



## ESTIMATION OF INVERSE DYNAMIC BEHAVIOR OF MR DAMPERS USING ARTIFICIAL AND FUZZY-BASED NEURAL NETWORKS

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### ABSTRACT

In this paper the performance of Artificial Neural Networks (ANNs) and Adaptive Neuro-Fuzzy Inference Systems (ANFIS) in simulating the inverse dynamic behavior of Magneto-Rheological (MR) dampers is investigated. MR dampers are one of the most applicable methods in semi active control of seismic response of structures. Various mathematical models are introduced to simulate the dynamic behavior of MR dampers. The Modified Bouc-Wen model is an appropriate model that has an acceptable accuracy in calculating the generated force of dampers compared to others. In this model displacement and voltage of a MR damper are known while the force generated by MR damper is considered as the unknown. Because of highly nonlinear characteristics of modified bouc-wen model determination of inverse dynamic behavior of MR dampers are generally done using ANNs and ANFIS. Since the ANNs and ANFIS have different mechanisms for emulating desired functions, their responses may be different. In this research the performance of a Back Propagation Neural Network (BPNN), Radial Basis Functions Neural Network (RBFNN) and ANFIS in estimating the inverse dynamic behavior of MR dampers are compared. The results emphasize on the advancement of ANFIS to the other methods studied in estimation of inverse dynamic behavior of MR dampers.

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**KEY WORDS:** inverse dynamic behavior of mr damper; back propagation neural networks; radial basis function neural networks; ANFIS; modified bouc-wen model

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## 1. INTRODUCTION

Because of their wide dynamic range, low power requirement, large force capacity, and fast response rate to a variable control signal, magneto-rheological (MR) dampers have emerged as newly developed semi-active control devices that have been mass-produced for commercial applications [1].

MR dampers use MR fluids to produce controllable dampers. MR fluids typically consist of micron-sized, magnetically polarized particles dispersed in a carrier medium such as mineral or silicone oil. They are the magnetic analogs of electro rheological (ER) fluids, and like ER fluids, the essential characteristic of the MR fluids is their ability to reversibly change from a free-flowing, linear viscous fluid to a semi-solid in milliseconds when exposed to a magnetic field [2]. Owing to these attractive properties, MR dampers have got applications in a variety of areas such as vibration control of stay cables in cable stayed bridges[3], seismic protection of infrastructures [4, 2 and 5], vibration damping of automotive seats and suspensions of vehicles and trains [ 6 and 7].

In order to characterize the performance of MR dampers, several models have been proposed to describe their dynamic behaviors. These include the phenomenological model proposed by Spencer et al. [8] based on a Bouc–Wen hysteresis model, neural network model developed by Chang and Roschke [9], fuzzy model by Schurter and Roschke [10], nonlinear black box model by Jin et al. [11]and polynomial model by Choi et al. [12]. Among these MR models, it is found from the literature [8] that phenomenological model and viscoelastic–plastic model can accurately describe the dynamic behaviors of the MR dampers, but the corresponding models for the inverse dynamics of the MR dampers are often difficult to obtain due to their highly nonlinear characteristics. For this reason there are some analytical and numerical methods to obtain the appropriate input signal namely as voltage or current. Some of analytical models are the inverse Bingham, inverse Polynomial, inverse Bouc-Wen and inverse modified Bouc-Wen models [13]. In recent decade some of scientists became interested to use the artificial methods in this field. Xia has introduced an inverse model of the MR damper using multi-layer perception optimal neural network and system identification [14]. Du et al. [1]are offered an approach to approximate the forward and inverse dynamic behaviors of MR damper using evolving radial basis function (RBF) networks to obtain parameters of RBF Networkusing genetic algorithm. Karamodin and Kazemi [15] developed an inverse neural network model to replicate the inverse dynamics of the MR damper using multi-layer perception neural network. Askari et al. [16] proposed a Takagi-Sugenofuzzy inverse model of dampers, derived using subtractive clustering, non-dominated sorting genetic algorithm II (NSGAI) and adaptive neuro-fuzzy inference systems (ANFIS).

In section 2 of this article, the phenomenological Bouc-Wen model of MR dampers will be introduced. In section3, BP and RBF neural networks and ANFIS are expressed. The results of training and testing the networks are illustrated in Section 4. Section 5 represents the results of verification of trained network with a different input data. Finally section 6 outlines the comparison of the three networks.

## 2. PHENOMENOLOGICAL BOUC-WEN MODEL OF MR DAMPERS

As mentioned in previous section, there are some analytical models like Bingham viscoplastic, Gamota and Filisko, Bouc-Wen and Phenomenological Bouc-Wen models to determine MR produced force [8]. Phenomenological Bouc-Wen model of MR dampers has been proposed by Spencer et al. at 1997 that can effectively portray the behavior of a typical MR damper as shown in Figure 1.

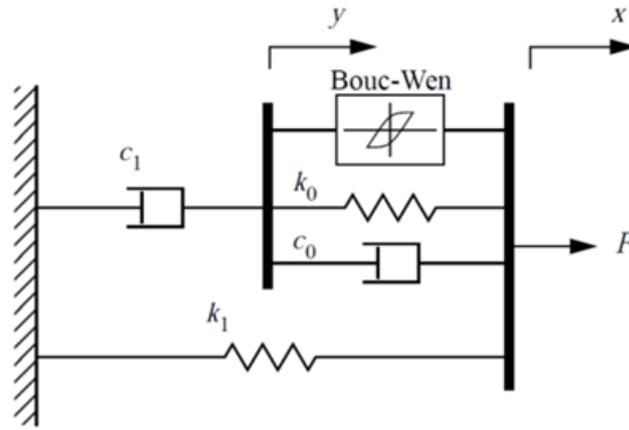


Figure 1. Phenomenological Bouc-Wen model of MR dampers [8]

This phenomenological model is based on a Bouc–Wen hysteresis model, which is tractable and is capable of representing a wide variety of hysteretic behaviors. The parameters for the model are shown in Table 1. They are determined from the experimental data with appropriate optimization method [8]. This model is validated in a variety of representative experimental tests. The verification results indicate that the phenomenological model of an MR damper is accurate over a wide range of operating conditions and is appropriate for control design and analysis. The phenomenological model is governed by the following equations:

$$F = c_1 \dot{y} + k_1(x - x_0) \quad (1)$$

$$\dot{y} = \frac{1}{(c_0 + c_1)} [\alpha z + c_0 \dot{x} + k_0(x - y)] \quad (2)$$

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

$$\alpha = \alpha_a + \alpha_b u \quad (4)$$

$$c_1 = c_{1a} + c_{1b} u \quad (5)$$

$$c_0 = c_{0a} + c_{0b} u \quad (6)$$

$$\dot{u} = -\eta(u - v) \quad (7)$$

According to the flowchart in Figure, having prescribed the patterns of displacement  $x$  and voltage  $v$ , the force  $f$  of the prototype damper will be obtained.

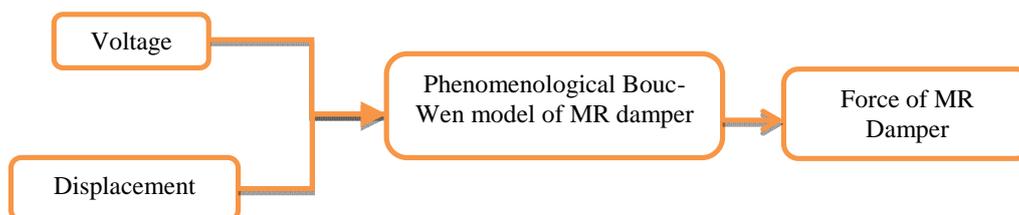


Figure 1. Flowchart of data acquisition process

Table 1. Parameter values of MR damper model [8]

Parameters	Unit	Value	Parameter	Unit	Value
$c_{0a}$	N.s/cm	21.0	$\alpha_a$	N/cm	140
$c_{0b}$	N.s/cm.V	3.50	$\alpha_b$	N/cm.V	695
$k_0$	N/cm	46.90	$\gamma$	cm <sup>-2</sup>	363
$c_{1a}$	N.s/cm	283	$\beta$	cm <sup>-2</sup>	363
$c_{1b}$	N.s/cm.V	2.95	A		301
$k_1$	N/cm	5.00	n		2
$x_0$	cm	14.30	$\eta$	s <sup>-1</sup>	190

### 3. INVERSE DYNAMIC MODEL OF MR DAMPERS USING ARTIFICIAL NETWORKS

The MR damper model discussed earlier in this paper estimates damper forces based on the inputs of displacement and voltage using Eqs.1-7. The damper displacement is the same as the displacement of the floor to which the damper is connected. Thus, the voltage signal is the only parameter that can be modified to control the damper force to produce the required control force. Therefore, it is essential to develop an inverse dynamic model that predicts the corresponding control voltage to be sent to the damper, so that an appropriate damper force can be generated. On the other hand, because of the highly nonlinear nature of the MR damper, a mathematical model for its inverse dynamics is difficult to obtain. Thus, in this paper using artificial networks, inverse dynamic emulators of MR dampers are generated and compared.

### 4. ARTIFICIAL NEURAL NETWORKS

#### 4.1. Back propagation neural networks

BPNN is usually based on the error back propagation to the multi-layer neural network. It was designated by Rumelhart and McClelland and their research team in 1986. Transfer function of BPNN usually uses Sigmoid function. It lays between the input and output arbitrary nonlinear mapping. This makes it a more extensively applicable to function approximation [17], pattern recognition, data compression field. BPNN is usually based on BP neurons in the multi-forward neural network structure [18]. Typical BPNN network structure is shown in Figure .

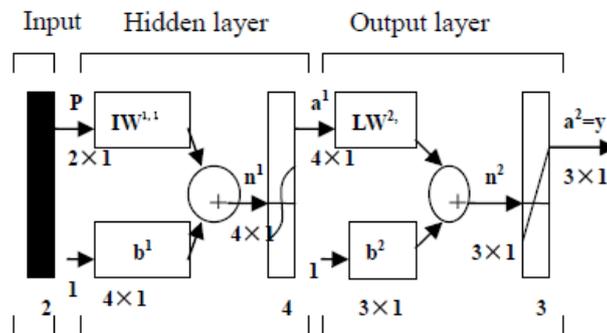


Figure 3. Back Propagation Neural Network [18]

In BPNN, synaptic weights are the only type of parameters and can be updated by learning algorithms. Based on error back propagation procedure, various gradient algorithms are developed for traditional neural network. First order gradient methods are stable, but very time consuming, and usually fail to converge to very small errors. Training speed and accuracy are significantly improved by applying second order gradient methods, such as Levenberg- Marquardt (LM) algorithm [19]. Table 2, shows the parameters of BPNN used in this study.

Table 2. BPNN Properties

training algorithm	Input Layer		Hidden Layer		Output Layer		Max Epoch
	Number of Inputs	Number of Layer	Neurons	Activation function	Number of Output	Activation function	
LM	5	1	60	tansig	1	purelin	1000

#### 4.2. Radial basis function neural networks

Generally, a RBFNN consists of three layers: the input layer, the RBF layer so called as the hidden layer and the output layer. The inputs of hidden layer are the linear combinations of

scalar weights and the input vector  $X = [x_1, x_2, \dots, x_n]^T$ , where the scalar weights are usually assigned to unity. Thus the whole input vector appears to each neuron in the hidden layer. The incoming vectors are mapping by the radial basis functions in each hidden node. The output layer yields to a vector  $Y = [y_1, y_2, \dots, y_m]$  for  $m$  outputs by linear combination of the outputs of the hidden nodes to produce the final output. Typical RBFNN structure is shown in Figure.

A radial basis function is a multidimensional function that describes the distance between a given input vector and a pre-defined center vector. There are different types of radial basis functions. However in RBFNN, usually a normalized Gaussian function is used as the radial basis function. Table 3, shows the parameters of RBFNN used in this study.

Table 3. RBFNN Properties

Input Layer		Hidden Layer		Output Layer	
Number of Inputs	Number of Layers	Max Neurons	Activation function	Number of Outputs	Activation function
5	1	60	Gaussian	1	purelin

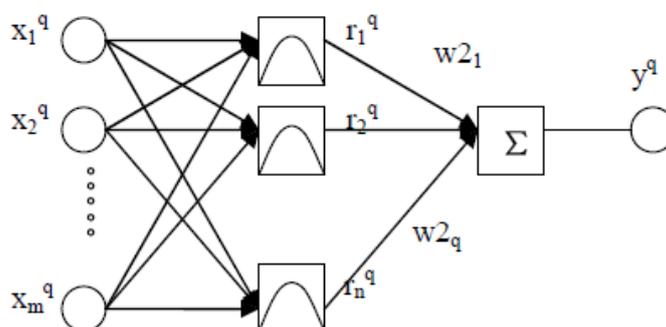


Figure 4. Radial Basis Function Neural Network [18]

## 5. ADAPTIVE NEURO FUZZY INFERENCE SYSTEM

ANFIS is a hybrid intelligent system introduced by Jang at 1993 [20], and has the ability of Fuzzy Logic (FL) to reason with neural network to learn. The goal of ANFIS is to find a model which will simulate correctly the inputs with corresponding outputs. The Fuzzy Inference System (FIS) is a knowledge representation where each fuzzy rule describes a local behavior of the system. ANFIS is the network structure that implements FIS and employs hybrid-learning rules to train. Figure(a), illustrates the reasoning mechanism for this Sugeno model. The corresponding equivalent ANFIS architecture is shown in Figure(b), where the nodes of the same layer have similar functions [21].

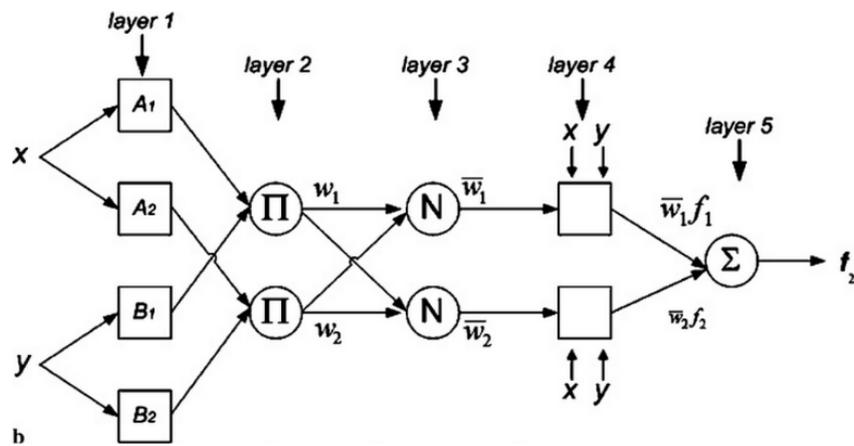
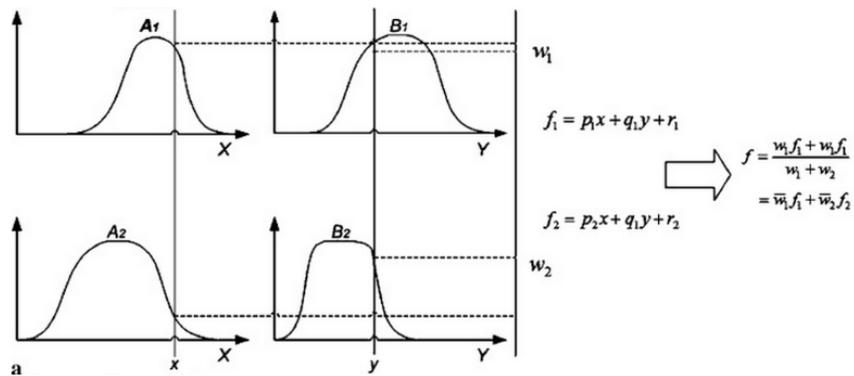


Figure 5. Adaptive Neuro-Fuzzy Inference System (ANFIS) [21]

### 6. DATA COLLECTION

In this paper the network models are trained using input-output data, generated analytically using the simulated MR model based on Eqs. 1-7. According to Figure 6, the networks calculate the voltage signal ( $V_{(t)}$ ) based on the current and previous history of measured displacement ( $x_{(t)}, x_{(t-1)}$ ) and desirable control force ( $F_{(t)}, F_{(t-1)}$ ). To insure creation of a valid model, data used for training must thoroughly cover the spectrum of operation in which the damper will function. For this reason, the training data contains displacements that range from  $\pm 10$  cm and whose frequency content ranges from approximately 0–3 Hz. Ranges of voltage signal and frequency are 0–10 volts and 0–3 Hz respectively. Signals used for training are produced using band-limited, Gaussian white-noise. Using these inputs, MR damper model was solved for 8 seconds, during which the corresponding damper force where determined. A time step of 0.002 seconds is used to produce a total of 4000 sets of data. Figure shows time histories of displacement, voltage, and damper force. Data for voltage was bounded below zero for all time to avoid use of negative voltages.

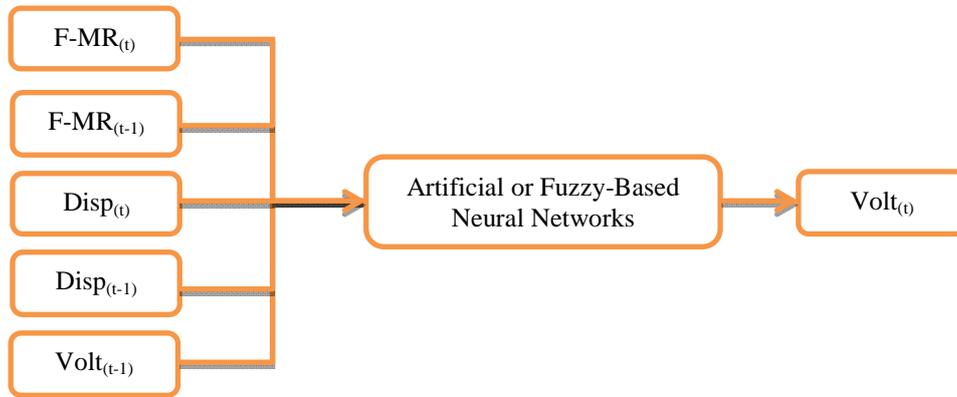


Figure 6. Flowchart of Inverse dynamic behavior of MR damper using networks

The networks were trained using only 35%, the results of which were illustrated in Figure 7. The remaining 65% of data were used as testing sets. Due to the random behavior of artificial networks, to study the reliability of the trained networks, and also to compare the validity of different models based on either of the types ANFIS, RBFNN or BPNN, all training and testing sets were selected randomly for 10 times. The performance criteria for the networks were compared, where Mean squared error (MSE) and performance factor ( $E_v$ ) are used as performance criteria. Performance factor ( $E_v$ ) has been calculated using Eq. 8 as follows:

$$E_v = \sqrt{\sum_{i=1}^N [v_d(i) - v_p(i)]^2} / \sqrt{\sum_{i=1}^N [v_d(i) - \text{mean}(v_d)]^2} \quad (8)$$

where  $v_d$ ,  $v_p$  and  $N$  are desired Voltage, predicted voltage and number of data respectively.

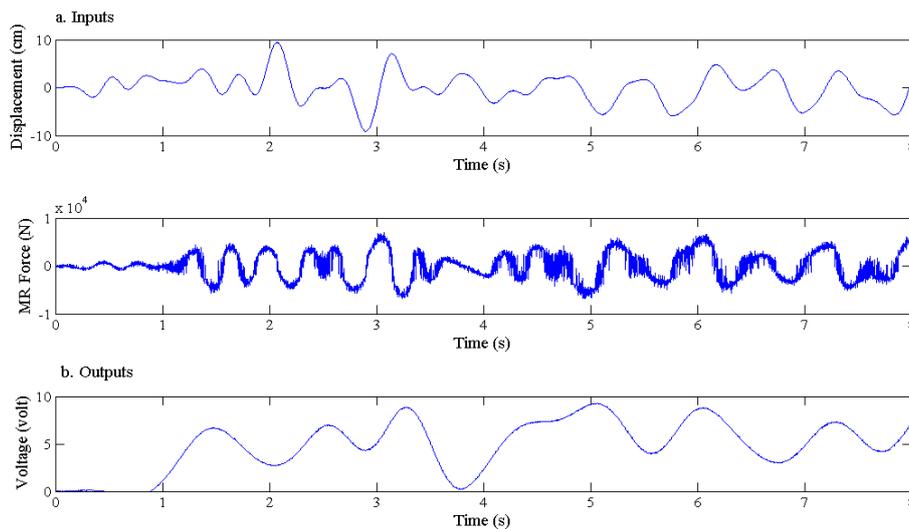


Figure 3. History of input and output data for training and testing the networks

### 7. RESULTS AND DISCUSSION

The desired voltage shown in Figure 7(b), was compared with the predicted voltages using the aforementioned three networks. They were then plotted in Figure. A performance comparison of the networks was shown in Figure 2-12. As one depicts, the BPNN has best performance in training process compared to other networks. However, in testing process the BPNN exhibits the worst prediction comparatively. This phenomenon is originated from overtraining or over fitting of BPNN.

ANFIS did not reveal good performance in training process whereas it displayed the best prediction with testing samples. This could originate from using fuzzy logic and neural network simultaneously.

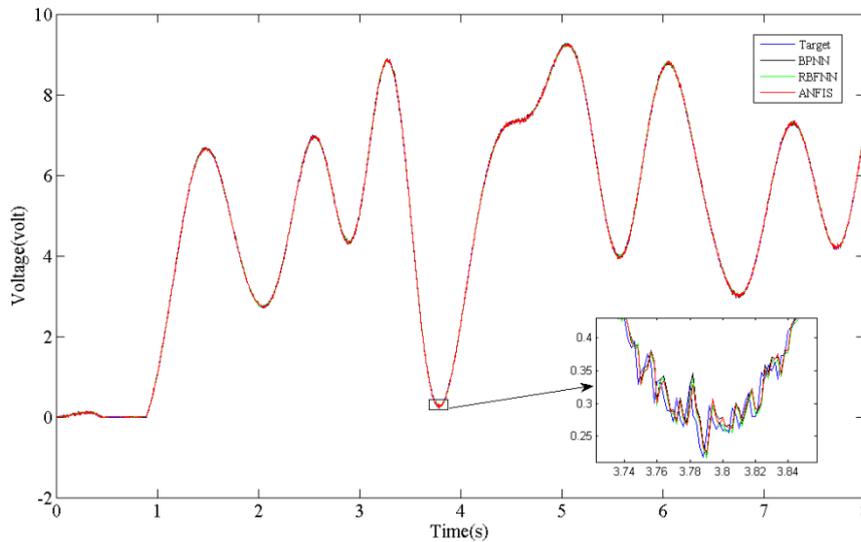
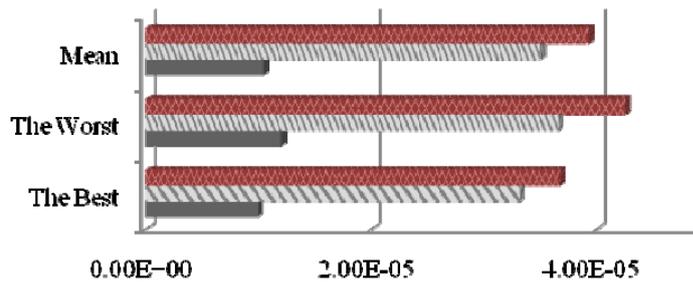


Figure 4. Comparison of Target Voltage and Predicted ones using Networks



	The Best	The Worst	Mean
■ ANFIS	3.67E-05	4.26E-05	3.93E-05
▨ RBFNN	3.32E-05	3.66E-05	3.51E-05
■ BPNN	9.94E-06	1.20E-05	1.04E-05

Figure 2. Comparison of MSE criterion in training process of networks

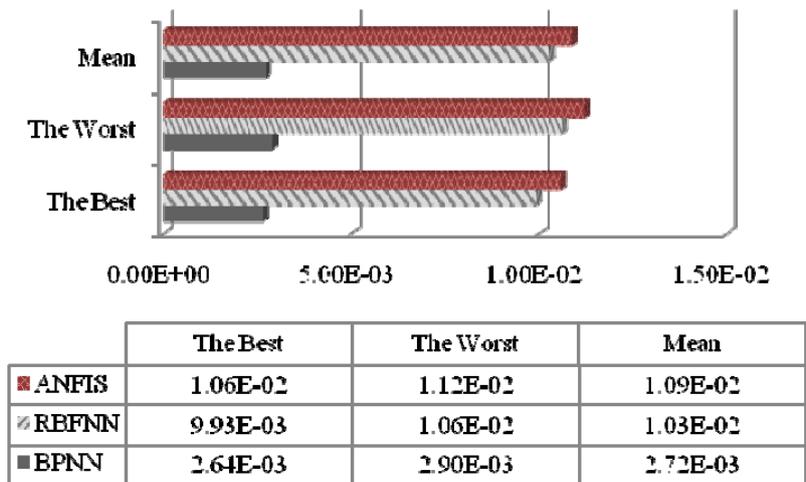


Figure 3. Comparison of the performance factor ( $E_v$ ) in training process of networks

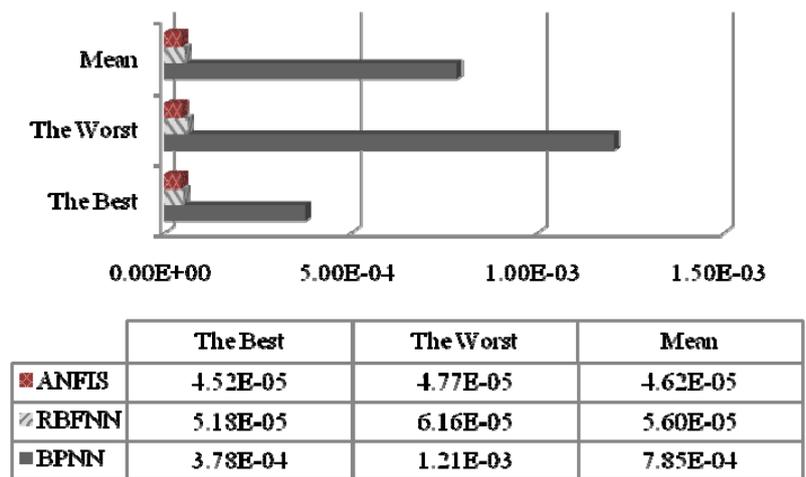


Figure 4. Comparison of the MSE criterion in testing process of networks

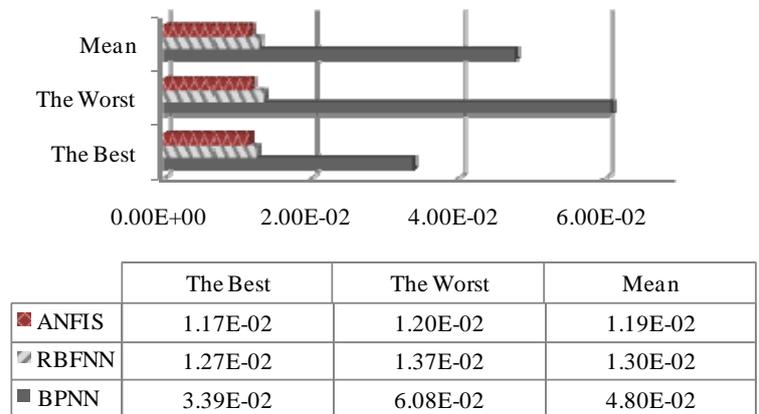


Figure 8. Comparison of the performance factor ( $E_v$ ) in testing process of networks

## 8. CONCLUSION

In structural control, optimal control force which suppresses the excitation of buildings, must be generated by a control device. In this paper MR damper as a reliable device in semi active control of structures has been used to generate the optimal control force to dissipate the excitation of structures. MR dampers work with input voltages and displacements to produce control forces. Considering the fact that inverse dynamic behavior of MR dampers is highly nonlinear, their modeling development could therefore be so difficult. In the present study, an inverse model of MR dampers has been proposed using Back Propagation Neural Network (BPNN), Radial Basis Function Neural Network (RBFNN) and Adaptive Neuro-Fuzzy Inference System (ANFIS) and their performances have been compared. In these networks the current and previous history of forces and displacements are considered as input while the voltages of MR damper is considered as the output. The networks have been trained and tested 10 times and the best, the worst and average of results are determined. Maximum differences of all runs did not exceed a fraction of a digit value, ensuring the reliability of the programs developed. Among the three types of neural networks developed and investigated, the BPNN presented the lowest errors in training process but lagged on the accuracy during testing process comparatively. This may be due to the overtraining phenomenon of BPNN. ANFIS however, performed the best prediction performance in testing process. RBFNN results similarly were satisfactorily close to those of ANFIS. Since in inverse dynamic behavior of MR dampers accuracy is of major concern, this paper may suggest utilization of ANFIS or RBFNN as emulator of inverse dynamic behavior of MR dampers.

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