第24回橋梁等の耐震設計シンポジウム
講演論文集（2021年7月）

NONLINEAR MODEL PARAMETER IDENTIFICATION OF SEISMIC ISOLATOR USING ARTIFICIAL NEURAL NETWORK

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1. INTRODUCTION

After the occurrence of 1923 Kanto Earthquake (Mw= 7.9), extensive damaged on bridges were observed due to inadequate seismic design restrictions. The lack of lateral strength design consideration resulted to a major damaged caused by tilting and overturning of the bridge deck[1)]. In response to that, the Japan seismic design code was revised, and seismic isolators were started to be implemented. During seismic ground movement, seismic isolators can lengthen the natural period of the structure and dissipate seismic energy which helped to reduced the structure's damage[2)]. Few years later, the remarkable 1995 Hashin-Awaji Earthquake (Mw = 7.1) happened, the structural damaged and bridges collapsed were caused by the insufficient ductility of columns and failure of bearings. Steel bearing damages shown its vulnerability under large ground motion, thus elastomeric bearings like high damping rubber bearing (HDR) and lead rubber bearings (LRB) were extensively used afterwards. After the 2011 Tohoku Earthquake, there were few recorded rubber bearings failures and majority of the seismic isolated bridges continued their main function[3)].

Therefore, using rubber bearing as seismic isolator between the connection of the sub-structure and super-structure was an effective way to reduced seismic damage. The Design Specification for Highway Bridges was published last 2012[3)]. It was proposed that the seismic performance of structural members with seismic isolators should be checked thoroughly using reliable numerical analysis method.

In current design practice, the nonlinear parameters of these seismic isolators must be identified. Nonlinearity of those bearings were covered by different factors like temperature, loading rate, strain rate, deterioration, for rubber bearings. Therefore, there were several proposed numerical models that covers some of these factors aside from the mostly used nonlinear models like Bilinear, Ramberg-Osgood, and Bouc-Wen model. First, an improved Rheology model that includes the rate-dependence of the high damping rubber bearings under dynamic cyclic loading test was proposed[4)]. Another study incorporated the bi-directional behaviour of high damping rubber bearing and proposed the modified Park-Wen model which includes pinching and stiffness degradation[5)].

In all of the mentioned numerical models, the initial procedure during seismic design was identifying the nonlinear parameters from experimental loading test, however it needs an assumption of initial nonlinear parameters input value and optimum algorithm methods for curve fitting was commonly used. A proposed optimization method called KH method was established, which makes the parameter identification curve fitting faster and reliable[6)]. However, the initial input value assumption doesn't converged all the time and could be time consuming. Nonlinear parameter identification could be also be complicated and difficult for some new proposal detailed numerical models or new developed devices with high performance and complicated behaviors.

In relation to this, based on the current standard, the method for checking and designing the seismic response of seismic isolators on bridges starts from the assumption of seismic isolator's nonlinear properties and the nonlinear parameter ranges were prescribed in the Road and Bridge Seismic Control Design Method Draft[3)],however the seismic bearing isolator types were limited. Currently, for new types of seismic isolators with no available guide specifications in the code, the accuracy of nonlinear parameter identification depends on the engineer's expertise, which could be subjected to bias, and becomes a trial-and-error process. Also, using optimum algorithm method could cause error depending on the initial parameter assumptions which makes it trial and error and time consuming. Therefore, this study proposed a method that will eliminate the initial value assumption problem by developing an ANN model that understand and predict the nonlinear parameters of a Super High Damping Rubber Bearing (HDR-S) cyclic loading test data under Bilinear model.

2. ANN BASED STRUCTURAL ANALYSIS AND CONTROL

Recently, the application of machine learning in structural design were rapidly increasing. A study used artificial neural network to develop a semi-active controlled based neural network of a magnetorheological (MR) damper for a based-isolated building. The developed model replicated the dynamic behaviour of the MR damper which helped to automatically predicted the force needed to resist the seismic forces[7)]. Another study used neural network to estimate the restoring force of an HDR bearing based on seven input parameters: maximum displacement, maximum load, displacement turning point, load turning point, displacement increment, load increment, and current displacement. The trained neural network model understand the nonlinear behaviour of the HDR bearing and predicted the restoring force without relying to any numerical model under dynamic loading, but the HDR parameters was fixed and cannot be generally used[8)]. Lastly, a developed neural network model was used to assess the seismic response analysis of laminated rubber bearing supported bridge. It was found that initial stiffness and coefficient of friction using Bilinear model were the critical key factors of the bearing's properties under seismic evaluation[9)].

3. PROPOSED METHOD

This study developed an artificial neural network (ANN) model that can predict the parameters of an HDR-S Cyclic Loading Test data under bilinear model. This study used Artificial Neural Network (ANN) for the AI model development as shown in Figure-1.

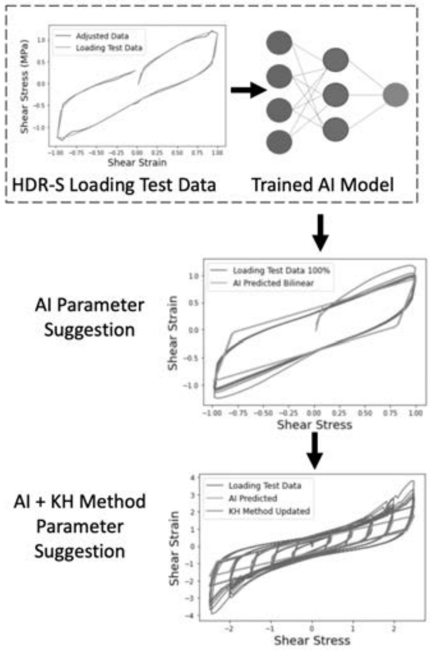

Figure-1 Proposed Methodology

Neural Network had the capability to learn the relationship between the input and output data with the proper setting of layers and hyperparameters. The methodology of this study were as follows:

(1) The shear stress from an an actual Super High Damping Rubber (HDR-S) bearing loading test result was normalized and numerically simulated using the emperical formula of bilinear model, each parameter range was decided based from the standard released by the Road and Bridge Seismic Control Design Method Draft.

(2) The AI model was trained using the shear strain data and the numerically simulated shear stress data using artificial neural network with specified hyperparameters, activation functions, and customized layers.

(3) After that, the trained AI model has been able to predict the nonlinear parameter of an HDR-S bearing loading test. The outputs were initial stiffness, stiffness ratio, and yielding force.

(4) It was later compared using optimum algorithm (KH Method) for parameter prediction and a combination of AI model and refining the KH method which eliminated the initial value assumption problem.The enhanced AI design process can be considered to make the seismic deisgn more efficient.

4. BILINEAR MODEL

This is the most used nonlinear model to interpret the seismic isolator's hysteretic behavior due to its parameters simplicity. This model coverered change in stiffness from linear to plastic state which undergoes to yielding and unloading state as shown in Figure-2.

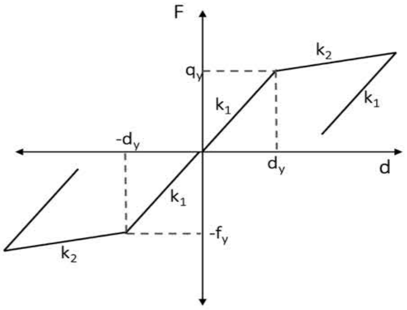

Figure-2 Bilinear Model

The elastic stage consist of the force, Fe, ranges from the initial displacement at zero, upto the yielding displacement d_y and - d_y, with the initial stiffness k_1. The current displacement represents d.

$$Fe = k_1 d \tag{1}$$

After that, yielding happens wherein the initial stiffness changes to secondary stiffness, k_2 during the plastic status. α was the ratio of the secondary stiffness and the initial stiffness as shown in equation 2.

$$\alpha = \frac{k_1}{k_2} \tag{2}$$

The restoring force, F was expressed as a combination of elastic and inelastic state as shown in equation 3.

$$F = (1 - \alpha) k_1 d \tag{3}$$

The yielding and unloading state was bounded by the condition of the elastic and plastic state changes, in which the yielding force q_c, had an important role.

5. DATA GENERATION

The shear strain data came from an actual HDR-S loading test result at 23 °C as shown in Figure-4. The data was originally in terms of force and displacement but was converted to shear stress and shear strain to make it universal without the effect of the bearing's cross section. The data consist of five different amplitudes ranging from 50%, 100%, 150%, 200%, and 250%, and each amplitude had five loops.

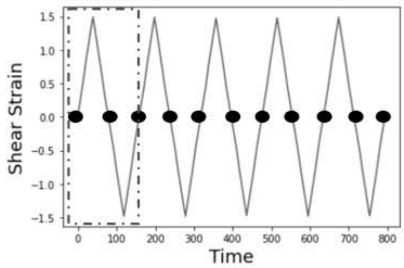

Figure-3 Loops Separation by Shear Strain

The loops were separated and normalized to 60 datapoints each as shown in Figure-3, to fit in the training and testing input data for ANN training. The normalization method used was nearest neighbor and the sample adjusted data in loop 1 was shown in Figure-5. 60 data points was the optimum size that was decided through trial and error training of the neural network model. The input data size was 120 due to the combination of 60 shear strain and numerically simulated 60 shear stress. The numerically simulated shear stress was based from the emperical formula of bilinear model and the range of each parameter was based from the Road and Bridge Seismic Control Design Method Draft. The numerical simulation at each amplitude produced an iteration of 1500 sets which makes it a total of 7500 dataset. It was separated to training and testing. 5000 was set to training and 2500 for testing. The data size and data values had a high impact on the training process and normalization should be done. The platform used for data generation was python and run at google colaboratory.

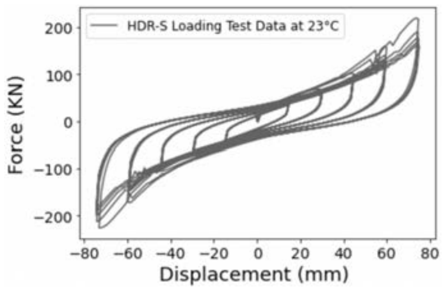

Figure-4 HDR-S Bearing Data at 23 °C

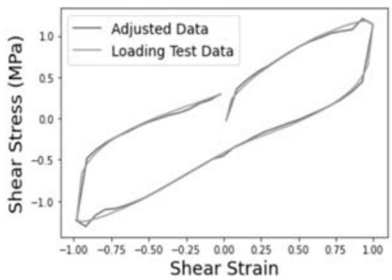

Figure-5 Adjusted Stress and Strain Data

6. TRAINING OF NEURAL NETWORK

The neural network model was under supervised learning therefore the hidden layers and hyperparameters needs to be carefully specified and will highly affect the training result. The developed AI model consist of a two-layer neural network with input size of 120, the hidden layer was 5000, and an output data of 3 was shown in Figure-6. The input size was combined with 60 data points of shear stress and 60 data points of shear strain thus the input layer is 120. The output layer, with size of 3, was representing the parameters of Bilinear model: initial stiffness, stiffness ratio, and yielding force.

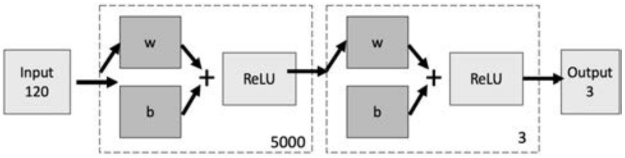

Figure-6 Neural Network Model

Since the ANN model focused on regression problem, the activation function used was rectified linear activation function (ReLU) as shown in Figure-7, was selected as the activation functions for both hidden layer and output layer, which output's a value from zero to any positive number. Therefore, the output values does not have any limitations on the positive values compare to other hyperparameters that was commonly used for classification that limits the values from zero to one.

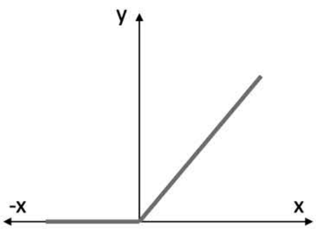

Figure-7 ReLU Activation Function

Root Mean Square Propagation (RMSProp) was used an optimization technique to eliminate the vanishing gradient problem. The initial learning rate was set to 0.001. It uses an adaptive learning rate which normalize and balance the momentum step size depending on the value of loss to avoid skipping the optimum gradient. This optimizer was highly recommended for development of neural network that involves regression problem.

The neural network continously updates each parameter weights all throughtout the training process until the loss approached to zero. The optimum loss depends on the human's tolerance and can be visualized during the prediction process. The loss function for training was mean square error (MSE) and mean average error (MAE) for the validation training were shown in equation 4 and equation 5.

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=0}^{n}(yi - yp)^2 \tag{4}$$

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=0}^{n}|yi - yp| \tag{5}$$

where in n is the total number of data, yi is the actual value, and yp is the predicted value.

7. AI MODEL EVALUATION

The validation was split to 90% training and 10% validation so that even if the model is on the training stage, it was already validated. The total training input was 120 by 4500 and the validation consist of 120 by 500 dataset. The testing data was 120 by 2500, and was tested separately after the training.

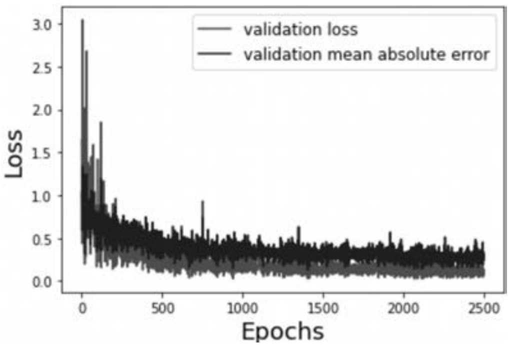

Figure-8 Validation Loss and Error

After 2500 epochs, the testing data mean average error was 0.08 and the mean absolute error was 0.26. This indicates a good AI model because both the losses was close to zero. The visualization of the loss and epochs was shown in Figure-8.

8. HDR-S NONLINEAR PARAMETERS PREDICTION

After the development of the AI model, an actual HDR-S bearing cyclic loading data was used to test the model.

The first loop at each amplitude was predicted which was shown from Figure-9 to Figure-13.

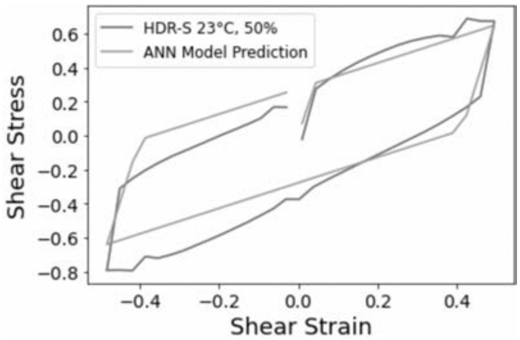

Figure-9 Bilinear Paratemer AI Prediction of Loading Test Data at 23 °C,50% Amplitude, Loop 1

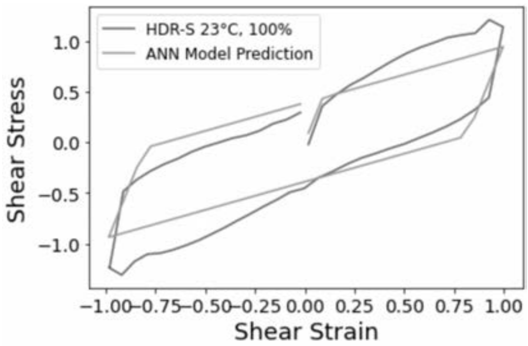

Figure-10 Bilinear Paratemer AI Prediction of Loading Test Data at 23 °C,100% Amplitude, Loop 1

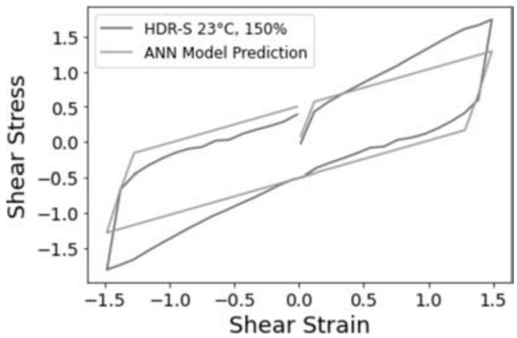

Figure-11 Bilinear Paratemer AI Prediction of Loading Test Data at 23 °C,150% Amplitude, Loop 1

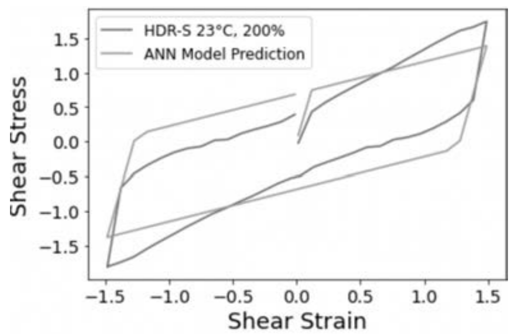

Figure-12 Bilinear Paratemer AI Prediction of Loading Test Data at 23 °C, 200% Amplitude, Loop 1

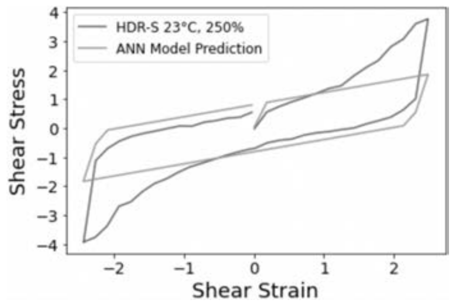

Figure-13 Bilinear Paratemer AI Prediction of Loading Test Data at 23 °C, 250% Amplitude, Loop 1

The predicted HDRS nonlinear parameter values was shown in table 1. The visualization of each parameter with respect to the amplitude was shown in Figure-14 to Figure-16. The yielding force prediction increases as the amplitude increases. After the 100% amplitude, the stiddness ratio decreases while the initial stiffness increases.

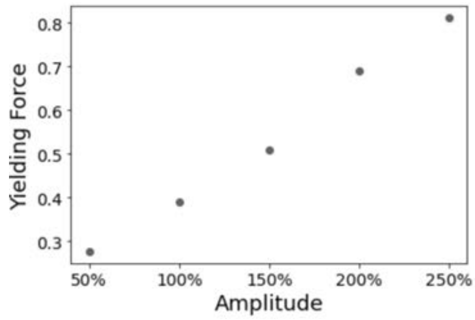

Figure-14 Yielding Force AI Prediction at Different Amplitude

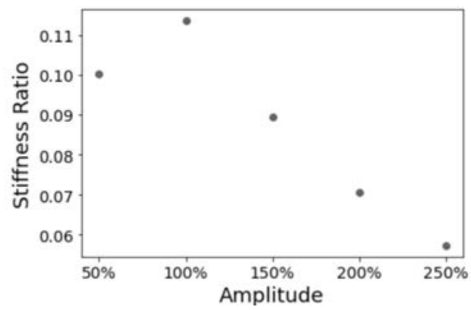

Figure-15 Stiffness Ratio AI Prediction at Different Amplitude

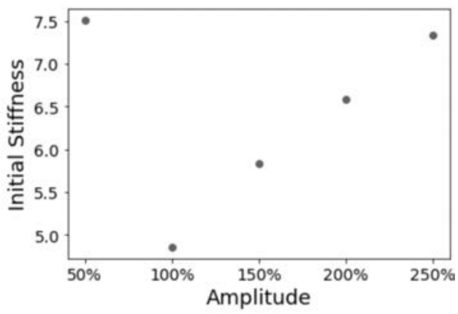

Figure-16 Initial Stiffness AI Prediction at Different Amplitude

To determine the correlation of the HDR-S bearing data to the predicted nonlinear parameters by AI model and KH Method, the contribution rate R, was obtained.

$$R^2 = \frac{{s_e}^2 - {s_{ea}}^2}{{s_e}^2} \tag{6}$$

Where in s_e was the summation of the squared difference of the experimental data and the average of the experimental data, while s_{ea} , was the summation of the squared difference of the experimental data and analysis data result. Figure-17 shows the HDR-S cyclic loading test data and the AI model nonlinear parameter prediction at 150% amplitude which has the highest contribution rate of 0.944, compare to other amplitude prediction. The parameter prediction using AI model for all the amplitudes was shown in Table-1. After that, to solve the initial problem assumption using KH method, the nonlinear parameter from AI model became the initial input for the KH method as shown in Figure-18. The contribution rate increased to 2%, however, the step size increased as shown in Table-2. On the contrary, using KH Method alone, requires an initial parameter value assumption which was produced randomly but bounded with the range based from the standard. The contribution rate was 0.966, but the step size range from 457- 955 as shown in Table-3. The step size was highly dependent on the initial random parameter assumption which makes this method a trial and error process and time consuming.

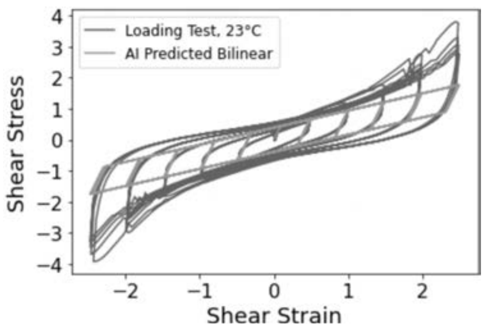

Figure-17 HDR-S Parameter Prediction using the AI Model

Table-1 AI Model HDR-S Parameter Prediction

Amplitude %	AI MODEL				
	α	k_1	q_c	*R*	*Step/s*
50	0.100	7.508	0.277	0.920	1
100	0.114	4.858	0.389	0.932	1
150	0.090	5.834	0.508	0.941	1
200	0.071	6.589	0.689	0.935	1
250	0.057	7.341	0.811	0.909	1

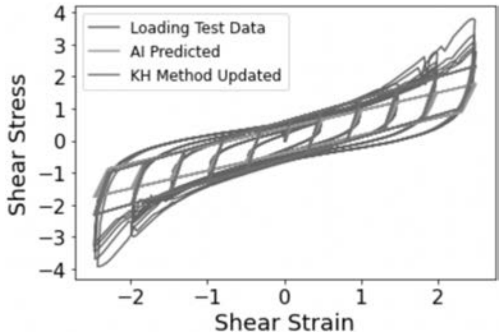

Figure-18 HDR-S Parameter Prediction using AI and KH Method

Table-2 AI Model with KH Method Parameter

Amplitude %	AI MODEL with KH Method				
	α	k_1	q_c	*R*	*Step/s*
50	0.086	8.157	0.592	0.966	156
100	0.097	7.188	0.594	0.966	139
150	0.097	7.188	0.594	0.966	92
200	0.097	7.188	0.594	0.966	97
250	0.085	8.223	0.592	0.966	102

Table-3 KH Method Parameter Optimization

Amplitude %	KH Method				
	α	k_1	q_c	*R*	*Step/s*
50	0.073	9.655	0.589	0.966	955
100	0.073	9.653	0.589	0.966	881
150	0.073	9.651	0.589	0.966	770
200	0.073	9.702	0.589	0.966	484
250	0.073	9.671	0.589	0.966	457

9. CONCLUSION

The study proposed a method to predict parameter for nonlinear hysteresis model from raw experimental data based on ANN that can predict the nonlinear parameters of a Bilinear Model. Setting up of the initial nonlinear parameters of the seismic isolator was an important part in design specially for the newly developed seismic isolators, and usually requires a lot of time and a trial and error process. This study concludes that:

(1) The proposed method shows that it eliminated the initial assumption value problem of optimum algorithm (KH Method) by the development of an AI model which directly learned the hysteretic bahaviour of an isolator under Bilinear Model and predicted the nonlinear parameters automatically.

(2) The AI model showed a significant improvement in the HDR-S cyclic loading data nonlinar parameter prediction

with a contribution rate of 0.94 which was close to KH method which had a contribution rate of 0.97.

(3) The AI prediction method was fast because it only required one step compared to KH Method.

The use of machine learning enhanced seismic design can be considered to make the seismic design more efficient and objective.

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