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Implementation of online model updating with ANN method in substructure pseudo-dynamic hybrid simulation

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Abstract. Substructure pseudo-dynamic hybrid simulation (SPDHS) is an advanced structural seismic testing method which combines physical experiment and numerical simulation. Generally, the key components which display nonlinearity first are taken as experimental substructures for actual test, and the remaining parts are modeled in simulation. Model updating techniques can be effectively applied to enhance the model precision of nonlinear numerical elements. Specifically, the constitutive model of the experimental substructure is identified online by the instantaneously-measured data, and the corresponding numerical elements with similar hysteretic behaviors are updated synchronously. Artificial neural network (ANN) can recognize the system which cannot be represented by definite numerical model, and thus avoids the structural response distortion caused by the inherent numerical model defects. In this study, a framework for online model updating in SPDHS with ANN method is expanded to implement actual test validation. Moreover, the effectiveness of ANN method is demonstrated by practical tests of a two-story frame model with bending dampers. Additionally, the unscented Kalman filter technique and offline ANN identification approach are both examined in the test validation. The experimental results show that, under the identical loading history, the online ANN method can significantly reduce the model errors and improve the accuracy of SPDHS.

Keywords: artificial neural network; online model updating; substructure pseudo-dynamic hybrid simulation

1. Introduction

Substructure pseudo-dynamic hybrid simulation (SPDHS) (Nakashima and Takai 1985, Nakashima *et al.* 1992, Tang *et al.* 2020, Phillips and Spencer 2013, Wang *et al.* 2012, Spencer *et al.* 2014), is an effective extension of the pseudo-dynamic test, in which physical experiment and finite element numerical simulation are coupled and calculated together. The key components which are expected to experience nonlinear deformations first are typically taken as the experimental substructures to perform the physical test, while the rest parts are regarded as the numerical substructures and simulated in computer with an assumed numerical model. SPDHS has an important application prospect in the field of seismic testing for large and complex structures.

In general, key components or parts of large complex structures such as energy dissipation braces, frame joints, piers and dampers, etc., may enter into nonlinear stage under strong ground motions. Actually, due to the limitation of equipment setup, only one or several critical components that are expected to experience nonlinearity first are physically tested in the laboratory, while the remaining components with similar properties and hysteretic behaviors are numerically modeled in the numerical substructure. However, for the critical elements that may display nonlinearity but cannot be physically tested, there may be large model errors in the assumed numerical model. The first type of error is derived from the model defects caused by the oversimplification of the numerical model; the second type of error originates from the uncertainty of the numerical model parameters. When the proportion of these nonlinear elements becomes large, the model errors will accumulate to a non-neglectable degree, which will in turn trigger the distortion of structural dynamic response. In order to reduce the model errors and improve the accuracy of SPDHS, various online model updating techniques are effectively introduced to the SPDHS, in which the hysteretic model of the experimental substructure is identified online by the instantaneously-measured data, and the corresponding parts with similar material properties and nonlinear behaviors in the numerical substructure are updated synchronously.

Online model updating techniques can be roughly divided into two categories: parameter updating method based on numerical model and non-parameter updating method based on intelligent algorithm. For the parameter updating method, the constitutive model of the component is assumed as a specific numerical model, and the numerical model parameters are estimated by using the parameter identification techniques, which can effectively reduce the second type of model errors. At present, parameter

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identification methods mainly include nonlinear multivariable optimization algorithm (Chuang *et al.* 2018, Yang *et al.* 2012, Kwon and Kammula 2013), unscented Kalman filter method (UKF) (Hashemi *et al.* 2014, Shao *et al.* 2016, Wu *et al.* 2016, 2018) and constrained unscented Kalman filter method (CUKF) (Wu and Wang 2014, Ou *et al.* 2017), etc. For the parameter identification techniques, when there are not enough parameters to represent the specific nonlinear behavior of the component, the risk of structural response distortion caused by numerical model defects cannot be avoided fundamentally. For example (Wang *et al.* 2020), Fig. 1 compares the hysteresis of an assumed initial Bilinear model, the corresponding updated Bilinear model with the UKF method, and the real BWBN (Bouc-Wen-Baber-Noori) model (Baber and Noori 1985). It can be seen that large model discrepancies exist between the assumed numerical models and the real one due to the absence of the degradation or pinching parameters in the original Bilinear model. This example indicates that the UKF updating method can instantaneously track the degradation and pinching behaviors which do not exist in the assumed Bilinear model by constantly adjusting the model parameters. It should be mentioned that the first type of model errors caused by the inherent model defects are still very large and cannot be ignored.

For the non-parameter updating method based on intelligent algorithm, there is no need to assign the numerical model of the component in advance. Instead, the hysteresis model can be accurately matched by artificial neural network, support vector machine as well as other intelligent algorithms. Artificial neural network (ANN) has been widely utilized in the field of nonlinear dynamic system identification. It can be applied to approximate any nonlinear function and model the system which cannot be described by definite mathematical model by constantly adjusting the connection weights of neurons in each layer. Since the artificial neural network can learn the hysteretic information that does not exist in the assumed numerical model, the ANN method has important engineering application value for accurately revealing the seismic performance of nonlinear components or structures and improving the accuracy of SPDHS.

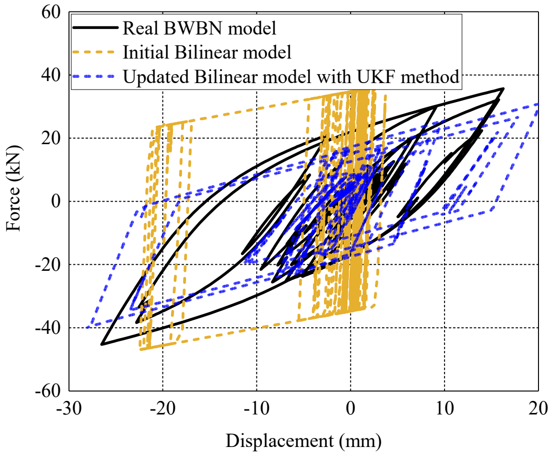


Fig. 1 Comparison of an updated Bilinear model with real response

In the past decades, ANN method has been gradually explored. In 2005, Yang and Nakano (2005) used neural network to identify the constitutive model of test substructure, and updated the corresponding parts in the numerical substructure. In 2008, Yun *et al.* (2008a) applied neural network with five input variables to fit the hysteretic model in the static reciprocating loading test. According to the positive and negative symbols of input variables at different positions of the hysteresis curve, displacement and restoring force form a one-to-one mapping. The feasibility of the proposed method in model identification was preliminarily proved (Yun *et al.* 2008b). Elanwar and Elnashai (2016) used an offline ANN approach to recognize the Bilinear model of a two-span steel frame, which does not conform to the fact of time-stepping loading in SPDHS. Wang *et al.* (2017a) proposed an updating method based on the online neural network algorithm, in which only the experimental data in the current loading step is used to train the neural network model, and the feasibility of this method was verified in numerical simulation. Wang *et al.* (2017b) added a feedback layer between the input layer and the hidden layer to improve the adaptability of the online neural network algorithm, and the effectiveness of this method was verified by experiments. In order to further improve the stability and adaptability of online neural network algorithm, Wang *et al.* (2020) proposed an updating method based on the online neural network with forgetting factor, in which a two-stage testing method framework of "offline pre-training + online fine tuning" is adopted. Firstly, a randomly initialized ANN model is offline trained by the existing test data of the key component, and the pre-trained ANN model is assigned as the initial constitutive model of the relevant parts with similar hysteretic behaviors in the numerical substructure. Afterwards, the inaccurate ANN model is online calibrated by the measured experimental data in the SPDHS. In addition, for the online training samples in each time step, the latest batch samples of experimental substructure in the current loading step are applied to form a dynamic sample window with forgetting factor to train the ANN model, and thus the adaptability of the online neural network method can be improved. By comparing with the UKF method, the effectiveness of the online neural network method with forgetting factor in online model identification was verified through numerical studies with inherent model defects considered. It is also demonstrated that the ANN method can not only track more hysteresis information with good generality, but also has high accuracy in predicting the restoring force even under different loading histories.

The objective of this study is to implement online model updating in SPDHS with ANN method. The two-stage testing method framework of "offline training + online fine-tuning" is expanded (Wang *et al.* 2020) to perform actual test validation. The feasibility and effectiveness of the ANN model updating scheme are experimentally verified by a two-story frame model with bending dampers, in which the experimental substructure of bending damper is tested in the laboratory and the remaining components are simulated in computer. In the test validation, the online ANN method, the online UKF method and the offline ANN identification approach are examined and compared.

2. Online model updating with ANN method in SPDHS

2.1 Introduction of model updating in SPDHS

In the SPDHS of large complex structures, online model updating has great potential to improve the model accuracy of the nonlinear components. To illustrate the principle of online model updating in SPDHS, an example of a frame structure with isolation bearings is presented, as shown in Fig. 2. It is expected that the isolation bearings will experience large nonlinear deformations under strong ground motion, which are difficult to simulate numerically. Therefore, one of the bearings which are expected to occur nonlinearity first is selected as the experimental substructure for actual physical loading test, while the remaining bearings and the upper frame structure are regarded as the numerical substructures and simulated in computer. According to the similarity of mechanical properties of the experimental substructure, the numerical substructures can be divided into two categories (Hashemi *et al*. 2014), namely the updatable numerical substructure (i.e., the numerically modeled bearings) and the non-updated numerical substructure (i.e., the upper frame structure) as shown in Fig. 2.

The updatable numerical substructure shares identical properties and hysteretic model with the experimental substructure, but does not necessarily experience the same loading history. Hence, the inaccurate constitutive model of the updatable numerical substructure can be updated online by the measured data from experimental substructure. It is assumed that the experimental substructure has equal or greater seismic demands compared to the updatable numerical substructure, which means it is expected to experience a specific type of nonlinear behavior prior to the updatable numerical substructure. In this case, the measured data that incorporate this nonlinear behavior of the experimental substructure can be used to calibrate the updatable numerical substructure, thus the updatable numerical substructure can present similar behavior under similar demand levels, especially under different loading histories. The non-updated numerical substructure presents a great difference in the hysteretic properties compared with the experimental substructure, and it typically remains in linear stage and can be numerically modeled reliably. The non-updated numerical substructure is not updated because it is not tested.

2.2 ANN method

The artificial neural network utilized in this paper is BP neural network (i.e., back propagation neural network), which is a multilayer feedforward neural network proposed by Rumelhart *et al*. (1986). BP neural network can realize any nonlinear mapping from input to output without knowledge of its specific mathematical equation. The weights and thresholds are adjusted continuously by the training algorithm to minimize the mean square error of the network objective function.

The topological structure of the neural network includes input layer, hidden layer and output layer, as illustrated in Fig. 3. The input layer accepts the input signals from the external environment. $x_1, x_2, ..., x_i, ..., x_n$ are the input signals of BP neural network, and $z_1, z_2, ..., z_l, ..., z_m$ are the output

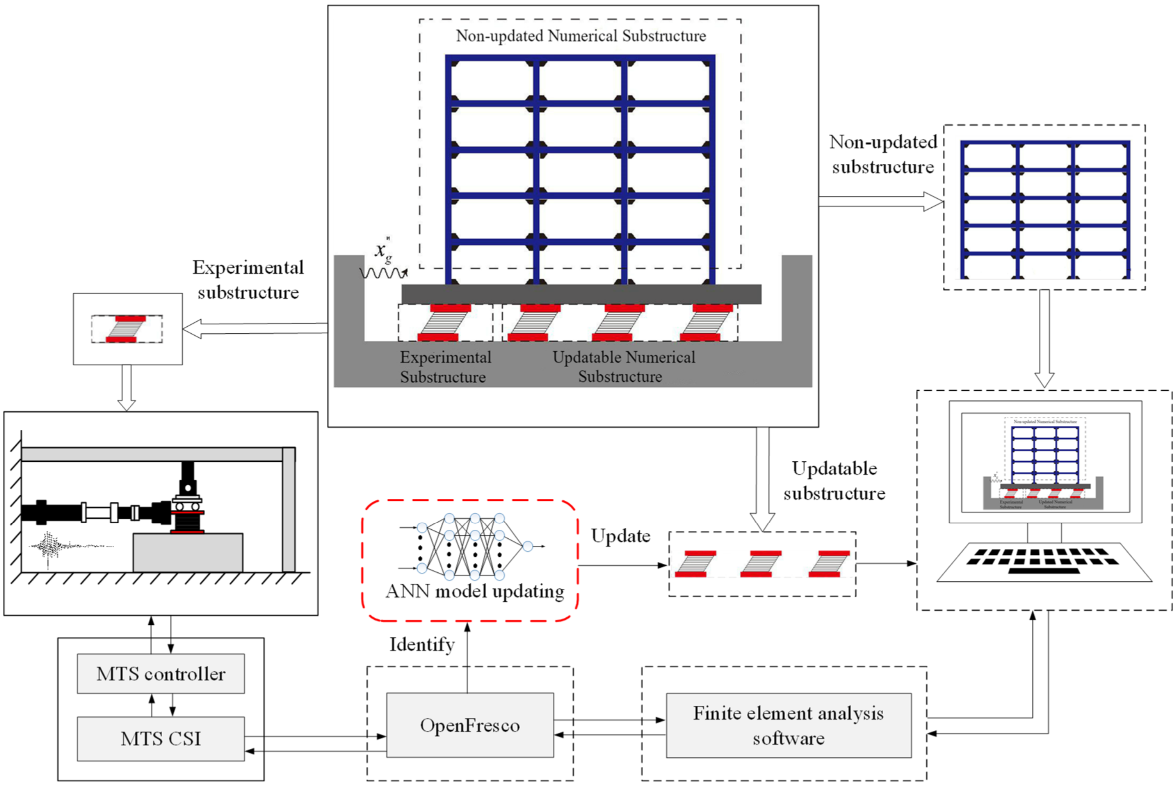


Fig. 2 Illustration for SPDHS with online model updating

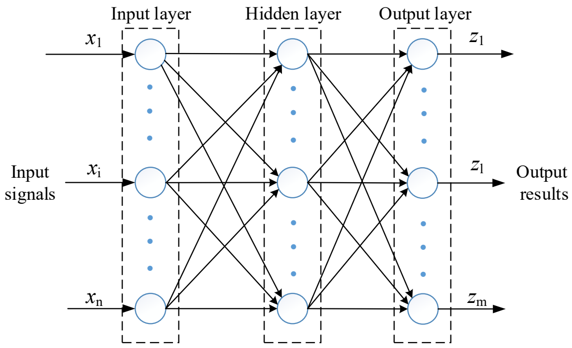


Fig. 3 Illustration for SPDHS with online model updating

results. The BP neural network expresses the nonlinear mapping relationship from *n* independent variables to *m* dependent variables.

The training process of BP neural network consists of two stages: forward propagation of signals and backward propagation of error. Levenberg Marquardt algorithm (LM) (Moré 1978) is commonly applied to adjust the weights and thresholds of the network along the direction of the fastest decline of the objective function. In this study, the LM algorithm is adopted to train the ANN model, which can be invoked in the MATLAB Neural Network Toolbox (2018).

2.3 Framework for online model updating with ANN method in SPDHS

To implement online model updating in SPDHS with ANN method, it is necessary to combine the traditional SPDHS process with the ANN method. The main concern of the actual test is the robust control problem. In this study, the two-stage testing method framework of “offline training + online fine-tuning” is adopted (Wang *et al.* 2020) and expanded to further ensure the robustness of the online identification process in the practical test validation.

Fig. 4 shows the expanded framework for online model updating with ANN method in SPDHS, in which three updating modules are added to the traditional SPDHS. Firstly, a randomly initialized ANN model is trained offline using the existing experimental data of the key structural component, and the pre-trained ANN model is taken as the initial constitutive model of the updatable numerical substructure. Afterwards, the SPDHS with model updating is conducted, in which the inaccurate ANN model is online calibrated by the online training samples of the experimental substructure. As will be presented in the following sections, the newly added updating modules will be discussed in detail.

2.3.1 ANN model initialization

In this study, ANN model is utilized to present the hysteretic behaviors of the updatable numerical substructure. The initial configuration of the updatable numerical substructure is set as the pre-trained ANN model which is offline trained by the existing experimental data of the critical structural component.

In general, ANN is relatively sensitive to initial weights and thresholds. For online learning of neural networks, random initialization of weights and thresholds cannot guarantee the stability of online gradients. The aforementioned ANN model initialization enables the initial weights and thresholds of ANN model to find a region close

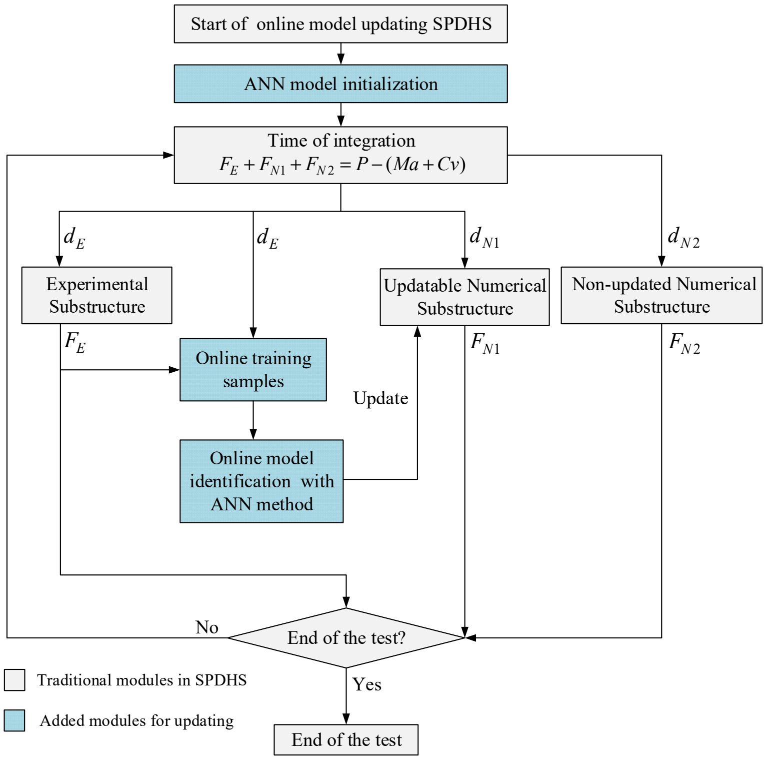


Fig. 4 Framework for online model updating with ANN method in SPDHS

to the optimal solution. Taking the offline pre-trained ANN model as the starting point of online model updating, the recognition system can work in a small range of uncertainty, so as to ensure the stability of the online neural network algorithm. Actually, the existing experimental data (such as quasi-static test or pseudo-dynamic test) of the key nonlinear component can be extended and applied to the SPDHS, which therefore provides reliable and a wealth of prior knowledge to improve the model accuracy of relevant numerical elements.

2.3.2 Online training samples

As a type of “black box” algorithm, there are concerns about unclear physical meaning and poor interpretability of ANN. In the process of online identification, the cumulative propagation and exaggeration of errors may appear. The selection of online training samples and the training weight settings of old-new samples have significant impacts on the stability and adaptability of online neural network algorithm in an uncertain state. In this study, the combination of “random offline samples + dynamic window samples with forgetting factor” are expanded as the online training samples in each loading step, so as to enhance the robustness of the online neural network algorithm for actual tests. Some samples are randomly selected from the offline training samples to ensure the good performance of ANN model in old tasks. The remaining samples are the latest batch samples of the experimental substructure of the current loading step, so as to form a dynamic sample window with forgetting factor. The new samples are given larger training weights, while the earlier historical samples smaller training weights, which enhances the adaptability of the online identification system.

(1) Random offline samples:

Based on the pre-trained ANN model, online calibration of the hysteretic model may lead to the so-called “catastrophic forgetting” problem. After learning new knowledge, the ANN model may almost completely forget the previously absorbed information. Therefore, in each loading step, some samples are randomly selected from the offline training samples and added to the current online training samples.

(2) Samples with forgetting factor in a dynamic window:

The nearest batch samples of the experimental substructure in the current loading step are utilized as the other part of the online training samples, which has both computational efficiency and stability. In general, the newly added samples which contain more fresh knowledge have not been trained yet, while the historical samples have been learned. There is a risk that the historical samples will annihilate the latest samples. A forgetting factor is introduced to give the latest samples larger training weights, while smaller training weights are assigned to the earlier historical samples. In this case, the adaptability and accuracy of the online neural network algorithm smaller training weights are assigned to the earlier historical samples are improved. The nearest batch samples of the experimental substructure in the current loading step are put into a sliding dynamic window with a fixed number of L. When the newest experimental sample enters, the earliest sample is removed, as shown in Fig. 5. The sliding window with L samples can be presented as follows.

$$Window = [(X_1,Y_1),\ldots,(X_i,Y_i),\ldots,(X_L,Y_L)] \tag{1}$$

where (X_L, Y_L) is the latest added experimental sample and (X_1, Y_1) is the earliest sample in the dynamic window. λ_i is the training weight of (X_i, Y_i) in the dynamic window, which is determined by the exponential forgetting method as follows.

$$\lambda_i = \frac{1-\mu}{1-\mu^L}\mu^{L-i} \tag{2}$$

$$\sum_{i=1}^{L}\lambda_i = 1 \tag{3}$$

where μ denotes the forgetting factor.

2.3.3 Online model updating with ANN method

In this updating module, the initial ANN model is also set as the previously pre-trained one. The inaccurate ANN model is online calibrated by the online training samples of the experimental substructure and the hysteretic model of

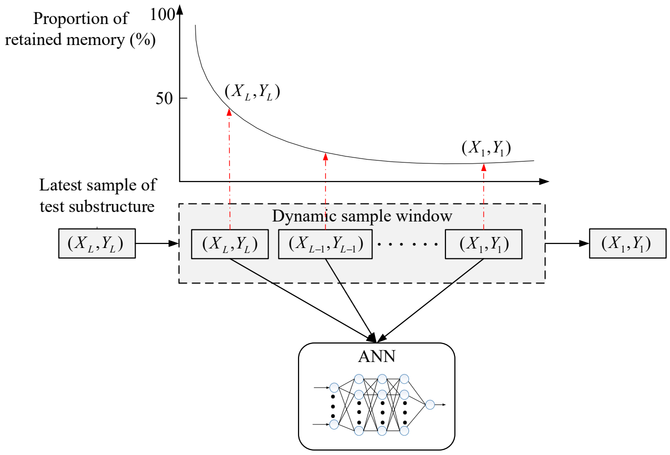


Fig. 5 Framework for online model updating with ANN method in SPDHS

relevant components in the updatable numerical substructure is updated simultaneously. Through online training of ANN model, the fresh information contained in the latest data is continuously calibrated into the hysteretic model to realize the rolling optimization of the model. LM algorithm is applied to adjust the weights and thresholds of ANN model. To prevent the gradient from falling too fast and guarantee the stability of the online identification system, the factor which controls the iteration step size should be small, and the suggested value is 10^{-5}.

2.4 Specific implementation process of the proposed methodology

The specific procedures are summarized as follows:

Step1 The existing experimental data of components are collected, and the offline sample database is constructed:

The existing test data, including quasi-static loading test, shaking table test or quasi-dynamic test, are collected to construct off-line sample database for off-line pre-training and initialization of neural network model.

Step2 Construct a pre-trained ANN model:

A randomly initialized ANN model is trained offline using the existing experimental data of the key structural component which are collected in Step1, and the pre-trained ANN model is taken as the initial constitutive model of the updatable numerical substructure. The detailed procedure of Step2 are listed as follows.

(a) Adjust the input and output variables of the pre-training data collected in Step1

By adjusting the input and output variables, the displacement and restoring force are formed as a one-to-one nonlinear mapping, such as a 6-variable input variable model [d_i, d_{i-1}, F_{i-1}, $F_{i-1}d_{i-1}$, $F_{i-1}\Delta d_i$, E_{i-1}], and the output layer is usually set to [F_i], namely restoring force.

(b) Data normalization

Since the data distribution of each input variable may be quite distinct, it is possible to appear non-convergence in the training process. Therefore, it is necessary to normalize the input variables and output variable to map them to the interval [0, 1]. For example, variable X is normalized to X_1

$$X_1 = \frac{X - min(X)}{max(X) - min(X)} \tag{4}$$

(c) Train the neural network model offline by the normalized pre-training data

Firstly, an ANN model with random initialization of weights and thresholds is established. And the structure of the neural network model, the number of hidden layer and hidden layer neurons are determined. Next, the ANN model is trained off-line by using the pre-training data normalized in Step 2 (b), and the pre-trained ANN model is regarded as the the initial constitutive model of the updatable numerical substructure for subsequent on-line model updating.

Step3 Online calibration in SPDHS:

For the existence of model errors between the pre-trained ANN constitutive model and the real one, it is necessary to online calibrate the inaccurate constitutive model. The specific process is as follows.

(a) Numerical integration of equation of motion

According to the global responses in the previous loading step, based on the equation of motion of the entire structure, the displacement of each substructure in the next loading step is solved by numerical integration scheme. The displacements of experimental substructure, updatable numerical substructure, and non-updated numerical substructure in the next loading step are set to d_{exp}, d_{num}, and d'_{num} respectively. After inputting the displacement of the experimental substructure, the restoring force of the experimental substructure can be measured as F_{exp}. And the restoring force of the non-updated numerical substructure can be calculated as F'_{num} by the finite element software.

(b) Data normalization of the experimental Substructure

Firstly, in the current loading step, the input and output variables of the experimental substructure data are adjusted to the previously defined input-output variable model. Next, the input and output variables are normalized to the interval [0, 1]. The processing method refers to Eq. (4), in which the maximum and minimum values are the corresponding ones acquired in Step2 (b).

(c) Data normalization of the updatable numerical substructure

Similarly, the input variables of the updatable numerical substructure in the current loading step are also supposed to be adjusted to the previously defined input variable model. Then, the input variables are normalized to the interval [0, 1] as shown in Eq. (4) for unified data processing.

(d) The selection of online training samples

The combination of "random offline samples + dynamic window samples with forgetting factor" are applied as the online training samples in each loading step. Some samples are randomly selected from the offline training samples to ensure the good performance of ANN model in old tasks. The remaining samples are the latest batch samples of the experimental substructure of the current loading step, so as to form a dynamic sample window with forgetting factor.

(e) Online train the ANN model

The online training samples in Step 3 (d) are input into the ANN model which is well trained in the previous loading step for model training.

(f) Restoring force prediction of the updatable numerical substructure

The normalized input variables of the updatable numerical substructure in Step3(c) are input into the well trained ANN model from Step3(e), so as to predict the dimensionless restoring force of the updatable numerical substructure. Then the dimensionless restoring force should be reversely normalized to acquire the desired restoring force F_{num} of the updatable numerical substructure. Next, the restoring forces of the three substructures (experimental substructure, updatable numerical substructure, non-updated numerical substructure) are fed back to the equation of motion. Repeat the above Step3 (a)-(f) until the ground motion input is completed.

3. Test setup

A platform for SPDHS with ANN model updating (MATLAB-Openfresco-MTS system) is built for actual implementation. The online neural network algorithm in the model updating module can be coded into MATLAB, which has instant access to the numerical substructure. Based on the expanded framework of methodology and established test system, a two-story frame model with bending dampers is selected to demonstrate the effectiveness of the online ANN updating method. In addition, the UKF estimation method and offline ANN identification technique are also examined and analyzed in the test validation. In the practical test, it is assumed that a very small control error of actuator exists and the force measurements acquired in each step are reliable. In other words, the experimental errors have a minor impact on the global structural response and can be disregarded.

3.1 Platform for SPDHS with online ANN model updating

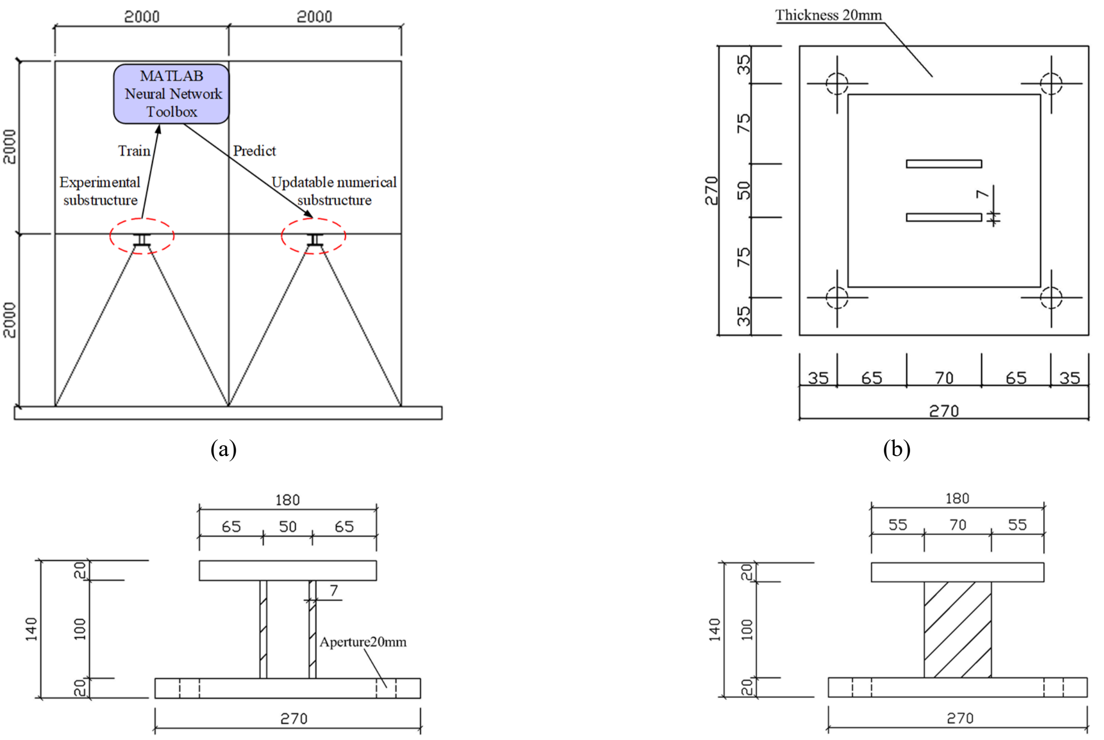
The actual SPDHS with online ANN model updating is conducted on the MATLAB-Openfresco-MTS platform established in the structural laboratory of Southeast University. The platform architecture mainly includes the following four parts.

(1) Interface software for data exchange between software and hardware: Openfresco (Schellenberg *et al.* 2009) is selected to realize the data communication between the finite element numerical calculation software and the laboratory loading control system.

(2) Numerical calculation software: In this study, MATLAB software is selected for the finite element analysis of the numerical substructure and the time-stepping numerical integration of the entire structure. TCP/IP protocol is utilized to realize data communication between MATLAB and Openfresco.

(3) Model updating software: In this research, the online neural network algorithm in the model updating module is coded into MATLAB, in which the Neural Network Toolbox (2018) in MATLAB is applied to online train the ANN model. Then the identified ANN model is utilized to online calibrate the updatable numerical substructure and predict the corresponding restoring force.

(4) Loading control system: In the test verification, the MTS loading control system is applied to carry out loading test on the experimental specimen. And MTS CSC (MTS computer simulation configurator) is adopted to realize the data communication between Openfresco and MTS control system. In the MTS CSC software, all the experimental configurations are defined to generate a mtscs file, including experimental control channel and mode, type and unit of feedback signals, etc. In



(a) (b) (c) (d)

Fig. 6 (a) Steel frame model with bending dampers; (b) top view of bending damper; (c) left view of bending damper; (d) elevation view of bending damper (Unit: mm) the test process, Openfresco connects with the MTS control system by calling the mtscs file.

3.2 Model description and ANN configurations

3.2.1 Model description

A two-story two-span steel frame with bending dampers is adopted as the test model, as illustrated in Fig. 6(a). The height and width of the steel frame are both 2000 mm. The frame columns and beams are made of hot-rolled H-beam steel (HN 200×100). Assuming that the floor stiffness is infinite, the interlaminar shear model is utilized to model the entire structure. The left and right bending dampers in the first story share identical material properties and hysteretic model. The concentrated mass in each story is 20222.8 kg. Classical Rayleigh damping is adopted, and the first and second modal damping coefficients are set to 0.05. The seismic ground motion recorded at simivalley Katherine Rd Station during Northridge Earthquake on January 17, 1994 is selected as the external excitation with a adjusted PGA of 300 cm/s^2. The explicit Newmark-β numerical integration method is adopted to solve the motion equation of the structure step by step and the integration step is set to 0.01 s.

In the test verification, the entire structure is divided into three parts: the left bending damper in the first story is set as the experimental substructure that is physically loaded in the laboratory; accordingly, the right bending damper in the first story with identical hysteretic behaviors is taken as the updatable numerical substructure and simulated in MATLAB; the two-story steel frame is left in the non-updated numerical substructure and numerically modeled in MATLAB with a reliable assumed model. For the ANN model updating method, the online neural network algorithm is programmed in MATLAB, in which the Neural Network Toolbox (2018) built in MATLAB is utilized to online train the ANN model. Openfresco is adopted to implement data communication and coupling calculation between the MTS loading control system and numerical calculation software MATLAB. The design drawings and experimental setup of the tested bending damper are shown in Figs. 6(b)-(d) and Fig. 7 respectively. Traditionally, the restoring force model of the updatable numerical substructure is set to the Bilinear model based on empirical assumption. The over-simplified Bilinear model is intentionally selected to examine the performance of the model updating identification techniques. In this case, the model defects between the assumed numerical model and the exact model and their potential effects on the structural response can be considered. The specific initial parameters of Bilinear model are presented in Table 1, in which α denotes the ratio of the post-yielding stiffness to elastic stiffness, k_0 is the elastic stiffness, and F_y represents the yield strength.

Fig. 7 Experimental setup of the tested bending damper of bending damper

Table 1 Initial parameters of the assumed Bilinear model

k_0 (N/mm)	α	F_y (N)
68000	0.008	35000

3.2.2 ANN configurations

Prior to running the actual model updating loading test, an ANN model is established to represent the initial hysteretic model of the updatable numerical substructure. The ANN configurations mainly involve the selection of ANN structure, the initialization of weights and thresholds of ANN model and parameter settings of the online neural network algorithm. Next, each issue will be discussed as follows.

(1) Selection of ANN structure

In this test validation, to ensure the ANN recognition ability of strong nonlinear behaviors, the number of hidden layers is set to 3 and the number of neuron nodes in each hidden layer is set to 10 based on experience (Wang *et al.* 2020).

For the complex nonlinear hysteretic relationship, the displacement and restoring force do not correspond to a linear mapping. The restoring force in the current step is not only related to the instantaneous displacement but also depends on the historical restoring force, past displacement and energy dissipation. Hence, it is necessary to adopt sufficient state variables to describe the restoring force in nonlinear cases. In this experimental validation, six input variables $[d_i, d_{i-1}, F_{i-1}, F_{i-1}d_{i-1}, F_{i-1}\Delta d_i, E_{i-1}]$ (Kim *et al.* 2012) are utilized in the input layer and one output variable $[F_i]$ in the output layer. d_i and F_i denote the displacement and restoring force in the i-th step respectively. E_{i-1} represents the cumulative energy dissipation up to the (i-1)-th step and $E_{i-1} = E_{i-2} + |F_{i-1}d_{i-1}|$. The activation functions in the hidden layer and output layer are set to “tansig” and “purelin” respectively. The topological structure of ANN model utilized in this study is illustrated in Fig. 8.

(2) Initialization of weights and thresholds of ANN model

Prior to this test validation, there is no available data about the hysteretic behaviors of experimental substructure. To obtain useful offline samples for pre-training and initialization of ANN model, the conventional SPDHS is firstly conducted on the test model as shown in Fig. 6(A). The displacement and restoring force of the experimental substructure in each loading step are extracted and 2500 groups of offline samples are acquired. Then, the offline samples are utilized to train a randomly initialized ANN

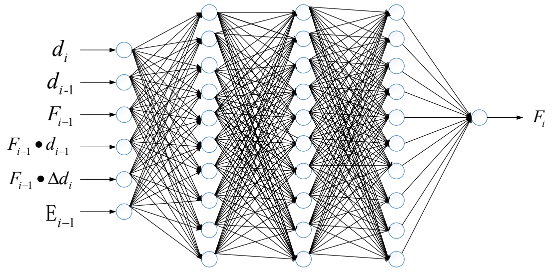


Fig. 8 Skeleton of the ANN structure with three hidden layers

model, and the pre-trained ANN model is set as the initial restoring force model of updatable numerical substructure in the SPDHS.

(3) Parameter settings of the online neural network algorithm

The objective function of ANN model is set as the mean square error (MSE), and LM algorithm is adopted to online train the ANN model. The control factor and the maximum iteration in the LM algorithm are set to 10^{-5} and 50, respectively. The momentum coefficient is set to 0.1 to prevent the ANN model from skipping the minimum point during the learning process. The online training samples contain two parts. For the first part, in each loading step, 500 samples are randomly selected from the available offline samples. For the remaining part, the latest 200 samples of experimental substructure in the current loading step are extracted and put into the dynamic sample window with forgetting factor to obtain current samples with adaptability. The forgetting factor is set to 0.1 by experience (Wang *et al*. 2020).

3.2.3 Test cases

To verify the feasibility and effectiveness of the ANN method in SPDHS with model updating, actual experimental tests in five cases were conducted in the laboratory. The specific model configurations are listed in Table 2. In the reference case, under similar loading histories, the constitutive model of the updatable numerical substructure shares similar hysteresis relationship with the experimental substructure. If preliminary ANN pre-training can be executed, it will be possible to offline calibrate the hysteresis model of the updatable numerical substructure based on the pre-trained ANN model without online model updating. Thus, the offline ANN calibration will be evaluated in this test validation. Currently, UKF method has been widely applied to the identification of nonlinear structural systems in civil engineering. Previous research results (Wang *et al*. 2020) show that the UKF method can effectively improve the reliability of the numerical model and enhance the simulation accuracy of the hybrid test. As a contrast, the UKF method is also examined in this test validation.

The initial parameters of the Bilinear model which are empirically selected are listed in Table 1. In this test validation, the pre-trained ANN model is obtained by offline training, in which the available offline training samples are acquired from the experimental data in the conventional SPDHS as described in section 3.2.2.

In the SPDHS with online UKF model updating, the initial hysteretic model of the updatable numerical substructure is set as the Bilinear model so that the state vector to be estimated is defined as.

$$\boldsymbol{Z} = [k_0, \alpha, F_y] \tag{5}$$

The initial value of vector $\boldsymbol{Z}$ is shown in Table 1. The initial state covariance matrix $\boldsymbol{P}_0$, process noise covariance matrix $\boldsymbol{Q}_0$ and measurement noise covariance matrix $\boldsymbol{R}_0$ are assumed as follows.

$$\boldsymbol{P}_0 = diag([10^3, 0.2, 1]) \tag{6}$$

$$\boldsymbol{Q}_0 = diag([10^{-6}, 10^{-6}, 10^{-6}]) \tag{7}$$

$$\boldsymbol{R}_0 = [10^2] \tag{8}$$

4. Test results

The hysteresis and restoring force response of the updatable numerical substructure are observed, and the prediction accuracy of restoring force is evaluated in four test cases. Since the updatable numerical substructure is subjected to the identical loading history with the experimental substructure, the absolute error between the predicted restoring force of the updatable numerical substructure and the measured restoring force of the experimental substructure is adopted as the error index to evaluate the prediction accuracy. When the absolute error is smaller, the hysteretic model of the updatable numerical substructure is closer to the experimental substructure, and the global dynamic response of the structure approaches the

Table 2 Four test cases in SPDHS

Case	Test type	CMES	ICMUNS	MUM
Reference	Reference SPDHS	Test loading	Identical with experimental substructure	No updating
Conventional	Conventional SPDHS	Test loading	Bilinear	No updating
Offline ANN	SPDHS with offline ANN calibration	Test loading	Pre-trained ANN model	No updating
Online UKF	SPDHS with online UKF model updating	Test loading	Bilinear	UKF method
Online ANN	SPDHS with online ANN model updating	Test loading	Pre-trained ANN model	ANN method

*Abbreviations: CMES, constitutive model of experimental substructure; ICMUNS, initial constitutive model of updatable numerical substructure; MUM, model updating method

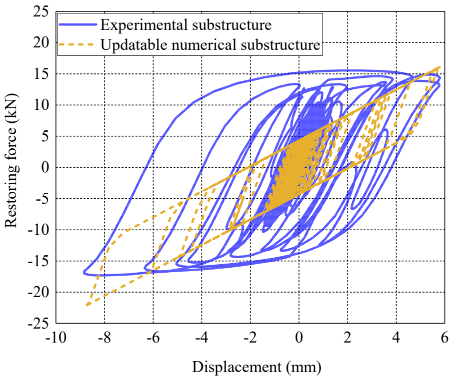


Fig. 9 Dampers hysteresis in conventional case

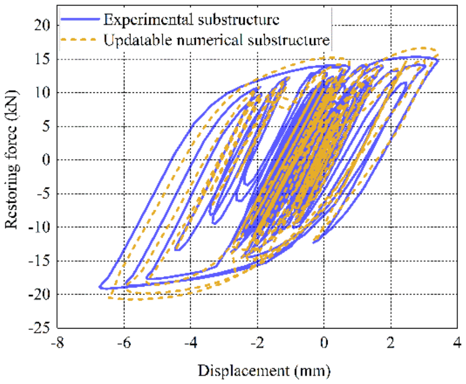


Fig. 11 Dampers hysteresis in online UKF case

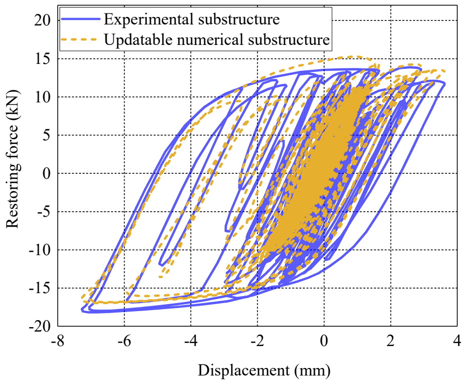


Fig. 10 Dampers hysteresis in offline ANN case

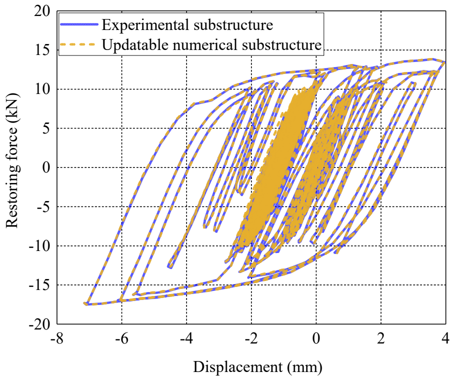


Fig. 12 Dampers hysteresis in online ANN case

exact state. The hysteresis and restoring force histories of the experimental substructure and updatable numerical substructure in four test cases are compared, as shown in Figs. 9-12. The error index to evaluate the prediction accuracy of restoring force is defined as follows.

$$|A_i| = |F_{E,i} - F_{N,i}| \tag{9}$$

where $F_{E,i}$ denotes the measured restoring force of the experimental substructure in the i-th step and $F_{N,i}$ is the predicted restoring force of the updatable numerical substructure in the i-th step.

The following observations can be obtained from Figs. 9-12.

(1) In the conventional SPDHS, when the model error between the assumed numerical model and the real model is large, substantial errors exist between the predicted restoring force of the updatable numerical substructure and the measured restoring force of the experimental substructure, especially at the response peaks. Therefore, it is necessary to apply model updating techniques to online calibrate the inaccurate restoring force model, so as to improve the performance of SPDHS.

(2) In the SPDHS with offline ANN calibration, compared with the conventional SPDHS, the hysteresis predicted by offline ANN method without model updating is improved, but the restoring force prediction error is still large in the time history. To further improve the restoring force prediction accuracy, it is essential to perform online calibration of the inaccurate hysteretic model with the instantaneously-measured data of the experimental substructure based on the pre-trained ANN model.

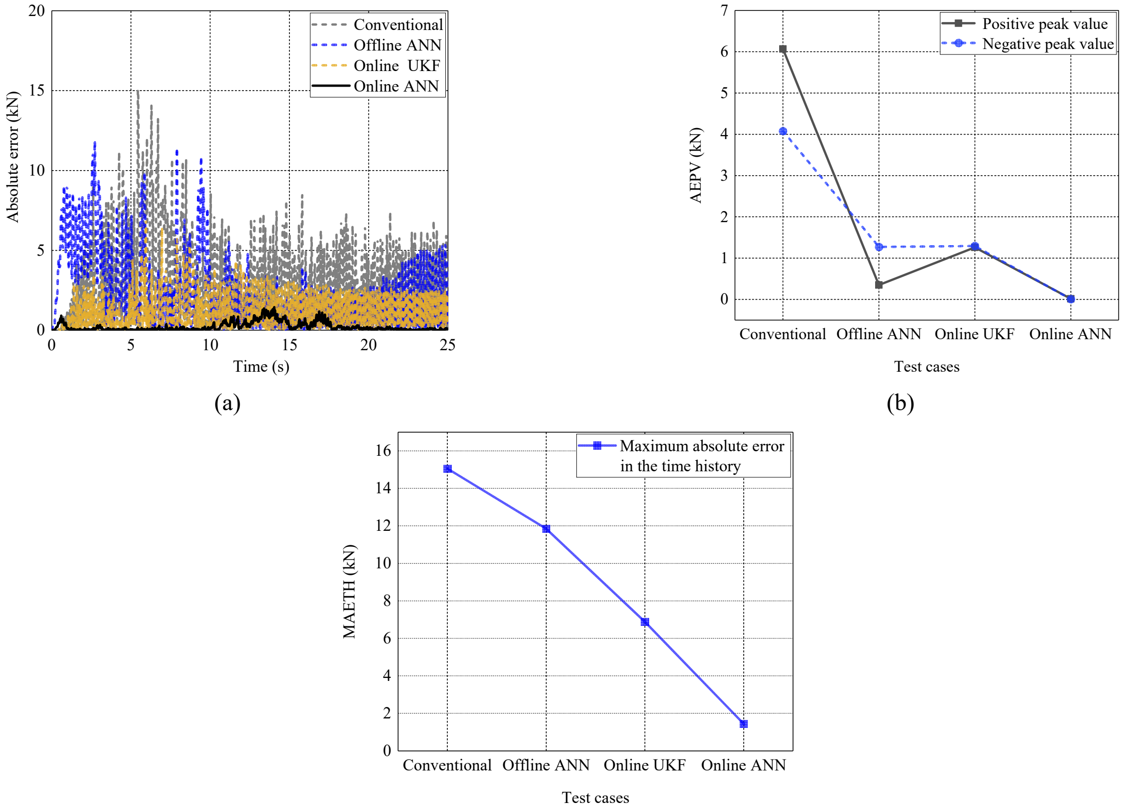
(3) In the SPDHS with online UKF model updating, model updating enables the Bilinear parameters to capture the hysteretic behaviors of the real model instantaneously, and the restoring force prediction accuracy of the updatable substructure is substantially enhanced. However, there are still some restoring force errors in the time history results.

(4) In the SPDHS with online ANN model updating, the hysteresis and predicted restoring force of the updatable numerical substructure agree well with those of the experimental substructure. Particularly, the restoring force prediction accuracy maintains good performance at the response peaks. The results show that the online ANN method has potential to effectively reduce the model error between the preset numerical model or the pre-trained ANN model and the exact hysteretic model. This method improves the restoring force prediction accuracy of the updatable substructure. To further evaluate the performance of different identification techniques, the experimental results obtained from the four test cases are compared and summarized as illustrated in Table 3 and Fig. 13.

Table 3 Restoring force analysis of updatable numerical substructure in four test cases

Case	Peak Value	PVES/ (kN)	PVUMS/ (kN)	AEPV/ (kN)	MAETH/ (kN)
Conventional	Positive	15.537	9.468	6.069	15.056
	Negative	17.303	21.381	4.078	
Offline ANN	Positive	13.893	14.242	0.349	11.847
	Negative	18.162	16.890	1.272	
Online UKF	Positive	15.334	16.595	1.261	6.882
	Negative	19.153	20.449	1.296	
Online ANN	Positive	13.846	13.864	0.018	1.445
	Negative	17.503	17.512	0.009	

*Abbreviations: PVES, peak value of experimental substructure; PVUMS, peak value of updatable numerical substructure; AEPV, absolute error of peak value; MAETH, maximum absolute error in the time history



(a) (b)

(c)

Fig. 13 (a) Absolute error histories of restoring force; (b) peak value of restoring force in the time history; (c) maximum absolute error of restoring force in the time history

It can be concluded from Table 3 and Fig. 13 that:

(1) In the conventional SPDHS, the maximum absolute error of the predicted restoring force of the updatable numerical substructure in the time history is 15.056 kN, and the peak values are 6.069 kN (positive) and 4.078 kN (negative).

(2) In the SPDHS with offline ANN calibration, the maximum absolute error in the time history is 11.847 kN, which is reduced by 21.31% than that of the traditional SPDHS. In addition, the absolute errors at the response peak are 0.349 kN (positive) and 1.272 kN (negative) respectively, which are decreased by 94.25% and 68.81% compared to those of the traditional SPDHS. Even though the offline ANN method can significantly improve the restoring force prediction accuracy at the response peak, there are still large restoring force prediction errors in the entire time history. For offline ANN applications, the identification of extremely complex hysteretic model is challenging, while online model updating makes it possible to calibrate such nonlinear behaviors into the updatable numerical substructure instantaneously.

(3) In the SPDHS with online UKF model updating, the maximum absolute error in the time history is 6.882 kN, which is reduced by 54.29% than that of the traditional SPDHS. Also, the absolute errors at the response peak are 1.261 kN (positive) and 1.296 kN (negative), which are 79.22% and 68.22% smaller than those of the traditional SPDHS, respectively. Actually, considering the diversity and complexity of nonlinear behaviors of structural elements, discrepancies due to inherent model defects may exist between the assumed numerical model and the real model. The experimental results indicate that the UKF updating method can instantaneously capture the complex behaviors which are not inherent in the assumed Bilinear model by constantly adjusting the model parameters. However, note that under the same loading history, due to the inherent model defects of the initial Bilinear model, the recognition ability of the online UKF method in the entire time history and at the response peak may be limited.

(4) In the SPDHS with online ANN model updating, the maximum absolute error in the time history is only 1.445 kN, with a substantial reduction of 90.40% compared to that of the traditional SPDHS. Also, the absolute errors at the response peak are 0.018 kN (positive) and 0.009 kN (negative), showing 99.70% and 99.78% reductions compared to those of the traditional SPDHS, respectively. The experimental results indicate that under the identical loading history, the online ANN method can significantly reduce the model error between the preset numerical model or the pre-trained ANN model and the real model. Moreover, the high prediction accuracy of restoring force can be achieved not only in the entire time history but also at the response peak. The average consuming-time of each step in this model updating test is 0.13s, and the calculation efficiency can meet the requirements of the slow pseudo dynamic substructure test.

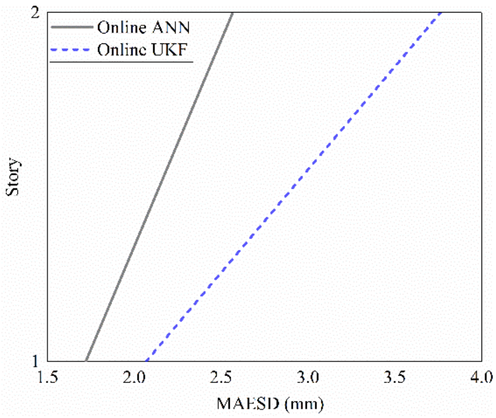


Fig. 14 MAESD (Maximum Absolute Errors of Storey Displacement) at different test cases

In order to evaluate the global performance of ANN method in mode updating, the maximum absolute error of storey displacement is applied for analysis. And the test results are compared with the online UKF method. The maximum absolute errors of storey displacement in .online ANN case and .online UKF case are illustrated in Fig. 14.

As shown in Fig. 14, the maximum absolute error of storey displacement at the first storey and the second storey are 1.721 mm and 2.567 mm respectively. Compared with the online UKF method, the prediction accuracy of storey displacement is improved by 17.78% and 31.77% respectively. The results show that the online ANN model updating method can effectively improve the accuracy of the global responses of the structure under similar loading histories.

5. Conclusions

The objective of this study is to implement online model updating in actual SPDHS with ANN method. A framework with ANN model updating scheme is expanded for performing test validation. In this research, it is assumed that the experimental substructure is expected to be the first to experience nonlinearity. The hysteretic model of the experimental substructure is identified online by the measured data, and the relevant components with similar properties and hysteretic behaviors in the numerical substructure are calibrated instantaneously. In the test validation, a platform to accommodate this need is established by combining the ANN method with hardware and software facilities, which can be provided as the system supporter for practical experiments. The effectiveness of the ANN method is validated by actual tests on a two-story frame model with bending dampers.

The test results show that the expanded framework with ANN model updating scheme for actual implementation is feasible and stable. In addition, under the identical loading history, the online ANN model updating method can substantially improve the model accuracy of critical nonlinear components in the numerical substructure, which benefits from its ability to model any nonlinear functions. Although there are concerns related to the calculation load and efficiency of the online ANN method, it is observed that this method can be well applied to the slow pseudo-dynamic substructure test.

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