MACHINE LEARNING BASED NONLINEAR PARAMETER IDENTIFICATION FOR HIGH DAMPING RUBBER BEARINGS

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The complicated nonlinear behavior of high damping rubber bearings needs deliciated nonlinear hysteresis model with multiple parameters. Those parameters need to be identified from experiments such standard quasi-static loading tests. However, general nonlinear model parameter identification methods such as curve fitting, Newton's methods et. al. may need to select initial parameter value carefully. Sometimes it is a trial-and-error process and requires engineer's expertise. This study trained an ANN model that aimed to identify the nonlinear parameters of an HDR-S bearing under Modified Bouc-Wen (MBW) model at ambient and low temperature. The suggested parameters were compared to an actual quasi-static experiment result and hybrid simulation.

1. Introduction

Based on the road bridge seismic design practice in Japan [1)], bilinear model was used for various types of seismic isolators. However, the nonlinear behavior of HDR-S bearing was greatly affected by different factors like changes in strain rate, loading direction, Mullin's effect, temperature, etc. In addition to that, there are newly developed seismic isolators, and the nonlinear behavior identification depends on engineer's expertise. Thus, there is a need for a different nonlinear model that includes additional uncertainties which makes the optimization process more difficult.

Therefore, this study trained an ANN model to predict the nonlinear parameters of Modified Bouc-Wen model from experiment data for HDR-S. The ANN model was trained from numerical simulation data only and then validation was conducted by prediction of quasi-static and hybrid simulation loading test data. The proposed machine learning based approach method suggest the initial nonlinear parameters using the trained ANN model which eliminates the trial-and-error process using conventional optimization methods, and it can be repeated using different nonlinear models.

2. High Damping Rubber Bearing (HDR-S)

The HDR-S specimen used in this study has a total rubber thickness of 30 mm and cross-sectional area of 0.0576 mm^2. To identify its nonlinear behavior, two experiments were conducted. First was quasi-static test in which the strain was pre-defined. The second test was hybrid simulation which identifies the HDR-S nonlinear behavior installed in a hypothetical 3-span bridge with regards to an input earthquake.

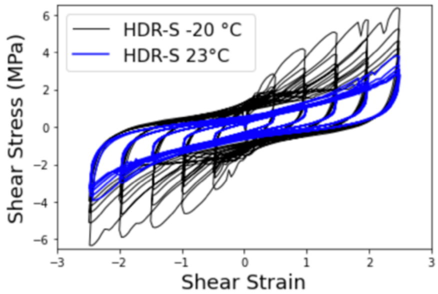

Fig. 1 HDR-S Quasi-Static Experiment Data

The HDR-S quasi-static loading results at ambient and low temperature were shown in Fig. 1. The data consists of five amplitudes ranges from 50% up to 250%, and each amplitude consists of five loops. There is a significant increase of shear stress at low temperature, and Mullin's effect was visible.

During hybrid simulation, the HDR-S nonlinear behavior was influenced by the bridge response to the input earthquake. A scaled factor of 1/6 was applied due to experiments facility limitations and similarity rule was used in the simulation of the needed parameters. The total mass was based on the standard vertical pressure of 6 MPa. The three-span bridge has a total of 8 piers as shown in Fig. 2, and two degree of freedom (2DOF) model was considered in the numerical simulation.

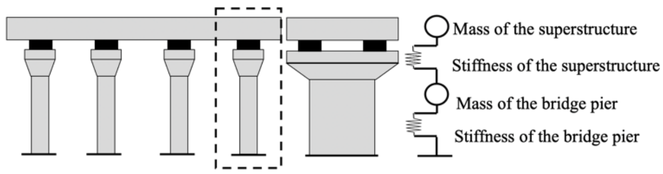

Fig. 2 Bridge Structural Model

3. Modified Bouc-Wen Model

To represent the HDR-S nonlinear behavior numerically, Modified Bouc-Wen model was used. The numerical equation of this model was shown in equation 1 and 2. The shear stress σ is influenced by the strain ε, pinching effect by parameter b, hardening and softening due to stiffness degradation which are represented by parameters γ and β, and z which is the plastic component with A generally equal to 1. During the data generation for ANN training, the parameters were expressed to shear strain and shear stress, and the ranges are as follows: α[0.1~0.06], G_1[8~20], β[0.5~2.0], γ[-4~-7], and b[0.2~0.5].

$$\sigma = \alpha G_1 \varepsilon + (1-\alpha) G_1 (1+b \varepsilon^2) z \qquad (1)$$

$$\dot{z} = A \dot{\varepsilon} - \beta |\dot{\varepsilon} z| - \gamma \dot{\varepsilon} z^2 \qquad (2)$$

4. Nonlinear Parameter Identification

The shear strain data of HDR-S quasi-static 23°C, 250% amplitude, loop 1, was interpolated and reduced to 60 data points using K-Nearest Neighbor (KNN) algorithm for numerical simulation preparation. The parameter ranges were randomly selected to simulate the shear force under Modified Bouc-Wen (MBW) model. A combination of 60 shear strain data and 60 shear stress with 1000 iterations were used as an input data for the ANN training.

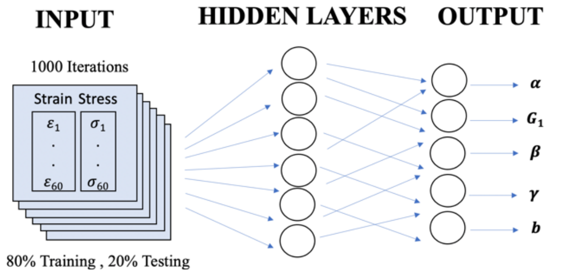

Fig. 3 ANN Model Architecture

The ANN architecture as shown in Fig. 3 consists of 120 by 1000 input features, 2 hidden layers, and five nonlinear parameters of modified Bouc-Wen Model as an output. The activation function used was ReLU because it's a regression problem and specific values was required as an output. RMSProp was the optimizer used with a learning rate of 0.0001. The loss function was mean squared error and should be near to zero. After 200 epochs, the training loss was 0.047 and the validation loss was 0.134. To visually examine the accuracy of the trained model, the ANN predicted nonlinear parameters were plotted and the hysteresis was compared to the normalized HDR-S quasi-static loading data as shown in Fig. 4. The comparison shows a high correlation with a contribution rate of 0.98.

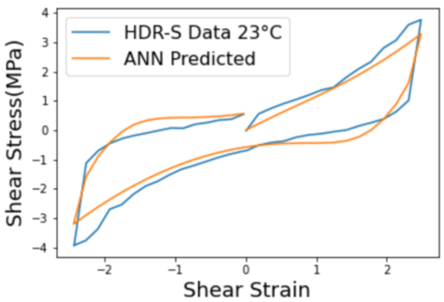

Fig. 4 ANN Predicted Parameters During ANN Training

5. Cyclic Loading Nonlinear Parameter Prediction

The HDR-S quasi-static data at 23°C and -20°C, 250% amplitude, loop 1, were reduced to 60 data points of shear strain and shear stress to fit for the ANN input data for nonlinear parameter identification. The trained ANN model and KH Method (Kuroda [2)]) predicted nonlinear parameters were plotted and the hysteresis was compared to the experiment data as shown in Fig. 5. The contribution rates for HDR-S data at 23°C were 0.97 for ANN and 0.98 for KH Method. On the other hand, at -20°C, the contribution rates were 0.86 for ANN and 0.88 for KH Method. There was a 1% up to 2% difference in the contribution rate between ANN and KH Method.

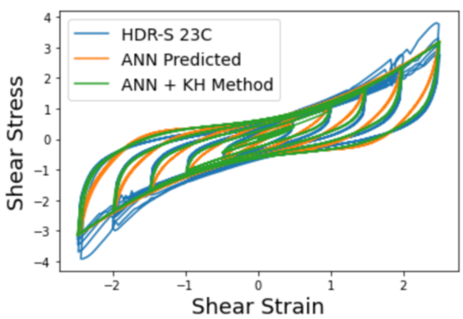

Fig. 5 HDR-S Quasi-Static Loading Predicted Nonlinear Parameters by ANN at 23 °C

6. Hybrid Simulation Comparison

The hybrid numerical simulation used and compared the predicted parameters from ANN model as shown in Fig. 6 and Fig. 7. The nonlinear behavior of HDR-S bearing was influenced by the superstructure and pier-seismic response therefore it depicts a more realistic scenario. It can be observed that Modified Bouc-Wen (MBW) Model nonlinear parameters on both ANN and KH method greatly fits the HDR-S data under ambient temperature (23°C) but had a significant difference at low temperature (-20°C).

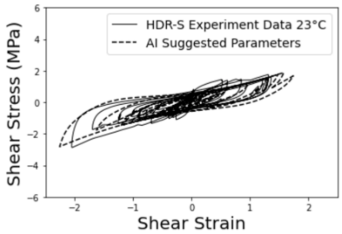

Fig. 6 HDR-S Hybrid Simulation Result Using the ANN Predicted Parameters at 23 °C

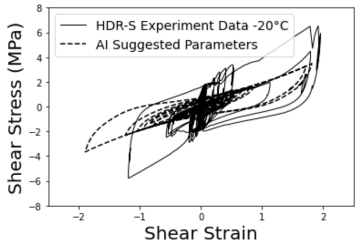

Fig. 7 HDR-S Hybrid Simulation Result Using the ANN Predicted Parameters at -20 °C

7. Conclusion

This study successfully trained an ANN model that aimed to predict the nonlinear model parameters from an HDR-S quasi-static experiment data with a contribution rate difference range of 1% up to 2% compared to the conventional KH method. The predicted nonlinear parameters had high correlation with the HDR-S data at ambient temperature (23 °C) based on both comparison to quasi-static and hybrid simulation. However, the predicted Modified Bouc-Wen model parameters had a significant difference at low temperature. The proposed machine learning based approach for nonlinear parameter identification significantly eliminates the trial-and-error and can be repeatedly trained using other nonlinear models. This approach lessens the actual experiment cost and makes the nonlinear initial parameter identification easier. Since modified Bouc-Wen model only covers the change in stiffness degradation and pinching, there's still some factors that needs to be considered to increase the correlation of the HDR-S nonlinear behavior like Mullin's effect and low temperature effect. Thus, using an advance model considering those factors are recommended for future study. The significant difference at low temperature creates a risk on HDR-S implementation to cold regions like Hokkaido and must be further studied. Improvement of the trained model will be done to cover a larger range of parameters and inclusion of different types of nonlinear model will be the future study.

References

1) Bridge Seismic Control Design Method Draft (2012), Seismic Isolation Structure Research Committee for Road and Bridges.
2) Kuroda, H., (2001) Visual Basic Engineering Calculation Program, Tokyo CQ Press, Tokyo, 69-7