Experimental MR Damper Modeling based on ANN

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***Abstract*— A model for a Magneto-Rheological (*MR*) damper based on Artifical Neural Networks (*ANN*) is proposed. The *ANN*-based model does not require regressors in the input vector. Additional to the electric current input, only one more sensor is needed to achieve a reliable *MR* damper model. The model is experimentally validated with two commercial *MR* dampers of very different properties. The Root Mean Square (*RMS*) of the error is used to measure the model accuracy. A *RMS* average of 7.1% in the damping force is obtained. Using the same experimental database, the *ANN*-based model is also compared with well-known *MR* damper models taking the Error to Signal Ratio (*ESR*) performance index as reference. Early results indicate *ANN*-based model outperforms previous *MR* models. *ESR* ranges from 1.8 to 10.8 %; however, for several experimental datasets the *ANN*-based model exhibits the lowest *ESR*.**

I. INTRODUCTION

A Magneto-Rheological (*MR*) damper is an hydraulic damper with metallic particles into the oil that change the rheological properties of the fluid when a magnetic field is applied; an electric current supplied through the damper coil is used to manipulate the magnetic phenomenon. The variation of the oil viscosity changes the damping ratio in the shock absorber, this property is named *semi-activity*. The oil viscosity is proportional to the *MR* damper force; however, the join of these mechanisms creates an highly nonlinear behavior in the damping force. The *MR* damper has been mainly applied in vibration control because it has low power requirements, fast response, simple structure and continuous adjustable damping force over a large span.

The main function of the *MR* damper in an automotive suspension is to absorb energy in order to get low accelerations of the sprung mass (i.e. automotive chassis) and low deflections in the wheel; thus, a reliable *MR* damper model is required to design the control system. Even though there are important contributions in this field [Guo et al., 2006]; there are still several needs because the nonlinear behavior of the *MR* shock absorber is a non-trivial modeling task.

Several mathematical models are available for modeling the nonlinear behavior of *MR* dampers; they can be classified as parametric and non-parametric models. Parametric models include the Bingham model [Stanway et al., 1987], the viscoelastic-plastic model [Gamota and Filisko, 1991], the phenomenological model [Wang and Kamath, 2006], the semi-phenomenological model based on the Bouc-Wen model [Spencer et al., 1996], the improved Bouc-Wen model [Yang et al., 2002], [Guo and Hu, 2005], the hyperbolic tangent function model [Kwok et al., 2006], [Guo et al., 2006], the inverse tangent function model [Çesmeci and Engin, 2010] and many others. The Bingham and the viscoelastic-plastic model can not reproduce the nonlinear behavior of an *MR* damper with high accuracy, while the other models can; however, they have many parameters to identify. On the other hand, some of these physical models use parameters of the internal structure of the shock absorber resulting in a particular model case.

In the non-parametric models, the coefficients do not have a physical meaning. Models based on look-up table, fuzzy logic and Artificial Neural Networks (*ANN*) are the representative non-parametric models for a *MR* damper. Polynomial models [Choi et al., 2001], [Hong et al., 2002], [Du et al., 2005], [Poussot-Vassal et al., 2008] and statistical models [Shivaram and Gangadharan, 2007] require many parameters to represent the nonlinear and semiactive behavior of the damping force; while the fuzzy models [Atray and Roschke, 2003],[Ahn et al., 2008] need an a priori knowledge in both frequency and time domain of the *MR* damper. For *ANN* models, the knowledge of the dynamic relationships between the variables is not required, only a well training step is needed; in addition, the number of parameters depends on the *ANN* architecture size and commonly the *ANN* design is based on the minimal dimensions criterion [Freeman and Skapura, 1991], which selects the possible lowest number of hidden layers with the possible lowest number of neurons.

The major effort in the *MR* damper modeling using *ANN* is focused on reproduce the inverse dynamics (force-electric current) of the shock absorber [Chang and Zhou, 2002], [Xia, 2003], [Wang and Liao, 2005], [Zapateiro et al., 2009], [Metered et al., 2010]; however, a recurrent neural network is required for achieving an optimal damping force signal, and normally the input vector is based on two or more signals (force, displacement and/or velocity) without considering the electric current. This type of *ANN* model increases the architecture size and the instrumentation cost in a suspension control system. On the other hand, commonly the modeling of the forward dynamics using *ANN* requires two ore more time delays of each input increasing the *ANN* architecture and its computing time [Kim and Roschke, 1999],

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[Savaresi et al., 2005], [Du et al., 2006], [Chen et al., 2009], [Ruiz-Cabrera et al., 2010], [Boada et al., 2011].

This research proposes a non-parametric model of an *MR* damper based on *ANN*, the model does not require regressors in the input vector and demands only one additional sensor to the electric current, i.e. its structure has low complexity for practical implementations of suspension control systems.

The outline of this paper is as follows: in the next section, the *ANN* design is described. Section III shows the experimental system and section IV presents the modeling results. Section V presents the effectiveness of the proposed *MR* damper model versus previous models reported in the literature. Conclusions are presented in section VI.

II. *ANN* Review

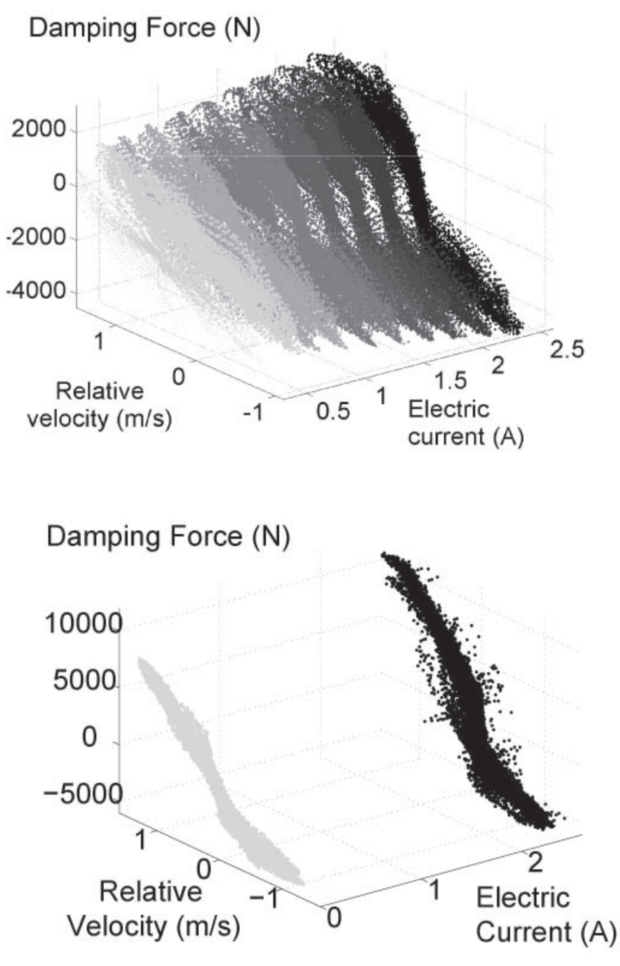

Fig. 1. Nonlinear behavior of the MR_1 (top) and MR_2 (bottom) damper force, respectively, respect to the control current and relative velocity.

An *ANN* is a computational model capable to learn behavior patterns of a process, it can be used to model nonlinear, complex and unknown dynamic systems, [Korbicz et al., 2004]. Based on the flow of signals, the *ANN* architecture can be classified into two major groups: *feedforward* and recurrent networks. *Feedforward* networks project the flow of information only in one way, i.e. the output of a neuron feeds to all neurons of the following layer [Hagan et al., 1996]; while, the recurrent networks have an output feedback signal.

In *MR* damper modeling using *ANN*, typically recurrent neural networks based on Nonlinear-ARX (*NARX*) structures, i.e. regressors in the input and/or output vector, have been proposed with high accuracy [Chang and Zhou, 2002], [Savaresi et al., 2005], [Wang and Liao, 2005], [Zapateiro et al., 2009], [Chen et al., 2009], [Metered et al., 2010], [Boada et al., 2011], etc. The *NARX* structure is defined as,

$$\begin{aligned} F_{MR} = \quad & f_{NL}(z_{def}(t), z_{def}(t-1), \ldots, z_{def}(t-k_1), \\ & \dot{z}_{def}(t), \dot{z}_{def}(t-1), \ldots, \dot{z}_{def}(t-k_2), \\ & I(t), I(t-1), \ldots, I(t-k_3), \\ & F_{MR}(t-1), \ldots, F_{MR}(t-k_4)) \end{aligned} \tag{1}$$

where k_i represents a specific number of time delays for each signal, z_{def} and $\dot{z}_{def}$ are the displacement and velocity of the damper rod provided from sensor measurements, I is the actuation signal and F_{MR} is the damper force (*ANN* output).

A comparison between a *feedforward* and recurrent neural network is considered for determining the accuracy degree in the damper force by adding the output feedback in the *ANN* structure. In addition, different arrays in the input vector are used to evaluate the *ANN* performance with time delays; the arrays with one, two and three regressors in the input vector are compared with the modeling performance of an *ANN* that does not have delays. Finally, the *ANN* performance is analyzed when one (velocity) or two (displacement and velocity) signals are used in the input vector.

The *backpropagation* algorithm is the most used training method since it allows to solve problems with complex net connections, [Freeman and Skapura, 1991]. The proposed *ANN* model was trained with *backpropagation*.

III. Experimental System

Two different industrial *MR* dampers have been exploited to perform a total of 5 tests. One damper has continuous actuation and considerable hysteresis at high frequencies with high deflections. It will be named MR_1 The other *MR* damper has only two levels of actuation and its hysteretic behavior is minimal. It will be named MR_2. Figure 1 shows the highly nonlinear behavior of both *MR* damping force respect to the velocity and electric current. MR_1 damper is actuated under various constant electric current inputs; while, the MR_2 damper only has two states of actuation.

An industrial system has been used to control the position of the damper piston. A data acquisition system commands the controller and records the position, velocity and force from the *MR* damper with a sampling frequency of 1,650 Hz. The displacement and electric current ranges were: ± 25 mm and 0 - 2.5 A, respectively. An additional sensor provides the velocity ($\dot{z}_{def}$) and position (z_{def}) measurements of the damper piston; although, in the proposed *ANN* structure only the velocity signal is considered. In this case, a self-generating tachometer generates the velocity measurement.

A series of training sequences have been proposed. The position emulates the suspension deflection and the electric current is the actuation signal. Table I shows the design of experiments used to identify the nonlinear behavior of both *MR* dampers under different sequences of position and actuation.

For displacement sequences, Amplitude-Modulated (*AM*), Frequency-Modulated (*FM*) and Stepped Frequency Sinusoidal (*SFS*) were used to analyze the *MR* damper dynamics in the transient response under changes in magnitude and frequency of the suspension deflection; Triangular wave with Positive and Negative Variable Slopes (*TPNVS*) sequence allows to know the dynamic behavior under constant velocity; and Road Profile (*RP*) represents the suspension deflection move when the vehicle passes under a specific surface.

For electric current sequences, Stepped Increments (*SC*) are used to study the effect of the current in the jounce and rebound of the *MR* damper under different displacements, since the MR_2 damper has not a continuous actuation only two levels of current were designed; Increased Clock Period Signal (*ICPS*) and Pseudo Random Binary Signal (*PRBS*) allow to analyze the transient response of the damping force when the current changes at different frequencies, the *ICPS* signal includes random changes in the amplitude and *PRBS* only switches between two electric current values. Figure 2 shows an example of a displacement and electric current sequences.

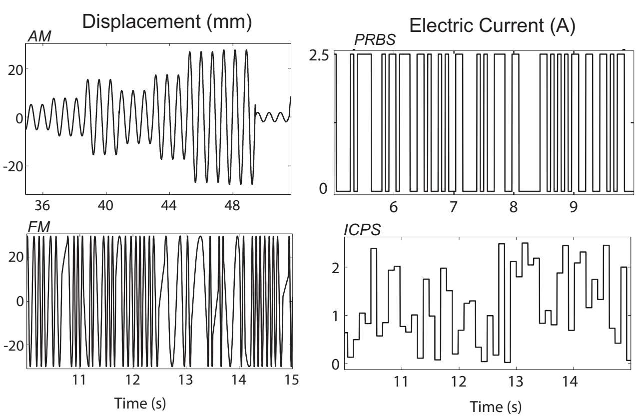

Fig. 2. Displacement (left plots) and electric current (right plots) sequences.

TABLE I
DESIGN OF EXPERIMENTS FOR IDENTIFYING AN *MR* DAMPER.

Experiment	Displacement sequence	Current sequence	
		MR_1	MR_2
1	*TPNVS*	*SC* (10)	*SC* (2)
2	*SFS*	*SC* (10)	*SC* (2)
3	*RP* (rough way)	*ICPS*	*PRBS*
4	*AM*	*ICPS*	*PRBS*
5	*FM*	*ICPS*	*PRBS*

IV. MODELING RESULTS

The *ANN* model obtained from the different experiments, presented in Table I, is used to characterize the dynamical behavior of the *MR* damper and evaluated by the Root Mean Square (*RMS*) performance index of the error, which is defined as,

$$RMS = \frac{1}{n}\sqrt{\sum_{i=1}^{n}\left(\hat{F}_{MR}(i) - F_{MR}(i)\right)^2} \qquad (2)$$

where, $\hat{F}_{MR}$ and F_{MR} represent the estimated and experimental damping force respectively and n is the number of total samples in the experiment. The percentage of error represents the *RMS* of the error normalized by the span of the damping force.

In automotive engineering, the experiment 2 is very useful to identify the mechanical characteristics of a damper for dissipating energy, the harmonic movement at different frequencies allows to analyze the *MR* damper properties for the confort and road holding objectives; therefore, this experiment is used to discuss the design of the *ANN* model as well as to present some qualitative results.

A. ANN *architecture.*

A Multilayer Perceptron (*MLP*) network, which corresponds to a *feedforward* system, is compared with a recurrent network. The input vector of the *MLP* network is composed by z_{def}, $\dot{z}_{def}$, I; while the recurrent network adds the *ANN* output (damping force). MLP has 4.38 % modeling error while recurrent has 3.8 % using experiment 2 in the MR_1 damper. The error percentage represents the average deviation between the modeled damping force and the real measurement based on the *RMS* value of the error. When the feedback of the *MR* damper force is considered, the modeling error decreases slightly; however, the *ANN* architecture and its computing time increase.

B. Signals in the input vector.

Taking into account an *MLP* network, two different input vectors have been compared. The former input vector uses the z_{def}, $\dot{z}_{def}$ and I; while the second one only includes $\dot{z}_{def}$ and I. The modeling error decreases 46.7 % (from 8.22% to 4.38%) by considering two signals; however, the instrumentation cost can increase if both signals are measured or the computing time can increase for a specific signal processing. Additionally, the *ANN* structure is more complex for the training and testing step.

C. Regressor choice.

Different arrays in the input vector of the *ANN* model have been evaluated with the experiment 2 over the MR_1 damper. The modeling error of the *ANN* when the number of regressors in the 2 input signals varies slightly (8.22 %, 8.24 %, 8.86 % 8.79 %); in this case, the velocity and electric current have the same number of regressors in each test (0, 1, 2 or 3). According to the modeling error, it is not significant to incorporate time delays in the input vector of the *ANN*. This poor effect of the regressors in the modeling performance is because the sampling time is very long in comparison with the response time of the damping force (1/25 Hz), and this response time limits at least 10 times the sampling time in the automotive system.

D. ANN-*size selection.*

Finally, the choice of the number of parameters (hidden layers and their neurons) of the non-linear parametric function can be easily made using a cross-validation approach. A 1-hidden-layer structure has been chosen by simulation tests, this structure guarantees the universal-approximation property [Sjöberg, 1995]. For determining the number of neurons in the hidden layer, the minimal dimensions criterion was used [Freeman and Skapura, 1991]; the best choice was with 10 neurons.

According to the above design issues, the *ANN* architecture used to model the *MR* damper dynamics is (2,10,1). The *ANN* input vector includes the signal of the relative velocity and the excitation signal (electric current) without considering regressors, while the damping force corresponds to the *ANN* output. Modeling results of the proposed *ANN* model, considering the 5 experiments, is shown in the Table II.

TABLE II

MODELING PERFORMANCE UNDER DIFFERENT EXPERIMENTAL TESTS.

MR damper	Experiment 1	2	3	4	5
MR_1	5.9%	8.2%	3.1%	4.1%	14.95%
MR_2	6.9%	6.8%	7.2%	8.0%	6.2%

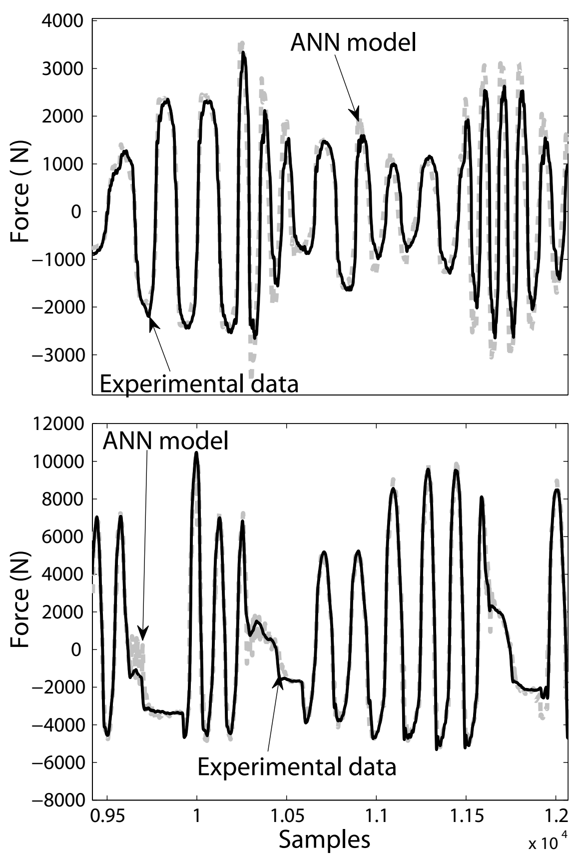

Fig. 3. Comparison between the real and modeled force using the MR_1 damper (up) and MR_2 damper (bottom).

The *RMS* average, considering all experiments, is 291.4 N for the MR_1 damper and 597.8 N for the MR_2 damper. Since the span of the force is ± 4000 N approximately for MR_1 damper and $[-6000$ to $11000]$ N for MR_2 damper, the obtained *RMS* average represents the 7.25% and 7.02% of punctual error in the force signal, respectively. Figure 3 presents a qualitative comparison in the transient response of the force obtained from experimental data and from *ANN* model; in this case, both *MR* dampers are subject to the experiment 5.

In order to test the capability of the *ANN* for modeling the nonlinear and hysteretic behavior of the *MR* damper, experimental data are compared with the *ANN* model in the characteristic diagram of Force-Velocity (*FV*); this diagram represents the effect of jounce and rebound and it is a tool for the engineers of automotive design in order to define the suspension capability for improving the comfort and road holding. Figure 4 shows the *FV* diagram of the MR_1 and MR_2 dampers using the experiment 2. Bottom plot in Figure 4 shows that the *ANN* can model the nonlinear behavior of the MR_2 damper with acceptable accuracy, only outliers are not included. Notice in the *FV* diagram that the MR_2 damper has minimal hysteresis and it is composed by two damping levels: 1) high damping force at current greater than 2.5 A and 2) low damping force at 0 A.

The MR_1 damper has a continuous actuation between 0 and 2.5 A. The *ANN* correctly models the nonlinear behavior at each current step; however, the hysteresis can not be modeled at low deflection velocities (± 0.5 m/s) using only one signal (deflection velocity), up plot in Figure 4. This hysteretic behavior occurs at high frequencies (greater than 10 Hz) with high amplitudes in the suspension deflection, and the velocity sensor does not contain the required information for representing the force dynamics at these frequencies; thus, an acceleration sensor could complement this missing force dynamics.

Although the hysteresis can not be modeled at high frequencies with high displacements, in general, the proposed *ANN* can be used to represent the *MR* damper dynamics since the hysteretic behavior appears at not typical deflection amplitudes in an automotive suspension and the frequencies out of the desired span for passengers comfort, i.e. the displacement pattern is out of the automotive operational zone of the damper.

V. RELATED WORKS

A comparative analysis is established with well-known models. Table III shows the different characteristics among the models, the Bingham model has the lowest number of parameters; but, it is not capable of describing the hysteretic forcevelocity behavior. Only the *ANN*-based model includes the electric current signal into the model structure. The algebraic models of [Guo et al., 2006] and [Çesmeci and Engin, 2010] need three input signals: the relative velocity, the relative acceleration ($\ddot{z}_{def}$) and the hysteretic velocity of the piston ($\dot{x}_0$); while the *ANN*-based model demands only two inputs.

TABLE III

MAIN CHARACTERISTICS OF DIFFERENT *MR* DAMPER MODELS.

Features	Bingham model	Model of [Guo et al., 2006]	Model of [Çesmeci and Engin, 2010]	Proposed *ANN*-based
Parameters	3	5	6	3 weight vectors
Hysteresis	No	Yes	Yes	Yes
I as input	No	No	No	Yes
Inputs	$f(\dot{z}_{def})$	$f(\dot{z}_{def}, \ddot{z}_{def}, \dot{x}_0)$	$f(\dot{z}_{def}, \ddot{z}_{def}, \dot{x}_0)$	$f(I, \dot{z}_{def})$
Fitting method	*NLSM*	*NLSM*	*NLSM*	Levenberg-Marquardt

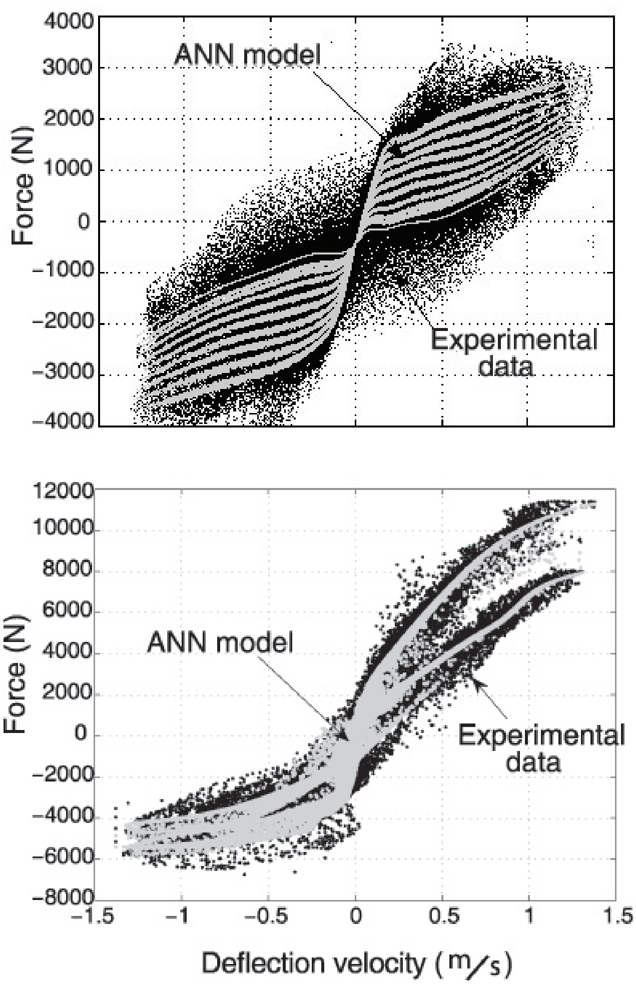

Fig. 4. *FV* diagram for the real and modeled force using the *MR*$_1$ damper (up) and *MR*$_2$ damper (bottom).

The Error to Signal Ratio (*ESR*) performance index is used for comparing the results. It is defined as the ratio of the average modeling error respect to the variance of the damping force F_{MR}, [Savaresi et al., 2005]:

$$ESR = \frac{\frac{1}{n}\sum_{i=1}^{n}\left(\hat{F}_{MR}(i) - F_{MR}(i)\right)^2}{\frac{1}{n}\sum_{i=1}^{n}\left(F_{MR}(i) - \mu_{F_{MR}}\right)^2} \quad (3)$$

where $\mu_{F_{MR}}$ is the mean of the experimental F_{MR}. An index value of 1 is a trivial model, 0 is highly accurate.

A *MR* damper models have been trained and tested with the same experimental data set. For each dataset, the 60% of the data were used for learning the models; while, the remainder for testing. The used learning methods in each model are presented in last row of the Table III. All of them were run in *Matlab*.

Table IV presents the obtained *ESR* in the testing step of different learned *MR* damper models. Boldface number represents the lowest *ESR* for each *MR* damper model.

Using the *ESR* performance index, the proposed *ANN* model generated the best modeling performance in all experiments for the *MR*$_2$ damper in comparison with the classical Bingham model and algebraic models reported in [Guo et al., 2006] and [Çesmeci and Engin, 2010]. However, in the *MR*$_1$ damper modeling which has continuous manipulation in the electric current signal, the hyperbolic tangent function model of [Guo et al., 2006] has lower *ESR* when the experiment was designed with modulated frequency in the sequence displacement over all span of interest in automotive engineering (0.1-20 Hz); in the remainder of experiments, the *ANN*-based were better.

It is considerable to assume an optimal modeling performance. The proposed *ANN* structure (2 10 1) improves the modeling performance (reducing from 9% to 62% the *ESR* index) of another parametric models when the *MR*$_2$ damper is considered. For the *MR*$_1$ damper, only in the experiments 3 and 4, the proposed *ANN* model had the best performance (reducing from 26% and 33% the *ESR* index); while, in the experiments with modulated frequency in the displacement sequence was better the algebraic model of the hyperbolic tangent function.

VI. CONCLUSIONS

A Magneto-Rheological (*MR*) damper model based on Artificial Neural Networks (*ANN*) is proposed. The *ANN* structure does not require regressors in the input vector and only one additional sensor (displacement or velocity) to the electric current signal is demanded to get a reliable model.

Experimental data of two commercial *MR* dampers have been used to verify the accuracy of the proposed *MR* damper model based on *ANN*. The average modeling error is lower than 7.25% by considering different experiments. The Force-Velocity diagram shows that the *MR*$_2$ damper can be modeled with high accuracy since this shock absorber has an on/off actuation and does not exhibit hysteresis. The *MR*$_1$ damper presents a more complex dynamics at high frequencies with high displacements. The *MR* damper model based *ANN* structure can not represent this hysteretic behavior with

TABLE IV

ESR PERFORMANCE INDEX FOR *MR* DAMPERS MODELS USING DIFFERENT DESIGN OF EXPERIMENTS

Model	*MR* damper	*ESR* (%)				
		Exp. 1	Exp. 2	Exp. 3	Exp. 4	Exp. 5
Bingham [Stanway et al., 1987]	MR_1	14.47	12.64	4.56	3.85	16.63
	MR_2	7.20	5.42	6.97	16.46	5.67
Hyperbolic tangent function [Guo et al., 2006]	MR_1	**9.63**	**5.34**	2.42	2.75	**6.32**
	MR_2	12.40	6.48	6.78	14.56	6.73
Inverse tangent function [Çesmeci and Engin, 2010]	MR_1	11.75	7.46	1.73	2.40	11.03
	MR_2	7.02	3.58	4.68	13.05	4.67
Proposed *ANN* (2 10 1)	MR_1	11.62	7.58	**1.10**	**1.77**	14.62
	MR_2	**4.69**	**2.95**	**4.25**	**10.82**	**1.78**

only the relative velocity signal. However, this displacement pattern is out of the automotive operational zone of the damper.

MR_1 model has the lowest *ESR* index for 3 of 5 experimental databses and i has as low as 2.75% *ESR* for the other 2 of 5 datasets. MR_2 model has the lowest *ESR* index for all experimental datasets. Due to reliability of the proposed *MR* damper model approach, this *ANN*-based model can be used to test semiactive suspension control systems.

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