An Inverse Model of Magnetorheological Dampers with Optimal Neural Network Architecture

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Abstract: - This paper presents an emulation of the inverse dynamics of magnetorheological dampers, using a dynamic model proposed [1], which is modified to describe the actual behavior of the device, also a perceptron neural network is constructed and trained under the method of Lagrange multipliers Levenberg-Marquard to emulate the inverse dynamics of magnetorheological damper, considering the direct neural control techniques for inverse model. Finally it is shown that the optimal neural network architectures presented in this paper provide a substantial improvement of performance in comparison to some neural network architectures reported in the literature.

Key-Words: - Semi-active Control, Identification, Observers, Inverse neural network model, RM damper

1 Introduction

The Magnetorheological (MR) damper is a promising semi-active device, which is widely used in vibration mitigation in structures [12], due to their low cost, energy efficiency and fast response. Other applications for which MR dampers are currently used are: in vibration control of vehicle suspensions systems [17], in heavy vehicle seating, in vibration control in helicopters [16] and in vibration control of bridge cables [13-15] and [20]. In recent years papers have been published focused on developing semi-active control systems, by using the magneto-rheological damper, which contains a fluid whose mechanical properties can be varied through a magnetic field, which allows to regulate the force that opposes the relative motion of the ends. The design of control schemes for such systems has been a difficult task due to the highly nonlinear behavior of MR damper. It is very difficult to determine its inverse dynamic characteristics. Despite this difficulty, there are many applications where these semi-active devices are used, one of the main applications reported in the literature is the development of seismic protection systems [8, 18,19]. In this paper, due to the advantages of neural networks for the process modeling of nonlinear systems with high nonlinearities, an inverse neural network model of MR damper is developed in order to emulate the inverse dynamics of the MR damper; the results show that the neural network model of MR damper is effective.

The organization of this paper is as follows: In Section 2 results related to the characterization of MR damper are briefly presented. Section 3 aspects of parameters estimation for damper are treated, a simplified dynamic model of MR dampers response is used to predict the force, which opposes the motion, and this force is function of voltage and the relative speed. Section IV methods to emulate the inverse dynamics of these dampers are described, considering the direct neural control techniques for inverse model. The development of an optimal perceptron neural network is presented, which emulates the inverse dynamics of MR damper and was trained under the method of Levenberg-Marquard. Section V it is obtained the optimal neural network architecture. This section includes the simulation results. Finally the conclusion is presented.

2 MR Damper Modeling

One of the first RM damper for which a mathematical model was constructed, is a prototype developed by Lord Corporation [3], the magnetorheological fluid, which consists of particles of iron suspended in hydrocarbon oil with a density of 3.28 [g / cm^3], the main cylinder containing the piston, the magnetic

circuit, a gas accumulator and 50 [ml] magnetorheological fluid (see Figure 1).
Other research works such as Spencer, BF, Dyke, SJ, Sain, MK and Carlson JD [2]. They are oriented towards the modeling magnetorheological dampers in order to represent the behavior of the device (see Figure 2), these authors use the structure of the Bouc-Wen model, which is extremely versatile and can exhibit a wide range of behavior of hysteresis.
The results reported in Spencer, BF, Dyke, SJ, Sain, MK and Carlson JD [2] show that this model accurately reproduces the real behavior of the damper under typical operating conditions.

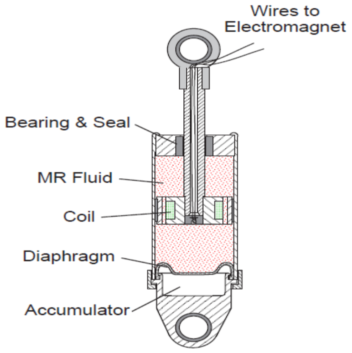

Figure 1. Schematic of MR Damper

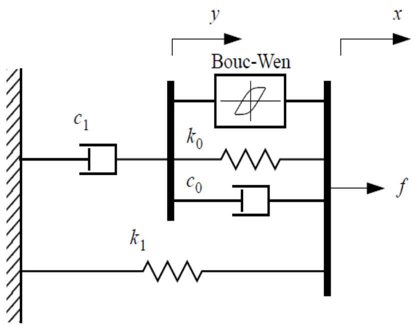

Figure 2. Mechanical model based on the structure of Bouc-Wen.

In [1] a dynamic model based on the friction model is proposed. The model is expressed as follows:

$$f = \sigma_0 z v + \sigma_1 \dot{z} + \sigma_2 \dot{x} \quad (1)$$

$$\dot{z} = \dot{x} - \sigma_0 a_0 |\dot{x}| z \quad (2)$$

Where f is the force provided by MR damper, $\dot{x}$ is the relative velocity between the ends of the damper, and the variable z corresponds to an internal state that describes the mechanical properties of magnetorheological fluid.
To take into account the effects that the magnetic field causes on magneto fluid, it is assumed that the current which determines the intensity of the magnetic field is proportional to the applied voltage.
In [4] a modification in the model proposed in [1] is carried on, equations (1) and (2) are changed, obtaining a modified model expressed by the following equations:

$$f = \sigma_0 z v + \sigma_1 \dot{z} + \sigma_2 \dot{x} \quad (3a)$$

$$\dot{z} = \dot{x} - \sigma_0 a_0 |\dot{x}| (1 + a_1 v) z \quad (3b)$$

In equations (3a) and (3b) the input voltage v has included, which regulates the behavior of magnetorheological fluid. Parameters, $\sigma_0, \sigma_1, \sigma_2$ are the stiffness terms and internal damping of the damper, while a_0 and a_1 are coupling terms of excitation voltage and the variable z corresponds to an internal state that describes the mechanical properties of magnetorheological fluid.
As this internal state *(z)* is not measurable, to carry out identification of the above mentioned parameters, it is necessary to propose the following observer:

$$\dot{\hat{z}} = \dot{x} - \sigma_0 a_0 |\dot{x}| (1 + a_1 v) \hat{z} \quad (4)$$

Where $\hat{z}$ is the estimate of z, and the estimation error is defined as: $\tilde{z} = z - \hat{z}$ thus, the estimation error dynamics is given by:

$$\dot{\tilde{z}} = \dot{x} - \sigma_0 a_0 |\dot{x}| (1 + a_1 v) \tilde{z} \quad (5)$$

Considering a Lyapunov function candidate $V = \frac{\tilde{z}^2}{2} > 0$ and assuming $(1 + a_1 v) > 0$, by the second Lyapunov method [5] guarantees that $\hat{z} \rightarrow z$ asymptotically due to:

$$\dot{V} = -\sigma_0 a_0 |\dot{x}| (1 + a_1 v) \tilde{z}^2 \leq 0 \quad (6)$$

3 Performance of MR Damper Model in open loop

Estimate unobservable parameters of the modified model of MR damper equations (3a-3b) is not an easy task, however note that substituting equation (3a) into (3b) yields:

$$f = \sigma_0 z v - \sigma_0 \sigma_1 a_0 |\dot{x}| z - \sigma_0 \sigma_1 a_0 a_1 |\dot{x}| z v + (\sigma_1 + \sigma_2) \dot{x} \quad (7)$$

The following parameters are considered:

$\vartheta_1 = \sigma_0$
$\vartheta_2 = \sigma_0 \sigma_1 a_0$
$\vartheta_3 = \sigma_0 \sigma_1 a_0 a_1$
$\vartheta_4 = \sigma_1 + \sigma_2$

Table 1. parameters for identification

Equation (7) can be reparameterized in the following manner:

$$f = U \vartheta \quad (8)$$

where
$U = [zv, -|\dot{x}|z, -|\dot{x}|zv, \dot{x}]$ and $\vartheta = [\vartheta_1, \vartheta_2, \vartheta_3, \vartheta_4]$.
It should be mentioned that when the model is written in parametric form equation (8), the implementation of any identification algorithm is straightforward.

The following values of the parameter identification were obtained from [11]:

$\sigma_0 = 1059300[Kg/(Vs^2)]$
$\sigma_1 = 5800[Kg/s]$
$\sigma_2 = 2300[Kg/s]$
$a_0 = 0.003[(s^2V)/(Kg * m)]$
$a_1 = -0.1444[V^{-1}]$

Table 2. Parameters for the model MR damper

With these values, the behavior of the model closely approximates the real behavior of magnetorheological damper [11]. According to Barbalat's lemma [4] the fact that $V \geq 0$ and $\dot{V} \leq 0$ it is possible to say that V is bounded$V \in \mathcal{L}_\infty$. Also, if $\dot{V}$ is uniformly continuous, then $\dot{V} \to 0$ as $t \to 0$, it is possible to show that $f \to 0$ as explained in [11].

In order to emulate the direct dynamic in open loop of the RM damper model given by equations (3a-3b), two random signals for displacement and voltage are used to evaluate the output behavior (*f*) of the RM damper. The inputs are given by

$x = 0.0115 \sin(8.6 \pi t)$

$v = 1.25 \sin(10.2 \pi t) + 1.25$

The figures (3) and (4) show the input and output of the MR damper Model respectively.

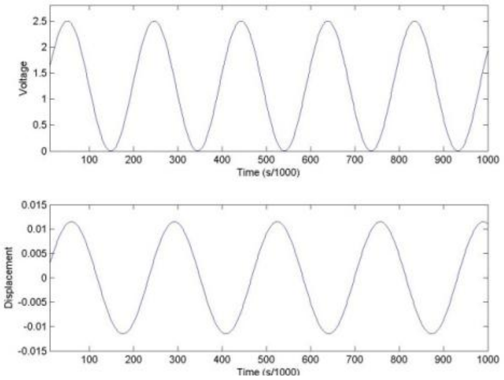

Figure 3. Inputs of the MR damper

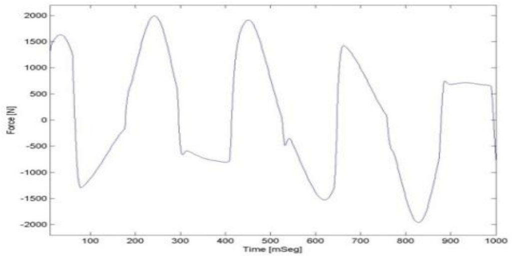

Figure 4. Output of the MR damper

The response of the open loop dynamics of the modified model equations (3a) and (3b), is shown in the following figures: 5 (a) shows the force vs time for different constant input voltages, 5 (b) force Vs displacement, 5 (c) force vs. speed

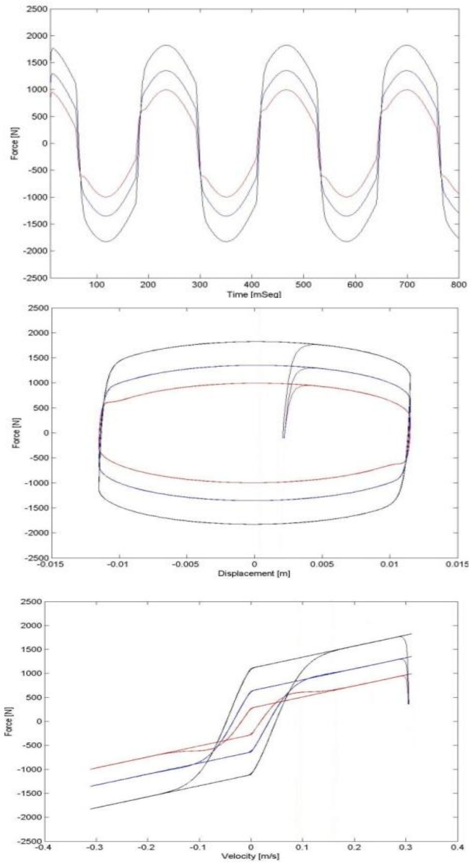

Figure 5. Dynamic behavior of MR Damper, for constant input voltages of 0.75, 1.5 and 2.25 [V].

4. Inverse Dynamic Model using Neural Networks

The inverse control consists of a strategy where a neural network constitutes a plant inverse model.

This mathematical model should be able to predict the voltage to be applied on the damper to generate the desired force.

Thus considers that de plant is represented for the non lineal input-output model given for [9]:

$$y(t+1) = \hat{g}[y(t),\dots,y(t-(n-1)),u(t),\dots,u(t-(m-1))] \quad (9)$$

where:

- *y(t+1)*: Plant output in the time $t + 1$
- *y(t-i)*: Plant output in the before instants , with $i = 0, \dots n + 1$
- *u(t-j)*: Plant input or control signal, with $j = 0, \dots m + 1$

We wish to obtain a neural network that approximate the plant inverse model ($\hat{g}^{-1}$), thus to compute the control signal, $\hat{u}(t)$, as follow:

$$\hat{u}(t) = \hat{g}^{-1}\begin{bmatrix} y(t),\dots,y(t-(n+1)) \\ \dots,r(t+1),u(t),\dots,u(t-(m+1)) \end{bmatrix} \quad (10)$$

Where we take, $(t + 1) = r(t + 1)$, for force the system to follow the reference, $r(t + 1)$

Network Inputs are now the process outputs, and the network output is the input current variable or control signal.
The train of this kind neural network can develop out line, with information that represents the wished behavior during the typical operation of the system. The optimization trouble for the neural network learning, could be formulate as the minimization of the follow functional [6]:

$$J(\theta, z^N) = \frac{1}{2N}\sum_{t=1}^{N}(u(t) - \hat{u}(t))^2 \qquad (11)$$

The model development to emulate the MR damper inverse dynamic, it could be tried as a trouble of the non linear system identification. The basis process of the identification is formed for 4 steps:

1. Collect a data set that describe how is behavior the system into its operation range;
2. Choose of the network structures, thus it includes for determine the number of the inputs, outputs, intermediates lawyer, excitation function, etc.
3. Training the network.
4. Validation of the network trained.

5. Optimal Network Architecture

To select the optimal neural network architecture that is able to emulate the inverse dynamics of the actuator, the first question we must ask is: what signals should I choose for training? And of course the equations (3a) and (3b) show that the dynamics of the damper is directly related to speed, rather than position. Under these considerations, it is selected first, a perceptron neural network model with 12 neurons in the intermediate layer, all of them with hyperbolic activation function. The neural network is trained with data from the modified model of magnetorheological damper [1] in open loop (see Figure 6), following the methodology of the four steps described above and
trained under the Levenberg-Marquard method, the inputs of the network are: speed, force and past samples of the voltage predicted by the neural network (see Figure 7). The figure (8) shows the prediction error, it is clear that the network parameters are linearized, the cost function of prediction error (Eq. 11) is minimal since the model predicts exactly the desired voltage (see figure (9)).
Finally the figures (10), (11) and (12) shown that for an architecture of 10 neurons in the intermediate layer, the neural network model is still accurate.
To emulate an optimal inverse dynamics of the MR damper, it is necessary that the neural network

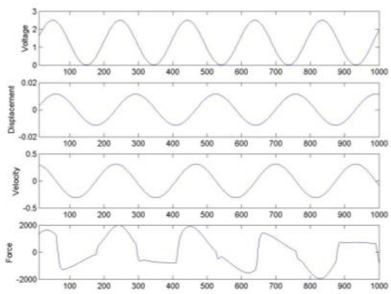

Figure 6. Training Data

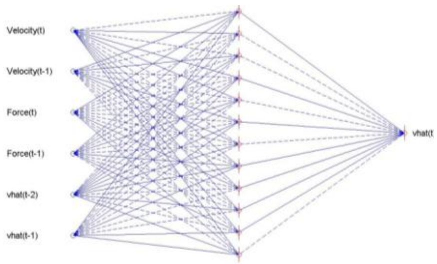

Figure 7. Architecture of the NN

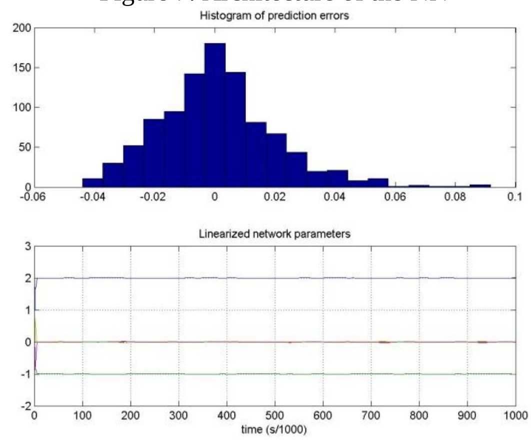

Figure 8. Prediction Error

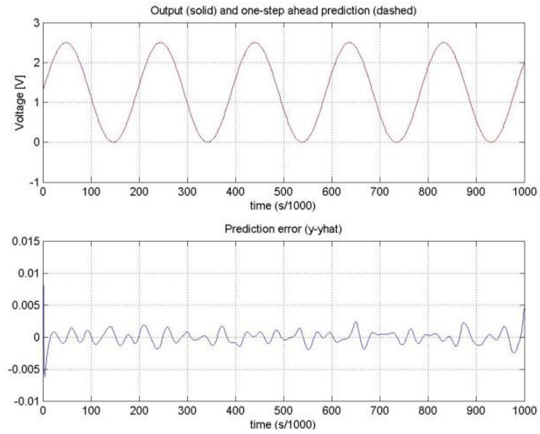

Figure 9. Neural Network Output

model proposed is accurate, it is also desirable that the network parameters are linearized, the prediction error (Eq. 11) is as small as possible with the least amount of neurons, and that under these conditions the model is able to emulate the inverse dynamics of the actuator, correctly predicting the desired voltage.

In this paper an optimal network that satisfies all the requirements to emulate an optimal inverse dynamics of the MR damper is presented.

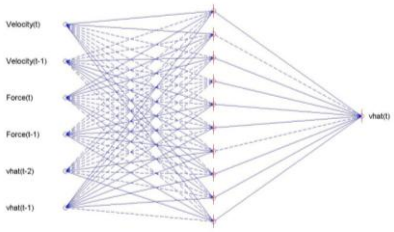

Figure 10. Architecture of the NN with 10 neurons

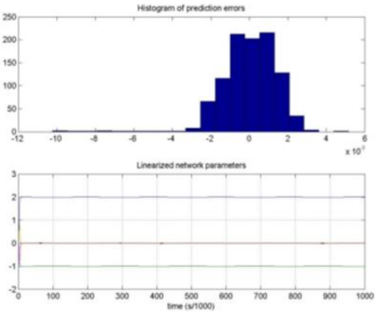

Figure11. Prediction Error

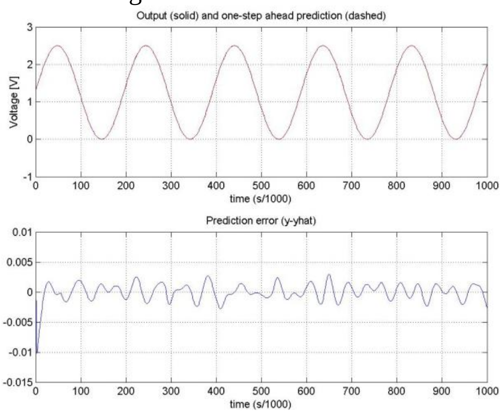

Figure 12. Neural Network Output

improvement of performance in comparison to neural network architectures reported in [7].

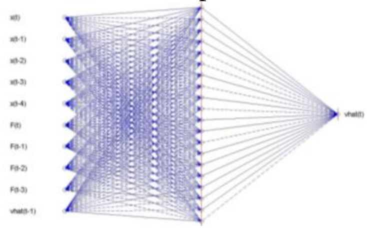

Figure 13. Architecture of the NN with 20 neurons

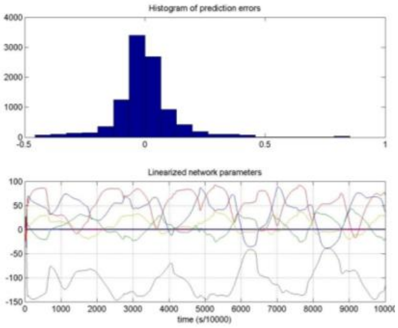

Figure14. Prediction Error

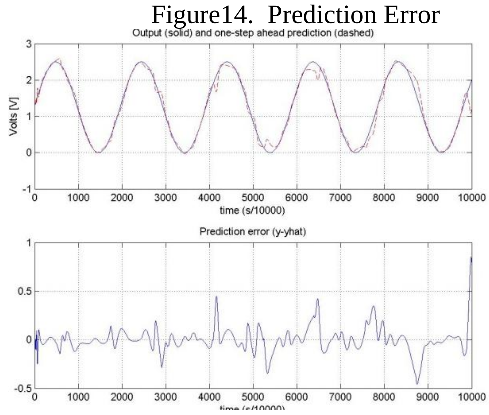

Figure 15. Neural Network Output

6 Comparison of some Neural Network

The architecture neural network reported on [7] is reproduced, in order to compare with the architecture proposed here. In [7] it is proposed a perceptron neural network model with 20 neurons in the intermediate layer, all of them with sigmoidal activation function and one output neuron with linear activation function.This neural network architecture is trained under the Levenberg-Marquard method, input signals and past for training (off-line)are: position, force and the feedback samples past the voltage predicted by the neural network (see Figure 13). As you can see the model of 20 neurons proposed in [7], the prediction error is acceptable, however, does not show optimal performance (see Figure 15), also, it does not make a linearization in the parameters of the network (see Figure 14). It is shown that the optimal neural network architectures presented in this paper provide a substantial improvement of performance in comparison to neural network architectures reported in [7].

7 Conclusions

This paper presents an emulation of the inverse dynamics of magnetorheological dampers, using a dynamic model proposed [1], which is modified to describe the real behavior of the device, also a perceptron neural network is constructed and trained under the method of Lagrange multipliers Levenberg-Marquard to emulate the inverse dynamics of magnetorheological damper, considering the direct neural control techniques for inverse model. Finally it is shown that the optimal neural network architectures presented in this paper provide a substantial improvement of performance in comparison to some neural network architectures reported in [7]. Finally, it can conclude that the optimal neural network architecture presented in this paper, reduce training time and makes the implementation easier.

To emulate an optimal inverse dynamics of the MR damper, it is necessary that the neural network model proposed is accurate. Direct Neural Network control via inverse modelling techniques allow to emulate the inverse dynamics of the damper very well, because with the behavior information of the damper model in open loop, it was possible to train the perceptron neural network model and correctly predict the desired voltage under an algorithm Levenberg-Marquardt.

The multilayer perceptron is an artificial neural network that processes information in parallel and learn by examples presented during training, in this work, this network was trained off-line and the reason was because current and past signals samples were used to be processed with the NNSYSID (Neural Network Based System Identification) [10] and it was observed that the network is trained successfully, it was able to get the essential characteristics of the plant, to process different inputs from the performance of the MR damper in open loop.

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