313. Parametric and Non Parametric Characterization of a Shear Mode Magnetorheological Damper

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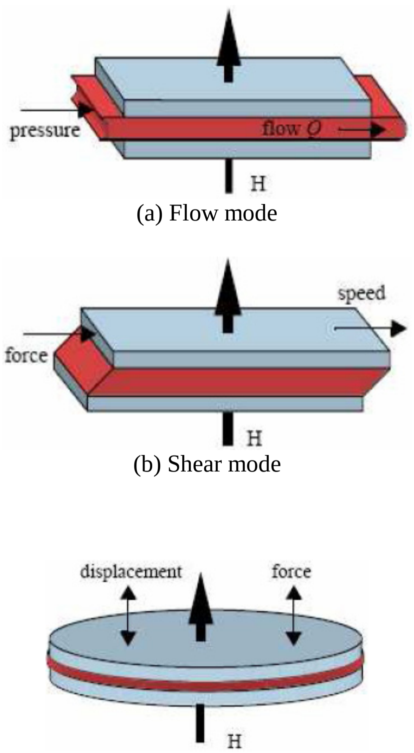
Abstract. MR (magnetorheological) dampers are versatile devices whose design is aimed to take the best of magnetorheological fluids: high yield strength, low power requirements, insensitivity to contaminants and hence, low cost. MR dampers have proven to be a good option for the mitigation of uncomfortable and hazardous vibrations in systems such as vehicles, buildings, bridges, etc. However, MR dampers are highly nonlinear devices that exhibit a hysteretic force-velocity loop. Their extensive applications in vibration control systems demand an accurate mathematical model. In this paper, two models for an MR damper operated in shear mode are presented: a parametric approach (Bouc-Wen model) and a non parametric one (neural network model).
Keywords: magnetorheological fluid, magnetorheological damper, Bouc-Wen model, neural networks.

1. Introduction

MR fluids are suspensions of magnetic particles in a carrier medium such as oil. The main characteristic of MR fluids is their ability to change their rheological behavior in the presence of a magnetic field, in a few milliseconds. This change in rheological properties is possible due to the magnetic moment induced in each magnetic particle when an external field is applied. The dipole-dipole interaction leads to the formation of anisotropic structures such as chains, columns or labyrinths while without a magnetic field, the particles are in Brownian motion and are distributed randomly [1].

MR fluids have some advantages over other technologies including electrorheological fluids: low power requirements, reliability, stability, fast response and low production costs. Due to these reasons, MR fluids have been implemented in several applications, especially in vibration suppression. Currently, MR fluid dampers are promising devices for the mitigation of hazardous vibrations in systems such as vehicles, buildings, towers and bridges [2].

Optimal MR damper design minimizes the volume of active MR fluid, size, dynamic response and power requirements [4]. One kind of damper that exploits these characteristics is the MR foam damper which is a low-cost device with no seals, bearings, or precision mechanical tolerances, that can be used in applications where moderate forces and high degree of control are required; a small amount of MR fluid is needed for its operation and is contained in an absorbent matrix, open-celled foam, sponge felt or fabric. Moreover, MR foam dampers are robust and not prone to gravitational settling [5].



(a) Flow mode

(b) Shear mode

(c) Squeeze mode

Fig. 1. Modes of operation of magnetorheological dampers

For control purposes, it is necessary an accurate model of the system devices. In this paper, two mathematical models for a shear mode MR damper will be obtained. The prototype dampers are to be used in the vibration control of scaled civil structures. One model is based on the so-called phenomenological Bouc-Wen model and the other is a neural network model. The paper is organized as follows: a brief theoretical background of the models will be presented followed by the description of the experimental setup. Then the numerical results are presented and finally the conclusions and future work are discussed.

2. Characterization of MR Dampers

The modeling of MR dampers is a challenging task because of the hysteresis loop characteristic of its force response. Several models have been proposed by researchers along the years; these can be classified in two groups: parametric models and non parametric models [2]. While parametric models usually require the knowledge of the device's physics, for non parametric approaches it is generally sufficient to count on the information provided by the experimental observations. Two popular models, the Bouc-Wen (parametric) and neural networks (non parametric) will be examined in this paper.

2.1 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 [6]. Spencer et al. [7] 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 Figure 1a. This is 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 damper is slightly different from the shear-mode damper studied here. In particular, Spencer et al. used a linear spring with an initial deflection to account for the pressure inside the cylinder as illustrated in Fig. 2.

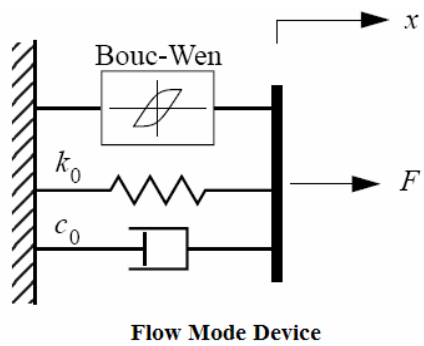


Fig. 2. The Bouc-Wen model proposed by Spencer et al

Because of the absence of this cylinder in the shear mode device, the linear spring is removed, as shown in Fig. 3 and the resulting mathematical model is:

$$F = c_0 v + \alpha z, \quad \dot{z} = -\gamma |v| z |z|^{n-1} - \beta v |z|^n + \delta v \qquad (1)$$

where F is the total force of the damper, c_0 is the damping coefficient of the damper, v is the piston velocity, z is an evolutionary variable that accounts for the hysteretic behavior of the damper and the parameters α, β, γ, δ and n can be adjusted to control the shape of the force-velocity hysteresis loop.

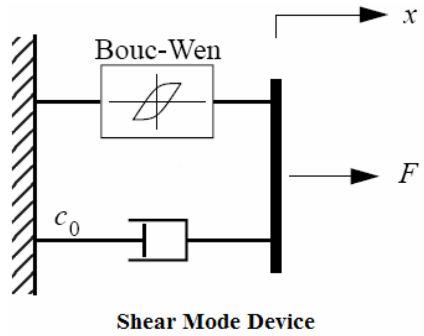


Fig. 3. The model for the shear mode damper

2.2 Neural Networks. Neural networks have been widely used in different research areas such as pattern recognition, and control due to their ability to model highly complex nonlinear systems. They can also overcome problems such as the time delay inherent in dynamic systems. Neural networks are like parallel processors that store information "learnt" from the experience and based on it can predict the response of the system. To this end, neural networks are trained with experimental information that covers all, or at least the most relevant cases that the system can face.

Neural networks can be classified as static or dynamic. Static networks do not have memory so the response to specific inputs will be the same no matter the order in which they are presented. On the other hand, dynamic or recurrent networks make use of the memory and feedback trajectories to compute the response to an input. Because the hysteresis phenomenon depends on the time history of the variables, a recurrent network will be used to model MR damper.

3. Experimental Setup

The experiments to model the MR damper were conducted at the Washington University Structural Control and Earthquake Engineering Laboratory (St. Louis, U.S.A.). The damper is a prototype obtained from the Lord Corporation (Cary, U.S.A.). The schematic of the damper is shown in Fig. 4. It consists of two steel parallel plates, separated by 0.635 cm. A paddle coated with foam saturated with an MR fluid 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 4.45x1.9x2.5 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 generator 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. 5, 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 were carried out as follows: the MR damper was excited with sinusoidal displacements (frequency: 0.5 - 5 Hz, amplitude: 0.20 - 0.80 cm) and currents between 0 and 1.6 A (~0.6 – 4 V). Data were sampled at a rate of 256 samples per second, with null means and the noise was removed with a low pass filter at 80 Hz. Control voltage was used for describing the models due to its linear relationship with the output current of the PWM circuit.

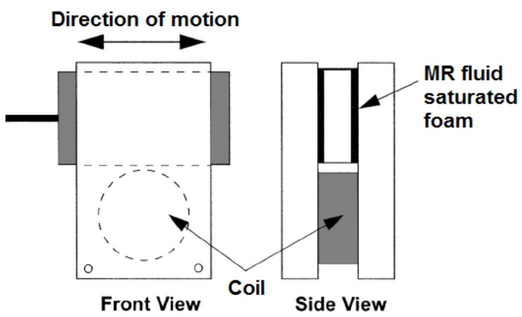


Fig. 4. Schematic of the foam MR damper

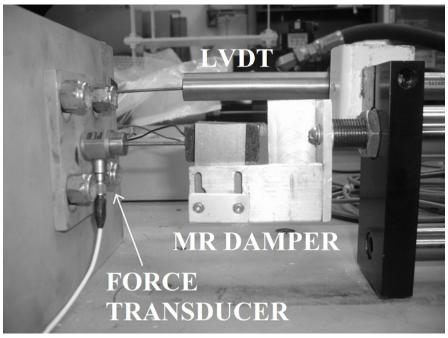


Fig. 5. Setup of the experiment

4. Numerical results

The hysteresis behavior is readily observed in Fig. 6. The displacement-force and force-velocity loops correspond to the response of the damper to a sinusoidal displacement input at 4 Hz and various control voltages. The amplitude of the sinusoidal wave is 0.80 cm. The force generated by the damper increases as long as the current through the coil increases until the fluid reaches the magnetic saturation and no higher forces are possible. This occurs when the control voltage is 3 V and higher. 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.

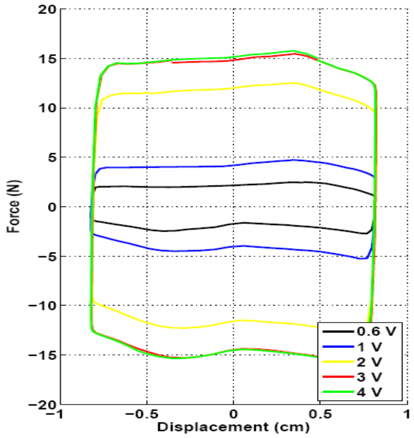
4.1 Bouc-Wen model results. The parameters of Eq. 1 do not show any dependency on the varying magnetic field. Individual sets of parameters were obtained for different sets of data with constant voltage and varying frequency and amplitude. By doing so, it was found that α and c_0 were the parameters that varied the most and did it in a linear fashion. Thus, they can be rewritten as:

$$\alpha = \alpha_a + \alpha_b u, \qquad c_0 = c_{0a} + c_{0b} u \qquad (2)$$

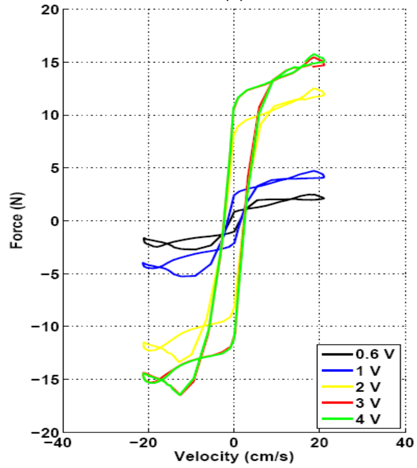
where u is the control voltage. The parameters were calculated by the FMINCON function, an optimization algorithm available in MATLAB. The objective function was chosen to be the sum of the squared error between the predicted and the experimental data. As a result, a set of parameters that fitted the experimental data was: c_{0a} = 0.0055 N·sec/cm, c_{0b} = 0.0055 N·sec/cm, α_a = 1.8079 N/cm, α_b = 8.0802 N/cm, β = 46 cm^{-2}, γ = 84.0253 cm^{-2}, δ = 807337 and n = 1. Fig. 7a shows a comparison of the predicted and experimental force responses when the damper is subjected to a 4 Hz sinusoidal wave at 3 V.

4.2 Neural Networks results. A neural network with the structure of Fig. 8 was trained to model the MR damper. It was found that a 3-layer network with 10, 4 and 1 neuron in each layer respectively was able to reproduce a set of experimental data. The transfer function of the neurons of the first and the second layers is a sigmoid tangent and that of the output layer is a purely linear transfer function. The inputs to the network are the displacement, the velocity, the control voltage; the output is the force and is fed back to the input. The inputs are passed through a 4-units-of-time memory register. The network was trained with a resilient backpropagation algorithm available in MATLAB. As a comparison, the network response to a sinusoidal input at 4 Hz, 0.40 cm amplitude and 3 V is shown in Fig. 9.

The experimental observations show that the response loops are smooth near the zero-velocity region, where the velocity and the acceleration have different signs. The predicted response by the Bouc-Wen model seems not to capture the smoothness exhibiting some discontinuity in slope at this point. It could be due to mistuning of the parameters or dynamics not considered by the model. On the other hand, the neural network does capture the smoothness. It had been shown in previous works [9] that the Bouc-Wen model is not sensitive to frequency in the band studied (0.5 to 5 Hz). For the neural network model to be insensitive to frequency as well, it is important that it is trained with enough representative data.



(a)



(b)

Fig. 6. Force response of the MR damper to (a) displacement and (b) velocity inputs

On the other hand, the Bouc-Wen model used here assumes that the voltage-dependent parameters vary linearly with the voltage. However, this assumption is no longer valid near the saturation region (in this case, near 3 V) and a force overestimation is perceived beyond this point. Further investigations should fix these terms to accurately model this behavior.

A numerical comparison is made by means of the error norms between the predicted force and the measured force as a function of time, displacement and velocity as a function of time:

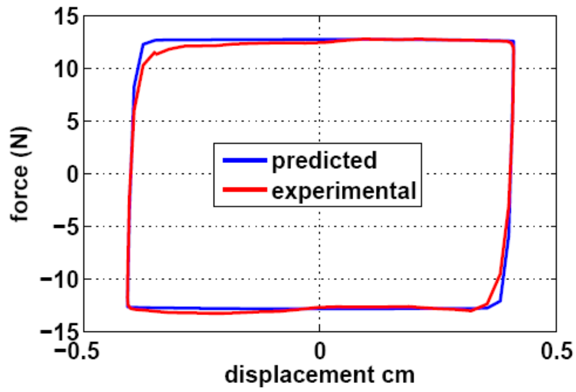
$$E_t = \frac{\varepsilon_t}{\sigma_F}, \qquad E_x = \frac{\varepsilon_x}{\sigma_F}, \qquad E_v = \frac{\varepsilon_v}{\sigma_F} \tag{3}$$

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

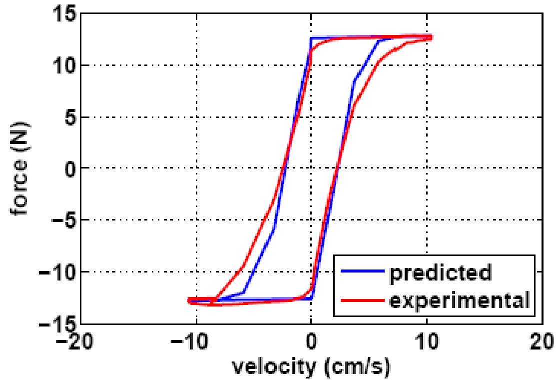
$$\varepsilon_x^2 = \frac{1}{T}\int_0^T (F_{\exp} - F_{pre})^2 \left|\frac{dx}{dt}\right| dt$$

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

where E_t, E_x and E_v are the time, displacement and velocity error norms respectively; F_{exp} is the experimental force, F_{pre} is the predicted force and μ_F is the mean experimental force. The resulting error norms, shown in Table 1, confirm the visual observations. The error norms were calculated using values from data on sinusoidal cycle at 4 Hz, 0.40 cm amplitude and 3 V.



(a) Force vs. displacement



(b) Force vs. velocity

Fig. 7. Bouc-Wen model force-velocity response

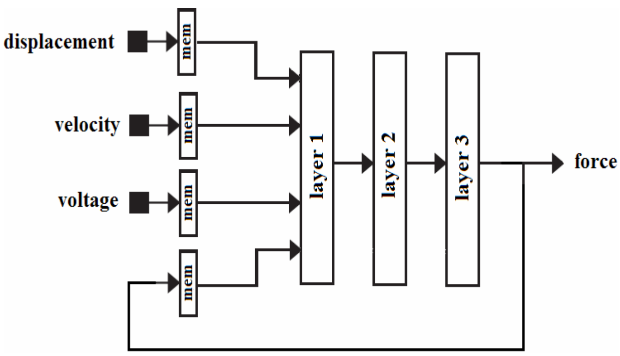
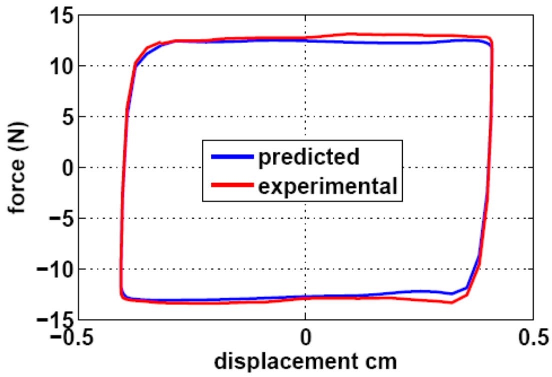
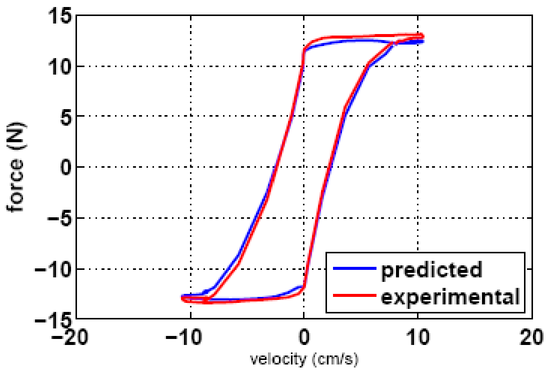


Fig. 8. Schematic of the neural network used to model the MR damper



(a) Force vs. displacement



(b) Force vs. velocity

Fig. 9. Neural network force-velocity response

Table 1. Error norms of the models studied.

Model	E_t	E_x	E_v
Bouc-Wen	0.0586	0.1205	1.1656
Neural networks	0.0301	0.0747	0.3793

5. Conclusions

Two models for the hysteresis behavior of a shear mode MR damper have been obtained. One parametric model based on the Bouc-Wen equations takes into account the both the viscous and hysteretic behavior of the damper while the neural network model was obtained based on the experimental information. Future work should include the improvement of both models and take into account another kind of inputs such as random displacements and voltages and the reduction of the complexity of the neural network model.

Acknowledgments

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