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NEURAL NETWORK MODELING OF FORWARD AND INVERSE BEHAVIOR OF ROTARY MR DAMPER

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Summary. This paper describes the modeling of a rotary MR damper applying the feed-forward back propagation neural network method. The forward and inverse MR damper behavior are modeled to estimate the force and to solve the force tracking task in real-time. The training and validation data are generated by dynamic tests of the MR damper mounted on a hydraulic testing machine. The training data for the forward model are velocity and current whereby the force is the target. The inverse modeling training data are absolute velocity and absolute force and the current is the target. This new approach is chosen because current is always positive and thereby leads to a small modeling error independently of the sign of velocity. The validation demonstrates that the proposed neural network approach can reliably represent both the forward and inverse dynamic characteristics of the rotary type MR damper.

1   INTRODUCTION

Magneto-rheological (MR) dampers have received considerable attention within the last decades mainly because of their design simplicity, low power requirements, large force range and robustness. Typically, a rotary type MR damper consists of a rotating disk which is enclosed in a rectangular metallic housing filled with the MR fluid. The MR fluid housed within the rotary type MR damper is operated in shear mode. The dissipative torque produced is transformed into a translational force through the crank shaft mechanism.
The most common models to describe the dynamic behavior of MR dampers are the Bouc–Wen model [1], the LuGre friction model [2] and the Dahl model [3]. These modeling approaches are fairly complicated due to the high degree of nonlinearities in the system under consideration. From a computational point of view the nonparametric neural network technique is very versatile in connection with most types of nonlinear problems [4].

Therefore, this paper applies this method to model the dynamic behavior of the rotary MR damper.

2   EXPERIMENTAL SET-UP

The experimental test set up and its schematic diagram are shown in Fig. 1. The dSPACE is used to output the desired displacement going to the INSTRON controller, to output the desired current going to the current driver KEPCO and to acquire the measured states such as MR damper force, acceleration of the crank-shaft, actual displacement and current. Sinusoidal and triangular displacements with different frequencies from 0.5 Hz to 2.2 Hz are applied. Triangular displacements are used in order to perform tests at constant damper velocity. Constant and half-sinusoidal currents with different frequencies from 0.5 Hz to 2.2 Hz are also applied. The current of the MR damper under consideration is limited to 4 A and the maximum displacement amplitude is constraint to 10 mm due to the crank-shaft mechanism. The measured data is filtered to remove measurement noise and offsets in order to get the training data for the neural networks.
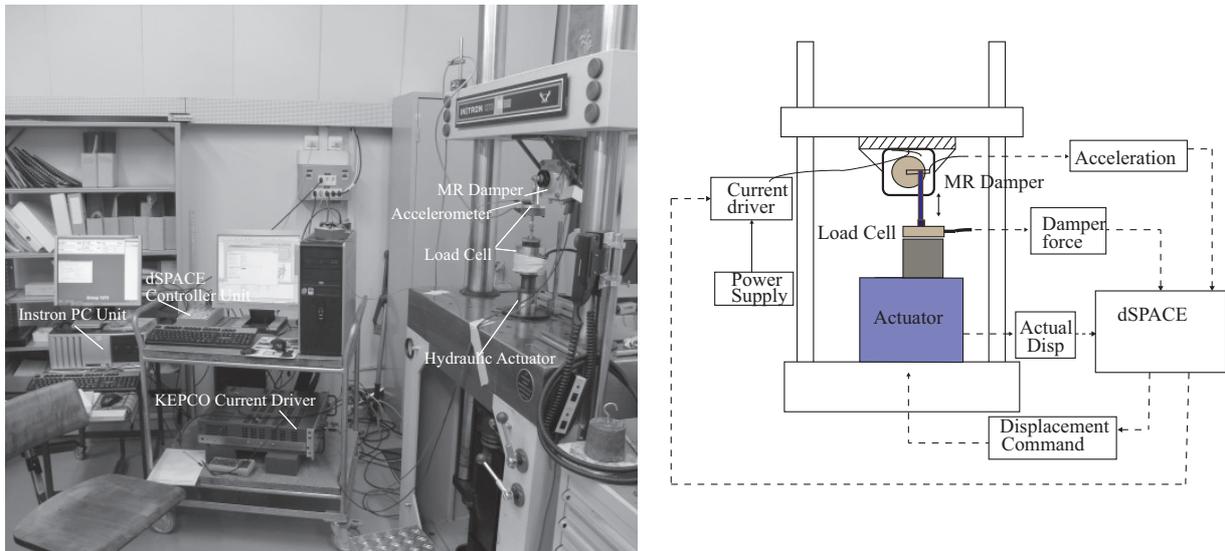

Figure 1. Experimental set-up and its schematic view

3   NEURAL NETWORK MODELING

Feed forward neural network (FFNN) is capable of modeling any nonlinear behaviour with acceptable accuracy. One data set is use as training data and another as validation set.

3.1 Forward MR damper modeling using FFNN

The identification methodology for the modeling of the forward dynamics of MR damper using the FFNN approach is illustrated in Fig. 2. The input states are current and velocity and their associated delay values. The velocity is required due to its significant influence on the hysteretic behavior of the MR damper. It is derived by numerical differentiation of the measured displacement. The noise resulting from the differentiation is removed by additional low pass filtering. The difference between modeled and measured MR damper force, i.e. the

error(k), is used to adjust the weights and the biases of the neural network model until a defined modeling error is reached. The feed forward neural network includes 2 hidden layers with 12 neurons in the first layer and 6 neurons in the second. The output layer includes one neuron and is chosen for input-output comparison. The numbers of layers and neurons have been found by trial and error. The transfer functions of the neurons of the two hidden layers are selected as tangent sigmoid function and the transfer function of the output layer is selected as linear function. The training algorithm is based on the Levenberg-Marquardt algorithm. The detailed mathematics of the neural network method is described well in [5].
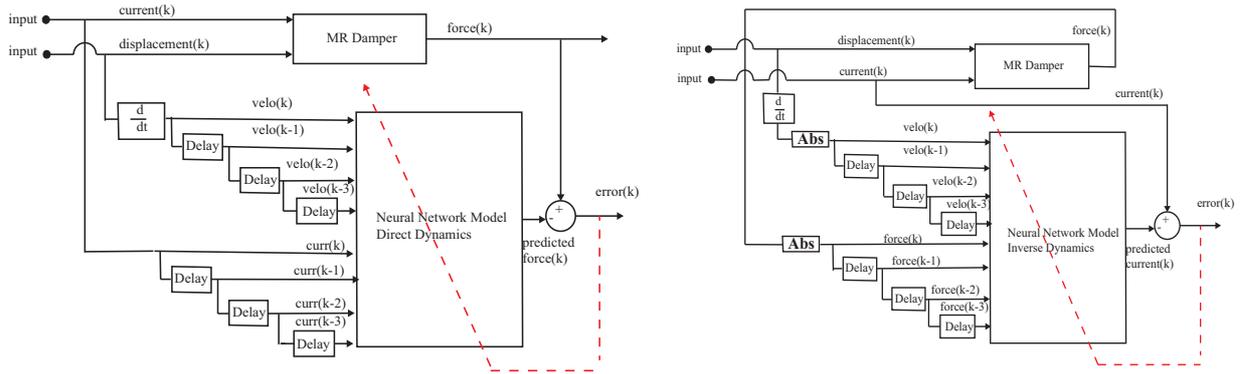

Figure 2. Forward and inverse neural network modeling of MR damper

3.2 Inverse MR damper modeling using FFNN

The architecture of the inverse model using the FFNN method is also shown in Fig. 2. The number of hidden layers and their transfer functions are chosen as before but the number of neurons in both hidden layers is 6. The significant change compared to the forward modeling is that the absolute values of velocity and force are used to train the neural network to get the estimated current because current is always positive. This new approach leads to small modeling error and the modeling error does not depend on the sign of velocity and direction of damper displacement, respectively.

4   MODEL VALIDATION AND DISCUSSION

The validations of both the forward and inverse MR damper models are shown in Fig. 3. The error of the forward model is depicted by comparing the measured and estimated forces resulting from 2 A and sinusoidal displacement (0.5 Hz, 4 mm). The modeling error of the inverse neural network approach is shown for the case of half-sinusoidal current input (0.5 Hz) and sinusoidal displacement (0.5 Hz, 6 mm). The inverse neural network is tested by a half-sinusoidal current because this is quite close to the current time history that is expected when emulating linear viscous damping except that the current spike during the pre-yield region is missing. The validation of the forward model shows an acceptably small error. The current estimated by the inverse MR damper model shows spikes that result from spikes in the measured displacement and force due to bearing plays between crank-shaft and INSTRON piston. Although these spikes have been partially removed by the filters to derive the training data, the estimated current is still spiky. The simple approach of filtering the estimated current cancels the spikes but leads to a still acceptably small time delay of approximately 0.05 s.

5 CONCLUSIONS

This investigation employed the back propagation feed forward neural network method to model the forward and inverse dynamics of an MR damper. The training data was taken on a prototype rotary MR damper that was connected to a hydraulic machine imposing sinusoidal and triangular displacements and constant and half sinusoidal current time histories. The goal of the forward MR damper model was to capture accurately the behavior of the MR damper behavior whereas the inverse MR damper model will later be used for the control force tracking when the MR damper will be connected to a shear frame. The novelty in the proposed neural network when modeling the inverse MR damper behavior is that the absolute values of velocity and force are used to estimate the damper current since current is always positive. The validations of both the forward and inverse MR damper models show that the applied neural network approaches capture the main MR damper dynamics with acceptable accuracy. However, the preliminary results demonstrate that the modeling accuracies can still be improved by further optimization of the filters that are used to process the measurement data to derive the training data for the neural network training.
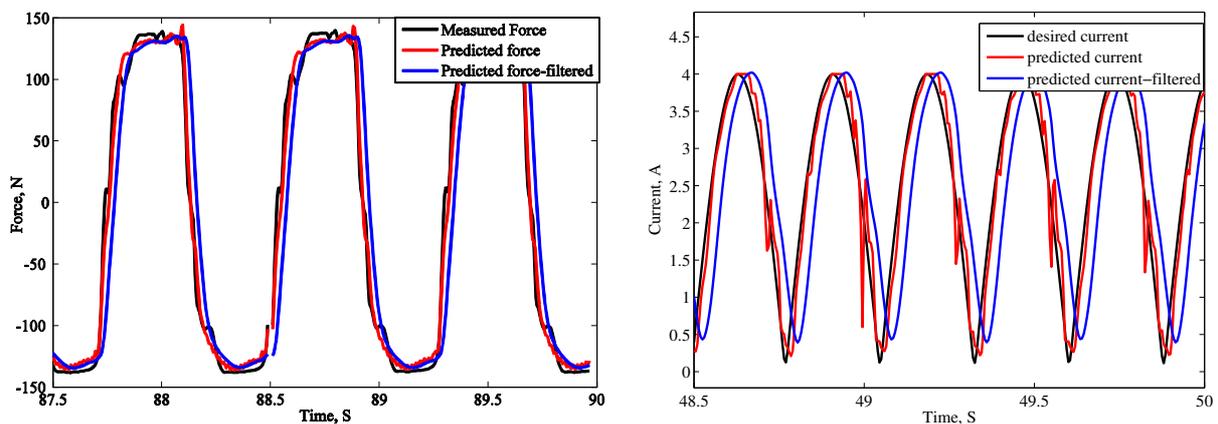

Figure 3. Validation of forward and inverse neural network models

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