NEURAL NETWORK BASED SEMI-ACTIVE CONTROL STRATEGY FOR STRUCTURAL VIBRATION MITIGATION WITH MAGNETORHEOLOGICAL DAMPER

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Abstract. *This paper presents a neural network based semi-active control method for a rotary type magnetorheological (MR) damper. The characteristics of the MR damper are described by the classic Bouc-Wen model, and the performance of the proposed control method is evaluated in terms of a base exited shear frame structure. As demonstrated in the literature effective damping of flexible structures is obtained by a suitable combination of pure friction and negative damper stiffness. This damper model is rate-independent and fully described by the desired shape of the hysteresis loops or force-displacement trajectories. The proposed neural network controller is therefore trained based on data derived from these desired force-displacement curves, where the optimal relation between friction force level and response amplitude is determined explicitly by simply maximizing the damping ratio of the targeted vibration mode of the structure. The neural network control is then developed to reproduce the desired force based on damper displacement and velocity as network input, and it is therefore referred to as an amplitude dependent model reference control method. An inverse model of the MR damper is needed to determine the damper current based on the derived optimal damper force. For that reason an inverse MR damper model is also designed based on the neural network identification of the particular rotary MR damper. The performance of the proposed controller is compared to that of an optimal pure viscous damper. The top floor displacement and acceleration of the base exited shear frame structure are selected as the performance parameters of this comparison. It is found by the simulations that the proposed control design yields a reduction in the structural response compared to the viscous case.*

1 INTRODUCTION

As large scale structures become increasingly slender and flexible the magnitude of dynamic response due to loading from wind, traffic and even earthquakes may increase beyond the acceptable level. Thus, the need for additional external damping is pronounced, where in particular the concept of semi-active control has received a great amount of attraction during the most recent decades. The Magnetorheological (MR) damper is one of the most popular types of semi-active devices. It is inherently dissipative and thereby stable, and it behaves roughly as a friction damper, where the friction force level can be altered real-time by simply changing the applied damper current. Thus, the MR damper is a cost effective device that combines some of the adaptability of active control with the low power requirements and reliability of pure passive dampers.

The main challenges arising in connection with the use of most semi active damping devices lies in the development of effective control laws, and in the subsequent digital and real-time implementation. Most control strategies for semi-active structural control fall into two main categories. The first one consists of control strategies that require accurate mathematical formulation for the plant model. Examples in this category are the H2/LQG, H∞ and the sliding mode control, where any active parts are simple clipped. Conversely, the second category contains control strategies that do not require an accurate mathematical model of the plant. Neural network and fuzzy control fall into this category. Several neural network based control strategies [1-3], neuro-fuzzy network based strategies [4,5] or neuro-predictive control methods [6] have been developed for different control aspects of MR dampers. The advantage of neural network based methods is that they mainly excel in the handling of uncertainties in nonlinear applications, which makes them suitable for both modeling and control of the inherently nonlinear MR damper.

It has been demonstrated in [7,8] that for semi-active control of flexible structures the combination of pure friction and a negative stiffness component yields very effective damping of structural vibrations. Therefore, this paper considers the development of a model reference neural network, which will track the desired hysteresis behavior of an ideal friction damper with negative stiffness. The proposed controller performance is compared with performance of an optimal viscous damper, and for the response of a simple shear frame structure subjected to harmonic base excitation the good performance of the proposed method is verified.

2 STRUCTURAL MODEL AND MR DAMPER PROPERTIES

The performance of the semi-active control strategies for the MR damper is in this paper assessed by the harmonic response of a base excited five-storey shear frame structure. The MR damper is collocated at the first floor of the shear frame, where the measuring data is collected. To apply the semi-active control strategy on the MR damper, an inverse model of the damper is needed to predict the damper current associated with the desired MR damper force. The equation of motion of the shear frame structure with MR damper and inverse MR damper model are discussed in the following sub-sections.

2.1 Equation of motion

In dynamic analysis of flexible structures the structural model is typically modeled by finite elements or determined by experimental modal analysis, whereby the equation of motion can be written in the form

$$\mathbf{M}_c \ddot{\mathbf{x}} + \mathbf{C}_c \dot{\mathbf{x}} + \mathbf{K}_c \mathbf{x} = -\lambda f + \mathbf{M}_c \, \mathbf{I} \left(-\ddot{x}_g \right) \tag{1}$$

where $\mathbf{M}_c$, $\mathbf{C}_c$ and $\mathbf{K}_c$ are the mass, damping and stiffness matrices in Cartesian coordinates, $\mathbf{x}$ is the displacement vector containing the displacements of the five concentrated masses, the dot represents the time derivative, f is the force of the external MR damper, $\boldsymbol{\lambda} = [1,0,0,0,0]^T$ is the connectivity vector that applies the semi-active force f to the first mass, $\mathbf{I} = [1,1,1,1,1]^T$ is the unity vector and $\ddot{x}_g$ is the ground acceleration. The schematic illustration of the shear frame structure with rotational MR damper is shown in Fig. 1.
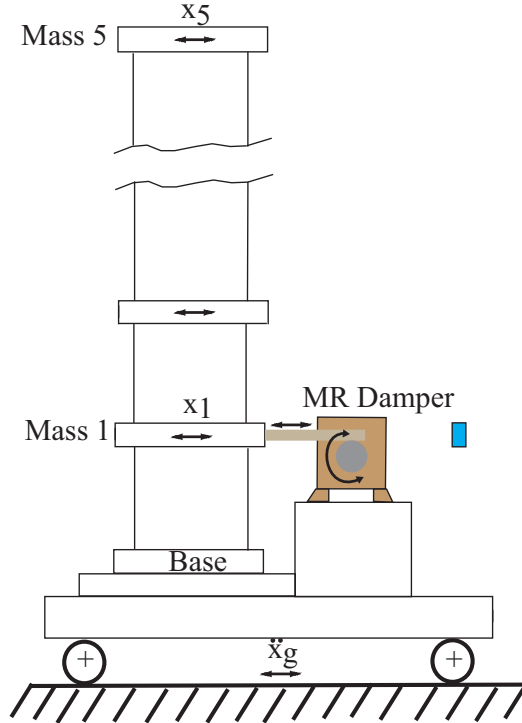

Figure 1: Shear Frame Structure with MR damper

2.2   MR damper model

The rotational MR damper is modeled using the classical Bouc-Wen hysteresis model. The parameters of the model have been calibrated by experiments, where the damper has been driven harmonically in a testing machine at various frequency-amplitude combinations. The modified Bouc-Wen model by Spencer et al. [9] was formulated for the cylindrical type MR damper. In the present case this model is slightly simplified, mainly because the cylindrical damper concept has no need for an accumulator chamber, which for the many cylindrical type dampers introduce an additional stiffness component. Figure 2 shows the close up of the rotary type damper at the Swiss Federal Laboratory of Material Science and Research (EMPA) and the schematic diagram of the classical Bouc-Wen model. For more information on the characteristics and modeling of the rotary MR damper please see Boston et al. [10].
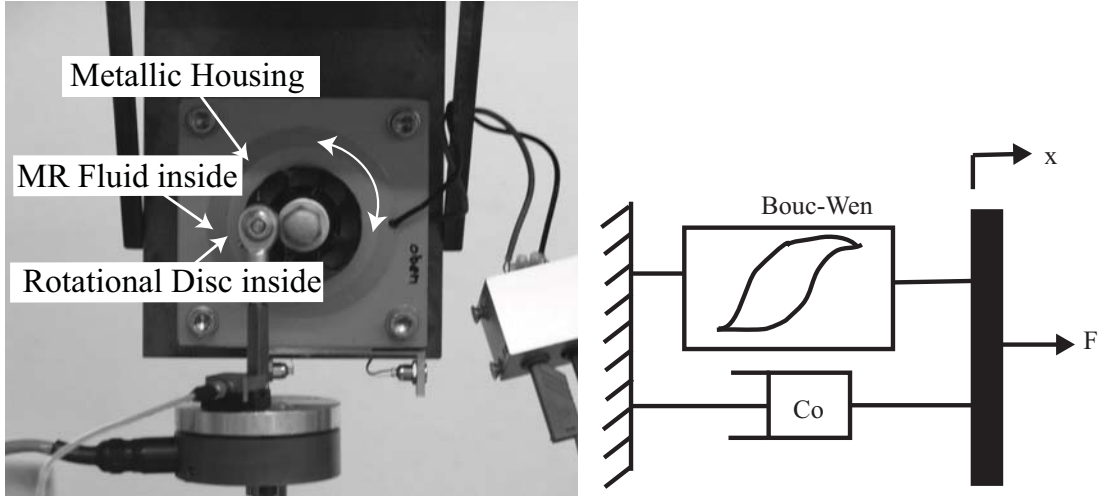
Figure 2: Rotational MR Damper and Bouc-Wen damper model

The governing equations for the damper force f predicted by the classical Bouc-Wen model can be written as follows:

$$f = \left(\alpha z + c_0 \dot{x} \right) \tag{2}$$

where the hysteresis effect follows from the evolutionary variable z controlled by the Bouc-Wen equation

$$\dot{z} = -\gamma \left| \dot{x} \right| z \left| z \right|^{n-1} - \beta(\dot{x}) \left| z \right|^{n} + A(\dot{x}) \tag{3}$$

The gain parameters on the hysteresis effect and the viscous effect are in the present case described by cubic and linear functions of the applied current, respectively:

$$\alpha = \alpha_a + \alpha_b u + \alpha_c u^2 + \alpha_d u^3 \quad , \quad c_0 = c_{0a} + c_{0b} u \tag{4}$$

The applied current u is described with a time delay relative to the desired current I by the following first order filter:

$$\dot{u} = -\eta (u - i) \tag{5}$$

The estimated parameters of the simplified Bouc-Wen model for the rotational MR damper are given in Table. 1.

MR Damper Parameters			
α_a	4.038	η	100
α_b	1.984	γ	410
α_c	7.901	β	410
α_d	-0.704	A	1000
c_{0a}	10	c_{0b}	100

Table 1: Parameters for Bouc-Wen Model

Typical force-displacement and force-velocity hysteresis loops for the rotational MR damper are shown in Fig. 3. It is seen that the MR damper behaves approximately as a friction damper, where the friction force level can be altered by changing the applied damper current. The opening of the force-velocity loops indicates some form of stiffness or inertia effects.
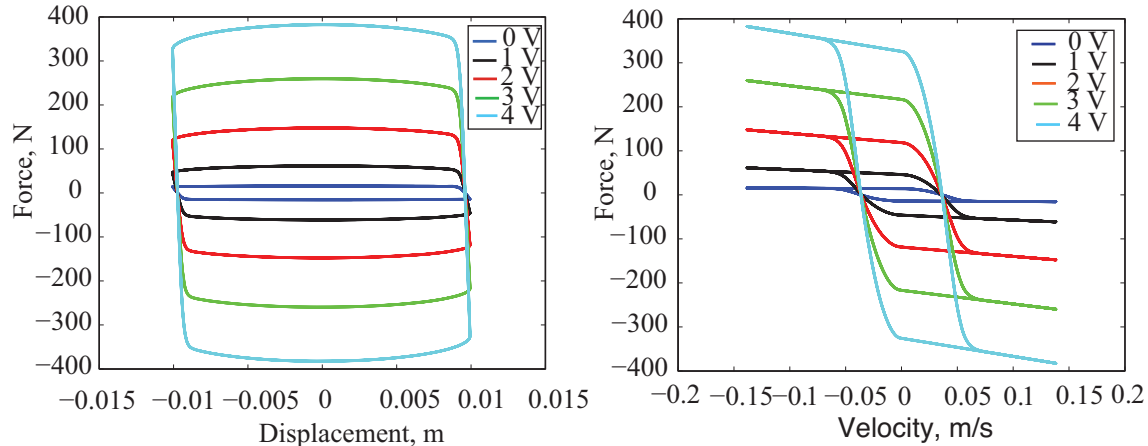

Figure 3: Force Displacement /Velocity hysteresis loops.

2.3   Inverse MR damper

The inverse model modeling for rotary MR damper is a quite complicated task due to high nonlinearity in MR damper dynamics. This work can be done by using parametric [10] such as Evolutionary Algorithm and also non-parametric system identification methods such as neural network identification approach [11, 12]. The inverse MR damper behavior is modeled to solve the force tracking task by MR damper in closed loop cycle. The training and valida-tion data are generated by dynamic tests of the MR damper mounted on a hydraulic testing machine. The inverse modeling training data are absolute velocity and absolute force and the current is the target. This approach has been chosen because current is always positive and thereby leads to a small modeling error independently of the sign of velocity. The inverse model of the MR damper is verified with totally independent set of input-output data. The model validation is thoroughly described in Bhowmik et al [14].

The inverse MR damper behaviour, i.e. the input states at time instant k are the damper velocity $\dot{x}_1(k)$ and desired control force $f_{des}(k)$ and the output state is current $I(k)$, is mod-elled by a neural network with the following architecture

$$I(k) = NN \begin{bmatrix} |\dot{x}_1(k)| & |\dot{x}_1(k-1)| & |\dot{x}_1(k-2)| & |\dot{x}_1(k-3)| \\ |f_{des}(k)| & |f_{des}(k-1)| & |f_{des}(k-2)| & |f_{des}(k-3)| \end{bmatrix} \tag{6}$$

The neural network based inverse MR damper model is used to solve the force tracking task.

3   CONTROL STRATEGIES

The present paper describes a neural network based model reference control strategy for the prediction of the desired force to control structural vibrations. To evaluate the perfor-mance of the proposed model reference controller, the optimal pure viscous damper force is also applied to the structure.

For linear damper models the characteristics of the damper are conveniently formulated in the frequency domain as

$$f(\omega) = gH(\omega)x \tag{7}$$

where g is the control gain and $H(\omega)$ is the associated frequency dependent transfer function.

The effective damping of the structure is evaluated in terms of its modal damping ratio, where the presence of the external damper generates a non-proportional damping with corresponding complex valued natural frequencies and mode shapes. The analysis of the damper modal vibrations is described by the two-component system reduction technique introduced by Main and Krenk [13]. In that formulation the response of the structure is represented by a linear combination of the two limiting mode shapes for the structure without damper $\mathbf{u}_0$ and for the structure with the damper fully locked $\mathbf{u}_\infty$, respectively. The linear combination can then be written as:

$$\mathbf{x} = \mathbf{u}_0 r_0 + \mathbf{u}_\infty r_\infty \tag{8}$$

The first term represents the classical undamped case, while the second term introduces the local effect of the damper described in terms of its ability to lock the structure at its location. The undamped mode shape is governed by the classical generalized eigenvalue problem

$$\left(\mathbf{K} - \omega_0^2 \mathbf{M} \right) \mathbf{u}_0 = \mathbf{0} \tag{9}$$

A similar eigenvalue problem exists for the case where the damper link is fully locked, defining ω_∞ and $\mathbf{u}_\infty$. The locked mode shape $\mathbf{u}_\infty$ is by construction orthogonal to the connectivity vector which yields the identity $\boldsymbol{\lambda}^T \mathbf{u}_\infty = 0$.

The two-component representation reduces the full dimensional problem to a two-dimensional problem, where the associated characteristic equation can be solved explicitly, providing expressions for the complex valued natural frequency and the corresponding modal damping ratio. Optimal calibration of the damper model is based on the maximization of the damping ratio. For the general damper format in (7) it is demonstrated in [14] that the optimal gain can be determined by the expression:

$$g_{opt} = \frac{1}{|H|} \frac{\left(\omega_\infty^2 - \omega_0^2 \right)}{u_0^2} \tag{10}$$

where u_0 is the amplitude of the undamped mode shape at damper location. This expression is in the following used to calibrate the control strategies.

3.1 Viscous damping strategy

The prototype damper model is the pure viscous model. For this model the damper force is directly proportional to the collocated velocity of the damper motion,

$$f = c\dot{x} \tag{11}$$

where c is the viscous parameter. When compared with the linear frequency representation of the damper force in Eq. 7, the damper transfer function for the viscous damper is

$$H(\omega) = i\omega \simeq i\omega_0 \tag{12}$$

while the gain value is

$$g = c \tag{13}$$

Substitution of (12) and (13) into (10) gives the following expression for the optimal viscous parameter:

$$c_{opt} \approx \frac{2(\omega_\infty - \omega_0)}{u_0^2} \tag{14}$$

where $\omega_\infty + \omega_0 \approx 2\omega_0$

The optimal viscous damper is without stiffness and is therefore a suitable benchmark example for damper models with negative stiffness.

3.2   Proposed Neural network based model reference control strategy

The proposed controller is developed based on a neural network model identification technique, where the neural network model is trained by a reference damper model. In this paper, the characteristics of the damper model are described by the desired shape of the hysteresis loop, which combines an amplitude dependent friction damper with a negative stiffness component. The optimal shape of this hysteresis loop has originally been identified and verified by Boston et al. [7]. The hysteresis loop is based on the assumption of pure harmonic displacement and velocity, which is used as the input to the proposed neural model, while the damper force based on the desired hysteresis loop is used as the output of the neural controller. The optimal shape of the force-displacement trajectory is shown in fig. 4.
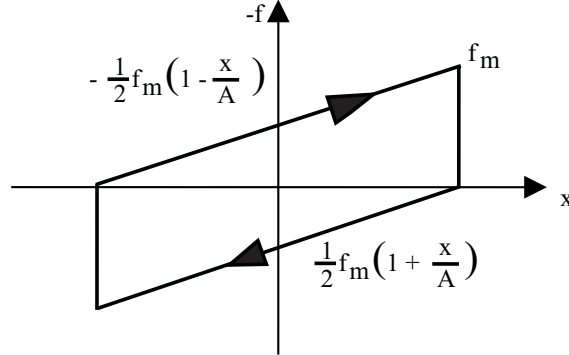

Figure 4: Force-Displacement Hysteresis model for Friction Damper with negative stiffness

The hysteresis model is inherently nonlinear, whereas the calibration formulation in (10) requires a linear damper model. Thus, an equivalent linear model is assumed to contain a viscous and a stiffness component,

$$f = c\dot{x} + kx \tag{15}$$

If x is a sinusoidal signal, the parameters of the linear equivalent model in (15) can be determined by equivalence over a full vibration period, see [14]. The yields the following equivalent linear model for the hysteresis loop in Fig. 4:

$$f = \frac{2f_m}{\pi \omega A}\dot{x} - \frac{f_m}{2A}x \tag{16}$$

where A is the amplitude of the damper displacement, k is negative stiffness and f_m is maximum force of the hysteresis loop. In frequency domain the model is expressed as

$$f = \frac{f_m}{A}\left(-\frac{1}{2} + i\frac{2}{\pi}\right)x \tag{17}$$

Comparison with the frequency representation in Eq. 7 gives the following expression for the transfer function of the linear equivalent hysteretic damper model:

$$H(\omega) = \left(-\frac{1}{2} + i\frac{2}{\pi} \right) \tag{18}$$

and the corresponding gain value:

$$g = \frac{f_m}{A} \tag{19}$$

From Eq.10 the optimal value of g is determined as

$$g_{opt} = 1.24 \frac{\left(\omega_\infty^2 - \omega_0^2 \right)}{u_0^2} \tag{20}$$

The optimal value f_m is determined as

$$f_m = g_{opt} A \tag{21}$$

where A is the amplitude of the displacement.

In this paper, a four-layer feed forward neural network is adopted which consists of one input, two hidden layers and a single output layer. The displacement and velocity with current state and five preceding values are taken as input and force at current state is output in the proposed neural network. The neural network controller is trained with training data generated at different amplitudes and at different frequencies of both the displacement response and the corresponding force data from the optimal friction model. The trained model is verified with independent data set and subsequently used in a closed loop implementation. The training algorithm used in the feed forward back propagation neural network is the Levenberg-Marquardt (LM) algorithm based on a least-square curve fitting.

4 NUMERICAL EXAMPLES

To evaluate the effectiveness of the proposed control strategy for the structural vibration mitigation with rotary MR damper, two numerical examples are considered. The first one is based on pure viscous damping strategy and the second one is our proposed neural network based model reference control (NN-MRC). Both the examples are discussed below

4.1 Viscous Damper

The viscous damping strategy using MR damper in closed loop is simulated for five storied shear frame structure with harmonic base excitation. The force-velocity and force-displacement hysteresis plots of the damper force and desired force from control law are compared for optimal viscous damping strategy and the result is quite satisfactory. The force tracking task by MR damper is quite well. From fig. 3, it is visible that MR damper has a force limit at zero current. For that reason it is not possible for MR damper to follow the desired force below the force limit at zero current. Here for this damper, force limit is 24 N.
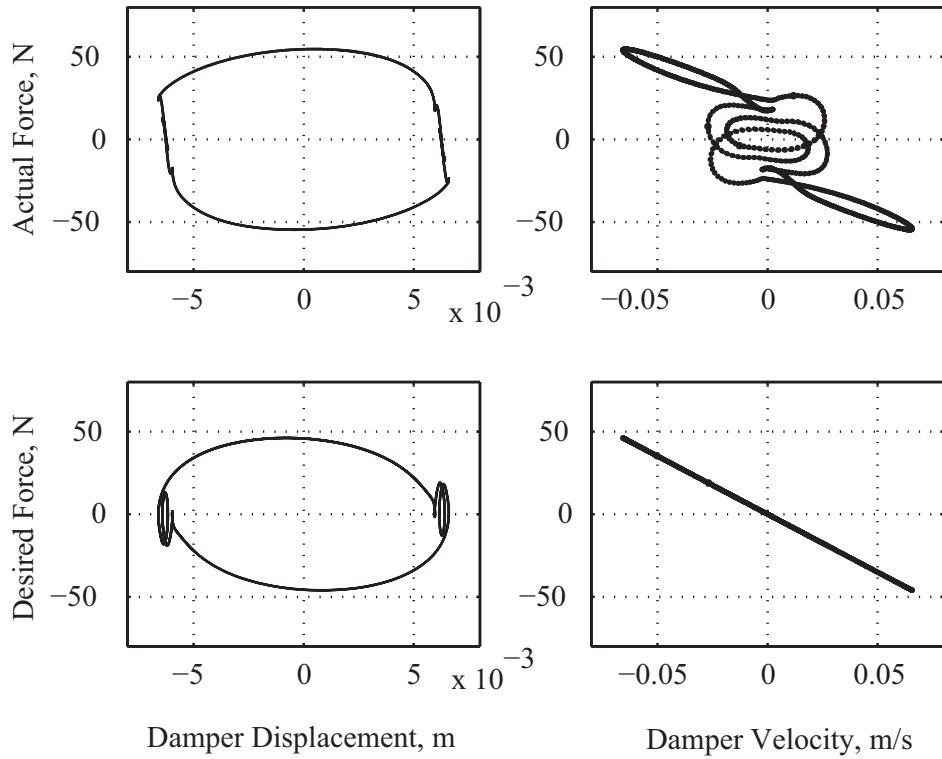
Figure 5: Force-Displacement and Force Velocity hysteresis diagram for viscous damper

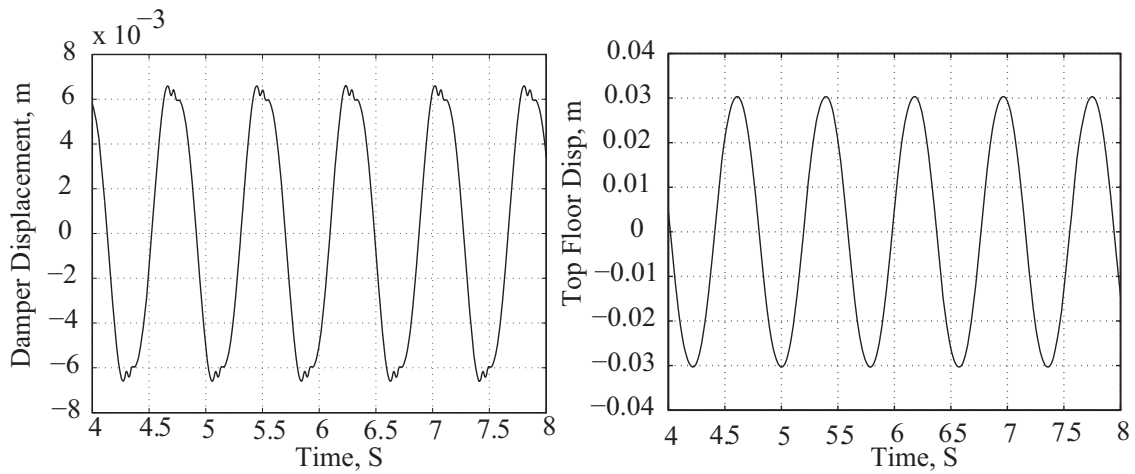The top floor displacement and damper displacement are shown in fig. 6.

Figure 6: Time history of damper and top floor displacement for viscous damper

The viscous damping strategy is also applied directly on structure without MR damper and compared the change in performance.

4.2   Model Reference Neural Controller

The proposed neural control strategy is applied for structural vibration reduction based on harmonic base excitation using MR damper in closed loop simulation. The Time history of damper displacement and top floor displacement are shown below.
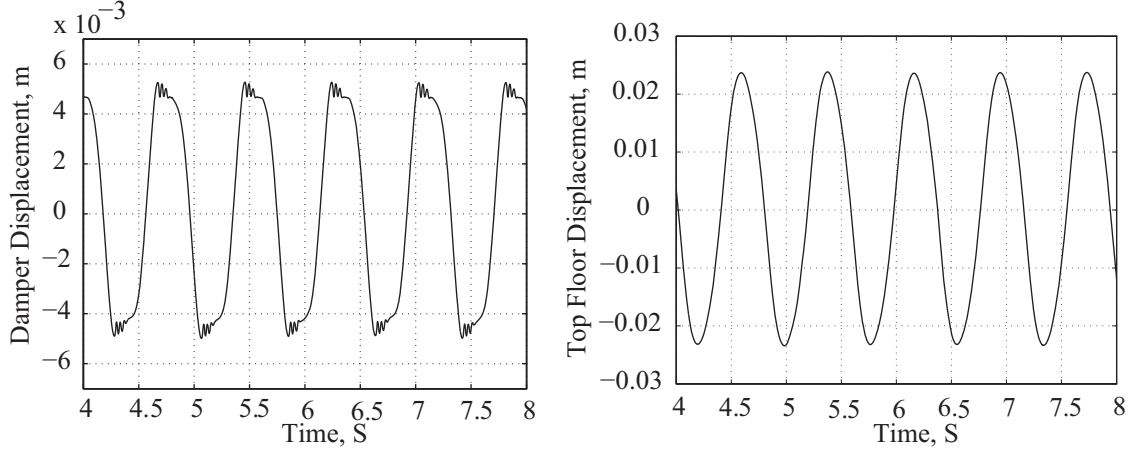

Figure 7: Force-Displacement and Force Velocity hysteresis diagram for neural controller

The hysteresis plots for force-displacement and force-velocity trajectories are shown in fig.8.
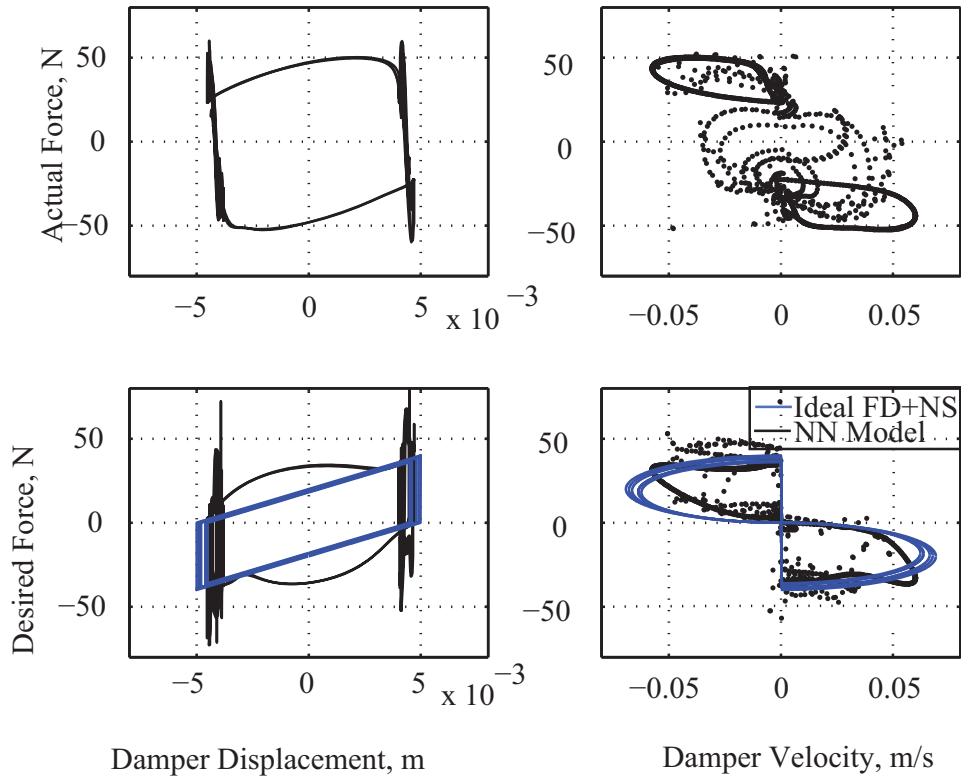

Figure 8: Time history of damper and top floor displacement for neural controller

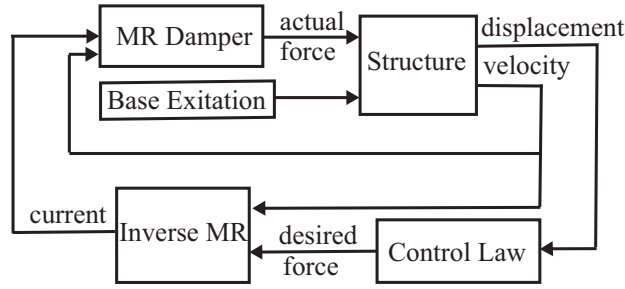The schematic diagram for the closed loop simulation is shown below

Figure 9: Schematic diagram for closed loop simulation

Force from an optimal friction damper with negative stiffness are calculated by analytical method and compared with the desired force prediction from neural network. Desired force from neural controller and the analytical force have some deviation because the slope of the desired force is not linear due to change in the motion of the damper. The damper displacement is slightly changed from pure sinusoidal due to some spiky effect in current output from inverse MR damper model. The current from inverse MR damper model is shown in fig. 10
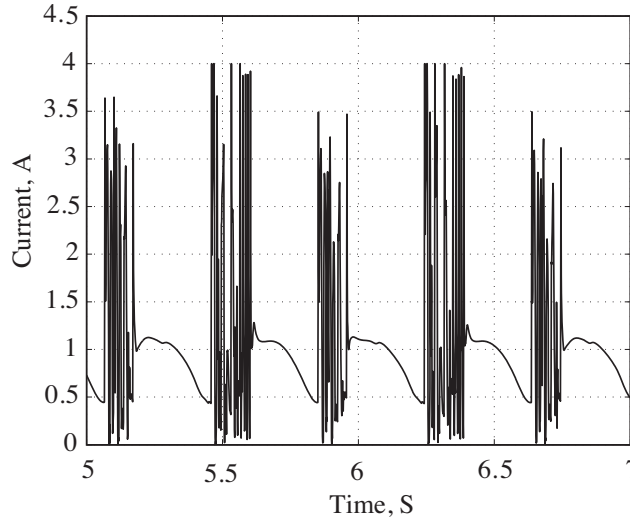

Figure 10: Time history of current from inverse MR model

The force-displacement and force-velocity diagram are shown in Fig. 8. The diagrams are quite satisfactory with compared with identical one. There is some deviation in the force prediction due to non-sinusoidal behaviour of the structural response. This is mainly due to some spiky current prediction by inverse MR model but overall the force tracking is quite satisfactory.

	Passive Viscous	Viscous with MR damper	NN-MRC
RMS(x_1^{max})	0.0091 m	0.0066 mm	0.0044 mm
RMS(x_5^{max})	0.036 m	0.030 m	0.024 m
RMS(a_1^{max})	0.64 m/s^2	0.81 m/s^2	0.80 m/s^2
RMS(a_5^{max})	2.02 m/s^2	1.81 m/s^2	1.76m/s^2

Table 1: Performance Parameters

5   CONCLUSIONS

In the closed loop simulation, two neural network models are used. One is for force tracking which is an inverse MR damper model and another is used for tracking reference damper model which is following hysteresis force-displacement behaviour for optimal friction damper with negative stiffness. RMS of the peak displacement and peak acceleration of each cycle for top floor and damper location are taken as performance parameters. From the performance parameters chart, it is clearly visible that proposed control method can reduce around 35% in damper displacement and 30% in top floor displacement. The damper displacement for viscous damping strategy with and without MR damper has deviation due to limitation MR damper force realization at zero current when MR damper is attached. The response of the top floor using semi active neural controller gives is quite satisfactory with compared to pure viscous damping. There is also significant improvement in acceleration term and but the acceleration contains some noise. The major advantage of the proposed controller is it is inherritently modeled with amplitude dependency and the inherent time-delay problem which is an important drawback of model based control can be solved in neural based control. In general, a neural network is trained under certain condition which can be used in a slightly modified but similar nature of the training state. The important feature of neural network is that it can handle nonlinearity so well that it can apply to nonlinear structural control also based on linearly trained neural model. This is the reason why neural network is used in this paper for structural control. The numerical study revealed that proposed neural based model reference controller can track the desired hysteresis behaviour of optimal friction damper with negative stiffness satisfactorily and the performance is better than optimal viscous damper.

ACKNOWLEDGEMENT

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