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Genetic Optimizing of Hard Computing vs Soft Computing for MR Damper Modeling and Proposing an Invertible Pseudo Static Model

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ABSTRACT

To describe nonlinear behavior of MR dampers as established semi-active devices employed to control vibrations, various models have been proposed which could be classified in hard and soft computing fields. However, only some could mimic hysteretic and highly dynamic characteristics of MR dampers appropriately directly and inversely which is a principle control attribute; more precisely, choosing a qualified invertible model plays a prominent role in a semi-active control, which has not come into sharp focus so far. Thus in this article, first, some best-proposed hard computing (parametric) MR damper models are chosen and identified by genetic optimization under the same conditions. Second, two fuzzy-genetic and neuro-fuzzy models using soft computing techniques are constructed. Then a pseudo static model is proposed, which unlike to accurate dynamic models, have no differential equations and is invertible. Finally, all models subjected to filtered Iranian and foreign earthquakes would be compared. During all phases, experimental data is generated utilizing a benchmark program equipped with large-scale MR dampers, which is proposed by American Society of Civil Engineering (ASCE). Comparisons bring two results: the fuzzy-genetic model is more precise than hard computing ones; and the proposed model performs more effectively than dynamic ones, as it not only demonstrates desirable accuracy and much higher rate, but could easily be inverted.

KEYWORDS

MR Damper Models, Benchmark Program, Optimization, GA, Fuzzy, Pseudo Static, Earthquake, Comparison.

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1- INTRODUCTION

Civil engineers persistently have been researching to mitigate vibrations of structures under seismic loads. For this purpose, structural control field has been increasingly studied and implemented in recent years. The field mainly divided into two fields including passive and active control systems. But to cover the shortcomings of these systems, the third field entitled semi-active control has been emerged that simultaneously represents the fail-safe capability of passive control and the adaptability of active control with no need to a great deal of energy.

One of the most widely accepted semi-active control devices is MR damper using controllable fluid consists of micron-sized, magnetically polarizable particles dispersed in a carrier medium like mineral or silicone oil Figure 1.

As MR dampers represent highly nonlinear dynamics and hysteretic behavior, researchers have presented many different parametric models involved differential equations [1] in last two decades. But the identification were time consuming and they were too complicated to be inverted to be applied in control process which needs inverted MR damper models for calculating the instant control voltages. To solve these problems static models have been proposed. However, they could not perform as accurately as dynamic models.

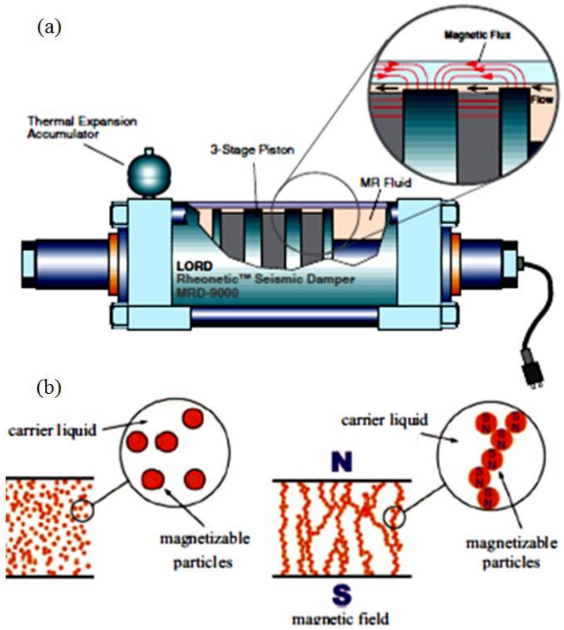

Figure 1: (a) The structure and (b) Behavior of MR damper before and after applying voltages

The second group of models is non-parametric models [2] utilized soft computing techniques [3] such as Artificial Neural Networks (ANNs), Fuzzy and Genetic Algorithm (GA). Although these models could potentially be computed and inverted easily, how to construct and optimize them to produce a fast and precise MR damper model for seismic loads might be challenging.

Moreover, an analogy between the performance of qualified soft computing models versus famous hard computing models under the same and critical conditions for identification and testing has not come into sharp focus so far.

Therefore, This study pursue four objectives: (1) introducing five well performance hard computing MR damper models; (2) constructing two qualified soft computing models; (3) proposing an invertible pseudo static model with desirable accuracy; and (4) identifying the models optimally and comparing them with each other. It is worthy to note, to provide competitive situation in the last phase, all the models would be optimized well by the same optimization method chosen to be GA in this article, which is known as one of the best optimization algorithms. In addition, to achieve factual and reliable results, real earthquake records and real corresponding instant control voltages are utilized in the process of generating experimental data for optimizing and comparing.

2- METHODOLOGY

To produce the experimental data, this article used a black-box model of large-scale MR damper integrated in a benchmark program proposed by American Society of Civil Engineering (ASCE) [4], which is used by the structural control community as a state-of-the-art model for numerical experience of seismic control attenuation. Then the earthquake records filtered by Seismo Signal software (Figure 2) are applied to the benchmark model so that 4-column data are generated. For instance, the data is depicted in Figure 3 for Nahavand earthquake.

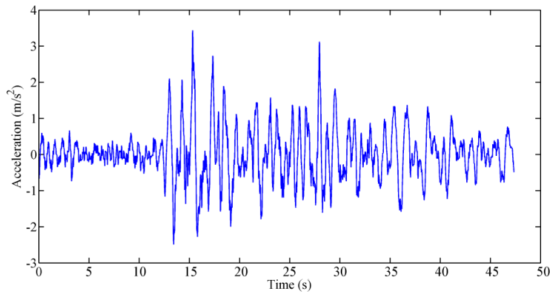

Figure 2: Nahavand earthquake record corrected in the frequency range of [0.1, 25] Hz

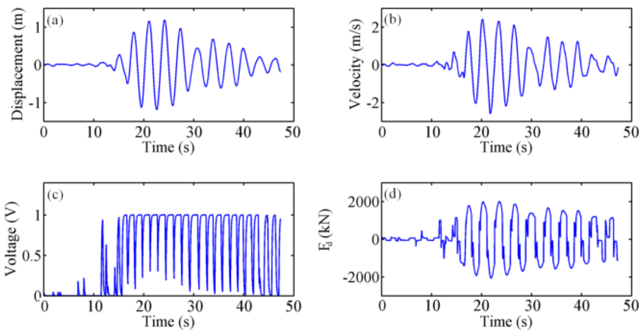

Figure 3: (a) Displacement, (b) Velocity, (c) Controlled voltage, and (d) Generated force in terms of time by applying Nahavand acceleration record in X direction to the benchmark program

The five well performance hard computing models chosen include Phenomenological [1], Modified Dahl [5], Modified LuGre [6], Normalized Bouc-Wen [7], and Modified Normalized Bouc-Wen [8] models proposed in recent years. The two soft computing models include Neuro-Fuzzy and Fuzzy-Genetic models constructed using ANFIS (Adaptive Neuro Fuzzy Inference System) [3] and GONFIS (Genetic-Optimized Neuro-Fuzzy Inference System) [9] approaches.

To optimize the models by GA, the article employs a systematic way to calibrate the parameters of the algorithm to get it work efficiently. Assuming a large number of evaluations (FE) of the objective function $error = \sqrt{\sum_i (F_i - F_{di})^2}$ and specifying the number of unknown model parameters L, the size of population N can be estimated:

$$\frac{FE}{N}\log(1-\frac{1}{N}) = -M - \log\sqrt{\frac{L}{12}} \tag{1}$$

where M is a small constant since it is the optimized amount of the *error* and the argument of the *log* in the process of obtaining the formula. Finally, the number of total generations can be found:

$$g_{converge} = \frac{FE}{N} \tag{2}$$

The proposed invertible pseudo static model is as follows:

$$F(t) = a(v)\exp\left(bv - c(v)\right) \cdot sign(\dot{x}(t)) + k_{\dot{x}}(v)\dot{x}(t) + k_x x(t)$$
$$a(v) = a_1 + a_2 v,\ \ c(v) = c_1 + c_2 v,\ \ k_{\dot{x}}(v) = k_{\dot{x}1} + k_{\dot{x}2} v \tag{3}$$

and the inverted model is:

$$v = \frac{[\ln(\dfrac{F(t) - k_{\dot{x}}(v)\dot{x}(t) - k_x x(t)}{a(v)\cdot sign(\dot{x}(t))}) + c(v)]}{b} \tag{4}$$

Using GA, the parameters of all models are identified optimally. For instance, Table 1 shows values of the parameters of the proposed model.

Table 1: Optimum value of parameters in the proposed pseudo static model

a_1	a_2	b	c_1	c_2	$k_{\dot{x}1}$	$k_{\dot{x}2}$	k_x
27.54	1193.89	0.34	-0.52	1.03	109.82	288.09	246.36

Now, all the 10 earthquake records are applied to the benchmark MR damper to generate the desired force F_d which the models produced forces F try to mimic. To assess how much the models are successful to emulate the origin data through vibration duration T_r, the 1-norm error (ε) is used:

$$\varepsilon = \frac{\|F_d - F\|_1}{\|F_d\|_1}, \quad \|f\|_1 = \int_0^{T_r} \|f(t)\| dt \tag{5}$$

The results for all the models under all ten seismic loads are shown in Figure 4. Specifically, to explore more about the performance of the proposed pseudo static model, it is studied under the El Centro record illustrated in Figure 5; thereafter, the output force of the proposed model is demonstrated in terms of physical parameters of the MR damper in Figure 6. As it is observed, the proposed model predicts the experimental data well.

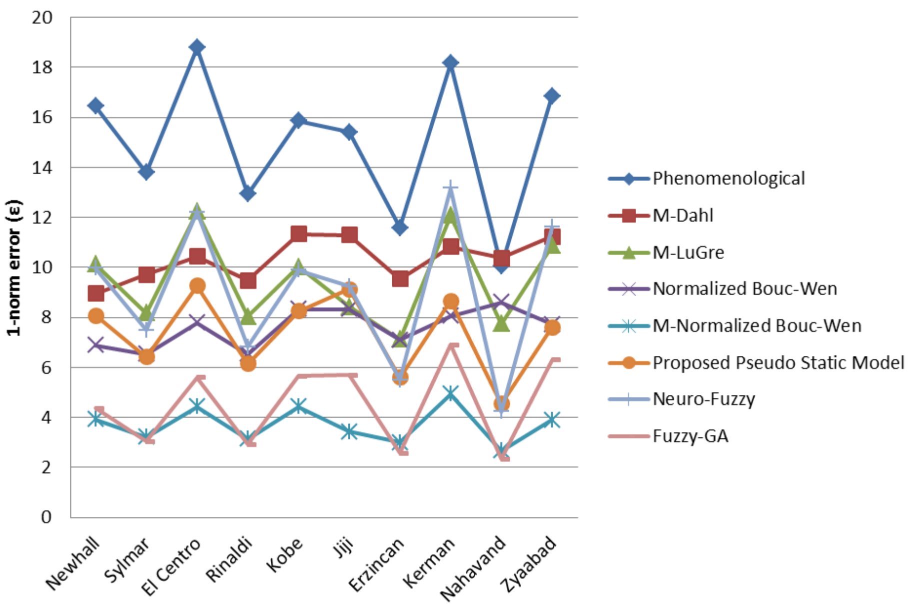

Figure 4: The 1-norm error (ε) diagram for all the models under real earthquake records in X direction and control voltages

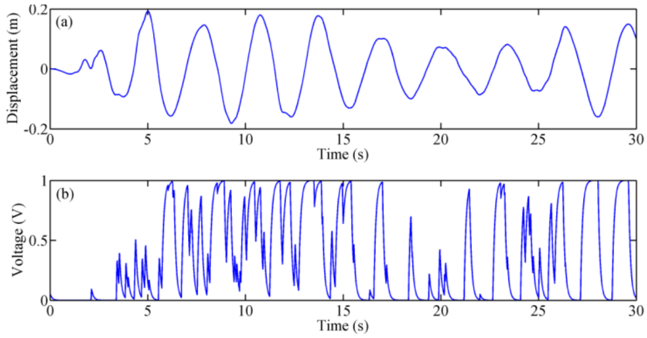

Figure 5: (a) Displacement and (b) Corresponding control voltages when the Y direction of El Centro excitation is applied to the benchmark program

3- CONCLUSIONS

Two results come from the comparisons. First, the hard computing Modified Normalized Bouc-Wen and the soft computing Fuzzy-Genetic models perform better than others. However, from the invertibility point of view, Fuzzy-Genetic model is superior to the mentioned hard computing model. Moreover, based on the diagram, in spite of the fame which the Phenomenological model has achieved, it may not be an appropriate model for large-scale MR dampers. Second, it is observed that the proposed pseudo static model mimics the experimental data significantly well by analogy with the complicated dynamic models; while it does not employ any differential equations, it would be optimized so rapidly, it is invertible and suitable for semi-active control of a structure equipped with MR dampers under seismic loads. Furthermore, the proposed model even performs better than the Neuro-Fuzzy model constructed by ANFIS known as one of the most well-known soft computing techniques. In sum, these reveal the great potential of Fuzzy-Genetic and pseudo static models for identification and control of MR dampers.

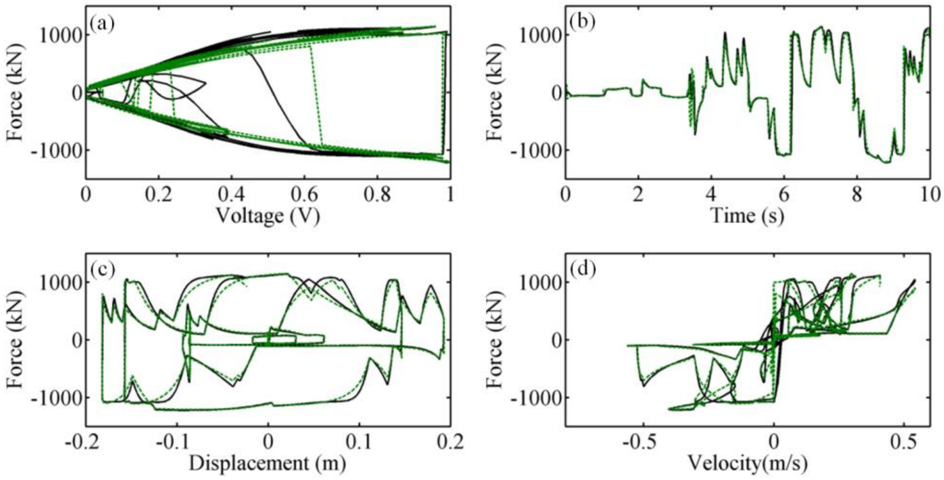

Figure 6: Comparison the proposed model predicted force (F) with the target force (F_d) in terms of (a) Voltages, (b) Time, (c) Displacement, (d) Velocity under El Centro excitation

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