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NON-PARAMETRIC MODEL FOR EMULATING
MAGNETORHEOLOGICAL DAMPER BEHAVIOR

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ABSTRACT

The magnetorheological damper allows variable control of energy dissipation in a simple design. Rapid response time and efficient power requirements make the device one of the most effective means possible for interfacing mechanical components with electrical controls. These properties are due to the MR fluids ability to change from a free-flowing liquid to a semisolid in milliseconds when exposed to a magnetic field, and instantly back to a liquid when the field is removed. But highly nonlinear dynamic behavior is a significant challenge for applying to a control system. Research by others has shown that a system of nonlinear differential equations can successfully be used to describe the behavior of a MR damper. The paper presents a neuro fuzzy model for 0.3 ton MR-damper using Adaptive Neuro-Fuzzy Inference system (ANFIS). The results show that the neuro fuzzy model can predict   the force of the damper for different excitation amplitudes and frequencies

KEY WORDS

Magnetorheological Damper-ANFIS.

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INTRODUCTION

In recent years applications of Magnetorheological (MR) dampers have been reported in various areas such as vehicle suspensions, seismic protection of buildings during earthquakes, semi-active control of sagged cables and engine mounts or fluid power systems. MR dampers are relatively inexpensive to manufacture because the fluid properties are not sensitive to contaminants. Other attractive features include their small power requirements, reliability, and stability. Requiring only 20–50 watts of power, these devices can operate with a battery, eliminating the need for a large power source or generator. Because the device forces are adjusted by varying the strength of the magnetic field, no mechanical valves are required, making a highly reliable device [1].

MR dampers use MR fluids to produce controllable dampers. MR fluids are suspensions of micron-sized magnetically soft particles in synthetic oil. When no current is applied to the damper, the fluid is not magnetized and the particles exhibit a random pattern. In the magnetized state, the applied magnetic field aligns the metal particles into fibrous structures, changing the fluid rheology to a near plastic state [2]. By tuning, the current supplied to the electromagnetic circuit of the damper, a variation of the magnetic field is obtained that allows for any level between the low forces in the "off" state to the high forces in the "on" state.

There are three main types of MR dampers which are different in the mechanical arrangement; the mono tube, the twin tube, and the double-ended MR damper. The mono tube has only one reservoir for the MR fluid and an accumulator mechanism to accommodate the change in volume that results from piston rod movement (Fig.1.a). The twin tube MR damper has two fluid reservoirs, one inside of the other and an inner and outer housing. The volume enclosed by the inner housing is referred to as the inner reservoir. Likewise the volume in the space between inner and outer housing is referred to as the outer reservoir as shown in Fig. 1.b. The third type of MR damper is called a double-ended damper since a piston rod of equal diameter protrudes from both ends of the damper housing (Fig.1.c). Hence there is no change in volume as the piston rod moves relative to the damper body [3].

Due to the highly nonlinear dynamic response of the MR dampers, seven simultaneous differential equations consists of 14 parameters are required to characterize the proposed model. However, more computational requirements are needed to obtain an exact solution. It is impractical to use an actual real time control situation. To deal with this problem in control situation, another model called nonparametric model can be used. Examples of Non parametric models are neural networks, fuzzy logic, neuro-fuzzy and polynomial models.

Yan and Zhou [4] proposed two Neuro-Fuzzy (NF) models. The first one, capable of predicting the damper force when voltage is known, is referred to as the forward model. The other proposed model was designed to predict the voltage, when the damper force is known. It is referred to as the inverse model. Wang and Liao [5] have also proposed a neural-network based model for direct identification of MR dampers. Their model consists of a recurrent neural-network in which the output is delayed and fed back to the input layer. The selected training method was the Levenberg- Marquardt algorithm and the training data was once again obtained with the use of the phenomenological model developed by Spencer Jr. et al. [6, 7]. The results show that the predicted damping force reasonably approximates the target data. The present work also includes an inverse

model of the damper, where the output is the command voltage. However, as mentioned by the authors, this is still a preliminary work and further research is still required before practical applications.

All previous works [8-13], in NF models obtained the training data from very clean displacement (no noise), which is hardly achieved in practice.

The objective of this paper is to construct a NF model for an MR-damper using ANFIS based on the improvement of the mathematical model to deal with noisy data.

CONSTRUCTION OF MR DAMPER

MR damper consists of a cylinder houses the piston, the magnetic circuit, an accumulator and MR fluid. The MR fluids are manufactured by suspending ferromagnetic particles in a carrier fluid. The ferromagnetic particles are often carbonyl particles, since they are relatively inexpensive. Other particles, such as iron-cobalt or iron-nickel alloys, have been used to achieve higher yield stresses from the fluid [14]. Fluids containing these alloys are impractical for most applications due to the high cost of the cobalt or nickel alloys (Fig.2).

A wide range of carrier fluids such as silicone oil, kerosene, and synthetic oil can be used for MR fluids. The carrier fluid must be chosen carefully to accommodate the high temperatures to which the fluid can be subjected. The carrier fluid must be compatible with the specific application without suffering irreversible and unwanted property changes. The MR fluid must also contain additives to prevent the sedimentation of and promote the dispersion of the ferromagnetic particles.

A top-level functional representation of the MR damper is shown in Fig. 3. The fluid transferred from above the piston to below (and vice-versa), must pass through the MR valve. Using an electromagnet, the MR valve is a fixed-size orifice with the ability to apply a magnetic field to the orifice volume. This results in an apparent change in viscosity of the MR fluid, causing a pressure differential for the flow of fluid which is directly proportional to the force required to move the damper rod.

The accumulator is a pressurized volume of gas that is physically separated from the MR fluid by a floating piston or bladder. The accumulator serves two purposes. The first is to provide a volume for the MR fluid to occupy when the shaft is inserted into the damper cylinder. The second is to provide a pressure offset so that the low pressure side of the MR valve is not reduced enough to cause cavitations of the MR fluid.

MODEL ANALYSIS OF MR-DAMPER

Adequate modeling of the control devices is essential for the accurate prediction of the behavior of the controlled system. Both parametric and non-parametric models have been developed to portray the observed behavior of MR-dampers. The parametric model consists of mechanical elements such as springs and dashpots to emulate the device behavior Fig. 4. The modified Bouc-Wen model was developed and shown to accurately predict the behavior of a shear mode [15].

Governing Equations

The equation governing the damping force (F) predicted by the device is:

$$F = c_1 \dot{y} + k_1 (x - x_o)$$

(1)

where

c_1: the viscous damping for force roll-off at low velocities.
k_1: the accumulator stiffness.
x : the relative displacement.
x_o : the initial deflection of the accumulator gas spring.

The internal displacement of the damper y and the evolutionary variable z are governed by the following equations [6]:

$$\dot{y} = \frac{1}{c_o + c_1} \{\alpha z + c_o \dot{x} + k_o (x - y)\}$$

(2)

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

(3)

where
c_o : the viscous damping at large velocities.
k_o: the viscous damping for force roll-off at low velocities.
$\dot{x}$: the piston velocity.
α: the Bouc-Wen parameter describing the MR fluid yield stress.
n: constant.

The adjustment of hysteresis parameters $\gamma, \beta, and\ A$ determines the linearity in the unloading region as well as the transition smoothness from pre-yield to post-yield region.

The parameters $\gamma, \beta, A, n, and\ k_1$ are considered fixed and parameters $c_o, c_1\ and\ \alpha$ are assumed to be functions of the applied voltage u.

$$c_0 = c_{oa} + c_{ob} u$$

(4)

$$c_1 = c_{1a} + c_{1b} u$$

(5)

$$\alpha = \alpha_a + \alpha_b u$$

(6)

If u_c is the applied voltage, then the dynamics involved in the MR fluid reaching rheological equilibrium is modeled by the first order filter:

$$\dot{u} = \eta(u - u_c)$$

(7)

where η is the time constant.

Dynamics of MR-Damper

In general, most modeling or parameter identification work on MR dampers adopts the numerical optimization approach and assumes that the experimental data are collected without noise corruptions, which is hardly achieved in practice.

Shirley J. D. [16] was observed that the response of the model is dominated by the input velocity and is extremely sensitive to change in velocity. This property causes the model to behave erratically when there is a sudden change in the velocity, which is the case when the velocity is evaluated numerically from the noise displacement. Then, a Low Pass Filter (LPF) is added to the MR-damper model in order to improve the ability of the model to deal with noisy displacement data.

The dynamics of the MR damper with LPF becomes:

$$\dot{y} = \frac{1}{c_o + c_1}\{\alpha\, z + c_o v + k_o(x - y)\} \tag{8}$$

$$\dot{z} = -\gamma|v - \dot{y}|z|z|^{n-1} - \beta(v - \dot{y})|z|^n + A(v - \dot{y}) \tag{9}$$

$$\dot{w} = A_f w + B_f \dot{x}$$
$$v = C_f w \tag{10}$$

where

$$A_f = \begin{bmatrix} 0 & 1 \\ -\omega_c^2 & -\sqrt{2}\omega_c \end{bmatrix} \qquad B_f = \begin{bmatrix} 0 \\ 1 \end{bmatrix} \qquad C_f = \begin{bmatrix} \omega_c^2 & 0 \end{bmatrix}$$

A_f, B_f and C_f are system matrices of LPF, w is the state of the filter and v is the filtered velocity, ω_c is the cut off frequency.

The 14 parameters α_a, α_b, c_{oa}, c_{ob}, k_o, c_{1a}, c_{1b}, k_1, x_o, γ, β, A, n and η which characteristic the MR damper are given in Table 1.

Neuro-Fuzzy Modeling

NF model is a non parametric model for emulating MR damper's behavior. It is faster than the mathematical model with keeping the error relatively small. The Neuro-Fuzzy is an application of ANFIS. ANFIS is a toolbox in MATLAB fuzzy logic used to determine the parameters required for the modeling of the damper. ANFIS uses a learning algorithm that combines the back-propagation gradient descent and the least square methods [17, 18].

The NF model can be obtained by the following three steps. First generate the training and checking data from mathematical model (equations 1, 4:6, 8:10). Second use ANFIS to train the NF model that relates displacement, velocity, and voltage signals as inputs and the force as the output of the MR damper. Finally validate the new model through comparison of its output to the output of the target model, given identical inputs.

Data used for training must thoroughly cover the spectrum of operation in which the damper will function. For 0.3 ton MR damper used in semi active controlled seat in large vehicles, the training data contains displacements that range from ±4 cm and whose frequency content ranges from approximately 0–3 Hz. Likewise, ranges of the voltage signal and frequency are 0–4 volts and 0–3 Hz, respectively. Signals used for training are produced using Gaussian white-noise.

RESULTS AND DISCUSSION

The theoretical response of the MR-damper due to a 1.5 Hz sinusoidal motion with amplitude of 1.5 cm is shown in Fig.5, for four constant voltage levels, 0 V, 0.5 V, 1.5 V and 2.5 V. As one can see from Fig.5 (a, b, c), in the range of small velocities the force variation displays an important hysteretic behavior, while for larger velocities the force varies almost linearly with the velocity. These two distinct rheological regions over which dampers operate are known as the pre-yield and the post-yield regions.

The displacement and force history with time are shown in Fig.6 (a, b), when white noise is added to sinusoidal displacement with 2.5 cm amplitude and 2.5 Hz frequency. It can be seen that the desired hysteretic behavior is destroyed by the noise inside displacement signals. When LPF is added the desired hysteretic behavior of MR damper is retained Fig.7.

Accuracy of the trained fuzzy model needs to be validated by comparing its behavior graphically and theoretically. Validation is done by input sinusoidal and random displacement with different values of amplitude and frequency for passive off (no voltage), passive on (maximum voltage) and random voltage. Figures 8-10 show the comparison between forces obtained from both the mathematical and present fuzzy model .

Results indicate that the NF model of the MR damper can predict the theoretical behavior of the MR damper with a high degree of accuracy.

CONCLUSIONS

MR dampers are versatile devices that can be used in many applications. The highly nonlinear dynamic nature of this device, however, has proven to be a significant challenge for researchers who wish to characterize its behavior. The paper presents an alternative method for modeling MR damper in the form of a neuro fuzzy inference system. ANFIS was used to determine the membership function that describes the behavior of the 0.3 ton model MR damper. Data used for training of the model was generated from numerical simulation of nonlinear differential equations. The NF model is shown to accurately describe the MR damper behavior while greatly reducing computational requirements and to be 10^3 faster than mathematical model. The NF model is more appropriate for control purposes due to its numerical simplicity.

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TABLE AND FIGURES

Table .1 Parameters for 20 ton MR-Damper

Parameter	Value	Parameter	Value
c_{0a}	21.0 N.sec/cm	α_a	140 N/cm
c_{0b}	3.50 N.sec/cm.V	α_b	695 N.sec/cm.V
k_o	46.9 N/cm	β	363 cm^{-2}
c_{1a}	283 N.sec/cm	β	363 cm^{-2}
c_{1b}	2.95 N.sec/cm.V	A	301
k_1	5.00 N/cm	n	2
x_0	14.3 cm	η	190 sec^{-1}
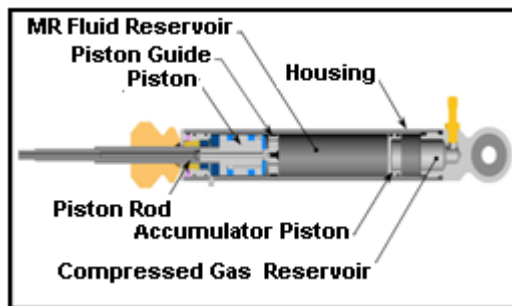
Fig .1.a Monotube MR Damper
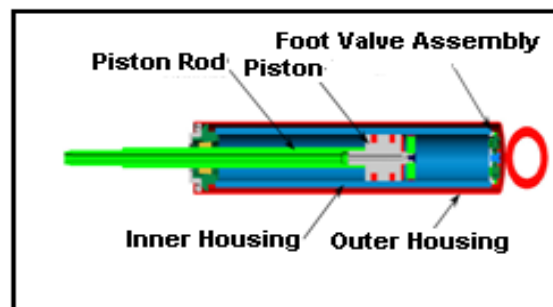
Fig .1.b Twin Tube MR Damper
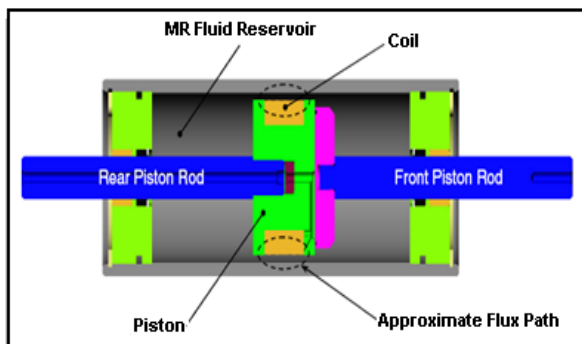
Fig .1.c Double Ended MR Damper
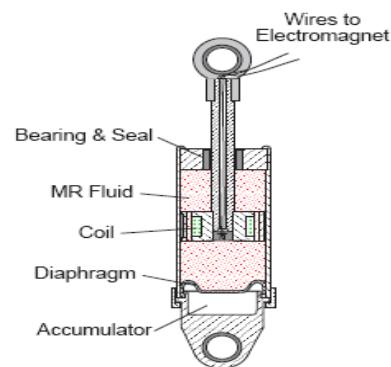
Fig .2 MR Damper
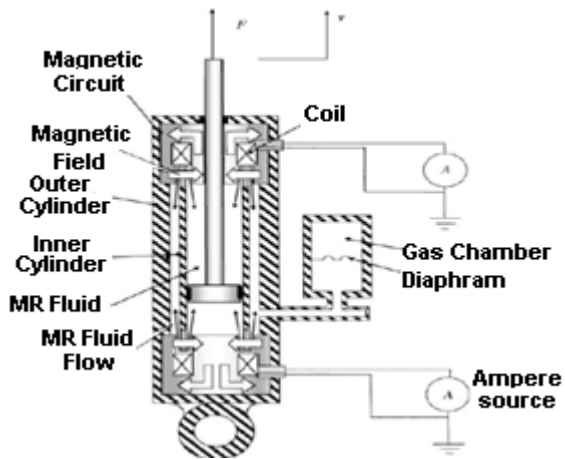
Fig .3. Functional of MR Damper.
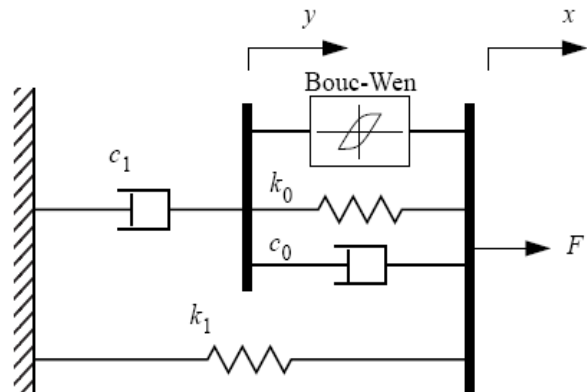
Fig .4.Modified Bouc-Wen Model
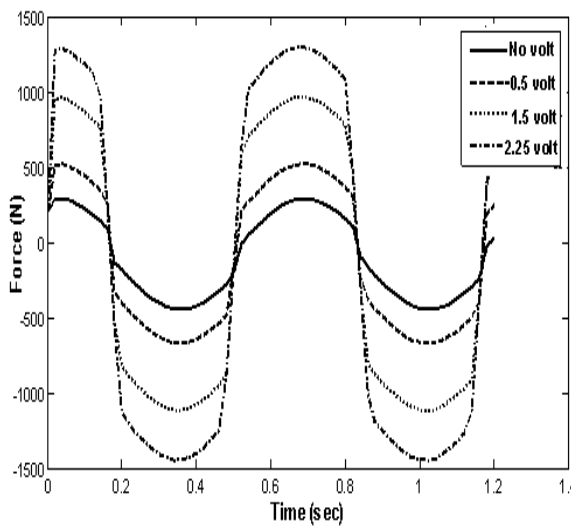
Fig .5.a Force Time at Different Voltage Values
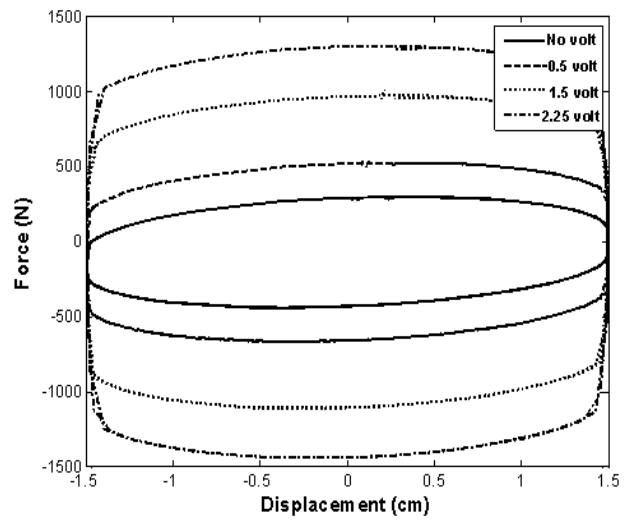
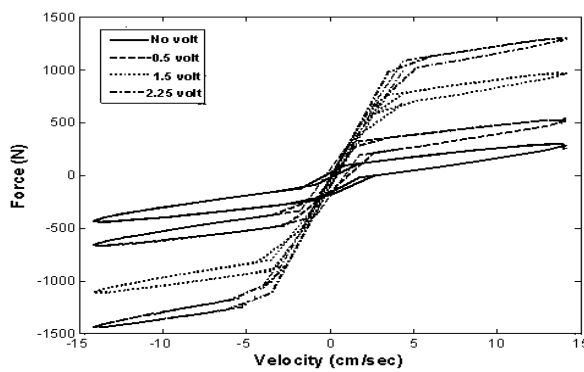Fig .5.b Force Displacement at Different Voltage Values

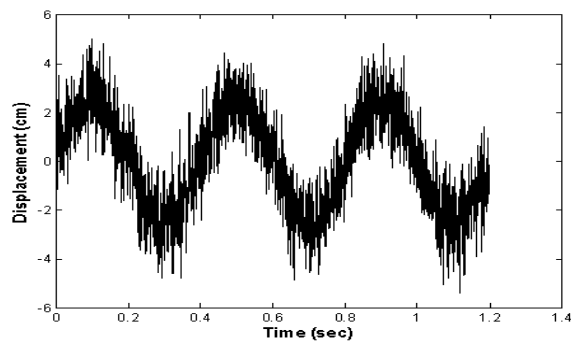Fig.5.c Force Velocity at Different Voltage Value
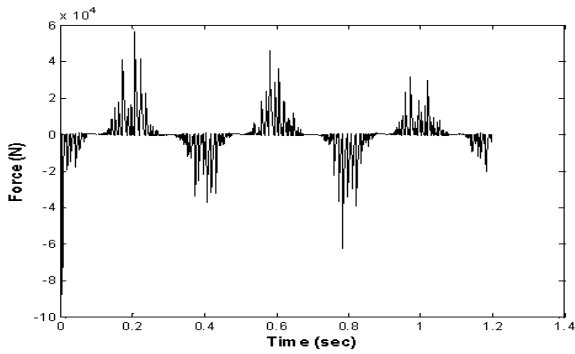

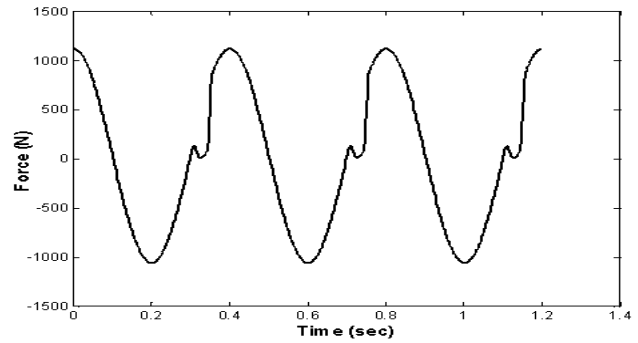Fig.6.a Noisy Displacement

Fig.6.b MR Force due to Noisy Displacement
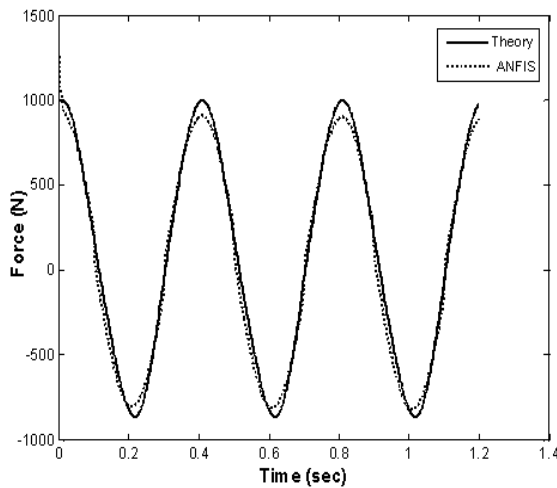

Fig.7. MR Force Obtained by Improved Model

Fig.8.Comparison between Force Predicted by NF Model and Force from Mathematical Model for 2.5 sin(5πt) and v=0
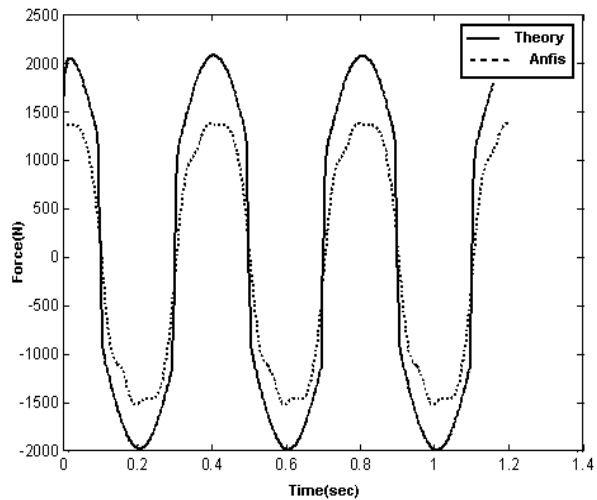

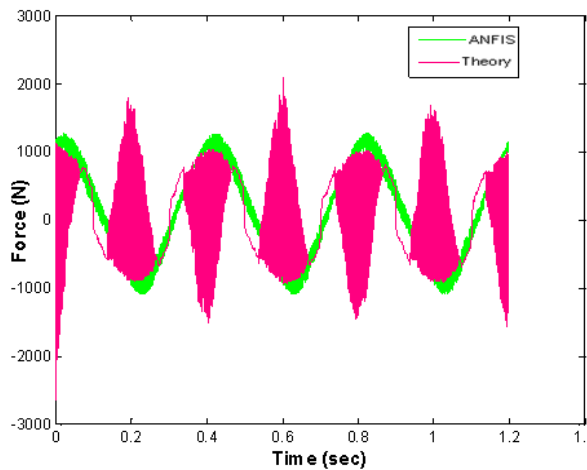Fig.9. Comparison between Force Predicted by NF Model and Force from Mathematical Model for 2.5 sin(5πt) and =2.25 v

Fig.10. Comparison between Force Predicted by NF Model and Force from Mathematical Model for sinusoidal displacement(2.5 sin(5πt)) and random volt
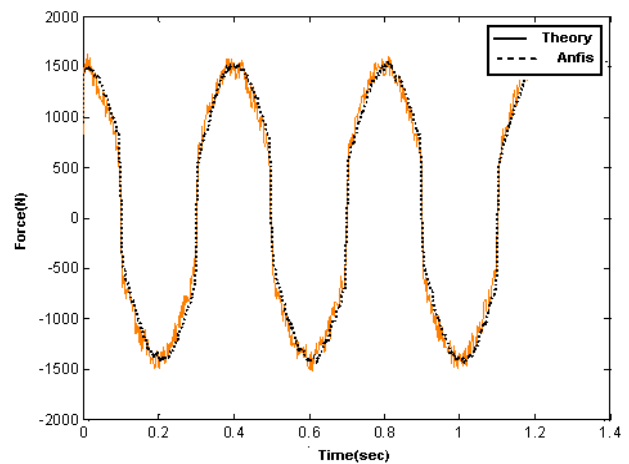

Fig .11 Comparison between Force Predicted by NF Model and Force from Mathematical Model for random displacement and random volt