ARTICIAL NEURAL-NET BASED HYSTERESIS IDENTIFICATION

However, all previous studies, including the previous one, have a decisive limitation in that they basically focus only on fitting experimental results and securing predictive power for pseudo-static studies. If the characteristics are understood through the pseudo-static experiment for analyzing the characteristics of hysteresis and a model with high explanatory power is constructed from it, then we need to use the model and apply it to the nonlinear dynamic analysis. Model construction through parameter estimation in the form of differential equations is very powerful in this respect, and there is no room for error. This is because, after building the established differential equation-based model on a platform for dynamic analysis, it can be input into the algorithm for solving differential equations in the nonlinear dynamic analysis process. However, in the case of a model of a form other than the form of differential equations, a solution to the relation related to differential-integration must be contained in the model itself.

Our study aims to provide a methodology to build a neural net-based hysteresis model that can be applied to dynamic analysis from pseudo-static experiments. To this end, from the results of the pseudo-static experiment, 1) an architecture that constructs the output from the input. First of all, we devised a method to add to the learning set not only the input of pseudo-static experimental results, but also the input of wide steps such as 2 steps, 3 steps, etc. And while constructing hysteresis models more easily for the experimental results, it was verified that they do not accompany errors even when they are used for dynamic analysis.

DUHEM-MADELUNG FORMULATION

The Duhum-Madalung (DM) formulation defines the relationship between the input function u and the output function z with any initial value z_0 of z as follows:

$$\frac{\mathrm{d}z}{\mathrm{d}u} = g(u, z, \mathrm{sgn}(\mathrm{d}u)) = \begin{cases} g^+(u,z) & \mathrm{d}u \geq 0 \\ g^-(u,z) & \mathrm{d}u < 0 \end{cases} \tag{1}$$

where sgn(·) is the signum function.

The above representation shows a connection between the sign function and rate-independence: these are basic ingredients of the analytic representation of hysteresis. With the aid of the Duhem operator, the relationship of hysteretic restoring force z versus displacement u and increment of the displacement du is described in a transformed three-dimensional subspace of the variables u, z, and g. The ascending and descending describing functions $g^+(u, z)$ and $g^-(u, z)$ constitute two surfaces in the subspace over the (u, z) plane.

It was described in Ni et al. (1999) that the DM model can produce two single-valued surfaces in the mapped subspace (u, z, g), for $\mathrm{d}u > 0$ and $\mathrm{d}u < 0$, respectively, for the differential type hysteretic models. The DM formulation, which takes into account the adaptability of various hysteretic types, can be seen as a nonparametrized generalization of the differential hysteretic models. Thus, the general properties that the DM formulation has are also possessed by specific differential models. On the other hand, the Duhem operator offers an accessible way to construct novel differential hysteretic models by prescribing specific expressions for the describing functions.

According to Eq. (1), the value of the describing function at each sampling instant can be further obtained as

$$g_k = \frac{\mathrm{d}z}{\mathrm{d}u} \approx \frac{z_k - z_{k-1}}{u_k - u_{k-1}}\,. \tag{2}$$

When the signals are digitized with high sampling rate, the describing function values g_k^+ or g_k^- can be obtained with enough accuracy from Eq. (2). This means that one has two ensembles of triplets consisting of (u_k, z_k, g_k^+), and (u_k, z_k, g_k^-), respectively, depending on the sign of the incremental. In Ni et al. (1999), , triplets of the $(u_k, z_k, g_k^\pm)$ data are constructed for identification. However, it can be impractical to set the $g_k^\pm$ for the parametric identification, and the triplets (u_{k-1}, u_k, z_{k-1}) can be directly obtained from the previous and current steps (Note that the triplets used in this study is approximately equivalent to that used in Ni et al. (1999). See Eq. (2). In order to embed the hysteretic structure of $g_k^\pm$, we constructed a deep neural network.

HYSTERESIS IDENTIFICATION USING ARTIFICIAL NEURAL NETWORKS

Artificial neural networks (ANNs) have recently been effectively applied in a wide range of civil engineering applications, and some attempts to use ANNs in the field of hysteresis identification were conducted (Dang and Tan, 2007, 2007; Ma et al., 2020). The aim of the ANN is to realize a very simplified model of the human brain, such that the different branch weights of an ANN are to be determined using random input/output training data. This means that the model unknowns may be calculated using any arbitrary experimental data if the hysteresis model can be explicitly or implicitly implemented by an ANN.

For the hysteresis identification, a network with a feature input layer and the number of features were specified, such that the triplets (u_{k-1}, u_k, z_{k-1}) is set as the input layer, and the feature of the input layer is 3. The constructed network comprises two fully-connected layers followed by a batch normalization layer and ReLU layers, and each layers has 5 neurons. The network has one output neuron because there is only one response value associated with each input vector. For the learning, the division of data was carried out. With these settings, the predictor vectors and response vectors are randomly divided, with 80% for training, 10% for validation, and 10% for testing. After the network has trained, the trained network was tested by comparing the predicted data with the actual data 1 step, 2 step, 5 step and 10 step apart.

The ANN-based identification is then conducted by implementing the proposed method to experimental data. From the test results, 2,281 triplets of (u_{k-1}, u_k, z_{k-1}) for each dataset are created according to Eq. (2) and are used for identification. It should be highlighted that the aim of this study is to build a model that predicts the force z_k based on the state of the previous step (u_{k-1}, z_{k-1}) and the displacement of the subsequent step u_k. If the value of the adjacent step is learned from only the given experimental result, a stiffer predictive model is constructed. Therefore, in this study, in order to construct a model that can provide predictions for a wider range of steps replacing differential equations, two points are randomly selected from the experimental results to construct training triplets.

To evaluate the proposed method, a total of four data sets were considered, two of which were generated by an analytical model and the other two were the test results of the cyclic tests performed on the composite beam-column connections conducted by the authors (see Figure 1). The first two data sets were generated from the original Bouc-Wen model (labeled as 'BW'), and the Bouc-Wen-Baber-Noori model which was developed to simulate the pinching behavior (labeled as 'BWBN', respectively. The other two data sets, named PN500C and PN500CSH, were chosen as the benchmark specimens for composite connections, respectively. Input and output were the incremental tip displacements and actuator force of the actuator, respectively. Detailed descriptions of the experimental program can be found in Kim and Lee (2017).

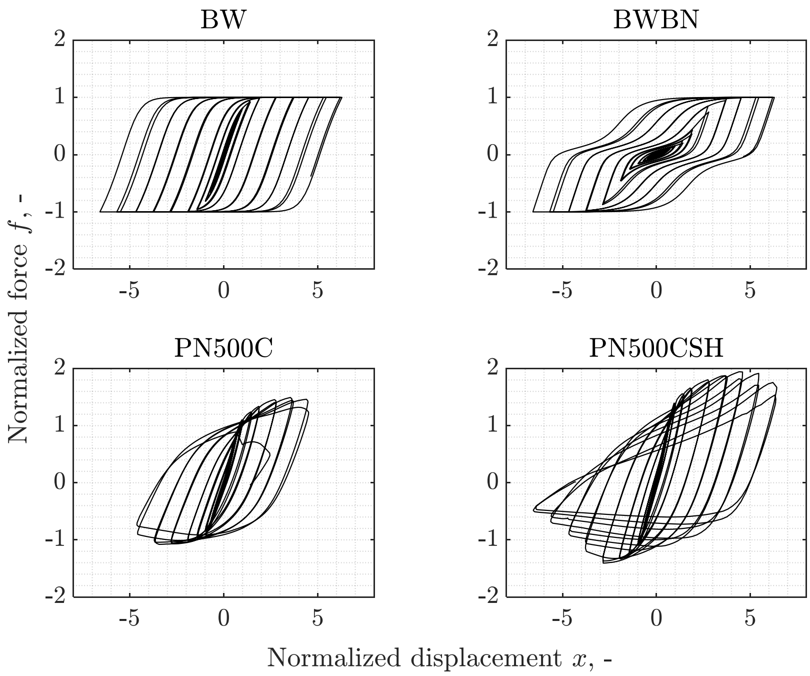
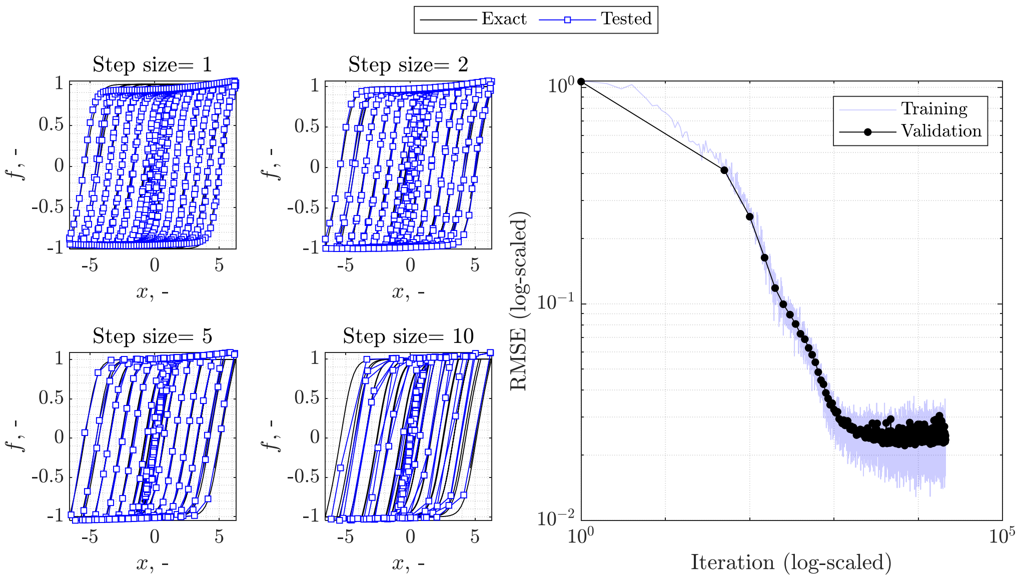
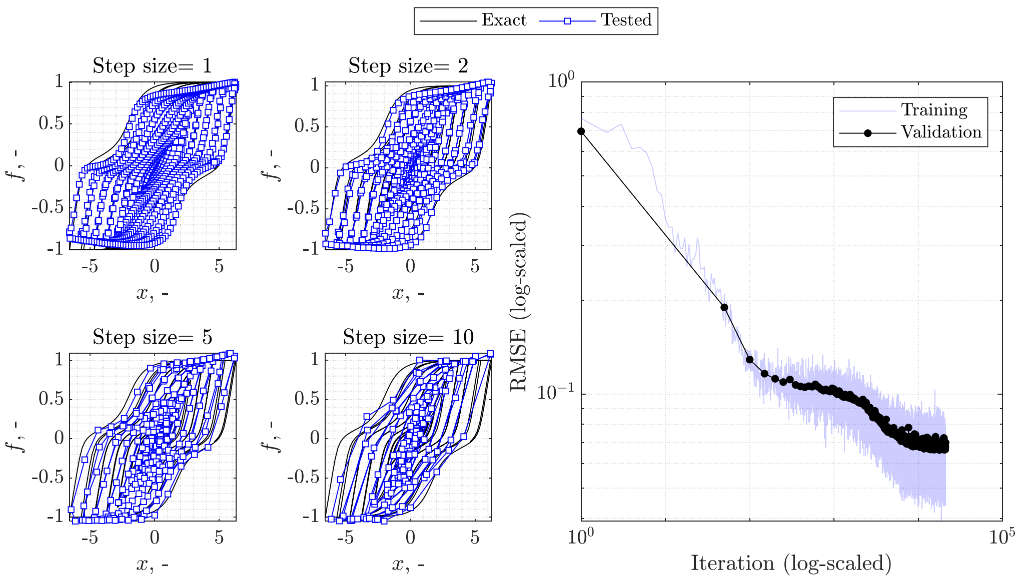


Figure 1 Tested data sets

Figure 2 show the theoretical hysteresis loops reproduced using the DM formulation and the predicted values for various step sizes of 1, 2, 5, and 10. It is seen that the predicted hysteresis loops agree with the tested hysteresis loops considered step sizes for both datasets. In the case of the Bouc-Wen model showing the simple hysteresis behavior, it can be confirmed that the prediction of the next large step of 10 steps is also relatively accurate. However, in the case of BWBN in which pinching is considered, as the size of the step increases, the prediction tends to be somewhat stiffer than the actual value. It is judged that this is because the ratio of sparsely sampled is not relatively high in composing the data set for learning, and it seems that the data set configuration is additionally needed to improve this



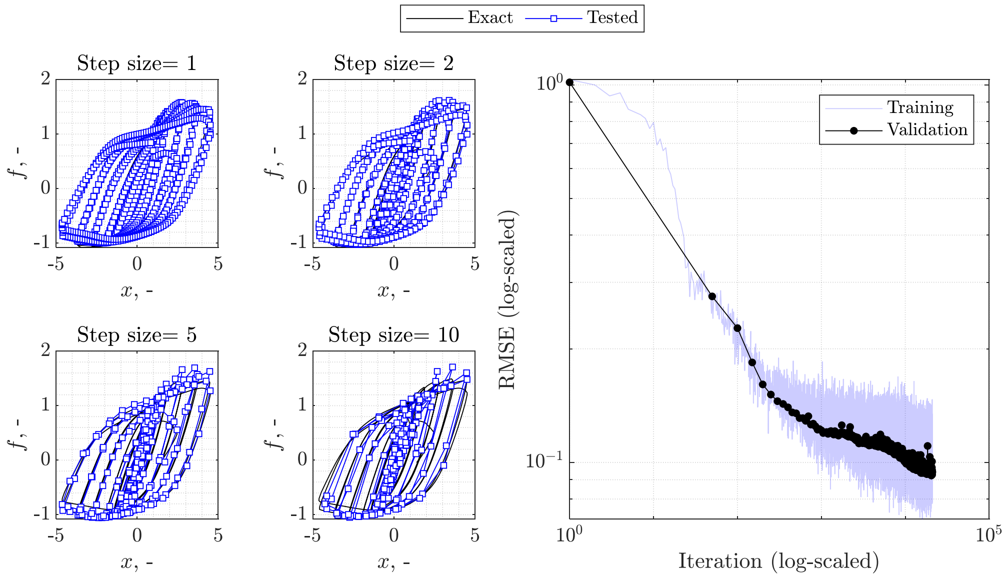
(a) BW



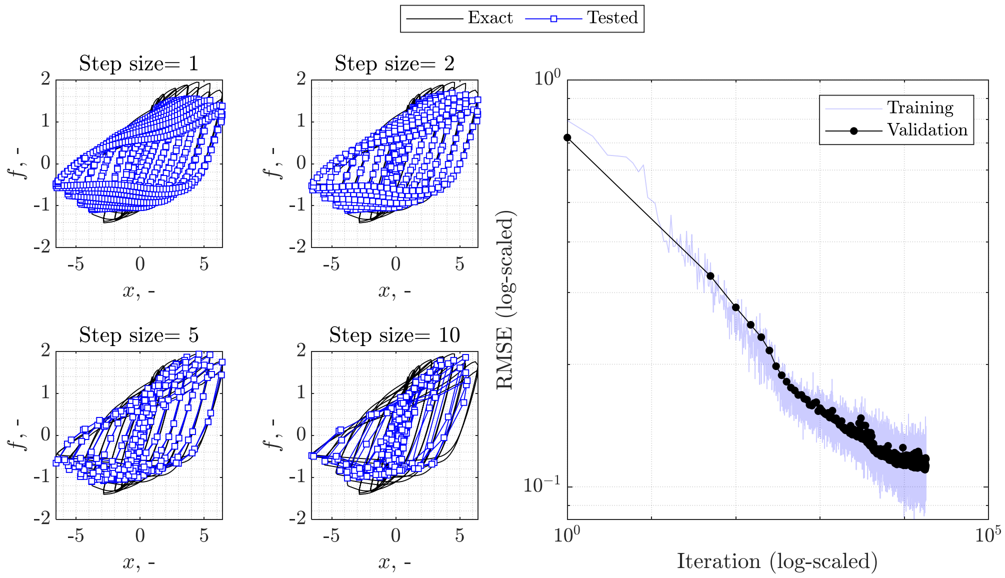
(b) BWBN

Figure 2 Simulated data and predicted results

Figure 3 show the tested hysteresis loops and the predicted values for various step sizes of 1, 2, 5, and 10. It is seen that the predicted hysteresis loops agree with the tested hysteresis loops considered step sizes for both datasets. In the case of the PN500C showing the asymmetric hysteresis behavior, it can be confirmed that the prediction of the next large step of 10 steps is also relatively accurate. However, in the case of PN500CHST in which a highly asymmetric behavior with large pinching is considered, as the size of the step increases, the prediction tends to be somewhat stiffer than the actual value. It is judged that this is because the ratio of sparsely sampled is not relatively high in composing the data set for learning, and it seems that the data set configuration is additionally needed to improve this. However, it should be noted that the identification of general hysteresis behavior is a process of identifying the parameters constituting the differential equation, and the integration process such as Runge-Kutta is required again in order to use it for simulation. The model proposed in this study is an estimator that directly estimates the next step without a separate integration process, and if its accuracy can be improved, it can be used in more applications.



(a) PN500C



(b) PN500CHST

Figure 3 Tested data and predicted results

SUMMARY AND CONCLUSIONS

This study intends to provide a methodology for developing a neural network-based hysteresis model applicable to dynamic analysis derived from pseudo-static experiments. To this purpose, the results of the pseudo-static experiment were used to develop 1) an architecture that produces output from input. The authors devised a technique to incorporate into the learning set not only the input of pseudo-static trial outcomes, but also the input of large steps, such as 2, 5 and 10, etc. It was shown that the predicted hysteresis loops agree with the tested hysteresis loops considered step sizes for both datasets. In the datasets in which a highly asymmetric behavior with large pinching is considered, as the size of the step increases, the prediction tends to be stiffer than the actual value. In order to resolve the low accuracy in predicting the next step, further studies are needed to improve the training set. However, it should be highlighted that the identification of general hysteresis behavior is a process of identifying the parameters constituting the differential equation, and the integration process such as Runge-Kutta is required again in order to use it for simulation. The model proposed in this study is an estimator that directly estimates the next step without a separate integration process, and if its accuracy can be improved, it can be used in more applications.

REFERENCES

Dang, X., Tan, Y., 2007. RBF neural networks hysteresis modelling for piezoceramic actuator using hybrid model. Mech. Syst. Signal Process. 21, 430–440. https://doi.org/10.1016/j.ymssp.2005.09.016

Kim, S.-Y., Lee, C.-H., 2017. Seismic Retrofit of Welded Steel Moment Connections with Highly Composite Floor Slabs. J. Constr. Steel Res. 139, 62–68. https://doi.org/10.1016/j.jcsr.2017.09.010

Ma, L., Shen, Y., Li, J., 2020. A Neural-Network-Based Hysteresis Model for Piezoelectric Actuators. Rev. Sci. Instrum. 91, 015002. https://doi.org/10.1063/1.5121471

Ni, Y.Q., Ko, J.M., Wong, C.W., 1999. Nonparametric Identification of Nonlinear Hysteretic Systems. J. Eng. Mech. 125, 206–215. https://doi.org/10.1061/(ASCE)0733-9399(1999)125:2(206)