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Inverse Model Control of An ER Damper System

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Abstract

Due to the inherent nonlinear nature of Electro-rheological (ER) fluid dampers, one of the challenging aspects for utilizing these devices to achieve high system performance is the development of accurate models and control algorithms that can take advantage of their unique characteristics. In this paper, the nonlinear damping force model is made to identify the properties of the ER damper using higher order spectrum. The higher order spectral analysis is used to investigate the nonlinear frequency coupling phenomena with the damping force signal according to the sinusoidal excitation of the damper.

Also, this paper presents an inverse model of the ER damper, i.e., the model can predict the required voltage so that the ER damper can produce the desired force for the requirement of vibration control of vehicle suspension systems. The inverse model is constructed by using a multi-layer perceptron neural network. A quarter-car suspension model is considered in this paper for analysis and simulation. Simulation results show that the proposed inverse model of ER damper can obtain control voltage of ER damper for required damping force.

Key Words : ER Damper, Inverse Model, Neural Network, Higher Order Spectra, Fuzzy Sky-hook

1. Introduction

Electro-Rheological (ER) fluids are colloidal suspensions which exhibit large reversible changes in flow properties such as the apparent viscosity when subjected to sufficiently strong electric fields. Since Winslow[1] reported on the ER fluid, many researchers have been studying the mechanism and application of ER fluids. The scientific challenges in the field of ER fluids and devices consist in the development of optimal control strategies and the mathematical modeling and numerical simulation. To take maximum advantage of ER fluids in control applications a reliable method is needed to predict their nonlinear response. Several phenomenological models characterizing the behavior of ER fluid devices have been presented.

In order to characterize the ER damping mechanism Stanway proposed a mechanical model commonly referred to as the Bingham model, which combines viscous and coulomb friction [2]. In this model, damping force of ER damper is expressed by the polynomial with the multiple power of piston velocity and the coefficients of polynomial change according to applied electric field. Mui[3] proposed dynamic model of ER damper including the equivalent inertia that consider coulomb resistance, fluid resistance and fluid flow. From the analysis of coefficients of damping force model, the damping force changes depend on the applied electric field as well as frequency of applied input.

Gamota and Filisko presented an extension of the Bingham model to describe the hysteretic response of ER fluid in the pre-yield and the post-yield region as well as at the yield point [4]. Focusing on predicting the behavior of an ER fluid device Powell proposed a mechanical analogue consisting of a viscous damper, a nonlinear spring and a frictional element in parallel [5]. This model is much easier to handle more mathematically than extended Bingham model as well as describe the hysteretic response of ER damper.

In this paper, analysis of higher order spectrum about measured damping force is performed and confirmed the existence of nonlinearity of ER damper. From the results, we propose damping force model expressed by the polynomial with the multiple power of piston velocity and show the accuracy of damping force model by comparing with experimental results.

Control of damping force of an ER damper is also very challenging because the strong nonlinearity and the semi-active relationship between the damping force and the input voltage. So the force generated by the ER damper cannot be commanded directly. In order to overcome these difficulties, several researches were done.

Choi proposed MR damper model that express the influence of magnetic field by the first order linear equation [6]. So he can obtain easily the inverse model of ER damper. Xia presents an inverse model which has been constructed by using a multi-layer perceptron optimal neural network and system identification [7]. Wang proposed inverse model for

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modified Bouc-Wen model of MR fluid damper using feedforward and recurrent neural networks [8].

In the case of ER damper model proposed in this paper, nonlinearity of electric field is included in damping force model. Therefore it is difficult to derive inverse model of ER damper from proposed damping force model. So we obtained inverse model of ER damper by using multi-layer perceptron neural network.

In order to show the applicability of inverse model, we performed simulation of fuzzy sky-hook control with ER damper model.

2. Nonlinear ER Damper Model

2.1 Configuration of test bench

The structure of ER damper is far different from that of the conventional hydraulic or electro-mechanical damper. This damper has inner and outer cylinders. The ER fluids flow the gap between two cylinders used as the electrodes with the plus and minus polarities, respectively. The damping force is controlled by the intensity of the electric field applied to the gap. ER fluid, Bayer Company's TPAI 3566, flows through the duct between cylinder and accumulator.

ER damper test equipment is designed and implemented to excite ER damper using hydraulic servo system with Moog J072-011 servo valve and MTS T-LP-type LVDT (Linear Variable Differential Transformer). Figure 1 shows a schematic diagram of the test equipment used for the measurement of ER properties. The high voltage amplifier used in this study is 10/10A Amplifier, which was manufactured by TREK Corporation. In order to measure the damping force of ER damper, load cell(SENSOTEC Corporation Model 45) was used and it's measuring range is ±8896N.

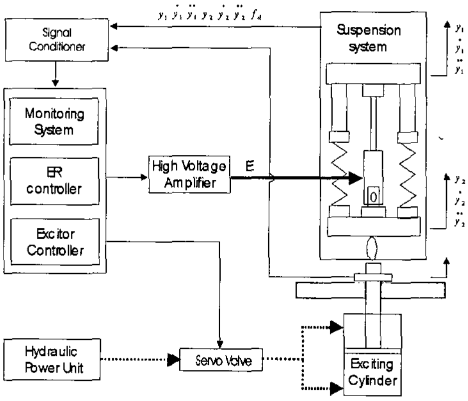


Fig. 1. Schematic diagram of the experimental setup

2.2 Nonlinear characteristics analysis of damping force using higher order spectra

There are situations in practice in which the interaction between two harmonic components causes contribution to the power at their sum and/or difference frequencies. This frequency interaction means that the signal energy concentrated in input frequency is distributed to other output frequencies and can understand as energy transfer between frequencies.

Therefore it can utilize by useful means to analyze the nonlinear properties of the system through the perception of correlation between modes and analysis of amplitude. This frequency interaction can observe using higher order spectrum [9, 10].

When is difficult to analyze the nonlinear interaction by first order moment(correlation) and power spectral density, high order spectral analysis is useful method to analyze the amplitude of energy which transferred by frequency interaction. High order spectrum is described by multiple Fourier transform of signal cumulant, the k-th order cumulant is represented by equation 1.

$$C_{k,y}(\tau_1,\tau_2,\cdots\tau_k) = E\{y(t)y(t+\tau_1)y(t+\tau_2)\cdots y(t+\tau_k)\} \quad (1)$$

We define equation (2) as higher order spectrum, equation (3) as bispectrum, and equation (4) as trispectrum by Fourier transform of k-th order cumulants.

$$S_{k,y}(f_1,\cdots,f_{k-1}) = \iint\cdots\int C_{k,y}(\tau_1,\cdots,\tau_{k-1})\cdot\exp\left[-j\sum_{i=1}^{k-1}2\pi f_i\tau_i\right]d\tau_1\cdots d\tau_{k-1} \quad (2)$$

$$S_{2,y}(f_1,f_2) = \iint C_{2,y}(\tau_1,\tau_2)\cdot\exp(-j2\pi(f_1\tau_2+f_2\tau_2))d\tau_1 d\tau_2 \quad (3)$$

$$S_{3,y}(f_1,f_2,f_3) = \iiint C_{3,y}(\tau_1,\tau_2,\tau_3)\cdot\exp(-j2\pi(f_1\tau_2+f_2\tau_2+f_3\tau_3))d\tau_1 d\tau_2 d\tau_3 \quad (4)$$

In order to present bispectrum and trispecturm as frequency function, equation (5) and equation (6)defines as auto-bispectrum and auto-trispectrum, k-th order moments are express as equation (7) and equation (8).

$$S_{2,y}(f_1,f_2) = E\left[Y(f_1)Y(f_2)Y^*(f_1\pm f_2)\right] \quad (5)$$

$$S_{3,y}(f_1,f_2,f_3) = E\left[Y(f_1)Y(f_2)Y(f_3)Y^*(f_1\pm f_2\pm f_3)\right] \quad (6)$$

$$R_{2,y}(\tau_1,\tau_2) = \iint E\left[Y(f_1)Y(f_2)Y^*(f_1\pm f_2)\right]\cdot e^{-j2\pi(f_1\tau_1+f_2\tau_2)}df_1 df_2 \quad (7)$$

$$R_{3,y}(\tau_1,\tau_2,\tau_3) = \iiint E\left[Y(f_1)Y(f_2)Y(f_3)Y^*(f_1\pm f_2\pm f_3)\right]\cdot e^{-j2\pi(f_1\tau_1+f_2\tau_2+f_3\tau_3)}df_1 df_2 df_3 \quad (8)$$

Where Y^* is the complex conjugate of Y. Bicoherence of equation (9) and tricoherence of (10) are used to analysis that the phase interaction is produced due to 2nd and 3rd order terms of nonlinear system.

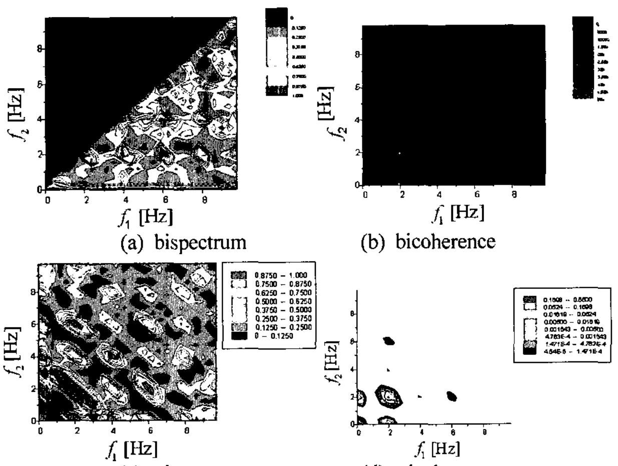
$$b^2(f_1,f_2) = \frac{|S_{2,y}(f_1,f_2)|^2}{E[|Y(f_1)Y(f_2)|^2]\cdot E[|Y(f_1\pm f_2)|^2]} \quad (9)$$

$$t^2(f_1,f_2,f_3) = \frac{|S_{3,y}(f_1,f_2,f_3)|^2}{E[|Y(f_1)Y(f_2)Y(f_3)|^2]\cdot E[|Y(f_1\pm f_2\pm f_3)|^2]} \quad (10)$$

Bicoherence and tricoherence satisfy in the range of $0\leq b^2\leq 1$ and $0\leq t^2\leq 1$. And it used to analysis of correlation of

f_1, f_2, $f_1 \pm f_2$, and $f_1 \pm f_2 \pm f_3$. In frequency component $f_1 \pm f_2$, and $f_1 \pm f_2 \pm f_3$, if bicoherence or tricoherence is near to '1', then the frequency energy is produced by only mode correlation of input frequency f_1 and f_2. Otherwise if bicoherence or tricoherence is near to '0', then we can consider that there are no phase relation and f_1, f_2, $f_1 \pm f_2$, and $f_1 \pm f_2 \pm f_3$ are inputted system independently. For these reason, bicoherence and tricoherence are used to analysis of phase correlation that generated by 2nd and 3rd terms of nonlinear system [11, 12].

From Figure 2, it is apparent that nonlinear characteristics can be achieved with the measured damping signal using higher order spectra analysis.



(a) bispectrum (b) bicoherence

(c) trispectrum (d) tricoherence

Fig. 2. Higher order spectrum of damping force signal at E=4kV/mm (input frequency=2Hz)

2.3 Modeling of damping force

From the subsection 2.2, we confirmed damping force model can expressed by k-th order polynomial. Therefore we proposed damping force model of 3rd order polynomial as equation (11).

In this paper, damping model considering 3th-order terms is suggested and equation (11) becomes

$$f_d = c_1 v + c_2 v\,|\,v\,| + c_3 v^3 \tag{11}$$

The coefficient c_1, c_2, and c_3 are obtained using least squared error methods. If the measured damping force is F_t, the error function Q is as follows.

$$\begin{aligned} Q &= E[(F_t - f_d)^2] = E[(F_t - c_1 v - c_2 v|v| - c_3 v^3)^2] \\ &= E[F_t^2] - 2c_1E[F_t v] - 2c_2E[F_t v|v|] - 2c_3E[F_t v^3] + c_1^2E[v^2] + c_2^2E[v^4] + c_3^2E[v^6] \\ &\quad + 2c_1c_2E[v^2|v|] + 2c_2c_3E[v^4|v|] + 2c_1c_3E[v^4] \end{aligned} \tag{12}$$

The coefficients of damping force model obtained from Gaussian random excitation signal are shown in Figure 3. The coefficient c_1 is increase lineally according to amplitude of electric field. And the coefficient c_2 changed rapidly between 1 kV/mm and 2 kV/mm. The coefficient c_3 decreased more than 2 kV/mm preferably.

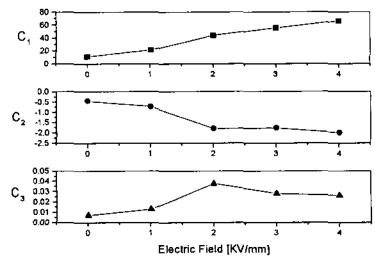
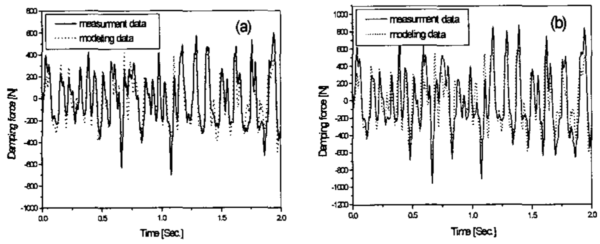


Fig. 3. Coefficients of nonlinear damping model with Gaussian input signal

Figure 4 show that the measured data of experiment system and modeling data of damping force simulation with random input signal with 2kV/mm and 3kV/mm. As a result, proposed damping force model shows a good performance.



(a) 2kV/mm (b) 3kV/mm

Fig. 4. Measured data and modeling of the damping force with random input signal

3. Inverse Model of ER Damper Using NN

Damping force model of ER damper is nonlinear about piston velocity and applied electric field. Therefore in order to generate reference damping force, it requires inverse model of ER damper [6-8].

In this paper, it is difficult to obtain inverse model of ER damper because proposed ER damper model is expressed by nonlinear equation about damping force and electric field. In order to overcome this problem, we used neural network for inverse model of ER damper because it has not only been successfully used in solving complex problems in pattern recognition and time series prediction, but also has been proposed for the identification and control of nonlinear dynamical systems. And the Levenberg-Marquardt Method was used to minimize the mean square error, due to its rapid convergence properties and robustness.

3.1 Structure of MLP network

The multi-layer perceptron network (MLP) is the most often used member in the neural network family due to its ability to model simple as well as very complex function relationships. To obtain inverse model, we proposed three layer feedforward MLP-network with 2 inputs, 1 output, 20 hidden neurons and one bias as shown as Figure 5. For these MLP-networks, the activation function of hidden layer is sigmoidal activation function and the activation function of output layer is linear activation function.

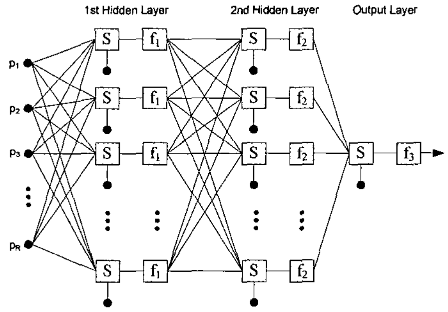


Fig. 5. Fixed structure neural network used for inverse modeling

3.2 Training of MLP to obtain inverse model of ER damper

Generally, a neural network must learn how to classify input patterns. It has been experimentally observed that as the number of layers of a network increases, it can classify more and more complicated patterns. A significant problem is how a network can determine the error between its output and the desired output. The network, then, overcomes the mismatch between desired and actual outputs by adjusting the weighing of interconnections. The backpropagation algorithm originally introduced by Minsky and Papert, solves this problems by using all of the processing elements and adjusting their total interconnections. It does so by propagating the output layer error to the preceding layer via the existing connections. This operation is then repeated until reaching the input layer

In this paper, the Gauss-Newton-based Levenberg-Marquardt (LM) method was used to minimize the mean-square error, due to its rapid convergence properties and robustness.

In order to train the neural network, we made 1000 data sets that consist of damping force, piston velocity, and electric field from damping force model. The 500 data sets of this used for training of neural network and the other data sets are used for verify the optimal network of inverse model. The learning rate and mean-square error goal of LM method are selected as 0.05 and 10-5 kV/mm respectively. Figure 6 shows the convergence characteristics of MLP network.

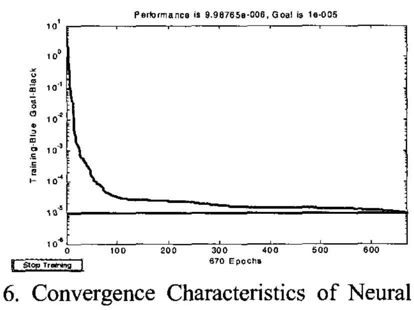
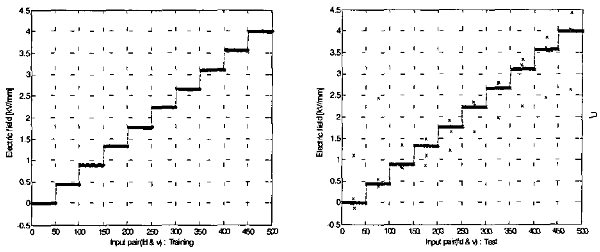


Fig. 6. Convergence Characteristics of Neural Network

Figure 7(a) shows the output electric field of Inverse model and its comparison with the desired electric field to the ER damper for training data set. Figure 7(b) shows simulation result using 500data sets for verification to inverse model. Mean square error of this simulation shows satisfied result by 0.022 kV/mm.



(a) Training Results (b) Test Results

Fig. 7. Target Electric Field vs. Output Electric Field

4. Simulations

4.1 Damping force control

An accuracy of damping force control of the ER damper depends upon the damper model. To demonstrate this, an open-loop control system to achieve a desirable damping force is established as shown in Figure 9. In the case of closed-loop control systems require additional sensor as load cell, thus most of case open-loop control system is used because of easy implementation.

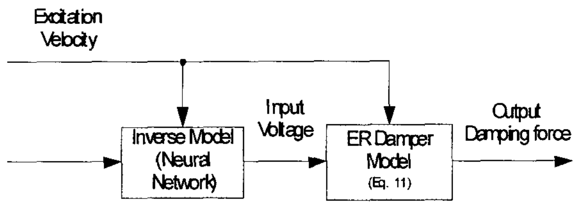
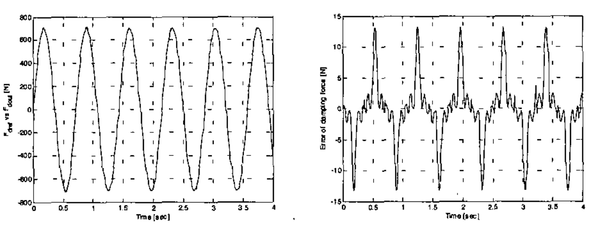


Fig. 8. Block diagram of damping force control



(a) f_{ref} vs f_{out} (b) Error of damping force

Fig. 9. Comparison of Reference damping force and Output damping force

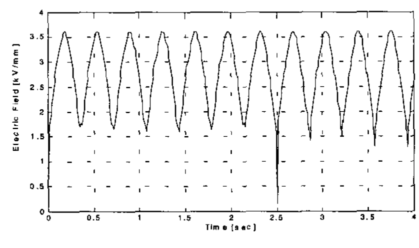


Fig. 10. Control input of ER damper

In order to verify the performance of inverse model the real damper system is required, but this paper simulate inverse model using proposed nonlinear ER damper model.

If the desired damping force is given, electric field is determined by inverse model to implement desired damping force. And then this electric field inputted to damper model.

Figure 8 shows the control performance of damping force in open-loop control system. The frequency and amplitude of desired damping force are selected as 1.4 Hz and ±700N. And excitation frequency and amplitude are given as 1.4Hz and 20 cm/s. The comparative results between the desired damping force and output damping force are shown in Figure 9. We clearly see that output damping force can follows well desired damping force. Figure 10 shows control input of ER damper.

4.2 Fuzzy Sky-hook control with ER damper model

In this section, we simulate quarter-car suspension system with ER damper fuzzy sky-hook control algorithm[13] as shown in Figure 11. The quarter-car suspension model parameters have the following values:

$$m_s = 368kg,\ m_u = 59.1kg,\ k_s = 45080N/m,\ k_t = 213640N/m$$

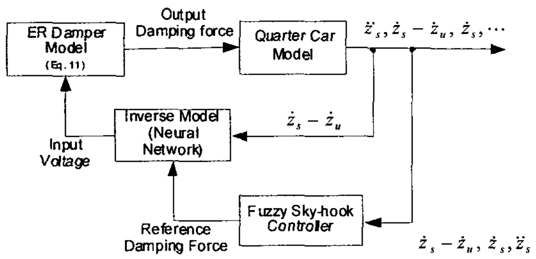
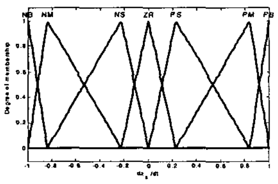
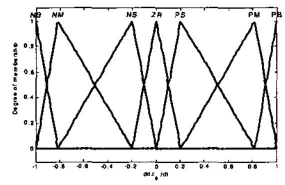


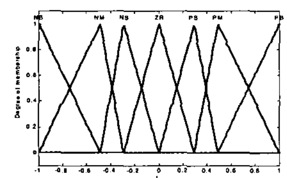
Fig. 11. Block diagram of Fuzzy Sky-hook control with ER damper model



(a) M.F. of velocity



(b) M.F. of acceleration



(c) M.F. of damping force

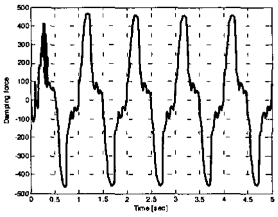
Fig. 12. Input/Output membership functions

The proposed fuzzy sky-hook control combines the fuzzy logic theory with the sky-hook principle to improve control performance. The piston velocity and acceleration are used as input of fuzzy logic controller (FLC) and damping force is used as output of FLC. For each inputs and output, a triangular membership function is used as shown in Figure 12. The FLC rule-base of fuzzy sky-hook controller is detailed in Table I.

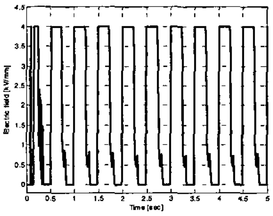
Table I Fuzzy control rule

		$\ddot{z}_s$						
		NB	NM	NS	ZR	PS	PM	PB
$\dot{z}_s$	NB	PB	PB	PM	ZR	ZR	ZR	NS
	NM	PB	PB	PM	ZR	ZR	NS	NM
	NS	PB	PM	PS	ZR	ZR	NS	NM
	ZR	PB	PM	PS	ZR	NS	NM	NB
	PS	PM	PS	ZR	ZR	NS	NM	NB
	PM	PM	PS	ZR	ZR	NM	NB	NB
	PB	PS	ZR	ZR	ZR	NM	NB	NB

Figure 13 shows comparison of desired damping force of fuzzy sky-hook controller and output damping force of ER damper model, and shows electric field input of ER damper. Figure 14 shows simulation results of fuzzy sky-hook with ER damper model and fuzzy sky-hook without ER damper model. From the simulation results, we confirmed that the inverse model of ER damper apply to fuzzy sky-hook control properly.

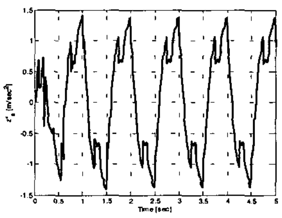


(a) f_{ref} vs f_{out}

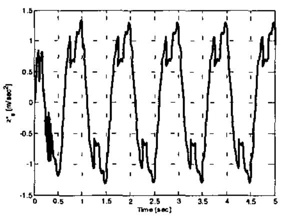


(b) Control input of ER damper

Fig. 13. Damping force and Control input



(a) Without ER damper model



(b) With ER damper model

Fig. 14. Acceleration of sprung mass

5. Concluding Remarks

In this paper, we performed characteristic test using nonlinear frequency by measuring of the damping force and signal process of bispectrum and trispectrum. And we confirmed existence of nonlinear properties through test results. The damping force model of ER damper is obtained by higher order equation of damper velocity terms and the simulation results are compared with the experimental data on the mechanisms responsible for the vibration of the damping characteristics of the precision equipment a real commercial car.

To generate desired damping force in applications of ER damper, the inverse model of ER damper is necessary. Therefore we implement inverse model by using MLP networks with 2 hidden layers and 1 output layers. In order to verify the performance of inverse model, damping force control was performed. And we confirmed the applicability of inverse model through the simulation of fuzzy sky-hook control with ER damper model.

We expect that the proposed ER damper and inverse model may be very useful for the vibration control of many relevant engineering applications.

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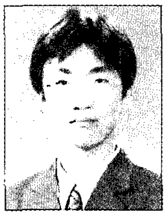

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