MOST COMPATIBLE NONLINEAR MODEL SELECTION FROM LOADING TEST RESULT USING MACHINE LEARNING

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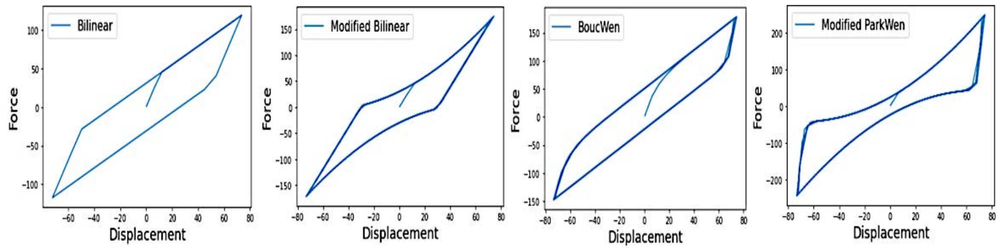
1. INTRODUCTION

Structure Isolation using isolation devices such as rubber bearing (RB), high damping rubber (HDR) bearing and Lead rubber bearing (LRB), has been continuously practiced and proved as one the best strategy to protect infrastructures like bridges from damage under strong ground-motion. However, the isolated bridges are considered difficult to be implemented in cold areas such as Hokkaido, due to the concern of hysteresis characteristic of those devices, which performs differently. Loading test results for rubber bearings showed that their completed thermo-mechanic behavior and advanced numerical model are needed for seismic design in cold area for rubber bearings. It is important for seismic design of isolated structure to select the best nonlinear hysteresis model for key nonlinear member such as rubber bearings and it is quite difficult for some high performance devices such as high damping rubber (HDR) bearings, or those with lead cores inside, such as SPR-S. Currently, the normal steps to determine the best hit nonlinear model is time consuming, highly dependent to engineers expertise, and a trial and error process. In relation to this problem, this study proposed a machine learning based method to train an AI model to select the most similar nonlinear model from experiment loading test data. In addition to that, the library of nonlinear models includes Bilinear (BL) model, Modified Bilinear (MBL) with Pinching, Boucwen (BW) model, and modified Park-Wen (MWP) model (Dang et. Al, 2013).

2. AI CLASSIFICATION MODEL

The development of the AI classification model includes two parts, the first one is [Model A], which classifies the nonlinear model of the loading test data per amplitude and ranges from 50%, 100%, 150%, 200%, and 250%. The second AI model is Model B, which uses more data per amplitude and will classify based on hysteresis loops. There were 5 hysteresis loops per amplitude which makes a total of 25 hysteresis loops. The model was trained separately because of different data size. Since the experiment data is not enough to train the AI model, the researchers used numerical simulation based on the four nonlinear model namely Bilinear (BL), Modified Bilinear (MBL), BoucWen (BW), and Modified Park-Wen (MPW) to generate force and displacement values, the visualization can be seen in Fig. 1. The displacement data at 250% amplitude was used for the numerical simulation to cover all of the displacement range. The parameters in each nonlinear model were set at a small and realistic range and was picked randomly to generate the data set. Model A has a data set of 400 data, which has 200 displacement and 200 force values, while Model B has a data set of 120 data, which consist of 60 displacement and 60 force values



Bilinear	alf	k1	qc		
	0.3 – 0.4	2 -9	30- 40		
Modified Bilinear	alf	k1	qc	b	
	0.3 – 0.4	2 - 9	30 -40	0.01-0.02	
BoucWen	alf	k	B	gamma	
	0.2-0.3	4-7	-0.3 – -0.2	-0.15 - -0.1	
Modified ParkWen	alf	k	B	gamma	b
	0.2-0.3	4-7	0.15-0.2	-0.15- - 0.1	0.00055-0.00065

Figure 1. Nonlinear Models and Parameter Range

The AI classification training of the two models both used a two-layer neural network with a difference in the data set input. During the training of Model A, the input data was 400 per data set and has a hidden layer size of 800 as shown in Fig. 2. For Model B, the input data was 120 per data set and has a hidden layer size of 400 as shown in Fig. 3. The activation function at the hidden layer was ReLU while it was Softmax at the output layer. The output data represents the four nonlinear models, but due to the Softmax activation function at the output layer, the AI model will give the highest probability score close to 1 on the most similar nonlinear model from the input data. Adam was used as an optimizer with a learning rate of 0.001. The learning rate greatly affects the training so it needs to be set properly. Categorical cross-entropy was used as the loss function because the number of classes is more than two. The validation split in training uses 10 percent of the input training data. After the training, Model A and Model B have a validation accuracy of 1.0 as shown in Fig. 4 and Fig. 5. The working environment is python with Keras library and was run on google colaboratory.

Keywords: Artificial Neural Network, Machine learning, Nonlinear Numerical Model, HDR Bearing
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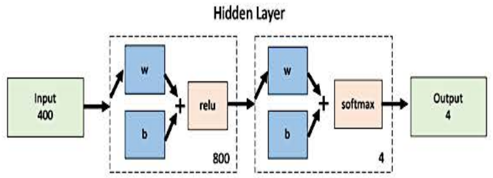

Figure 2. Model Summary of Model A

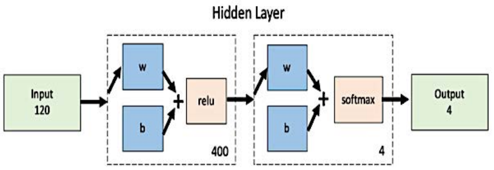

Figure 3. Model Summary of Model B

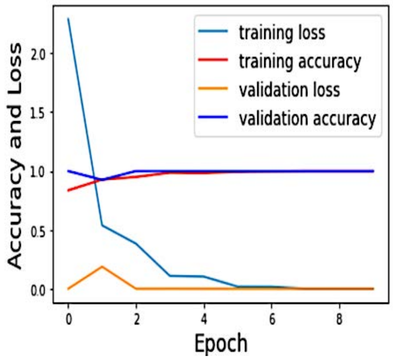

Figure 4. Model A Accuracy and Loss

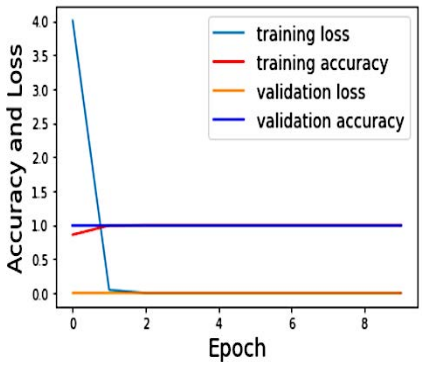

Figure 5. Model B Accuracy and Loss

3. CYCLIC LOADING TEST PREDICTION

The cyclic loading data was from an HDR bearing loading test result with three confined temperature testing of 0 °C, -20 °C, and 23 °C as shown in Fig. 6. The loading test data was adjusted to fit the input size for Model A and Model B prediction. The results for Model A prediction was shown in Fig. 7. From 50% upto 150% amplitude, the prediction was modified bilinear and bilinear, but as the amplitude increased to 200% and 250%, the prediction was Modified Park-Wen model. The loading test data at 23 °C has a bit discrepancy on the fourth amplitude compare to the 0 °C and -20 °C data which can be further analyzed. The model B prediction results were shown in Fig. 8, from hysteresis loops 1 upto 15, the predictions were majority on modified bilinear, but after the 15th hysteresis loop, the majority of the predictions are Modified Park-Wen (MPW). From hysteresis loops 20 to 25, the prediction was all Modified Park-Wen, which strongly supports the Model A predictions.

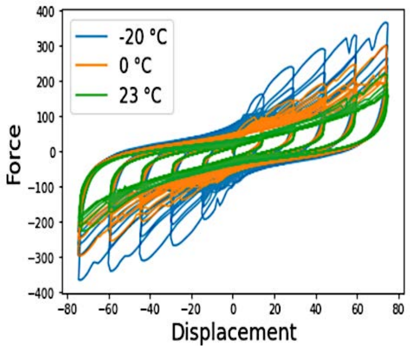

Figure 6. Experimental Data

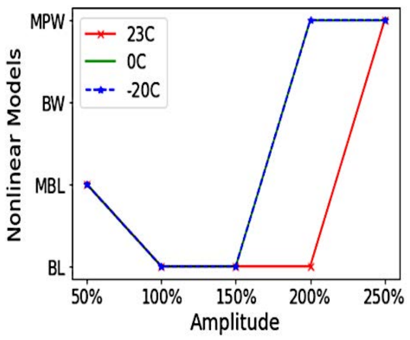

Figure 7. AI Prediction of Model A

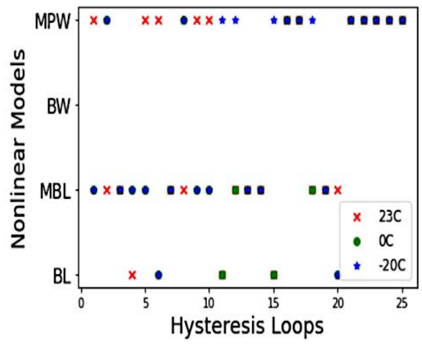

Figure 8. AI Prediction of Model B

4. CONCLUSIONS

Based on the AI nonlinear classification of [Model A] and [B] results, the neural network can be trained to recognize hysteresis loops easily. This study developed two AI models using Artificial Neural Network (ANN) with different sizes of input data for comparison. These models initially predicted the most compatible nonlinear model from the HDR loading test data per amplitude and hysteresis loops. The validation accuracy was 1.0 and the loss was approaching to zero which shows a good result. In the prediction part, the results shows that in the 50% upto 150% amplitude, Bilinear (BL) and Modified Bilinear (MBL) governs, but on the large amplitudes, which are from 200% and 250% amplitude, it becomes Modified Park-Wen (MPW). The changes of prediction results from Bilinear which is the traditional nonlinear model to be used in the design, into Modified Park-Wen (MPW) model on large amplitudes can be taken into consideration in deciding what model to be used for design. The proposed method will help to accelerate the design process because the trained AI models will initially suggest the possible nonlinear models to be used. The loading test data predictions have the same trend for both 0 °C and -20 °C, however at 200% amplitude, 23 °C had a different result which might be evaluated further and might be related to ambient temperature changes.

REFERENCES

Dang, J. et al.: Nonlinear Numerical Hysteresis Model for Bi-directionally Loaded Elastomeric Isolation Bearings, *Journal of Japan Association of Earthquake Engineering,* Vol. 2, 2013