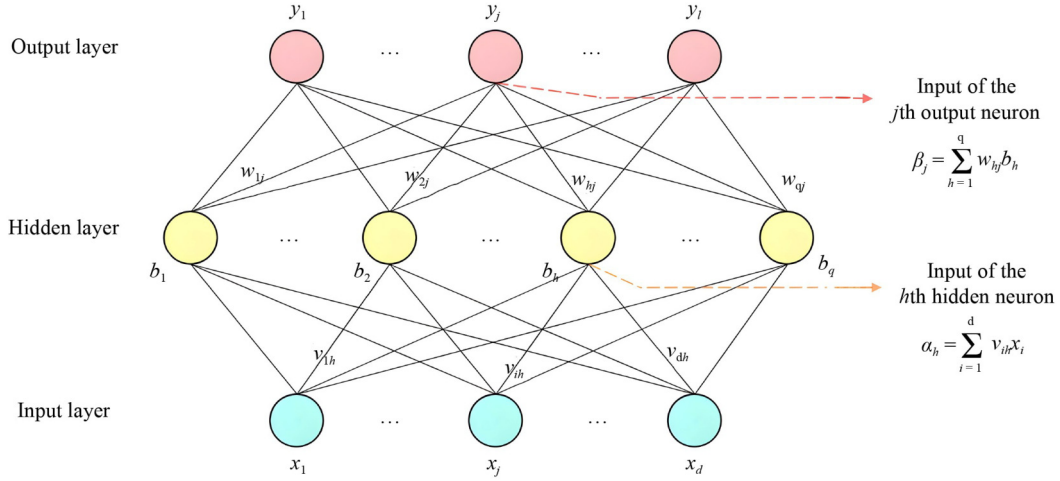


Fig. 2 Structure diagram of BP NN.

$\alpha_h = \sum_{i=1}^d v_{ih} x_i$ and the input received by the j_{th} neuron in

the output layer is denoted as $\beta_j = \sum_{h=1}^q w_{hj} b_h$, where b_h is the output of the h_{th} neuron in the hidden layer. Assume that the activation functions in the hidden and output layers are both sigmoid functions, the output of the NN model for a training example (x_k, y_k) is denoted as:

$$\hat{y}_j^k = f(\beta_j - \theta_j). \quad (6)$$

Then the mean square error for (x_k, y_k) is expressed as:

$$E_k = \frac{1}{2} \sum_{j=1}^l (\hat{y}_j^k - y_j^k)^2. \quad (7)$$

There are $(d + l + 1)q + l$ parameters to be determined in the network of Fig. 2. The update equation for any parameter v is as follows:

$$v \leftarrow v + \Delta v. \quad (8)$$

The connection weights w_{hj} from the hidden layer to the output layer are derived as an example. The BP algorithm is based on a gradient descent strategy that adjusts the parameters in the direction of the negative gradient of the target. For the error E_k , given the learning rate η , the following Eq. (9) can be obtained.

$$\Delta w_{hj} = -\eta \frac{\partial E_k}{\partial w_{hj}} = -\eta \frac{\partial E_k}{\partial \hat{y}_j^k} \cdot \frac{\partial \hat{y}_j^k}{\partial \beta_j} \cdot \frac{\partial \beta_j}{\partial w_{hj}}. \quad (9)$$

According to the definition of β_j , it is obvious that

$$\frac{\partial \beta_j}{\partial w_{hj}} = b_h. \quad (10)$$

According to the property $f'(x) = f(x)(1 - f(x))$ of the Sigmoid function, it follows that

$$g_j = \frac{\partial E_k}{\partial \hat{y}_j^k} \cdot \frac{\partial \hat{y}_j^k}{\partial \beta_j} = -(\hat{y}_j^k - y_j^k) f'(\beta_j - \theta_j) = \hat{y}_j^k (1 - \hat{y}_j^k) (y_j^k - \hat{y}_j^k). \quad (11)$$

By substituting Eqs. (10) and (11) into Eq. (9), the update formula for w_{hj} can be obtained in the BP algorithm, as follows

$$\Delta w_{hj} = \eta g_j b_h. \quad (12)$$

Similarly, other thresholds and weights can be derived, including $\Delta \theta_j$, Δv_{ih} , Δw_{ij} .

To avoid overfitting, the NN model used in this study adopted the four-layer NN architecture of [11-25-25-1], as shown in Fig. 3. Simultaneously, a fixed learning rate η is set to 0.1. The sigmoid function was used for the activation function of both the hidden and output layer neurons. And the NN Toolbox in MATLAB was used to create and train the NN model. Ensuring consistent distribution ranges across all dimensions of the data can enhance the performance of the optimizer. Therefore, min-max normalization was applied to the data before inputting it into the model.

3 Simulation case of neural network restoring force model

In this study, a two-story single span rigid frame is used as a simulation example to verify the prediction effect of the proposed NN restoring force model. The numerical simulation results of the OpenSees analysis software were used as the benchmark. The specific design parameters of the two-story single-span frame were as follows: height of 4 m, span of 5 m, section size of the frame column of 500 mm × 500 mm, and section size of the frame beam of 300 mm × 350 mm, as shown in Fig. 4. The concrete strength grade was C30, longitudinal reinforcement was HRB335, and stirrup was HPB235. The frame was

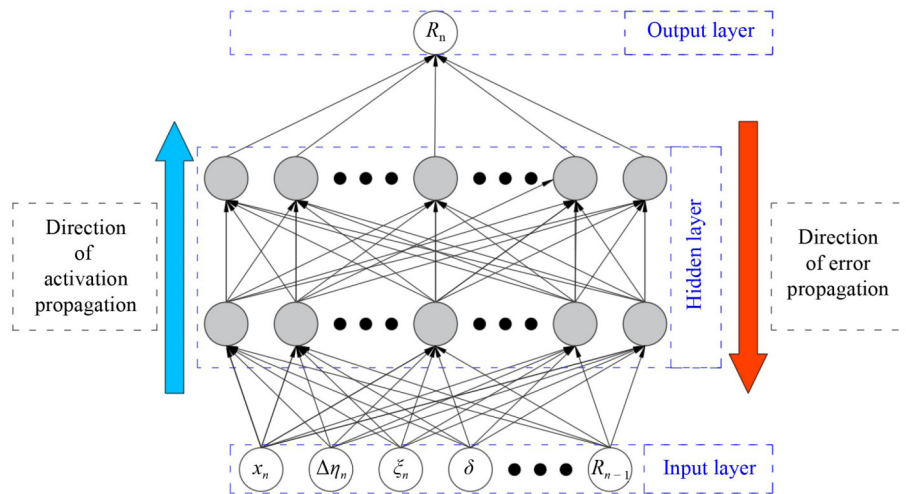


Fig. 3 Network architecture of NN restoring force model.

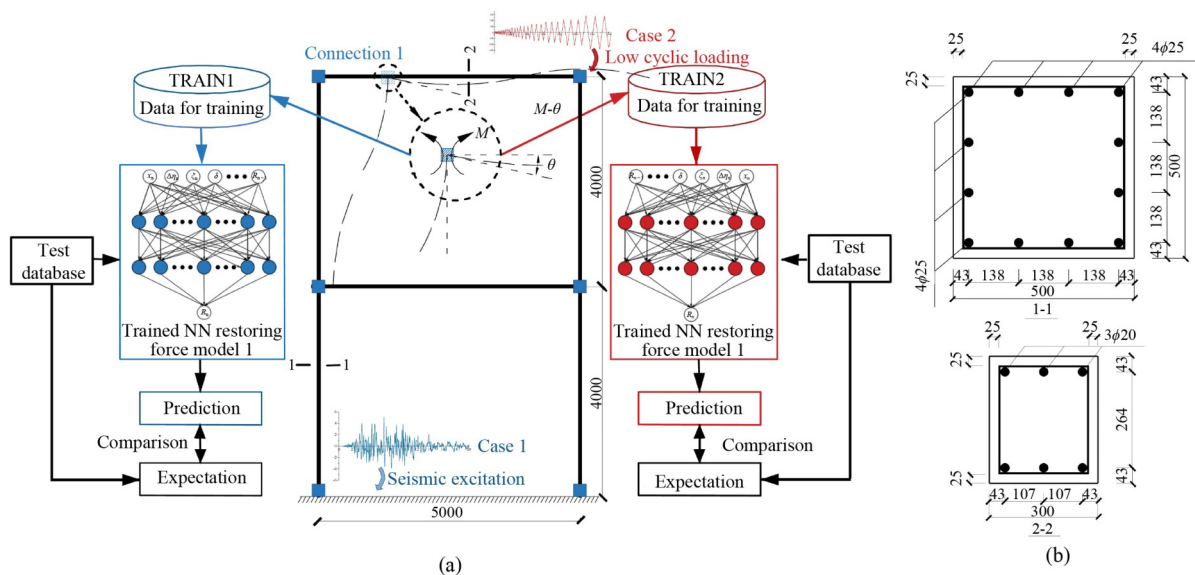


Fig. 4 Schematic diagram of NN restoring force model numerical verification and frame structure model: (a) dimension drawing of frame structure model and Schematic diagram of NN restoring force model numerical verification; (b) frame beam column section reinforcement diagram.

modeled in OpenSees, with the two-dimensional model shown in Fig. 4(a). This model consists of 6 nodes, with the bottom nodes fixed to the foundation, while all other nodes have three degrees of freedom. The frame beams and columns were modeled using nonlinear beam-column elements, and the beam-column sections are simulated with fiber sections. The nonlinear constitutive models Concrete02 and Steel02 were adopted for concrete and steel reinforcement, respectively. The Concrete02 model can account for the tensile mechanical properties of concrete, where the loading and unloading stiffness and peak tensile stress of the tensile segment of concrete degrade gradually under compression. The Steel02 constitutive model incorporates the hysteretic strengthening effects of reinforcement under low-cycle cyclic loading. The model uses nodal mass sources, with

the mass of each beam-column joint set to 20.4 t. The mass is calculated based on the representative values of gravitational loads under the ultimate limit state of load-carrying capacity.

After establishing the model, two types of data sets were used to train the NN restoring force model. The first type of training data set, TRAIN1, was composed of structural response data obtained by simulating five seismic wave acceleration time-history excitations. The second type of training data set, TRAIN2, was composed of structural response data obtained from a structural quasi-static loading simulation. The moment-rotation data of the left beam-column joint (Connection 1) on the top floor of the frame were used as the structural response data. The TEST data set was composed of structural response data obtained by simulating the acceleration

time-history excitations of another five seismic waves. The NN restoring force model trained by the two kinds of training data set was used to predict the response of the left beam-column joint, and the prediction of the NN restoring force model was compared with the expectation of the TEST data set. Figure 4(a) shows a schematic of the numerical verification of the proposed NN restoring force model. The selection of two types of training data sets mainly corresponds to two types of actual scenarios of data acquisition: 1) obtaining structural response data under seismic wave sequence excitation by shaking table tests and structural health monitoring; 2) obtaining structural response data from cost-effective and widely applicable quasi-static test. In this section, two simulation cases are calculated for the two types of data-acquisition scenarios.

3.1 Simulation case 1 of neural network restoring force model trained by TRAIN1 from seismic excitation

Five seismic waves recorded in the FEMA-P695 specification [44] for medium-distance field vibrations were selected as the training seismic waves, as shown in Table 2. The peak ground acceleration (PGA) of each seismic wave was amplitude-modulated to 510 cm/s^2 , the sampling time was 0.01 s, and the interception time was 20 s, therefore each seismic wave had 2000 data points. The structural analysis model used TRAIN1 seismic waves for nonlinear time-history analysis. The rotation θ_n and moment M_n of the left beam-column joint on the top floor at each time step were extracted, and the input and output variables shown in Eqs. (4) and (5) were sorted. Then, a training data set TRAIN1 of 10000 training samples for M_n - θ_n restoring force model of the left beam-column joints on the top floor was obtained.

Training data set TRAIN1 was used to train the

proposed NN restoring force model of the joint. After training, the trained model was expected to exhibit the ability to identify the restoring force model of the same component under other loading conditions. Another five test seismic waves of the FEMA-P695 far-field seismic record in Table 3, including TEST1–TEST5, were used to excite the structural model as the TEST data set. The sampling time of 0.01 s was also used for the five test seismic waves. The TEST data set of the restoring force model of the left beam-column joint can be obtained by sorting the structural response after excitation according to the input and output variables. The data of the TEST data set were used to test the trained NN restoring force model and observe the fitting effect of the proposed NN restoring force model.

The NN restoring force model trained by the TRAIN1 data set was used to predict the moment of the beam-column joint on the top floor at each time step in the TEST data set. The NN's predicted moment M_p was compared with the expected moment M_e obtained from OpenSees simulations in the TEST data set through time-history response and hysteresis curve analysis. The comparison of the results of the five test waves and relative errors were shown in Fig. 5.

3.2 Simulation case 2 of neural network restoring force model trained by TRAIN2 from quasi-static loading

According to the American test specification ACI [45], low-cycle reciprocating loading was carried out on the structure according to interlayer drift ratios of 0.2%, 0.25%, 0.35%, 0.5%, 0.75%, 1.0%, 1.4%, 1.75%, 2.20%, 2.75%, and 3.50%, and the amplitude of each interlayer drift ratio was cyclically loaded three times, as shown in Fig. 6. Based on the base shear, vertex displacement, joint rotation θ_n , and moment M_n calculated by the OpenSees

Table 2 The seismic waves in training data set TRAIN1 for NN restoring force model

Data set	Number	Event	Magnitude	Station name	PGA (g)	PGA time point (s)	Modified factor
TRAIN1	1	Imperial Valley	6.5	Delta	0.35	10.04	1.486
	2	Kocaeli, Türkiye	7.5	Duzce	0.36	9.87	1.444
	3	Landers	7.3	Coolwater	0.42	14.83	1.238
	4	Loma Prieta	6.9	Capitola	0.53	6.35	0.981
	5	San Fernando	6.6	Hollywood	0.21	7.82	2.476

Table 3 The seismic waves in testing data set TEST for NN restoring force model

Data set	Number	Event	Magnitude	Station name	PGA (g)	PGA time point (s)	Modified factor
TEST1	6	Friuli, Italy	6.5	Tolmezzo	0.35	4.04	1.486
TEST2	7	Hollister	6.5	SAGO	0.38	1.21	1.368
TEST3	8	Kobe	6.9	Shin-Osaka	0.24	6.93	2.167
TEST4	9	Northridge	6.7	Beverly	0.52	8.14	1.000
TEST5	10	Superstition Hills	6.5	Poe Road	0.45	6.26	1.156

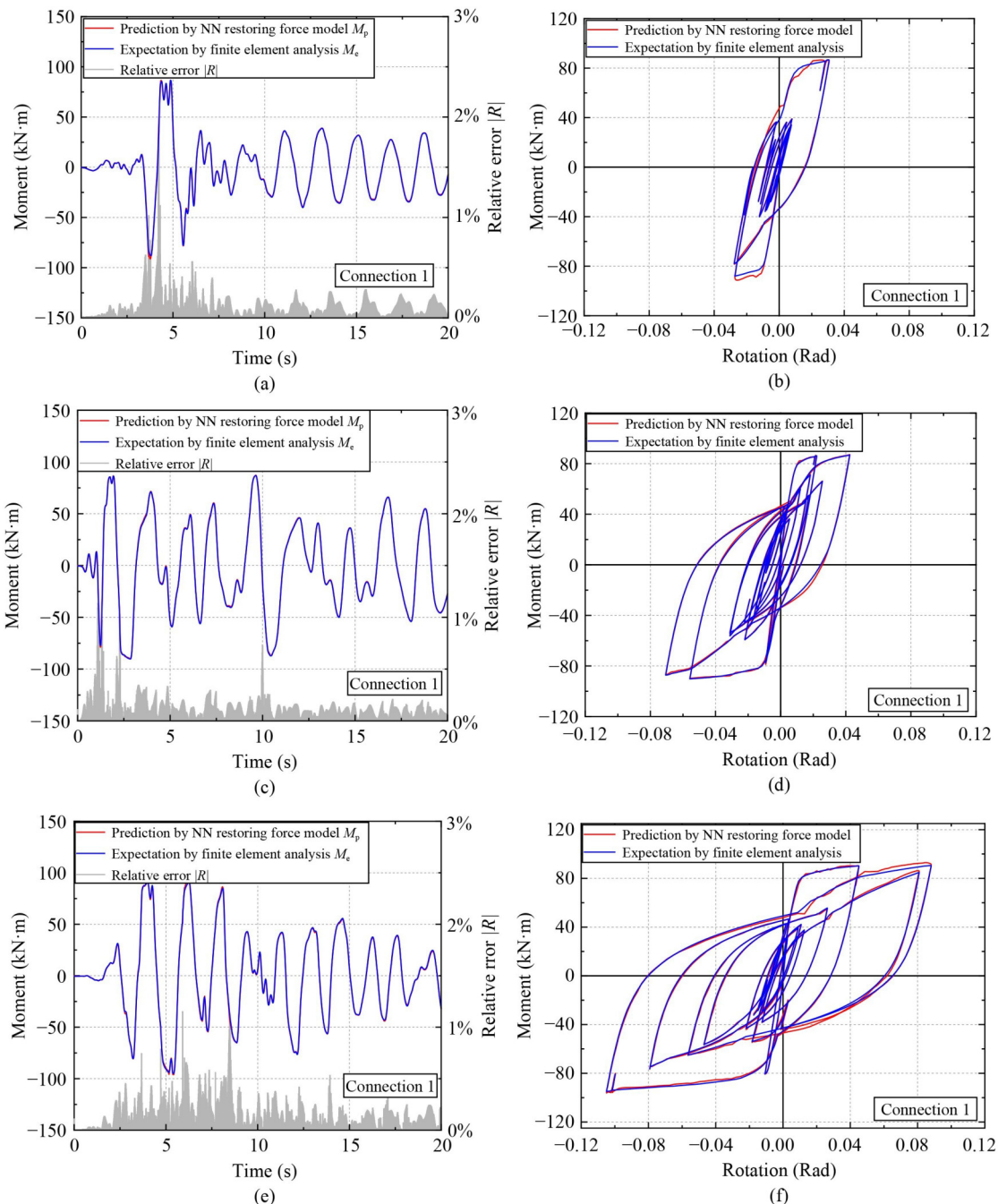
model, the overall hysteretic response of the structure and joint hysteresis curves were drawn as shown in Fig. 7. By sorting the data of joint rotation θ_n and moment M_n according to the input variables of Eq. (4) and output variables of Eq. (5), the training data set TRAIN2 for M_n – θ_n restoring force model of the left beam–column joint on the top floor can be obtained. The number of training data sets TRAIN2 was consistent with the number of loading steps in the loading sequence, which was 3582. The training data sets TRAIN2 were obtained from the quasi-static loading test.

The NN restoring force model trained by the TRAIN2

data set was used to predict the moment of the beam–column joint on the top floor at each time step in the TEST data set (5 test waves in Table 3). The NN's predicted moment M_p was compared with the expected moment M_e obtained from OpenSees simulations in the TEST data set, through the time-history response and hysteresis curves. The comparison results for the 5 test waves and relative errors were shown in Fig. 8.

3.3 Prediction effect analysis

After comparing predicted results of the NN restoring



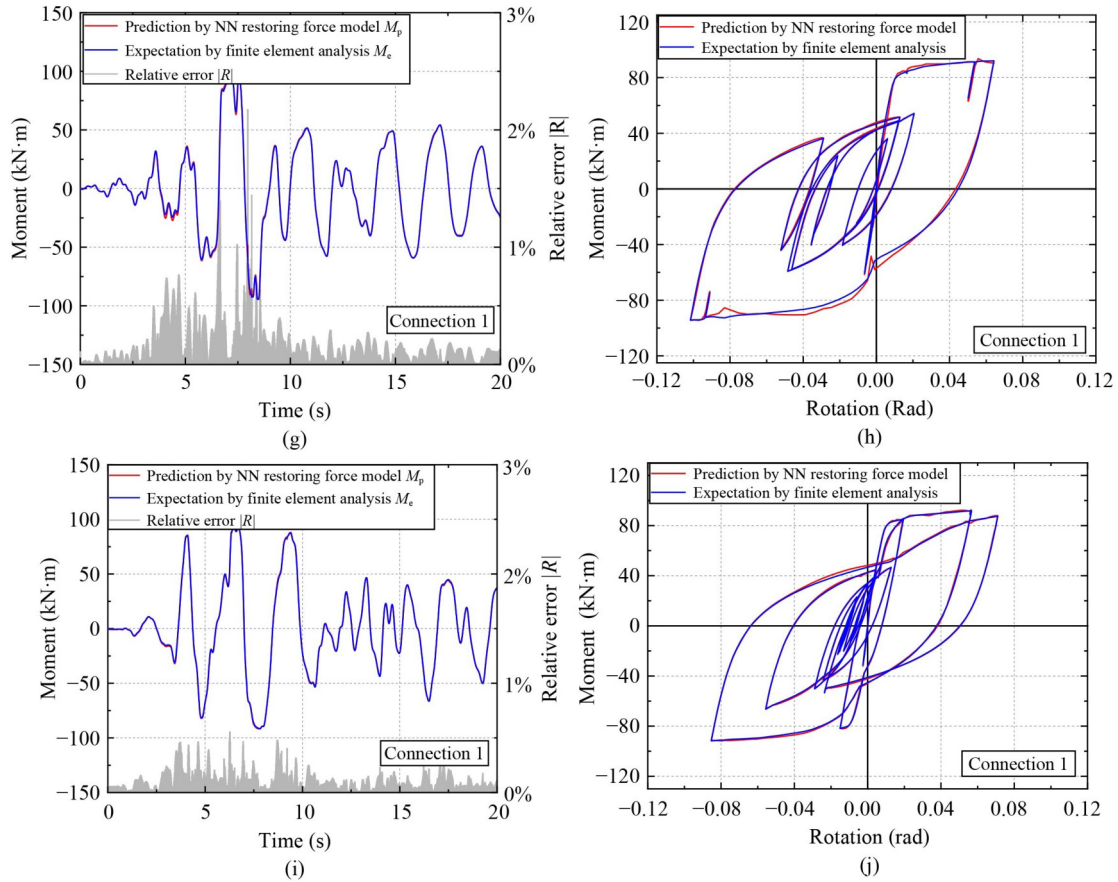


Fig. 5 Fitting effect on time-history response and hysteresis curve of NN restoring force model trained by TRAIN1: (a) time history of moment prediction and error under Friuli wave excitation; (b) predicted hysteresis curve under Friuli wave excitation; (c) time history of moment prediction and error under Hollister wave excitation; (d) predicted hysteresis curve under Hollister wave excitation; (e) time history of moment prediction and error under Kobe wave excitation; (f) predicted hysteresis curve under Kobe wave excitation; (g) time history of moment prediction and error under Northridge wave excitation; (h) predicted hysteresis curve under Northridge wave excitation; (i) time history of moment prediction and error under Superstition hills wave excitation; (j) predicted hysteresis curve under Superstition hills wave excitation.

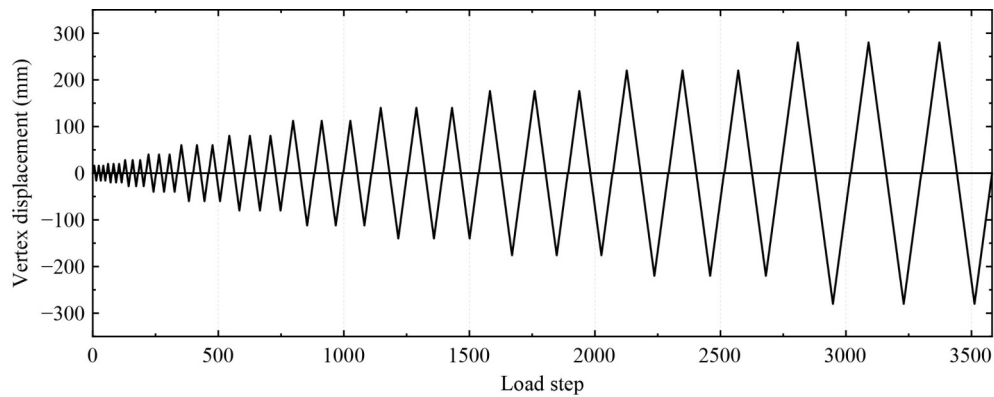


Fig. 6 The quasi-static loading sequence of training data set TRAIN2 of NN restoring force model.

force model trained by TRAIN1 and TRAIN2 and expected results in the TEST data set, respectively, it can be observed that the NN restoring force model trained by TRAIN1 and TRAIN2 can accurately identify the restoring force in terms of the time-history and hysteresis curves. As can be seen from the errors at each time step

in Figs. 5 and 8, for the moment response of the joint under the same test seismic wave, the overall prediction errors of the NN restoring force model trained by TRAIN1 are smaller than those of TRAIN2. The prediction effect of the NN restoring force model at the peak moment response under the five test seismic waves

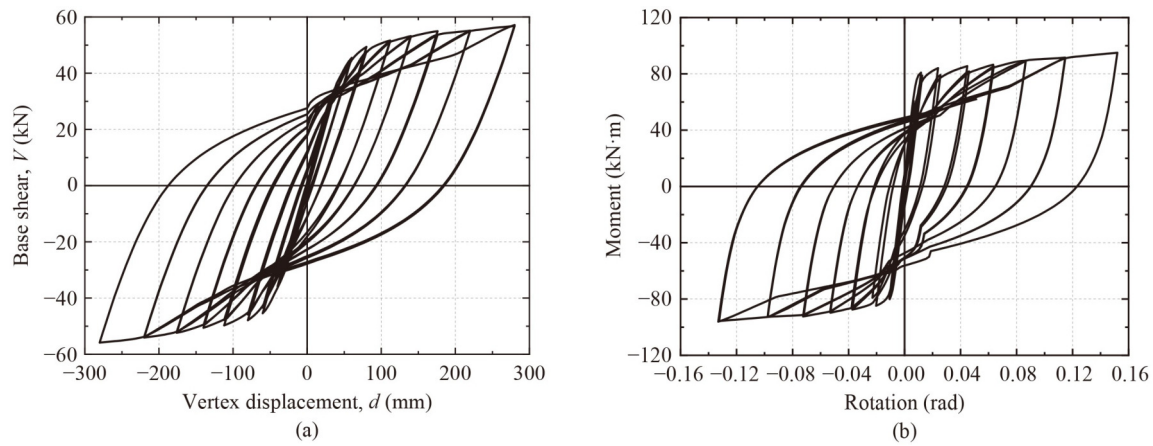
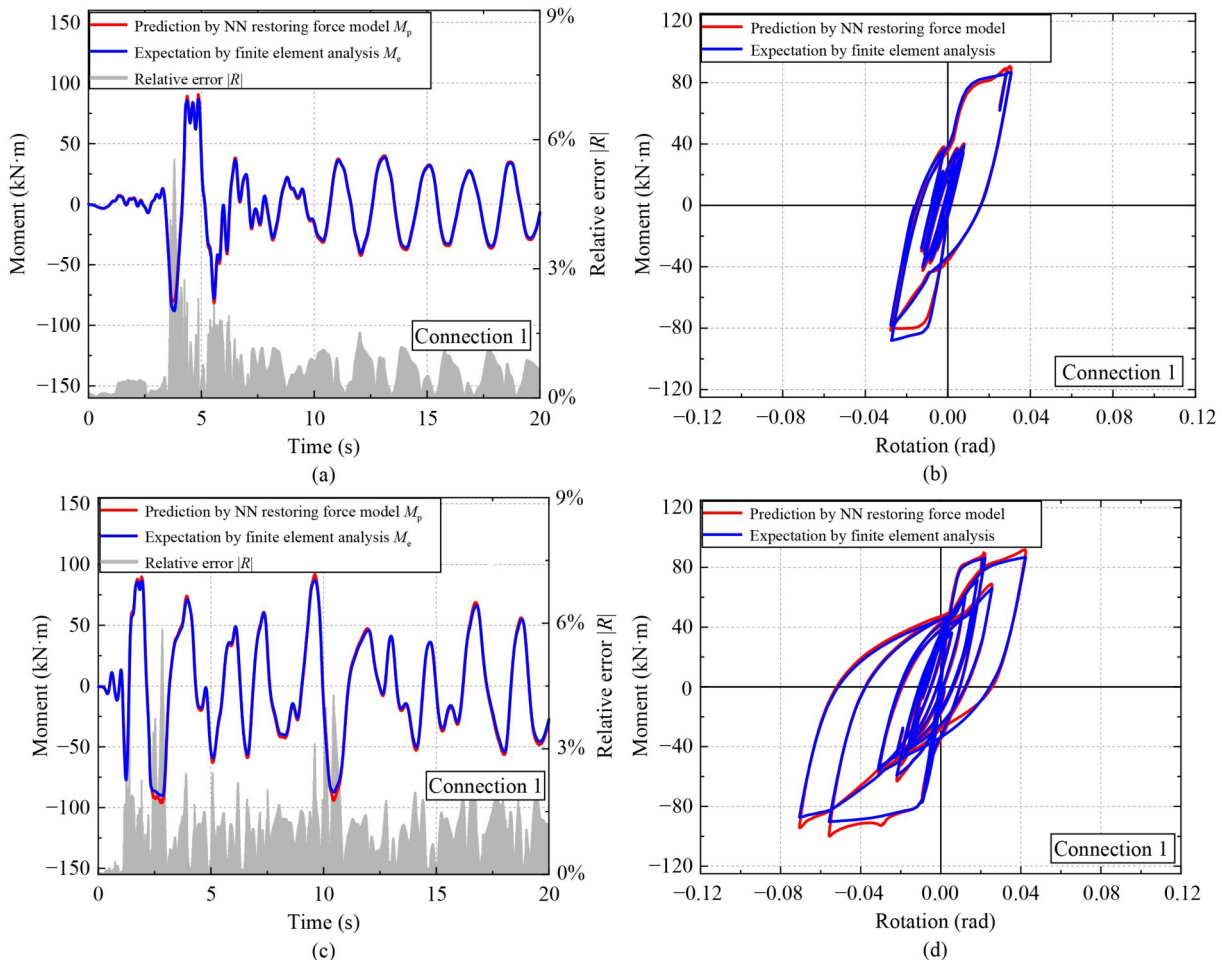


Fig. 7 Hysteretic curve of structural response under quasi-static loading : (a) the overall hysteretic response of the structure; (b) hysteretic response of left beam-column joint on the top floor.

was compared, as listed in Table 4. It can be seen that the minimum absolute prediction error ΔM at the peak moment response of the NN restoring force model trained by TRAIN1 was only 0.383 kN·m under the Friuli wave, and the maximum absolute prediction error was -0.901 kN·m under the Northridge wave. The prediction error percentage of the moment response was controlled within 1.5%. The minimum absolute prediction error ΔM at the

peak moment response of the NN restoring force model trained by TRAIN2 was only -1.498 kN·m under the Northridge wave, and the maximum prediction error was 5.286 kN·m under the Hollister wave. The entire predictive error percentage of the NN restoring force model trained by TRAIN2 can be controlled within 7.5%. The training samples cause prediction error difference between the NN restoring force model trained by data



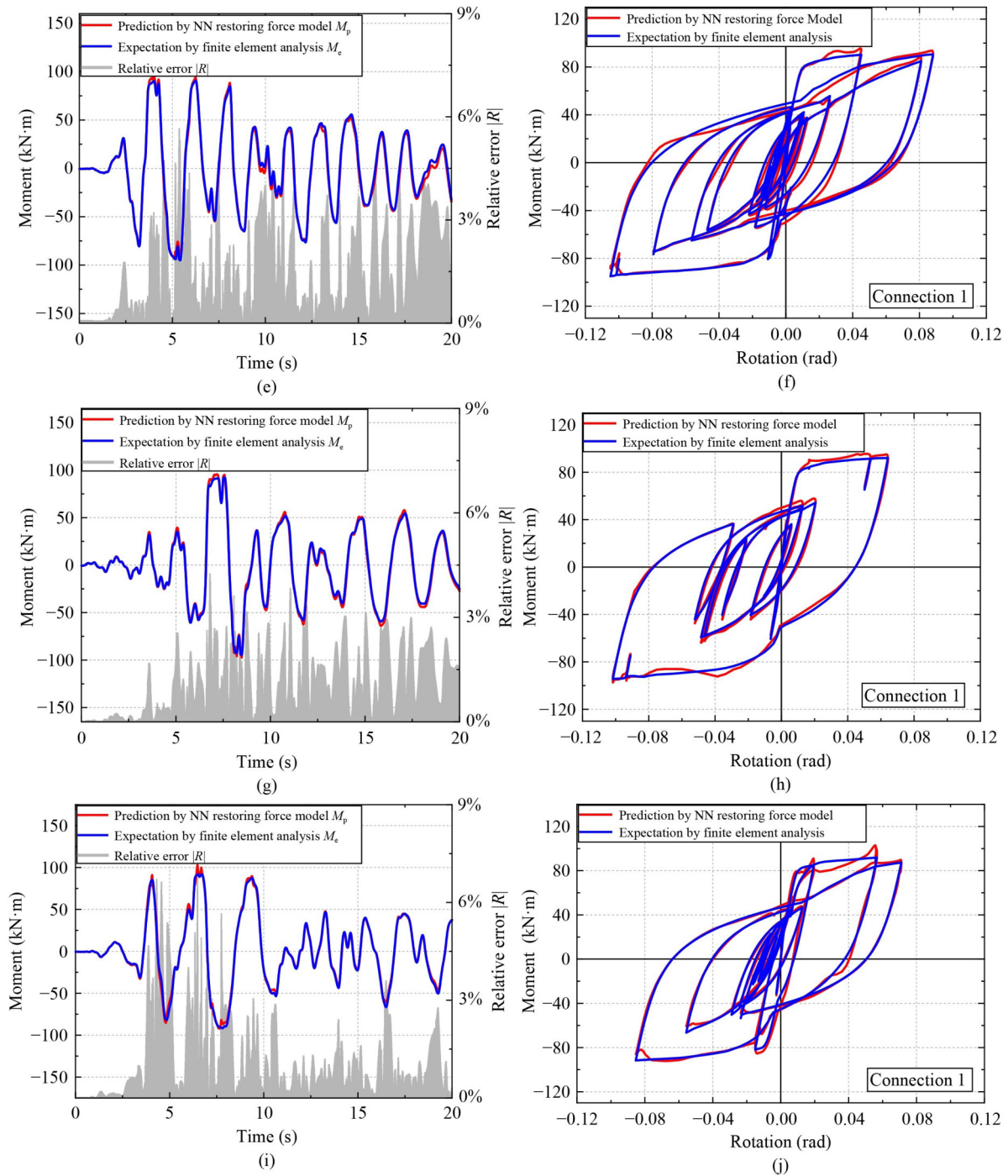


Fig. 8 Fitting effect of time-history response and hysteresis curve of NN restoring force model trained by TRAIN2: (a) time history of moment prediction and error under Friuli wave excitation; (b) predicted hysteresis curve under Friuli wave excitation; (c) time history of moment prediction and error under Hollister wave excitation; (d) predicted hysteresis curve under Hollister wave excitation; (e) time history of moment prediction and error under Kobe wave excitation; (f) predicted hysteresis curve under Kobe wave excitation; (g) time history of moment prediction and error under Northridge wave excitation; (h) predicted hysteresis curve under Northridge wave excitation; (i) time history of moment prediction and error under Superstition hills wave excitation; (j) predicted hysteresis curve under Superstition hills wave excitation.

sets TRAIN1 and TRAIN2. On the one hand, the training sample sizes of TRAIN1 and TRAIN2 are 10000 and 3582, respectively. TRAIN1 provides more training samples; On the other hand, TRAIN1 training samples are derived from pseudo-dynamic and shaking table tests

loaded with real seismic wave displacement sequences, which could provide richer hysteretic response information for the NN restoring force model. However, the data samples of TRAIN2 were derived from the quasi-static test loaded with an ordered low-cycle

Table 4 Prediction effect of NN restoring force model at response at the peak moment response

Event	TEST	TRAIN1			TRAIN2		
	Expected peak moment $ M_c _{\max}^*$	Predicted peak moment $ M_p _{\max}^*$	Prediction error ΔM	Percentage error	Predicted peak moment $ M_p _{\max}^*$	Prediction error ΔM	Percentage error
Friuli	88.037	88.420	0.383	0.435%	83.572	−4.465	−5.072%
Hollister	90.233	89.575	−0.658	−0.729%	95.519	5.286	5.859%
Kobe	94.992	95.842	0.850	0.895%	92.036	−2.956	−3.112%
Northridge	94.457	93.556	−0.901	−0.954%	92.959	−1.498	−1.585%
Superstition Hills	91.818	91.292	−0.526	−0.573%	94.893	3.075	3.349%

*Note: moment unit kN·m.

reciprocating sequence, and the joint response information provided by the training samples was relatively insufficient.

In general, the NN restoring force model with 11 group input variables considers the possible eight-path hysteretic forms of structures under elastic-plastic conditions and the influence of hysteretic energy consumption and asymmetric loading history on the restoring force response. The results of the numerical examples show that the relative errors of the moment response prediction of the NN restoring force model trained by seismic and low-cycle reciprocating excitations are controlled within 1.5% and 7.5%, respectively. Therefore, the NN restoring-force identification method can be applied to the calculation of the nonlinear seismic response of structures induced by the time-history excitation of ground motion.

4 Hybrid analysis method of structural seismic response based on neural network restoring force model

The substructure hybrid test divides the structure into experimental and numerical substructures. Upon completion of the dynamic differential equation in the current step, the computer sends the solved displacement to the numerical and experimental substructure, respectively. After calculation or loading, the restoring force $R_n(t)$ (numerical substructure) and $R_e(t)$ (experimental substructure) of the structure are returned to the computer respectively to solve the displacement of the next step, thus completing the dynamic analysis of the overall structure step by step. However, the substructure hybrid test method is limited by the scale of the substructure and delay effect. With reference to the concept of the substructure hybrid test, a hybrid analytical method of the structural seismic response based on NN restoring force model was established in this study. The potentially severe nonlinear region of the complete structure is divided into several NN substructures, and the elastic region is divided into principal numerical substructures. The NN restoring force model was trained using quasi-static test data to identify the restoring force

of the NN substructure in the same region under dynamic action. Combined with the main numerical substructure, a platform was built to complete the data interaction between several NN substructures and numerical substructures for the analysis and calculation of the dynamic response of the entire structure step by step.

The results of the simulation case in Section 3 show that the relative errors of the moment response prediction of the NN restoring force model trained by the low-cycle reciprocating excitation are controlled within 7.5%. In terms of restoring force identification, the NN restoring force identification method actually provides a new idea in addition to the numerical constitutive simulation and substructure test loading. The proposed hybrid analysis method can extend the hysteretic behavior rules of components or joints, obtained from quasi-static experiments, to the numerical simulation of the entire structure under seismic excitation, and it directly avoids the limitations of site, scale, and time of the hybrid or shaking table tests. Furthermore, the application of the NN restoring force model trained by shared and conducted experimental data, unlike numerical simulation, does not require many assumptions regarding restoring forces.

In this study, the NN restoring force model recognition, numerical substructure restoring force calculation, and nonlinear dynamic differential equation solution modules were built in MATLAB, and the corresponding interfaces of each module were written. In each time step cycle, driven by the dynamic differential equation solution module, the displacement and restoring force data interactions between this module with the NN restoring force recognition module and numerical substructure restoring force calculation module are progressively completed. And the dynamic response of the entire structure under earthquake action is obtained in the gradual transmission and calculation of the closed-loop interaction.

The nonlinear dynamic differential equation solving module is programmed by the precise integration method proposed by Zhong et al. [46–47]. The precise integration algorithm reduces the order of the second order ordinary differential equation to the first order ordinary differential equation by introducing the equation of state, and then

introduces the fine calculation of the exponential matrix and the approximate solution of the inhomogeneous term to realize the fine solution of the dynamic equation. And linear systemization is used to implement the nonlinear processing for precise integration method [48–50].

Figure 9 shows the computational flow diagram of the hybrid analysis method for the structural seismic response based on NN restoring force model. First, the structural parameters M , C , and R_0 were initialized, and the integral step of the calculation method and the external load excitation sequence P of the input seismic wave were determined. Subsequently, the initial generalized displacement response of structure X_0 is input to complete the initialization of the analysis method. After the completion of the initial stage of the proposed analysis method, the solution of the structural response enters the progressive recursion stage. In the nonlinear dynamic differential equation solving module, the displacement of the $i + 1$ step is obtained based on the restoring force of the i step, including the displacement X_{i+1}^{NN} of the NN substructure and displacement X_{i+1}^N of the numerical substructure. Then, X_{i+1}^{NN} and X_{i+1}^N are sent to the trained NN restoring force model and numerical substructure restoring force calculation module, respectively, to obtain the restoring force R_{i+1}^{NN} of NN substructure and R_{i+1}^N of

numerical substructure, respectively. Among them, the recognition of NN substructure restoring force was performed in the trained NN restoring force model. The output variable restoring force response R is obtained by inputting the input variable group, constructed by displacement, into the trained NN restoring force model. The training data set of the NN restoring force model was obtained from the quasi-static tests performed or shared in the same region, enabling it to characterize the hysteretic behavior of the structure under load excitation. The stiffness matrix of the elastic numerical substructure was directly constructed based on the numerical constitutive model and design parameters. The obtained restoring force response quantities are fed back to the nonlinear dynamic differential equation solving module, and the dynamic balance equation of the next step can then be solved to obtain the displacement response quantities for the next step. Therefore, the nonlinear seismic response of the structure can be solved step-by-step by the transfer of the restoring force and displacement responses among the NN restoring force model, numerical substructure restoring force calculation, and nonlinear dynamic differential equation solution modules.

In summary, the complete and detailed calculation steps of this method are as follows.

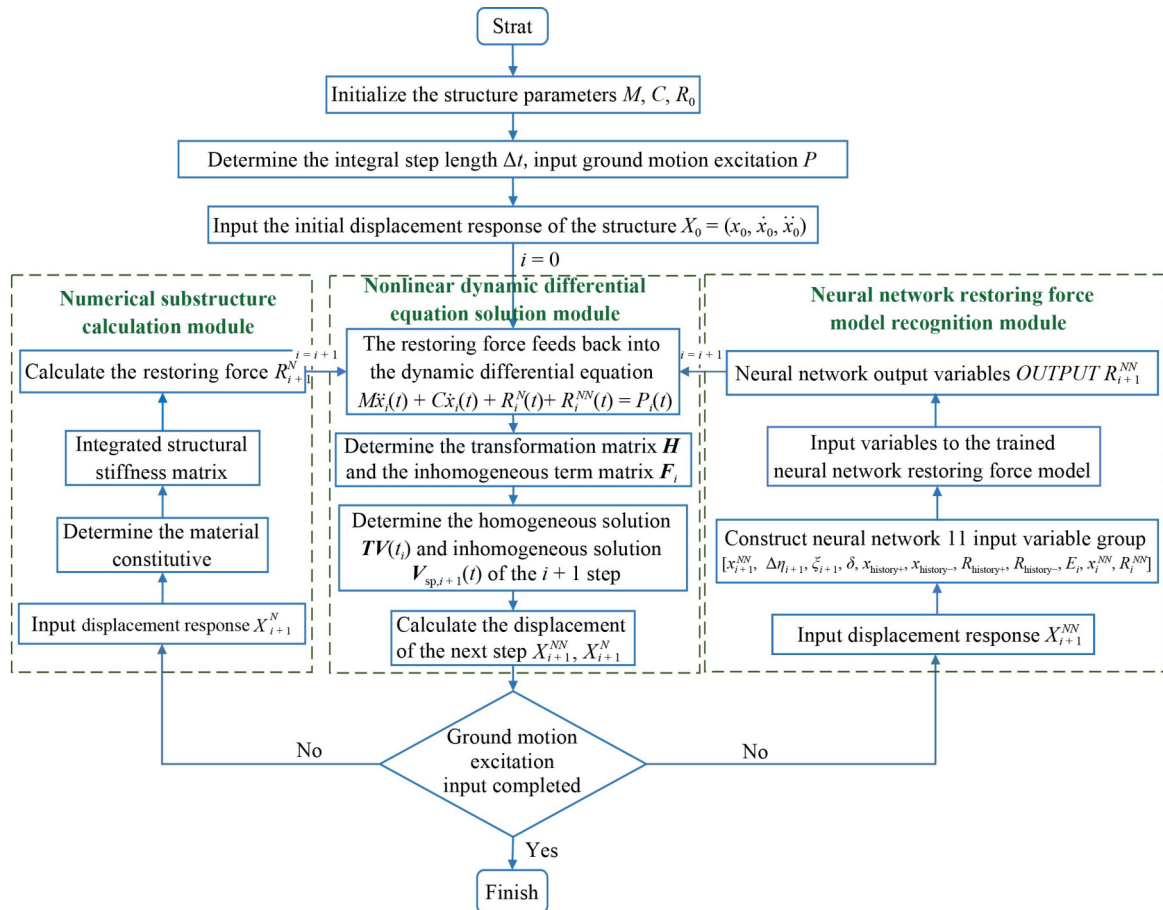


Fig. 9 The flow diagram of hybrid analysis method of structural seismic response based on NN restoring force model.

Step 1): Based on the analysis of the structural damage mechanism, the entire structural model was divided into nonlinear and linear elastic regions, and several NN substructures and principal numerical substructures were formed.

Step 2): The NN restoring force model is trained with the training data set to enable it to recognize the hysteretic behavior of the substructure under dynamic action. The training data set originates from quasi-static test data conducted on or shared for the substructure and is organized according to the input and output sets specified in Section 2.

Step 3): After initializing the structural parameters M , C , and R_0 , the integral step length and external load excitation sequence P of the input seismic wave were determined.

Step 4): The dynamic equation was discretized in the time domain, and the motion equation of the entire structure was solved in the dynamic differential equation-solving module. According to the restoring forces R_i^{NN} and R_i^N at i step, the displacement response X_{i+1}^{NN} of NN substructure and X_{i+1}^N of the numerical substructure at $i+1$ step were deduced recursively.

Step 5): The displacement response quantity X_{i+1}^{NN} was transferred to the NN restoring force module of the substructure, obtaining the restoring force response quantity R_{i+1}^{NN} . The numerical substructure displacement response X_{i+1}^N was transferred to the numerical substructure calculation module to obtain the restoring force response R_{i+1}^N .

Step 6): The restoring force R_{i+1}^{NN} of NN substructure and R_{i+1}^N of the numerical substructure in step $i+1$ were sent to the dynamic differential equation-solving module.

Step 7): Steps 4)–6) were repeated until the input of the seismic excitation was completed.

5 Simulation example of hybrid analysis method for structural seismic response based on neural network restoring force model

The purpose of this method was to establish the NN restoring force model to identify the nonlinear characteristics of the key parts of the structure and to apply it to solve the dynamic response of the entire structure. Ideally, to verify the rationality and accuracy of this method, first, the test data of key nonlinear parts obtained from quasi-static tests shared or performed at a lower cost were used to train the NN restoring force model. Then, the hybrid analysis method proposed in this paper was used to calculate the response of the entire structure under seismic wave excitation. Simultaneously, a pseudo-dynamic or shaking table test of the entire structure under the same seismic wave excitation was

performed to obtain its real response. Finally, the calculation results of the proposed method were compared with the experimental results of the entire structure.

The purpose of this study was to verify this method; therefore, the numerical simulation results of OpenSees were used as the benchmark to represent the experimental results. The OpenSees simulation data of the nonlinear key parts under low cyclic loading were used as training samples to train the NN restoring force model. Finally, the structural responses under earthquake excitation obtained by the proposed analysis method were compared and analyzed with those obtained from the OpenSees simulation under the corresponding seismic excitation to verify the reliability of the proposed analysis method.

5.1 Simulation example model and parameters

In this section, the effectiveness of the hybrid analysis method based on NN restoring force model is verified by numerical simulation of a multi-degree-of-freedom (MDOF) nonlinear frame. The model was a single-story single-span frame with a height, span, and damping ratio ζ of 5 m, 5 m, and 0.05, respectively. The section sizes of the frame column and frame beam were 500 mm $\times$ 500 mm and 300 mm $\times$ 350 mm, respectively. The concrete strength grade was C30. The longitudinal reinforcement was HRB335 and the stirrup was HPB235. The numerical example model was established in OpenSees. The nonlinear beam column element was used to model the frame columns, while the beam with hinges element was used to model the frame beams, with plastic hinges placed at both ends of the beams. Fiber section models were used for both the beam and column sections for simulation. Nonlinear constitutive models of Concrete02 and Steel02 were used to simulate the hysteretic performance of the concrete and steel bars. The frame model used nodal mass sources, with 21.2 t assigned to each of the two beam–column nodes. The numerical MDOF 2D model established in OpenSees is illustrated in Fig. 10(a).

After the model was established, the same loading system as in Subsection 3.2 was used to perform a pseudo-static low-cycle loading on the MDOF model, and the pseudo-static hysteretic curve of the beam–column joint was obtained, as shown in Fig. 11. The hysteretic curve of the beam–column joint was obtained to generate the TRAIN data set as training samples according to the 11 input variables group $[\Delta\eta_n, \xi_n, x_n, \delta, x_{\text{history}+}, x_{\text{history}-}, R_{\text{history}+}, R_{\text{history}-}, E_{n-1}, x_{n-1}, R_{n-1}]$ and single output variable group $[R_n]$ of NN restoring force model. According to the analytical method proposed in this study, the frame structure was divided into a numerical and NN substructures based on structural damage analysis. The two plastic hinge sections at the ends of the

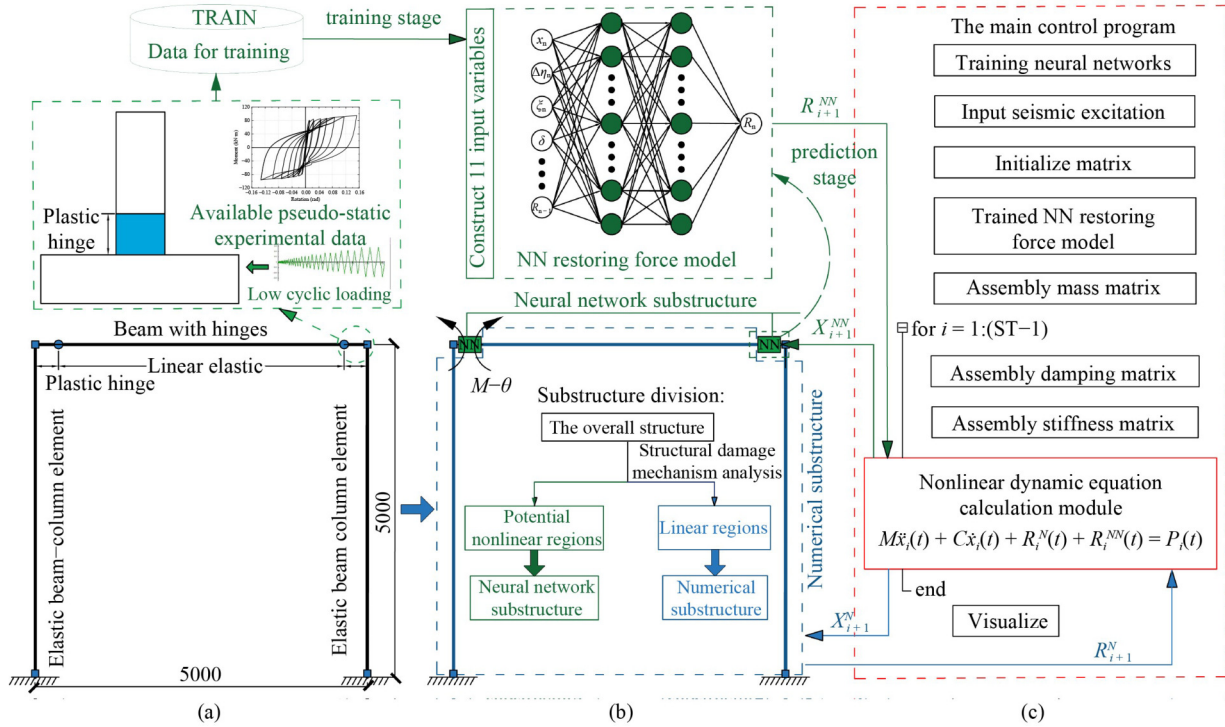


Fig. 10 OpenSees model of MDOF example and schematic of structural calculation flow using the proposed method: a) OpenSees numerical structure model; b) calculation model after substructure partition; c) the main control program in MATLAB.

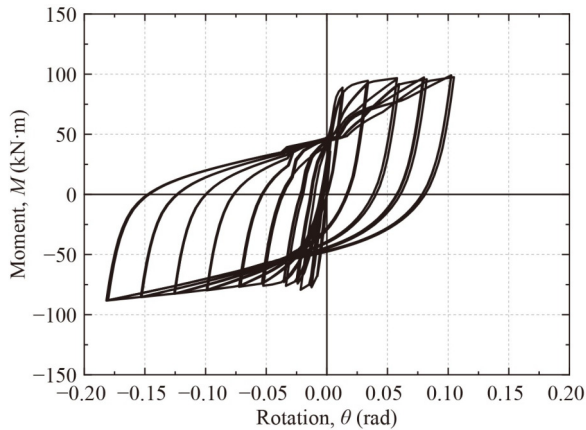


Fig. 11 Hysteretic curves of structural beam-column joints under quasi-static loading.

frame beams were considered as the two NN substructures, while the other parts of the frame beams and columns were treated as the numerical substructure, as detailed in Fig. 10(b).

First, the NN restoring force model modules introduced in Sections 2 and 3 were built in MATLAB. The NN restoring force model was trained using the acquired TRAIN data set to enable it to identify the restoring force in the plastic hinge region of the frame beam end. The nonlinear dynamic differential equation solution module using the precise integration method was developed in MATLAB. The main numerical substructure of the frame was then established. Based on the cross-sectional

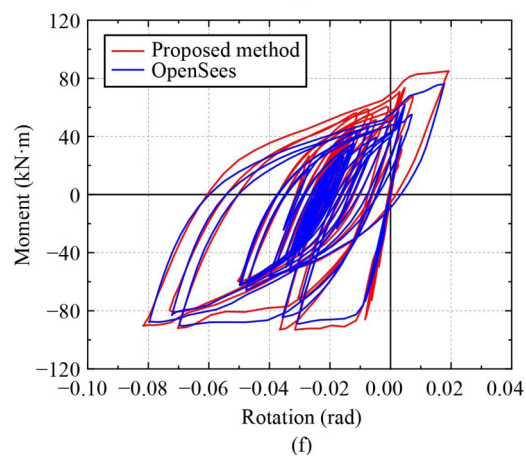
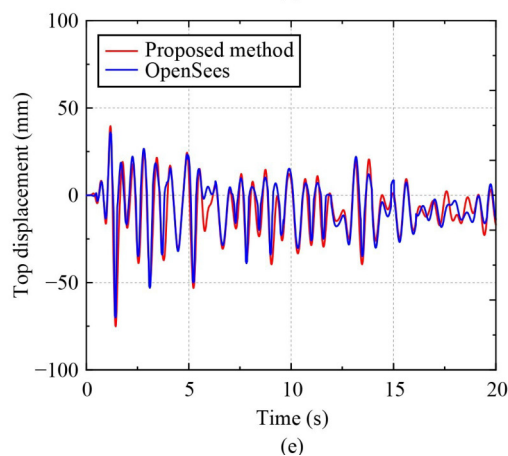
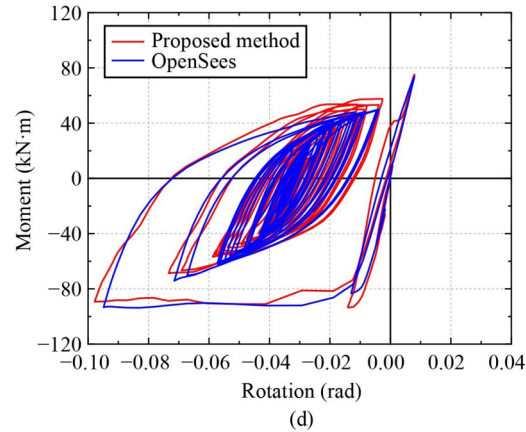
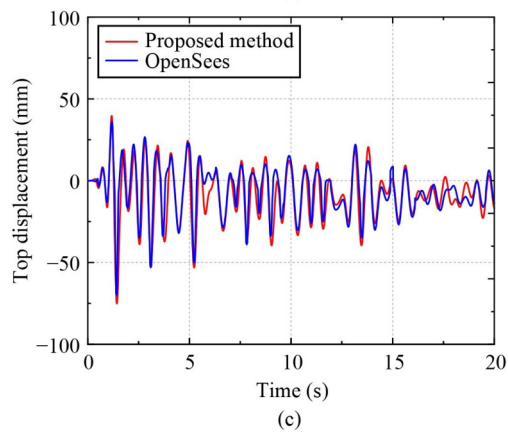
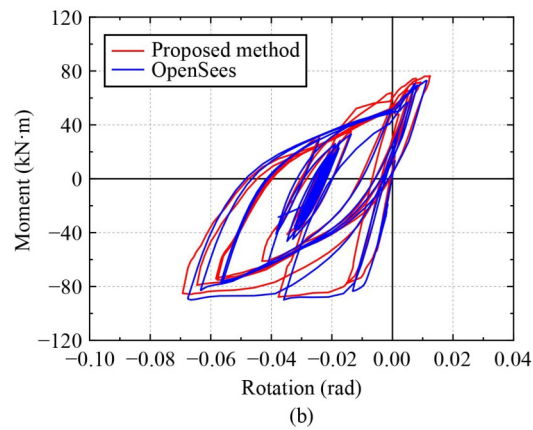
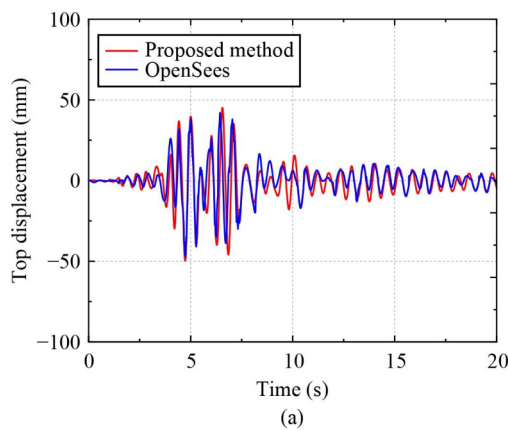
properties and material constitution of the members, the individual member stiffness matrices are assembled to obtain the total stiffness matrix for the four frame nodes, with a total of 12 degrees of freedom. The restoring forces of the rotational freedom at the plastic hinge of the beam end, namely the NN substructure, were obtained from the trained NN restoring force model. The obtained restoring force response signal R is fed back to the dynamic differential equation solving module, enabling the start of the dynamic equilibrium equation for the next time step to solve for the displacement response of each degree of freedom, thereby achieving the step-by-step solution of the structural response. For detailed procedures, please refer to Section 4. The calculation diagram of the MDOF example using the proposed method is shown in Fig. 10.

5.2 Results analysis

The global and local structural response results obtained using the proposed method were compared with those from the OpenSees structural analysis model under corresponding seismic excitations, as shown in Fig. 12. The calculation results indicate that the proposed method achieves good overall fitting performance in the vertex displacement response time-history curve and the joint hysteretic curve, with well-matched waveforms and accurate hysteretic behavior descriptions. However, there are still certain errors in the local regions of the time-history curve for the vertex displacement response and

the hysteretic curve of the joint. The existing prediction errors mainly originate from the NN restoring-force model. The numerical case results in Section 3 indicate that the established NN restoring force model, trained with low-cycle reciprocating test data, exhibits certain errors in predicting the restoring force time-history response of the joint. The proposed hybrid analysis method is used to perform step-by-step solving for the nonlinear dynamic response analysis of the MDOF model. In the process of predicting the restoring force at the current i th step for the NN substructure using the NN restoring force identification model, the input variables R_{i-1} and x_{i-1} significantly depend on the analysis results

from the previous time step, leading to the accumulation of restoring force identification errors during the step-by-step solving process. Moreover, the restoring force R_i calculated at the current step, containing errors, is input into the nonlinear dynamic differential equation solving module, causing certain errors in the displacement response calculated for the next step. In the dynamic analysis of the entire structure, the prediction of the restoring force for the current step of the NN substructure relies on the predicted value from the previous step, and the errors in the restoring force calculated at the current step are propagated to the dynamic differential equation solving module. This prediction error, along with its step-



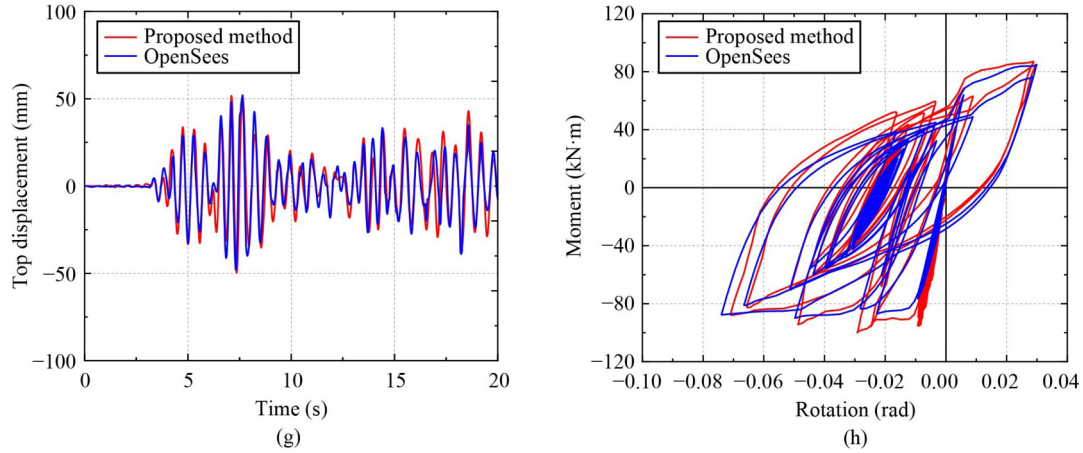


Fig. 12 The response time history and hysteresis curve of the method proposed in this paper under TRAIN training data set: (a) predicted vertex displacement time history under Friuli wave excitation; (b) predicted joint hysteresis curve under Friuli wave excitation; (c) predicted vertex displacement time history under Hollister wave excitation; (d) predicted joint hysteresis curve under Hollister wave excitation; (e) predicted vertex displacement time history under Kobe wave excitation; (f) predicted joint hysteresis curve under Kobe wave excitation; (g) predicted vertex displacement time history under Northridge wave excitation; (h) predicted joint hysteresis curve under Northridge wave excitation.

by-step propagation during the calculation process, causes an accumulation of errors in the final results. Overall, the fitting results are satisfactory, with errors within an acceptable range.

The simulation results of this MDOF case show that the NN restoring force model, trained with hysteretic data samples for low-cycle reciprocating simulation, of local components obtained by OpenSees can identify the restoring force of the component under seismic excitation. Combined with the substructure hybrid analysis method proposed in this study, the overall response of the structure under seismic excitation can better fit the numerical simulation results of the overall structure under the corresponding seismic waves obtained by OpenSees. Therefore, for the above simulation example, if the hysteresis results from the most frequently used pseudo-static test in seismic engineering are used instead of the results of finite element software analysis as the training samples of the NN restoring force model, the research achievement of the pseudo-static test can be transformed and applied to the seismic performance analysis under real seismic excitation through the proposed method in this paper with high practical value.

6 Conclusions

The objective of this study is to establish the hybrid analysis method of structural seismic response based on NN restoring force model, which can utilize NN algorithm as a means of restoring force identification to extend the hysteretic performance of nonlinear complex components obtained from quasi-static test to the time history analysis of the seismic response of the whole structure. The following conclusions were obtained from

the simulation verification example of the proposed NN restoring force model and the structural hybrid analysis method.

1) An eight-path hysteretic model NN recognition theory is proposed at the level of restoring force model recognition, which can cover and identify linear and nonlinear conditions in structural or component hysteretic models. The corresponding complete set of input variables $[\Delta\eta_n, \xi_n, x_n, \delta]$ can be used to realize the single-valued mapping of hysteretic paths.

2) An 11-input variable NN restoring force model based on eight-path hysteresis model recognition theory was developed. The input variable set $[\Delta\eta_n, \xi_n, x_n, \delta, x_{\text{history}+}, x_{\text{history}-}, R_{\text{history}+}, R_{\text{history}-}, E_{n-1}, x_{n-1}, R_{n-1}]$ can effectively predict the restoring force of a single output variable $[R_n]$, and the algorithm is developed with a double hidden layer NN architecture [11-25-25-1]. The prediction results relative errors of the NN restoring force model under the sample training of the seismic excitation training set, TRAIN1, and quasi-static loading training set, TRAIN2, are controlled within 1.5% and 7.5%, respectively.

3) The hybrid analysis method of structural seismic response based on NN restoring force model, including the NN restoring force model recognition, numerical substructure restoring force calculation, and nonlinear dynamic differential equation solution modules, is highly modular with strong feasibility. The simulation results of this MDOF case are presented to verify the accuracy of the proposed method in terms of the time-history curve of the structure displacement response and the hysteretic curve of the joint. The nonlinear dynamic response of the structure can be well fitted, and the errors mainly originate from the input errors of the NN input variable group.

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Competing interests The authors declare that they have no competing interests.

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