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MODELING THE RESPONSE OF A FLUID DAMPER: CONSTITUTIVE MODELS AND NEURAL NETWORKS

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Abstract

A combination of a physically motivated constitutive model and a neural network is presented to approximate the response of a fluid damper developed for seismic protection of structures. The performance of the proposed technique is validated against experimental data.

1. Introduction

Conventional seismic design of buildings and bridges relies on the ability of structures to behave inelastically and dissipate the induced seismic energy through hysteretic action. Commonly, structures are designed to absorb earthquake energy through localized damage of their supporting members.

An alternative approach to dissipate the seismic energy is to introduce damping devices within the structural system, thereby preventing the development of undesirable damage. Different dissipative devices have been proposed, including friction dampers, viscoelastic solid and fluid dampers and lead extrusion dampers. In particular, fluid dampers have received considerable attention because of their small size and ability to dissipate a substantial amount of energy. A critical review of the various energy absorbing systems has recently been presented by Constantinou and Symans (1993).

The dynamic analysis of structures equipped with additional dampers requires the availability of constitutive models that approximate with fidelity the response of added dampers. The dynamic response of fluid dampers is, in general, nonlinear viscoelastic and depends primarily on their construction, the shape of their orifice and the type of fluid used. Previous studies concentrated on the development of macroscopic linear constitutive models to approximate the response of these devices.

In this paper, we advance the concept of combining a simple physically motivated model and a neural network to approximate the response of a practical fluid damper designed for seismic protection of structures.

2. Motivation

Traditional fluid dampers utilize a cylindrical-shaped orifice and produce forces proportional to the square of the velocity of the piston rod; this performance is usually unacceptable in shock isolation. Other types of fluid dampers, initially developed for military applications and recently tested for seismic protection of structures (Constantinou and Symans, 1993), have orifices with specially shaped passages to alter flow characteristics with fluid speed. The response of these dampers is nearly viscous at low frequencies, whereas for frequencies beyond 4 Hz the response exhibits substantial elasticity. A classical Maxwell model was found capable of predicting this response in a satisfactory manner.

A photograph of the damper studied herein is shown in Figure 1. The damper consists of an outer cylinder and a double ended piston rod that pushes an electrorheological (ER) fluid through a stationary annular duct. This device can be used as a passive damper or as a semiactive damper, since the mechanical properties of the ER-fluid within the damper can be modified when a voltage is applied across the outer cylinder of the bypass and the inner rod. More information about the construction and response of

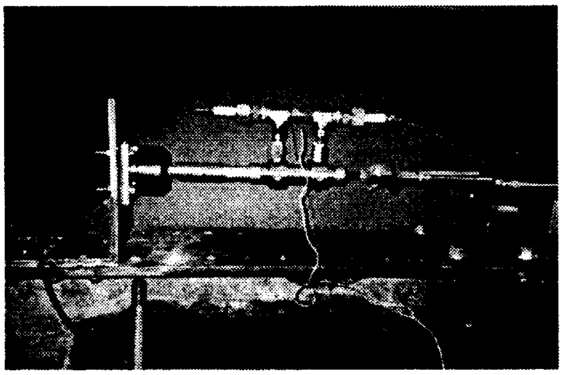

Figure 1. Photograph of fluid damper

the damper under the presence of electric field can be found in Makris *et al.* (1995).

When the damper is purely passive (no electric field), its response is nearly linear viscoelastic. Minor nonlinearities in the response are observed when the piston-rod reverses motion. When the damper is activated with the presence of an electric field, the nonlinearities in the response become more pronounced. Figure 2 shows recorded time histories and force-displacement loops from the damper in the absence of electric field (E=0.0 kV/mm) and in the presence of electric field (E=3kV/mm). All the data in Figure 2 was generated with a 0.4 Hz sine wave with 0.1 or 0.2 inch amplitudes (left and right, respectively).

In principle, the dynamic response of the damper can be approximated with physically motivated constitutive models based on the mathematical theories of viscoelasticity and viscoplasticity (Makris *et al.*, 1993; Graesser and Cozzarelli, 1989). Nevertheless, when nonlinear response prevails, such an approach becomes rather complicated and involves stiff differential equations. Note that the solution of these equations may involve a considerable computational effort. On the other hand, when a neural network alone is used to predict both transient and steady-state response of the damper, the prediction is mediocre. This is due to fact that earthquake inputs contain a small number of large spikes and a non-smooth spectrum. Figure 3 illustrates the prediction of the recorded force from the damper by the neural network when subjected to the 1992 Petrolia earthquake displacement input.

The philosophy advanced herein is to use the simplest possible physically motivated model to approximate the linear component of the damper response and a neural network to capture the nonlinear behavior in addition to the remaining part of the linear response. In this way, the localized spikes of the response are approximated with the physical

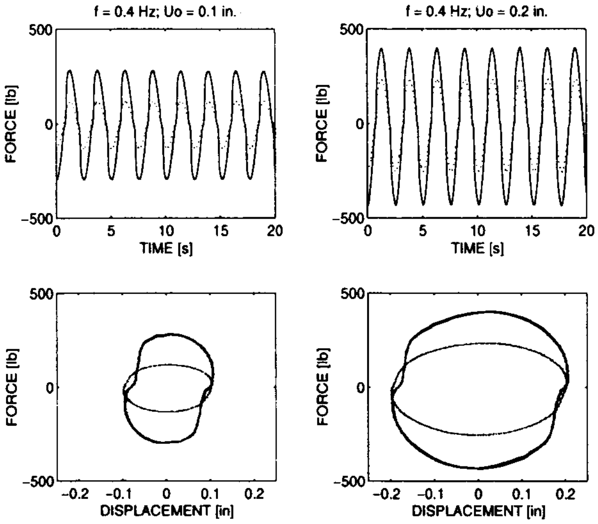

Figure 2. Recorded time histories (top) and force-displacement loops (bottom) of semiactive fluid damper with E= 3 kV/mm (solid line), and no field, E= 0 kV/mm (dotted line)

model and the neural network has to predict a response with smaller variability in amplitudes.

In the present study, our effort concentrates on characterizing the damper response in its purely passive stage (E=0.0 kV/mm). Nevertheless, the devel-

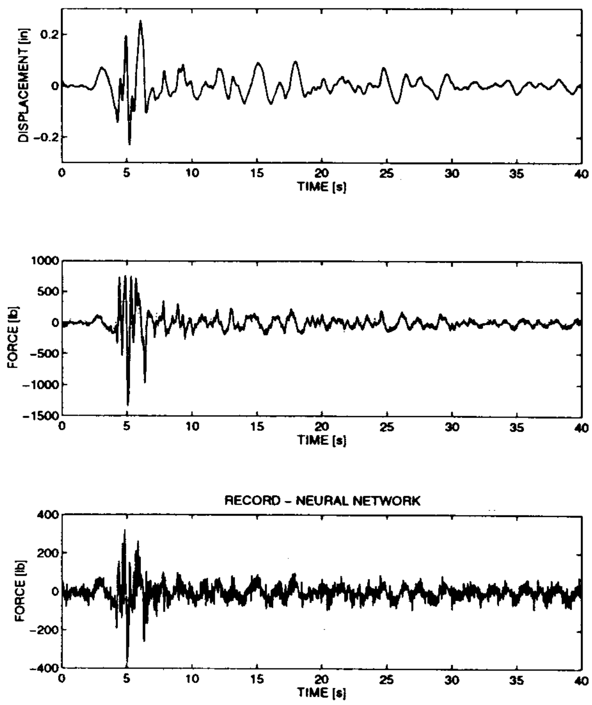

Figure 3. Top: displacement time history of the 1992 Petrolia earthquake; center: recorded and predicted force with neural network; bottom: difference between recorded force and neural network prediction

oped procedure is general and can be used to characterize the damper response at any of its stages.

3. Macroscopic constitutive model

The simplest physically motivated model that approximates, to a certain extent, the response of the fluid damper is the classical Maxwell model of viscoelasticity

$$P(t) + \lambda\frac{dP(t)}{dt} = C\frac{du(t)}{dt} \tag{1}$$

where *P(t)* and *u(t)* are the force and displacement histories developed at the piston-rod of the damper, λ is the relaxation time of the damper and C is the zero-frequency-damping constant. Parameters λ and C must be calibrated by fitting experimental data extracted from dynamic testing.

The equivalent linear mechanical characteristics of the fluid damper have been determined using the testing arrangement shown in Figure 1. A hydraulic actuator imposed a displacement on the piston rod and the force needed to support the damper cylinder was measured by a load cell that was connected between the damper and the reaction frame (left side of picture). Harmonic displacement histories at different frequencies were imposed and the recorded force-displacement histories were used to extract the mechanical characteristics of the damper. Figure 2 shows such recorded force-displacement loops at frequency 0.4 Hz and amplitudes 0.1 and 0.2 inches.

The linear part of the response is expressed in the frequency domain through the dynamic stiffness, $\mathcal{K}(\omega)$, defined as

$$\mathcal{K}(\omega) = K_1(\omega) + iK_2(\omega) = \frac{P(\omega)}{u(\omega)} \tag{2}$$

where $P(\omega)$ and $u(\omega)$ are the Fourier transforms of the force and displacement histories respectively. $K_1(\omega)$ is the equivalent storage stiffness of the device and represents the elastic part of the response whereas, $K_2(\omega)$, is the equivalent loss stiffness of the device and represents its ability to dissipate energy. $K_2(\omega)$ is related to the energy dissipated per cycle, W_d, by

$$K_2(\omega) = \omega C(\omega) = \frac{W_d}{\pi u_0^2} \tag{3}$$

where u_0 is the amplitude of the harmonic displacement and $C(\omega)$ is the damping coefficient of the device. Once the loss stiffness, $K_2(\omega)$, is computed, the storage stiffness, $K_1(\omega)$, is provided by the relation

$$K_1(\omega) = \sqrt{\left(\frac{P_0}{u_0}\right)^2 - K_2^2} \tag{4}$$

where P_0, is the amplitude of the harmonic force. Figure 4 shows the experimentally measured equivalent storage stiffness and damping coefficients of the damper. The prediction of the Maxwell model given by Equation (1) is shown with solid line. Parameters C=460 lb-sec/in and λ=0.0216 sec were calibrated so that the Maxwell model results in the best possible fit for the damping coefficient. In this way, the phase of the response will be approximated with accuracy from the Maxwell model, and the amplitudes will be refined by the neural network.

4. Identification of the total damper response

In order to capture the true amplitudes of the response and some of the nonlinear behavior, a neural network model is introduced in conjunction with the aforementioned Maxwell model. Neural networks consist of many interconnected simple processing elements called units (nodes), which have

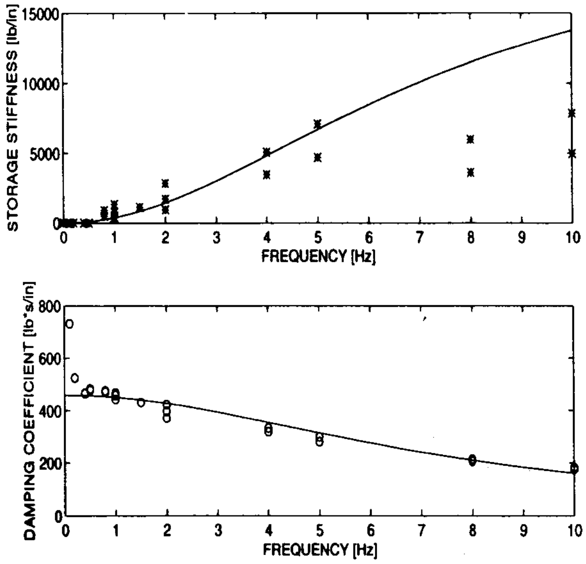

Figure 4. Equivalent storage stiffness (real part), damping coefficient (imaginary part) of the fluid damper at no field (E=0.0 kV/mm)

multiple inputs and a single output. The inputs are weighted and added together. This sum is then passed through a nonlinear function called the activation function such as a sigmoidal function, a Gaussian-type function or even a hard limiter like the signum function. The processing units or neurons are interconnected; the strength of the interconnections is denoted by parameters called weights. These weights are adjusted, depending on the task at hand, to improve performance. They can be either assigned values via some prescribed off-line algorithms, while remaining fixed during operation, or adjusted via a learning process on line. Neural networks are classified by the network structure topology, type of processing elements used and kind of learning rules implemented.

The type of neural network used here is the feedforward multilayer neural network, where no information is fed back during operation. The back-propagation algorithm is used to adjust the weights of the neural network during training; details can be found in Hertz (1991).

Neural networks have been used extensively to model the behavior of nonlinear plants. They have also been used in the control of systems and failure diagnostic problems. They have proven especially successful in cases where traditional control techniques failed to give satisfactory results, see Antsaklis (1992), Antsaklis (1993), Hou (1992), Konstantopoulos (1994), Konstantopoulos (1995), Miller (1990), Narendra (1990) and Warwick (1992) for details. A theoretical study of the modeling of mechanical behavior using neural networks has been presented by Masri *et al.* (1993).

Herein, the neural network is trained with the difference-signal between the recorded force on the damper and the prediction of the macroscopic Maxwell model. Displacement histories from three different earthquakes have been used as input to the fluid damper. The resulting force needed to maintain the motion was recorded with the load cell shown in Figure 1. Figure 5 shows the three input displacement histories and the difference-signals between the recorded force and the prediction of the Maxwell model. These difference-signals have been used to train the neural network. The three input histories are records from the 1940 El Centro earthquake, the 1985 Mexico City earthquake and the 1987 Whitter Narrows earthquake. The neural network used has two hidden layers with 30 and 25 neurons in the first and second hidden layers respectively. The inputs to the neural network were the current and delayed values of the induced displacement histories together

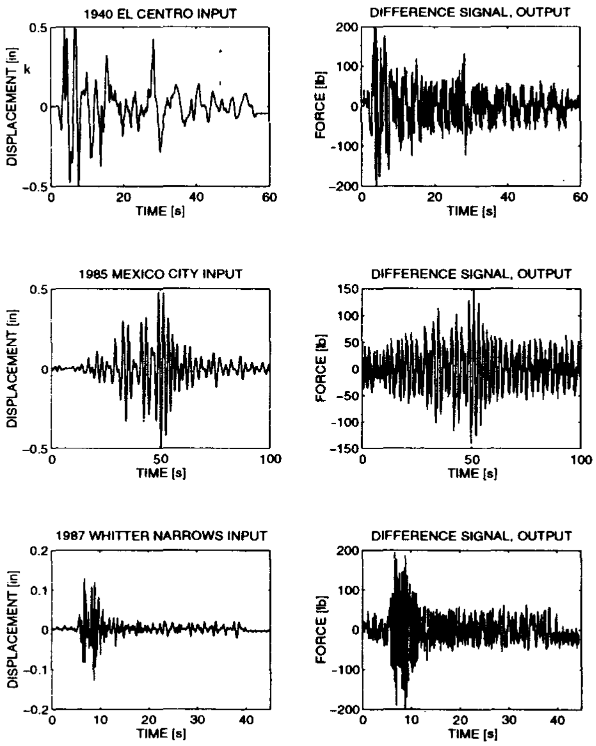

Figure 5. Input and output pairs used to train the neural network

with delayed values of the neural network output, which is the resulting force.

Figure 6 (top-left) compares the recorded damper response with the prediction of the Maxwell model. Figure 6 (bottom-left) shows the difference-signal of the two time histories shown above. The input to the damper is the displacement history of the 1992 Petrolia earthquake. A neural network was used

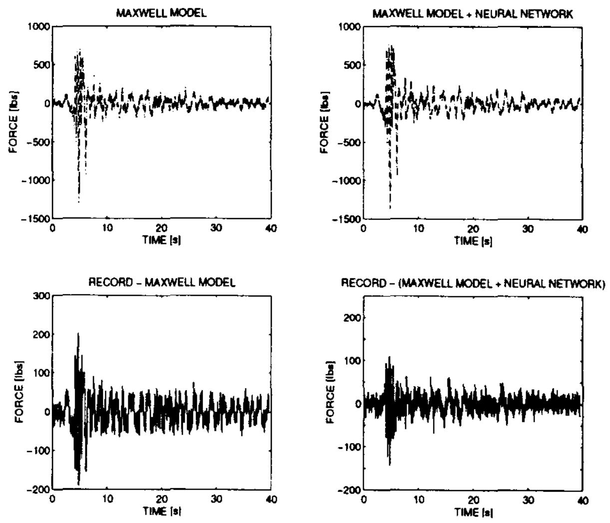

Figure 6. Comparison of the predictions from the Maxwell model alone (top-left) and a combination of the Maxwell model and neural network (top-right); the bottom plots show the difference-signals

to approximate this difference-signal. Figure 6 (top-right) shows the prediction of the combined Maxwell model and neural network. The difference of the recorded and predicted responses is shown on Figure 6 (bottom-right). Comparing the two difference-signals in the bottom plots, one observes that the combined model results in a better prediction. Nevertheless the improvement is not dramatic. This is because the response of the passive device that we are investigating is nearly linear and the Maxwell model predicts satisfactorily most of the response. In other cases, however, where the damper operates under the presence of strong electric field, the nonlinear behavior is more pronounced and the proposed modeling technique could show considerable advantages. Comprehensive testing of the damper under the presence of electric field is currently underway.

5. Conclusions

In this paper, a combination of a physically motivated constitutive model and a neural network was used to approximate the response of a passive fluid damper developed for seismic protection of structures. The proposed method utilizes the simplest possible macroscopic model to approximate the linear part of the damper response and the neural network is introduced to account for the remaining response. The neural network used was trained with the difference-signals between the recorded response of the damper and the prediction of the Maxwell model. The study reported herein shows that the proposed method is practical and can be used with no difficulty to predict the response of devices where nonlinear response prevails.

Acknowledgments

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