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# Modeling and identification of a class of MR fluid foam dampers

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**Abstract.** This paper presents the results of a series of experiments conducted to model a magnetorheological damper operated in shear mode. The prototype MR damper consists of two parallel steel plates; a paddle covered with an MR fluid coated foam is placed between the plates. The force is generated when the paddle is in motion and the MR fluid is reached by the magnetic field of the coil in one end of the device. Two approaches were considered in this experiment: a parametric approach based on the Bingham, Bouc-Wen and Hyperbolic Tangent models and a non parametric approach based on a Neural Network model. The accuracy to reproduce the MR damper behavior is compared as well as some aspects related to performance are discussed.

**Keywords:** smart fluid; magnetorheological; MR damper; Bingham; Bouc-Wen; Hyperbolic tangent; neural network.

## 1. Introduction

Magnetorheological (MR) dampers are devices that have been widely studied during the last fifteen years. Its characteristics make them attractive for implementation in systems such as vehicles and civil engineering structures to protect them from hazardous vibrations and to improve human comfort. MR dampers can generate a high force with low energy requirements and a simple mechanical design at low production costs. Its main component, the MR fluid, is a substance that can change the rheological behavior in the presence of a magnetic field, allowing for controllability.

It is well known that, for successful control, the system components (sensors, actuators and others) should be accurately modeled. MR dampers are highly nonlinear devices with hysteresis that may cause serious problems to stability and robustness (Sain, *et al.* 1997). The force response to the velocity input describes a hysteretic loop which makes it a challenging task to find a model that can reproduce its behavior. Several models have been proposed for MR dampers: the Bingham model (Stanway, *et al.* 1987), the Bi-viscous model, the polynomial model, the Bouc-Wen model (Spencer, *et al.* 1997), Neural network models (Zhang and Roschke 1998), ANFIS based models (Schurter and Rochke 2000) and others derived from the previously mentioned ones are some examples.

This paper presents the results of modeling a shear-mode MR damper using the Bingham, Bouc-Wen,

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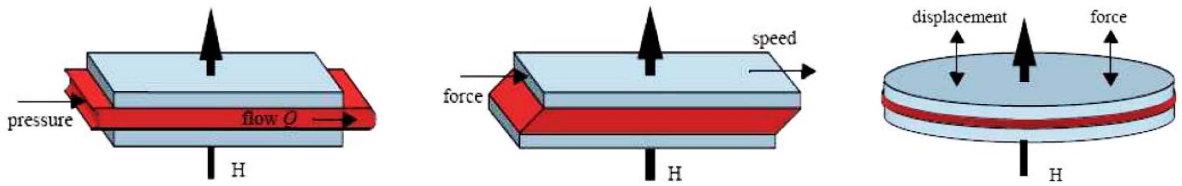
Hyperbolic-Tangent and Neural Network models. Section 2 will give a brief overview of MR dampers. Then, Section 3 gives a description of the MR damper models used in the experiments. Following the experiment setup explained in Section 4, the results of the experiments will be presented in Section 5. Finally, the conclusions and future work are discussed in Section 6.

## 2. Magnetorheological dampers

MR dampers use MR fluids to construct a versatile damping device. These fluids can reversibly change their rheological properties when a magnetic field is applied. Because the strength of the magnetic field controls the yield stress of the fluid, devices utilizing MR fluids are expected to be applicable for a wide range of situations. Its exceptionally low power and mechanical simplicity make them attractive for civil engineering applications (Dyke, *et al*. 1996, Jansen and Dyke 2000). The forces of the MR damper can be controlled in real time by changing the current applied to the electromagnet so that it can react to changing excitations or new objectives. Additionally, MR dampers guarantee stability since they cannot supply energy to the system and are relatively inexpensive to manufacture and maintain. Their insensitivity to temperature fluctuations makes them suitable for both indoor and outdoor applications (Yang, *et al.* 2002).

In general, MR dampers operate in (a) flow mode, (b) shear mode and (c) squeeze mode, or a combination of them. These configurations are illustrated in Fig. 1. Flow mode operated MR dampers are perhaps the most common practical examples. They have been widely studied and used in servo-valves, dampers, shock absorbers and actuators while shear mode devices can be applied to clutches, brakes, chocking and locking devices, dampers and structural composites (Lord Corporation 2007). Squeeze mode dampers are less common than the others but several examples can be found in literature. For instance, the damping of an elastic beam has been tested by Bashtovoi, *et al*. (2002). The aim of that study was to control the vibration of a plate by using an MR fluid. Another example can be found in the work by Wang, *et al*. (2006) who used an MR fluid in place of lubricating oil in squeeze film damper (SFD) to build a variable-damping SFD controlled by a magnetic field to control the vibration of rotor systems.

Large-scale MR dampers for structural control have been constructed. For instance, a 30-ton MR damper with a bypass valve was constructed by the Sanwa Tekki Corporation in Tokyo, Japan for experimental testing (Oh, *et al.* 2004). Another example is provided by Yang, *et al.* (2002) who discusses the performance of a 20-ton MR damper built in cooperation between the Lord Corporation and the University of Notre Dame. As a conclusion of their experiments, the MR damper is claimed to be adequate for a wide range of civil engineering structural applications due to MR fluids simplicity, low input power, scalability and inherent robustness.




(a) Flow mode. (b) Shear mode. (c) Squeeze mode.

Fig. 1 Modes of operation of magnetorheological dampers

## 3. Characterization of MR dampers

The modeling of MR dampers is a challenging task due to the hysteretic behavior observed. Several approaches have been proposed, including parametric (e.g., Bingham, Bouc-Wen and Hyperbolic Tangent models) and non parametric models (e.g. Neural Networks, Fuzzy Logic and ANFIS models). The main difference between parametric and non parametric models is that parametric identification requires assumptions on how the mechanics of the device is and how it can be modeled while the latter does not necessarily need this kind of information explicitly (Zapateiro, *et al*. 2007). In this paper, a comparison between the Bingham, Bouc-Wen, Hyperbolic Tangent and Neural Network models will be presented.

### *3.1. Bingham model*

The Bingham model has been widely used for modeling electrorheological (ER) and MR dampers. It is based on the Bingham plastic model which assumes that a body behaves as a solid until a minimum yield stress is exceeded (i.e. the point from which a material undergoes plastic deformation) and then exhibits a linear relationship between the stress and the rate of shear or deformation. This relationship is mathematically expressed as

$$\tau = \tau_y \cdot \mathrm{sgn}\dot{\gamma} + \eta\dot{\gamma} \tag{1}$$

where $\dot{\gamma}$ is the shear strain rate and $\eta$ denotes the plastic viscosity of the fluid, i.e., the Newtonian viscosity at zero field (Butz and Von Stryk 2002). To characterize the ER dampers, Stanway, *et al.* (1987) proposed a model that consists of a viscous dashpot placed in parallel with a Coulomb friction element, as shown in Fig. 2.

The force generated by the device is given by

$$F = f_c \cdot \mathrm{sgn}(\dot{x}) + c_0\dot{x} \tag{2}$$

where $c_0$ is the damping coefficient and $f_c$ is the frictional force, which is related to the fluid yield stress. This model assumes that the fluid is rigid in the pre-yield condition.

### *3.2. Bouc-Wen model*

The hysteresis model of Bouc as modified by Wen is one of the mathematically simplest yet effective models that can represent a large class of hysteretic behavior (Sain, *et al.* 1997). Spencer, *et al.* (1997) proposed a phenomenological model of a flow-mode MR damper based on the Bouc-Wen hysteresis model. They started their investigation based on the simple mechanical model shown in Fig. 3(a). This

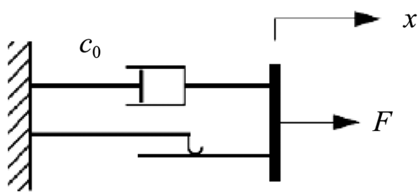



Fig. 2 Bingham mechanical model

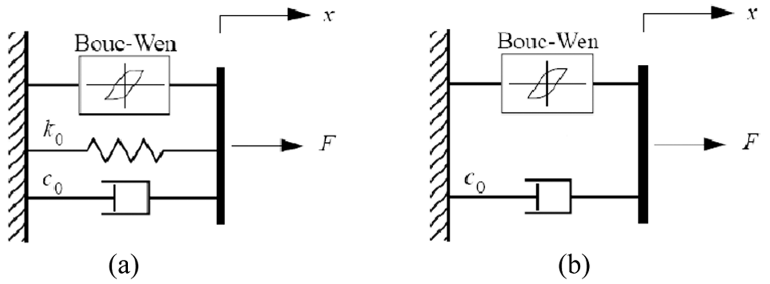



Fig. 3 Mechanical Bouc-Wen model for a (a) Spencer, *et al.* (1997) MR damper, and for a (b) shear-mode MR damper

will be the starting point to model the shear-mode device. It consists of a viscous dashpot and a spring in parallel with a hysteretic element described by the Bouc-Wen equations. However, that device is slightly different from the shear-mode damper studied here. In particular, Spencer, *et al.* (1997) use a linear spring with an initial deflection to account for the pressure inside the cylinder. Since the shear-mode damper does not have any cylinder or accumulator, the mechanical model is simplified as illustrated in Fig. 3(b). The mathematical model is:

$$F = c_0 v + \alpha z \tag{3}$$

where $F$ is the force of the damper, $\dot{x}$ is the velocity, $c_0$ is the damping coefficient and the evolutionary variable $z$, that accounts for the hysteretic component, satisfies

$$\dot{z} = -\gamma|v|z|z|^{n-1} - \beta v|z|^n + \delta v \tag{4}$$

where $\alpha$, $\beta$, $\gamma$, $\delta$ and $n$ are design parameters that can be adjusted to control the shape of the force-velocity hysteresis loop.

### 3.3. Hyperbolic tangent based model

Gavin (2001) used a simplified version of the model by Gamota and Filisko (1991) for an ER damper. The mechanical model is illustrated in Fig. 4. It consists of two Voight viscoelastic elements connected by an inertial element that resists motion through the Coulomb friction element. The state equation of the model is:

$$\frac{d}{dt}\begin{bmatrix} x_0 \\ \dot{x}_0 \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ -(k_0+k_1)/m_0 & -(c_0+c_1)/m_0 \end{bmatrix}\begin{bmatrix} x_0 \\ \dot{x}_0 \end{bmatrix} + \begin{bmatrix} 0 & 0 \\ k_1/m_0 & c_1/m_0 \end{bmatrix}\begin{bmatrix} x \\ \dot{x} \end{bmatrix} + \begin{bmatrix} 0 \\ -1/m_0 \end{bmatrix} f_0 \tanh(\dot{x}_0/V_{ref})$$

$$\hat{f} = [-k_1 \ \ -c_1]\begin{bmatrix} x_0 \\ \dot{x}_0 \end{bmatrix} + [k_1 \ \ c_1]\begin{bmatrix} x \\ \dot{x} \end{bmatrix} \tag{5}$$

where $k_1$ (spring) and $c_1$ (dash-pot) model the pre-yield viscoelastic behavior while $k_0$ and $c_0$ model the post-yield behavior; $m_0$ is the inertia of the device and the fluid, $f_0$ is the yield force; $x_0$ is the plastic deformation and $\dot{x}_0$ is its rate and they uniquely describe the state of the system. This model takes the displacement $x = x_0 + x_1$ and the velocity $\dot{x}$ as the inputs. There is only one nonlinear term, tanh, and it is separated from the dynamics of the system. The hyperbolic tangent is used as an approximation to the

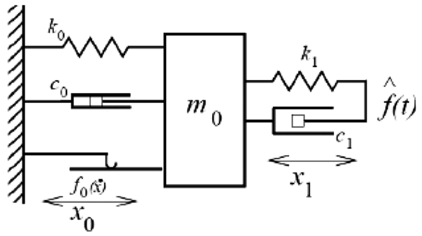



Fig. 4 Hyperbolic tangent mechanical model

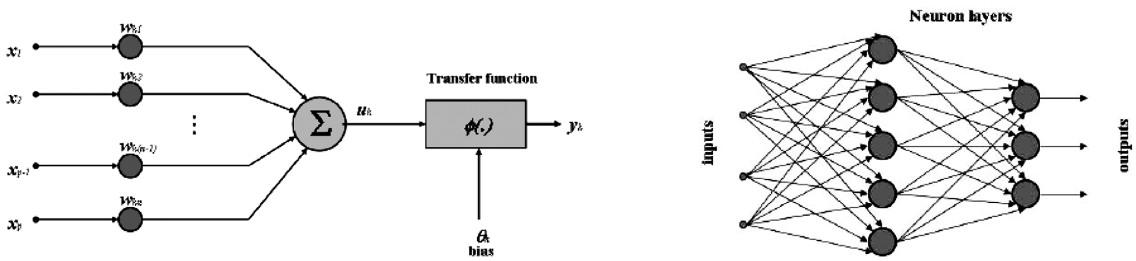
signum function. The term $f_0\ \tanh(\dot{x}_0/V_{ref})$ approximates the yielding mechanism. $V_{ref}$ is a reference velocity which governs the sharpness of the yield function. The system takes into account the dynamic effects of pre-yield visco-elasticity, bulk compressibility and the device's stiffness and inertia when the velocity changes sign.

### 3.4. Neural networks

Neural networks have been widely used in different research areas such as pattern recognition, control and stock market prediction due to its ability to model nonlinear systems. They can overcome important problems and take into account issues such as the time delay inherent in dynamic systems (Zhang and Roschke 1998). Neural networks can be thought of as parallel processors that have retained information from previous experiences and use it to predict the response of a system. Neural networks are trained with experimental data that describes all, or at least the most relevant scenarios that the system can face. The ability of neural networks to learn complicated nonlinear systems will be exploited to find a model that describes the hysteretic behavior of MR dampers.

The schematic of a neuron and that of a neural network are shown in Fig. 5. A neuron consists of input vectors, output vectors, weight vectors and a bias. The weight vector and the bias are modified during the training session so that the network can learn the behavior of the system. The neuron is the basic unit of the network; it takes an input (generally a vector) and computes the dot product of the input vector and the weight vector and adds the bias, if it exists. This result is passed through a transfer function which will give the final output of the neuron. Typical transfer functions are sigmoid, hard limiters or purely linear functions. Neurons are arranged in layers and their outputs form the input to the next layer. Mathematically, the output of a neuron is

$$y_k = \phi(\mathbf{X} \cdot \mathbf{w}) + \theta_k \tag{6}$$




(a) (b)

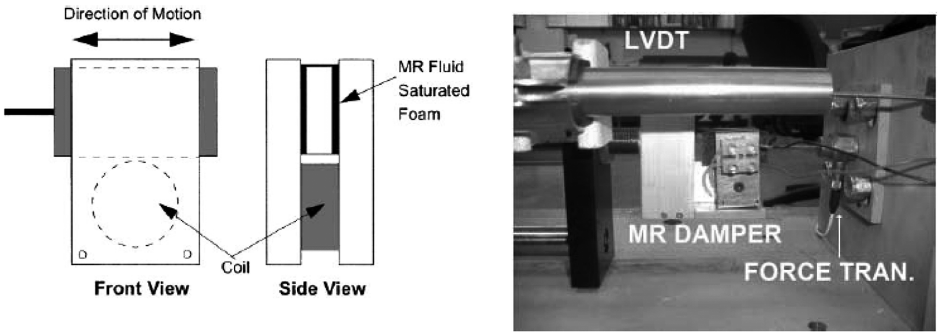
Fig. 5 (a) Model of a neuron (b) Schematic of a neural network where $\phi(\cdot)$ is a transfer function, $\mathbf{X}$ is the input vector, $\mathbf{w}$ is the weight vector and $\theta_k$ is the bias.

Neural networks can be classified as static or dynamic networks. Basically, a static network does not have memory so the output is the same no matter how the inputs are presented to the network. Dynamic networks, on the other hand, do have memory and the output depends on the time history of the inputs and/or the outputs of some or all of the layers. The fact that the hysteresis phenomenon depends on the time history of the variables that cause it suggests that a dynamic network is the best choice to model the MR damper.

## 4. Experiment setup

The experiments to model the MR damper were performed at the Structural Control and Earthquake Engineering Laboratory (Washington University in St. Louis). The MR damper used is a prototype obtained from the Lord Corporation (Cary, N.C.). A schematic of the MR damper is shown in Fig. 6(a). It consists of two steel parallel plates, separated by 0.635 cm. A paddle covered with an MR fluid saturated foam is placed between the steel plates. The thickness of the paddle used is 0.315 cm. A coil placed in the bottom of the device generates the magnetic field. The dimensions of the device are 4.45×1.9×2.5 cm. The configuration of the damper allows it to produce forces up to 20 N. The magnetic field is generated by the current supplied by a pulse width modulator (PWM) circuit whose maximum output is 2 A. This device is voltage-controlled and its input-output relationship is linear.

As shown in Fig. 6(b), the MR damper is placed on the piston of a hydraulic actuator. This actuator, 2000 lbf rated, is used to apply forces to the MR damper. A force transducer is placed in series with the damper and a linear variable differential transformer (LVDT) is used to measure the displacement. The velocity is then calculated using a central differences algorithm. The experiments are carried out as follows: the MR damper is excited with sinusoidal displacements at frequencies between 0.5 and 5 Hz; currents between 0 and 1.6 A (control voltage between 0.6-4 V); and amplitude displacements between 0.20 and 0.80 cm. Data are sampled at a rate of 256 samples/sec, with null means and the noise is removed with a low pass filter at 80 Hz. Control voltage will be used for describing the models due to its linear relationship with the output current of the PWM circuit.




(a) (b)

Fig. 6(a) Schematic of the prototype MR damper (b) Experimental setup

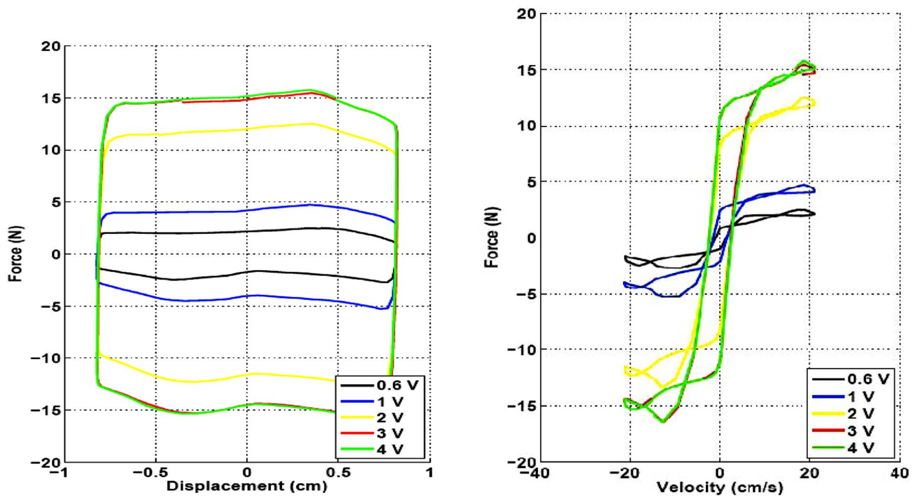
## 5. Numerical results and analysis

The nonlinear behavior of the MR damper is observed in Fig. 7. Those loops correspond to the experimental response of the damper when it is subjected to a sinusoidal displacement at 4 Hz, an amplitude of 0.80 cm and different levels of voltage. The force fluctuations observed in the force-displacement loops as displacement goes from the maximum to the minimum values and vice versa are due to friction in the hydraulic actuator. The force-velocity curve shows that at 0.6 V (H0 A), the device operation is approximately linear, typical of purely viscous devices. As long as the voltage increases, the force also increases in an almost linear fashion up to a point where the fluid is magnetically saturated and it is not possible for the device to generate greater forces. This case happens at 3 V and above; as can be seen, the force produced at 3 V is almost the same as that at 4 V.

The objective of the experiment is to compare some analytical models of the MR damper. In this study, a comparison between two models (Bouc-Wen and Neural Network) is made. The parameters of the Bouc-Wen model are found by optimization techniques (FMINCON function, available in MATLAB) and the neural network model is designed using the toolbox also available in MATLAB.

### *5.1. Bingham model results*

A Bingham model was estimated to compare its ability to predict the force response with other models. Fig. 8 shows the results corresponding to the case of 4 Hz sinusoidal wave at 3 V, in which the parameters obtained were $f_c$=10 N and $c_0$=0.2 N·s/cm. In general, the main concern of using the Bingham model for control analysis is that it reproduces a one-to-one relationship between the force and velocity. However, from the experiments, it is immediately observed that the Bingham model does not reproduce the hysteretic force-velocity loop although it makes a good estimation of the forces at high velocities.




(a) (b)

Fig. 7 Typical displacement-force (left) and force-velocity (right) curves of an MR damper

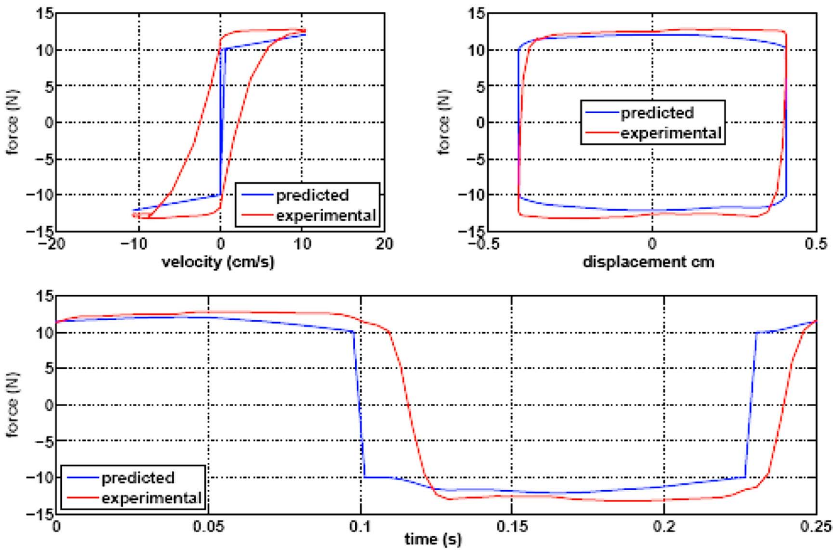



Fig. 8 Predicted and experimental force responses using the Bingham model

### 5.2. Bouc-Wen model results

The Bouc-Wen model is able to reproduce the hysteresis force-velocity loops. In order to find a relationship between the predicted force and the magnetic field, several sets of Bouc-Wen parameters were obtained to fit experimental data at different levels of constant voltage. It was found that the damping coefficient, $c_0$ and $\alpha$ are the parameters that vary with the voltage and did it in a linear fashion, so these parameters are rewritten as:

$$\alpha = \alpha_a + \alpha_b v, \quad c_0 = c_{0a} + c_{0b} v \tag{7}$$

where $v$ is the voltage. The following parameters, that fit the experimental results, were obtained: $c_{0a}$= 0.0055 N·sec/cm, $c_{0b}$=0.0055 N·sec/cm, $\alpha_a$=1.8079 N/cm, $\alpha_b$=8.0802 N/cm, $\beta$=46 cm$^{-2}$, $\gamma$=84.0253 cm$^{-2}$, $\delta$=80.7337 and $n$=1. Fig. 9 shows a comparison of the predicted and experimental force responses when the damper is subjected to a 4 Hz sinusoidal wave at 3 V, where good agreement is observed.

### 5.3. Hyperbolic tangent model results

Using the set of experimental sinusoidal excitations, $m_0$, $V_{ref}$, and $c_0$ are determined to be independent of voltage. The following four parameters tend to vary linearly with voltage:

$$\begin{aligned} k_0 &= k_{0a}v + k_{0b} \\ k_1 &= k_{1a}v + k_{1b} \\ c_1 &= c_{1a}v + c_{1b} \\ f_0 &= f_{0a}v + f_{0b} \end{aligned} \tag{8}$$

Parameters that fit the experimental results are: $k_{0a}$=0.0193 N/cm, $k_{0b}$=0.5383 N/cm, $k_{1a}$=148.4435 N/cm, $k_{1b}$=- 47.4474 N/cm, $c_0$=0.7494 N/cm/s, $c_{1a}$=0.0385 N/cm/s, $c_{1b}$=0.0044 N/cm/s, $f_{0a}$=4.9328 N, $f_{0b}$= -1.3704 N, $m_0$=0.00008 N/cm/s$^2$ and $V_{ref}$=0.330 cm/s. Fig. 10 compares the predicted and experimental

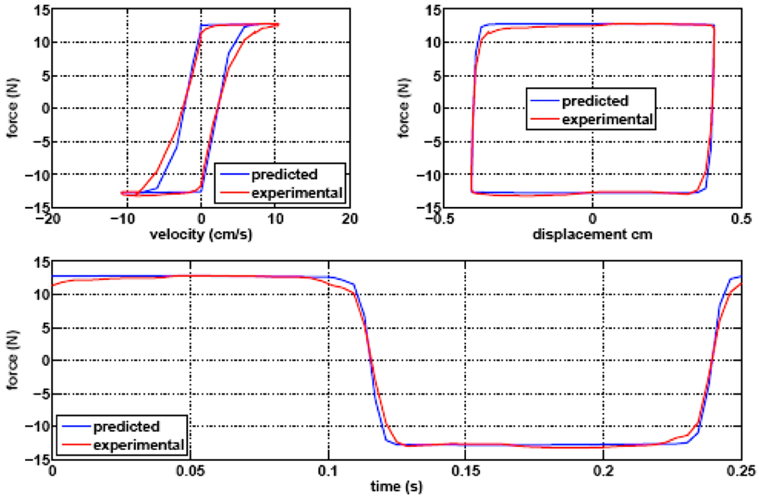



Fig. 9 Predicted and experimental force responses using the Bouc-Wen model

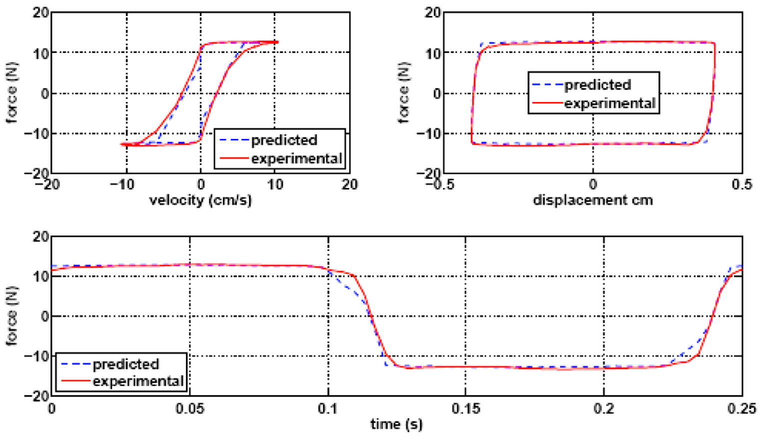



Fig. 10 Predicted and experimental responses of the Hyperbolic Tangent model

force responses when the damper is excited at 4 Hz sinusoidal wave at 3 V. The sharp change in the slope of the force around 0.12 cm/sec is characteristic of the model, but the perturbation near zero-velocity region in the force-velocity curve is due to friction in the hydraulic actuator. The hyperbolic tangent model is accurately able to model the hysteretic behavior of the damper.

### *5.4. Neural networks results*

In order to evaluate the feasibility of modeling the MR damper with a neural network, it was trained using data representing different frequencies and voltages. The network takes four inputs: displacement, velocity, voltage and force. The fourth input (force) is the feedback from the output. Additionally, the network is dynamic, and the inputs are stored in memory for a period of time and are updated after each output computation. The structure of the network during the training session is shown in Fig. 11(a). This structure allows for fast and more reliable training. Basically, given four inputs, the network must

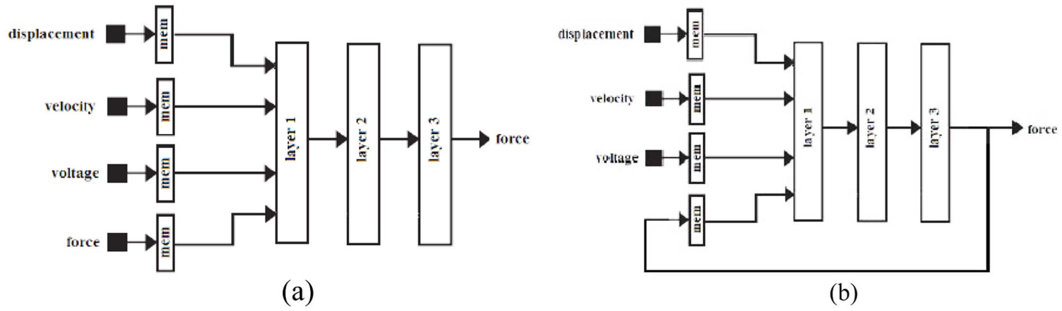



Fig. 11(a) Schematic of the NN for training (b) Schematic of the NN model

reproduce only the fourth one. The final model is shown in Fig. 11(b). Thus, training the network is a two-step procedure in which the first one is to train the network of Fig. 11(a) and the second one is to test the network of Fig. 11(b) with the same data until a desired performance is achieved. After a trial and error process, it was found that a network with 3 layers (with 10, 4 and 1 neurons in each layer) and 4 units-of-time length memory is a good model for the MR damper. Sigmoid tangent transfer functions are used in the first two layers while a purely linear transfer function is used in output neuron. Following the training procedure, the estimation of the neural model for a 4 Hz sine wave at 3 V is shown in Fig. 12 where good performance can be observed.

A quantitative comparison is done based upon the errors between the predicted force and the measured force as a function of time, displacement and velocity, as defined in Eq. (9). These are the errors between the predicted force and the measured force as a function of time, displacement and velocity. The models are compared based on the following set of error norms:

$$E_t = \frac{\varepsilon_t}{\sigma_F}, \quad E_x = \frac{\varepsilon_x}{\sigma_F}, \quad E_v = \frac{\varepsilon_v}{\sigma_F} \tag{9}$$

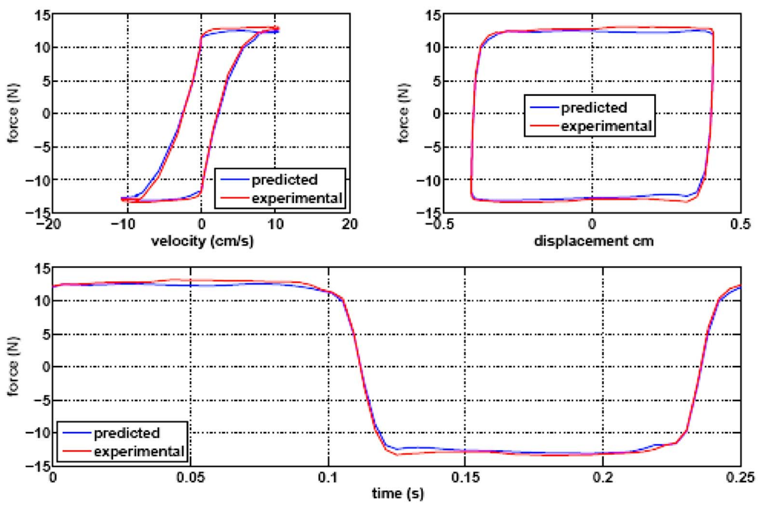



Fig. 12 Predicted and experimental forces using a neural network

Table 1 Error norms for the models studied

| Model | $E_t$ | $E_x$ | $E_v$ |
|---|---|---|---|
| Bingham | 0.4734 | 0.3052 | 5.6954 |
| Bouc-Wen | 0.0586 | 0.1205 | 1.1656 |
| Hyp. Tangent | 0.0620 | 0.1166 | 1.1785 |
| Neural networks | 0.0301 | 0.0747 | 0.3793 |

where[1]:

$$\varepsilon_t^2 = \frac{1}{T}\int_0^T (F_{\exp} - F_{pre})^2 dt$$

$$\varepsilon_x^2 = \frac{1}{T}\int_0^T (F_{\exp} - F_{pre})^2 \left|\frac{dx}{dt}\right| dt$$

$$\varepsilon_v^2 = \frac{1}{T}\int_0^T (F_{\exp} - F_{pre})^2 \left|\frac{dv}{dt}\right| dt$$

Table 1 shows the error norms between the experimental and predicted responses of each model when compared on a sinusoidal displacement at 4 Hz at 3 V basis. The error calculation is performed using values from one cycle. The better matching of experimental and predicted data of the neural network is confirmed with the error norm values.

Experimental observations show that the force-velocity loop appears to be smooth near the zero-velocity region, where the velocity and the acceleration have different signs. It has been observed that the neural model is capable of capturing this smoothness of the experimental data while the predicted response by the Bouc-Wen or the Hyperbolic Tangent models exhibit some discontinuity in slope at this point, which could be due to mistuning of the parameters or dynamics not considered by the model. It had been shown in previous works (Zapateiro, *et al*. 2007) that the Bouc-Wen model is not sensitive to frequency in the band studied (up to 5 Hz). It is important that the neural network is trained with enough representative data to make it insensitive to frequency as well.

The success of a neural network is not only the accuracy of its prediction but also its complexity. The model presented in this paper is still more complex than others proposed in previous works (e.g. Zhang and Roschke 1998). In order to obtain a neural model suitable for real time control, improvement of the network can be achieved by suppressing unnecessary weights or reducing the number of neurons and the length of the memory.

## 6. Conclusions

MR dampers are devices that feature interesting characteristics such as high force generation, low power requirements, fast response and simple mechanical design. However, finding a model that describes its behavior has become a challenge because of the high nonlinearities of its force response. In this paper 4 models for an MR damper have been studied. Three of them are based on the mechanical dynamics of the device, namely, Bingham, Bouc-Wen and Hyperbolic Tangent models while the other was a neural network.

[1]exp: experimental; pre: predicted; $\mu_F$: force mean.

It was shown that the Bingham model is the least accurate due to its inability to reproduce the hysteretic behavior of the damper. On the other hand, fairly good approximations were obtained with the other three models. It is well known that neural models can learn complicated nonlinear relationships among variables with good prediction results. As expected, the trained neural network could reproduce the force response of the damper to a high degree of accuracy.

Future work is aimed to improve the neural network by eliminating unnecessary elements such as weights and neurons so that the final network is less complex yet reliable. Efforts should also be addressed to find a model to compute the variable that controls the magnetic field of the device to obtain a desired force, which is important during real time control.

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