Research Note

Design and Implementation of Genetic-Fuzzy Controller for an Electric Seismic Shake Table

Mehdi Soleymani[1*], Bahador Ghanbari Sini[2], and Mahmoud Hamidizadeh[2]

1. Department of Mechanical Engineering, Faculty of Engineering, Arak University, Iran,
* Corresponding Author; email: m-soleymani@araku.ac.ir
2. Graduate Student of Mechatronic Engineering, Department of Mechanical Engineering, Faculty of Engineering, Arak University, Iran

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ABSTRACT

A supervisory genetic-fuzzy controller is proposed for the motion control of an electric shake table, LARZA, in this paper. The controller comprises of two loops, an inner PI loop and a genetic-fuzzy supervisor. The fuzzy controller is devised, based on the prior experience, such that the tracking error is minimized. Furthermore, for optimizing the fuzzy supervisor controller, a genetic algorithm is utilized. For this purpose, a mathematical model is developed for the shake table. Moreover, the model is validated based on the test data. The parameters of the supervisor controller are then tuned based on the model response variables using the genetic optimization approach. The controller is implemented in the shake table and its performances is studied. The test results reveal the effectiveness of the proposed controller in decreasing displacement, velocity, and acceleration tracking errors for two sample earthquakes.

Keywords:
Shake table; Fuzzy; Supervisory control; Genetic algorithm; Tracking error

1. Introduction

Seismic shake tables are employed to simulate earthquake excitations in structural dynamics tests [1-4]. Shake tables, depending on their payload and powertrain system, may be classified as electric or hydraulic types. Hydraulic shake tables are usually utilized for the test of full-scale or heavy structural models. On the other hand, electric shake tables are suitable for the test of laboratory-scale or light structures. Aside from size and type of a shake table, the criterion for effectiveness of a shake table is its performance at earthquake profile tracking. As a matter of fact, the less the tracking error, the more efficient the seismic shake table will be. The main core of a shake table is its control system.

The control system is to minimize the tracking error via a feedback control system. For this purpose, kinematic data of the table are measured and compared with those of the reference, the real earthquake profile data, continuously. The error signals are then fed to the controller and the proper control input is calculated based on the error feedback. Several control approaches have been examined for control of the seismic shake tables. Azalée, a six degree of freedom shake table, utilizes a control strategy with three loops. The first loop is for tuning servo valves with proportional and derivative gains. The second one reduces the error between command and actuator motion. Finally, the third loop is used for correcting the control command in case of structural damage based on inversion of the initially measured system transfer function. Although it is the largest test facility in Europe that provides full scale structural tests, the hydraulic actuators impose some performance limitations on the system. Besides, the control strategy needs a specific sequence with initial excitation and an incremental increase in test level [5]. Seki et al. proposed an adaptive feedback compensator for control of a shake table and mounted structure. They presented a novel control system to track earthquake acceleration profile. An adaptive system proposed to tackle the disturbances from the table and the structure mounted on it [6]. Yang et al. improved the tracking characteristics of a laboratory shake table via a three state feedback and feed-forward control algorithm based on pole-assignment principle. The best tracking performance, using this control approach, was achieved at 1-30 Hz frequency range [7]. Time delay control (TDC) was used for improving tracking performance of a shake table by Lee et al. [8]. This controller could successfully compensate for the tracking degradation due to the system delays. However, the proper operating frequency range was still limited to 0-30 Hz [8]. Chase et al. [9] developed a controller to reduce acceleration spikes in the earthquake profile tracking procedure. In a work done by Jibnao et al., the control of an array of nine sub-tables with 16 servo actuators was considered and a DSP controller was proposed for this purpose [10]. Airouche et al. studied the application of a variety of controllers ranging from amplitude phase control (APC), adaptive harmonic cancellation (AHC) to adaptive inverse control (AIC) and online iteration (OLI) for controlling a shake table. Strano et al. employed sliding mode control for a laboratory seismic simulator. Shen et al. proposed an adaptive feed-forward controller for control purpose of a shake table [10-12].

Fuzzy controller, due to its advantages, may be a good match for the control of a shake table. First of all, it is possible to enter the knowledge of an expert, directly in the control design procedure. Moreover, it has a high potential for adaptation. Furthermore, it has an inherent robustness that makes it a proper choice for systems like the shake table, which suffer from various uncertainties in the model and excitations. This control approach has been successfully employed for the shake table control purpose by some researchers [13]. Genetic algorithm is one of the popular and efficient optimization approaches being employed increasingly in the engineering applications in recent years. This algorithm may also be employed for the optimization of the controllers. By combining genetic algorithm and fuzzy control concepts, as a soft computing approach, genetic-fuzzy controller is emerged. Several works have been done on the application of this control approach in engineering applications [14-15]. However, no work has been done on utilizing this control approach for the shake table control. This work addresses the application of genetic algorithm in optimization of fuzzy control system in shake tables.

An electric shake table developed at Arak University, LARZA is employed as the control plant. A hierarchical control system is proposed for motion control of this shake table. The control system is composed of two loops, including a PI loop as the internal and main loop and a genetic-fuzzy controller as the supervisor. Moreover, a model is developed for the LARZA in this work, and the model is validated via the test procedure devised for the shake table. The valid model is then employed for the optimization of parameters of the fuzzy supervisory controller. Finally, the controller is implemented in the shake table and its performance is evaluated via a test. Configuration of this paper is as follows: First, the shake table configuration is introduced. Mathematical modeling of the shake table and the validation procedure is described afterward. Finally, control design, optimization, and implementation are presented, and the test results are discussed.

2. Modelling and Validation

The employed shake table, LARZA, is an electromechanical laboratory-scale single degree of freedom seismic shake table that can simulate moderate earthquakes with maximum acceleration amplitude up to 2 g. The power source of the shake table is a 1 kWatt permanent magnet synchronous AC servo motor. The rotational motion of the electric motor is converted to linear motion using a ball-screw mechanism. The specifications for the shake table is summarized as Table and Figure (1).

Eqs. (1) to (3) depict dominant dynamic equations for the AC motor in *d*-*q* coordinate system.

$$\frac{d}{dt} i_d = \frac{1}{L_d} v_d - \frac{R}{L_d} i_d + \frac{L_q}{L_d} \rho \omega \, i_d \tag{1}$$

Table 1. LARZA specifications.

Specification	Value
Motor Type	AC Permanent Magnet Synchronous Motor
Motor Power	1 kWatt
Table Dimensions (B × L)	750 × 550 mm
Displacement (mm)	±90
Maximum Velocity (mm/s)	1000
Maximum Acceleration (g)	2
Maximum Payload (kg)	35
Ball-screw Lead (mm)	20
Data Acquisition System	200ks/s, 16 Bit DAQ Card
Acceleration Sensor	Dual-Axis MEMS ADXL203 Accelerometer with a Measurement Range of ±1.7g
Displacement Sensor Resolution (μm)	5

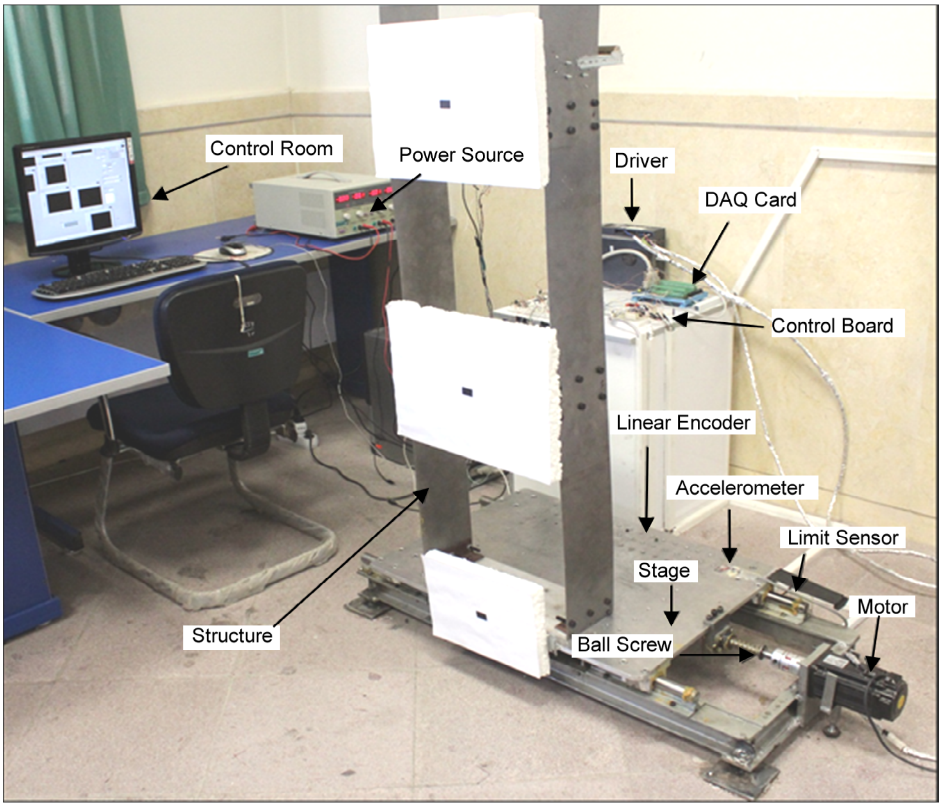

Figure 1. LARZA shake table.

$$\frac{d}{dt}i_q = \frac{1}{L_q}v_q - \frac{R}{L_q}i_q + \frac{L_d}{L_q}\rho\omega i_d - \frac{\lambda\rho\omega}{L_d} \quad (2)$$

$$T_e = \frac{3}{2}\rho\left[\lambda i_q + \left(L_d - L_q\right)i_q i_q\right] \quad (3)$$

In the equations above, L_d and L_q are inductances (1) for the d and q axes respectively. R is the electric resistance of the stator windings. i_d and i_q are currents of d and q axes respectively. v_d and v_q are voltages of d and q axes respectively. ω is angular velocity of the rotor. λ is the flux amplitude induced by the rotor permanent magnets at the stator phases. ρ is the number of pole pairs. T_e is electromagnetic torque [16].

As for the permanent magnet synchronous electric motor, $L_d = L_q$, Eq. (3) may be rewritten in the following form:

$$T_e = \frac{3}{2}\rho\lambda i_q \quad (4)$$

The governing dynamic equations for the motor shaft are also as follows:

$$\frac{d}{dt}\omega = \frac{1}{j}(T_e - \beta\omega - T_l) \tag{5}$$

$$\frac{d\theta}{dt} = \omega \tag{6}$$

where j is the equivalent rotational inertia at the motor shaft, β is the viscous damping coefficient at the motor bearings, and θ is the shaft rotation angle [16]. The equations for ball-screw are as follows:

$$T = \frac{FL}{\xi} \tag{7}$$

where T is the motor output torque, F is transmitted linear force to the ball-screw, ξ is the ball-screw efficiency, and L is lead of the ball screw. For a typical ball-screw, the efficiency may be considered as a constant 90 percent value [17].

In order to measure the accuracy of the model, its performance is compared with that of the real shake table, LARZA at the simulation of two earthquakes i.e. Kobe and Chalfant. The employed controller is also the fuzzy supervisory one introduced in the next section. As it is seen in Figures (2) to (9), although there is a discrepancy between the model and test acceleration responses for the Kobe and Chalfant earthquakes at higher frequencies which impose a light uncertainty on the model, the model has acceptable accuracy in simulating LARZA behavior at tracking the above-mentioned earthquakes in both time and frequency domains.

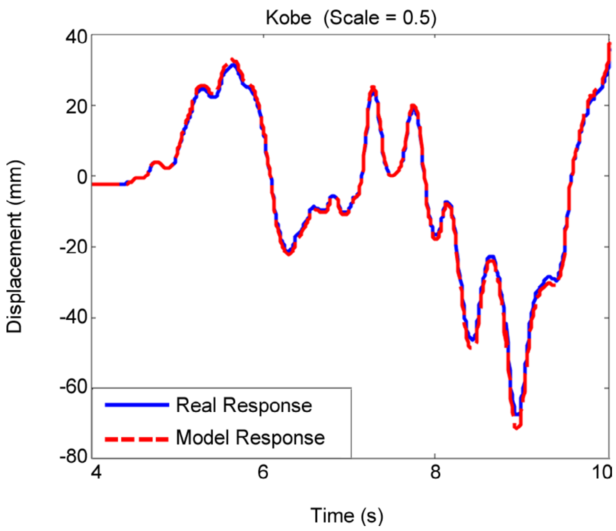

Figure 3. Displacement results for Kobe earthquake.

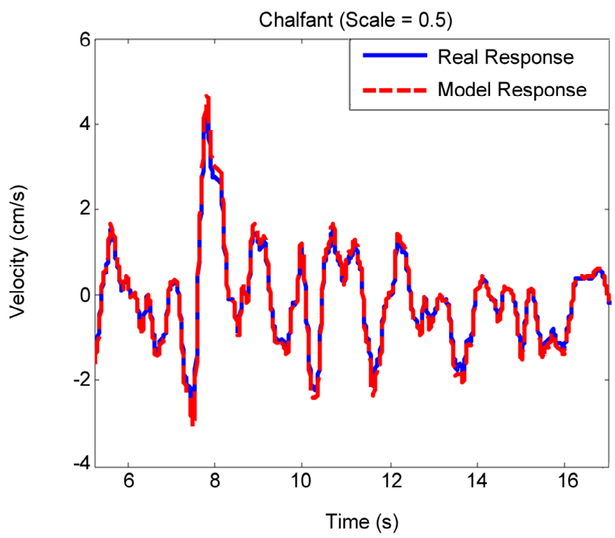

Figure 4. Velocity results for Chalfant earthquake.

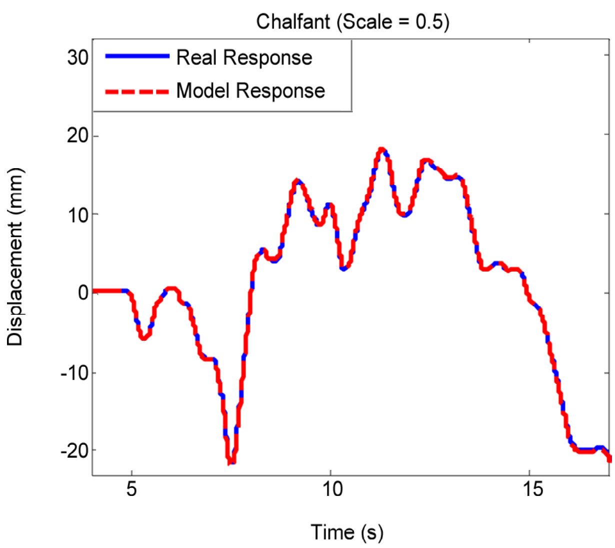

Figure 2. Displacement results for Chalfant earthquake.

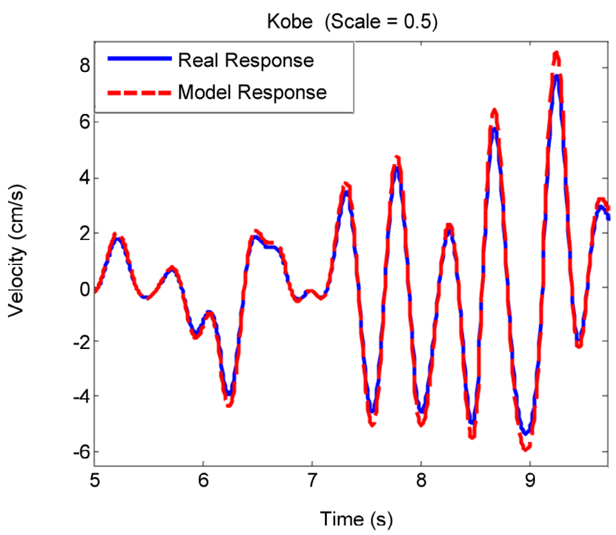

Figure 5. Velocity results for Kobe earthquake.

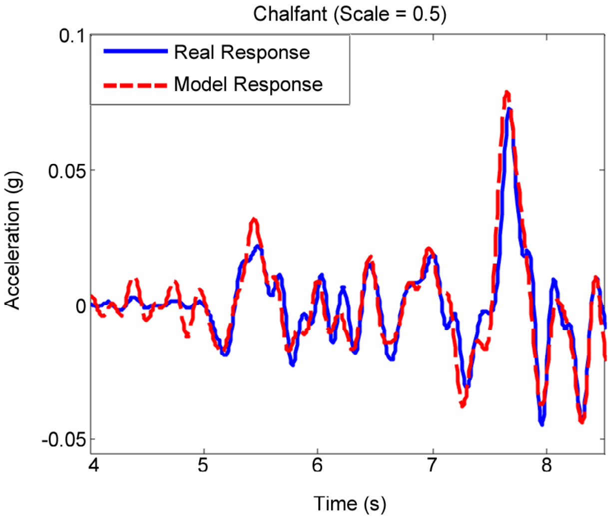

Figure 6. Acceleration results for Chalfant earthquake.

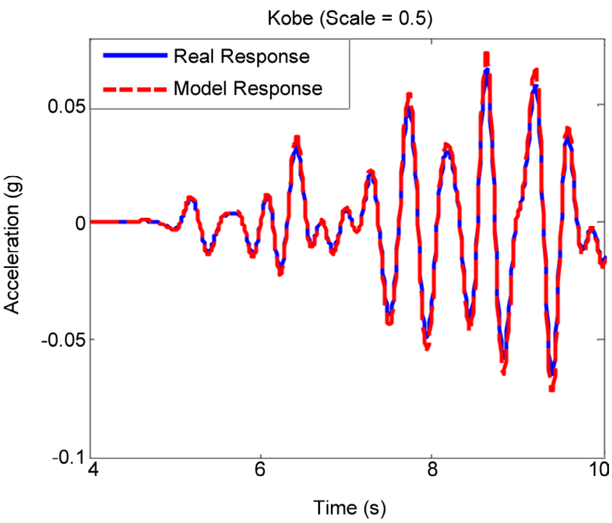

Figure 7. Acceleration results for Kobe earthquake.

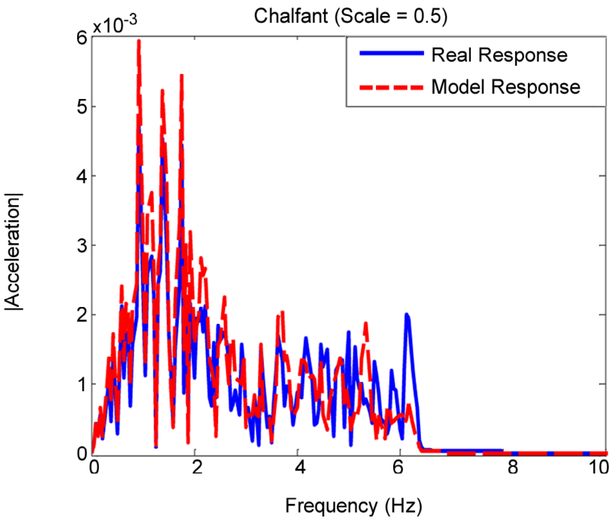

Figure 8. Acceleration results for Chalfant earthquake in frequency domain.

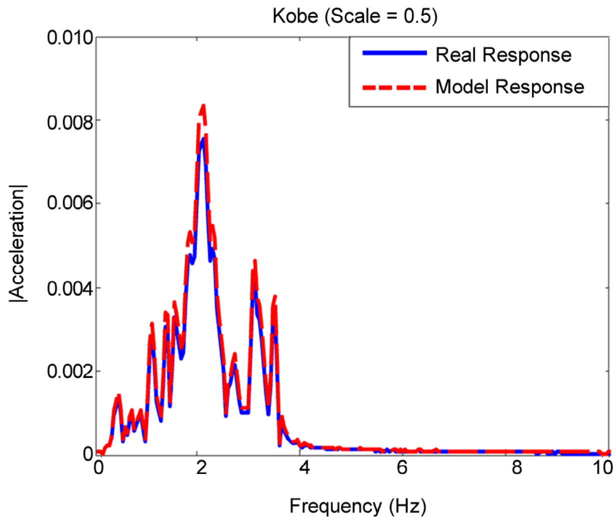

Figure 9. Acceleration results for Kobe earthquake in frequency domain.

3. Control Design

The proposed controller, as shown in Figure (10), is a genetic-fuzzy supervisory controller. The controller is composed of two loops. The main core, the PI controller, is responsible for reduction of the tracking error via speed feedback. The supervisor controller, on the other hand, is responsible for enhancement of the internal loop performance via modifying the control command. In this control scheme, the reference signals as well as the feedback signals are sent continuously to both controllers, and the final control command is calculated based on the core and supervisor controllers combined.

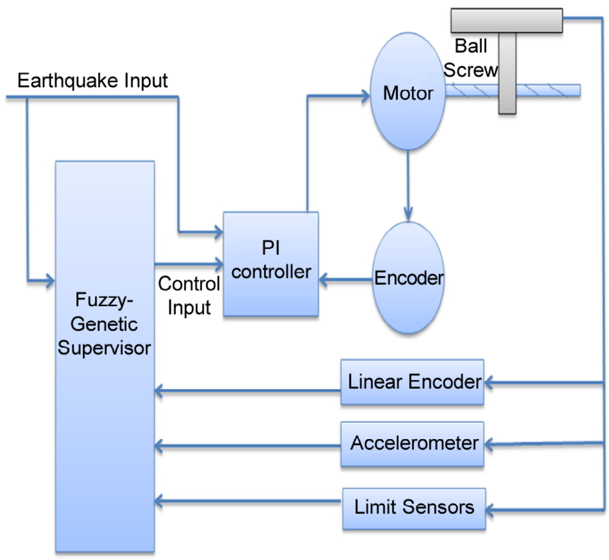

Figure 10. Schematic diagram for the fuzzy-supervisory genetic diagram.

The reference signal for the motor speed control is calculated via converting the table desired velocity, earthquake velocity, to the motor required speed using equation below.

$$\omega = \frac{v}{L} \tag{8}$$

where ω is the motor desired rotational speed called reference signal and v is table linear velocity that corresponds to the earthquake horizontal velocity.

3.1. Fuzzy Supervisory Controller

The fuzzy supervisor decision is made based on the displacement and velocity tracking errors using a rule base. The proposed FLC in this work is a Mamdani-type fuzzy system. The normalized values of the inputs are calculated by dividing them by their estimated maximum values. The output of the FLC is also the scaled value of actuator force that must be scaled back later. The logical 'AND' has been implemented with the minimum (min) operator and the defuzzification method is the center of gravity.

Table (2) depicts the fuzzy rules for the supervisor controller. The rules written as verbose statements have been devised to minimize the tracking error via compensation of PI controller error.

In this table, $Err_{displacement}$ is displacement tracking error and $Err_{displacement}$ is rate of displacement error, i.e. velocity tracking error. Moreover, NB, NM, NS, NSS, Z, PSS, PS, PM, and PB stand for negative big, negative medium, negative small, very negative small, zero, very positive small, positive small, positive medium, and positive big, respectively. Furthermore, as shown in Figure (11), each input is described by seven membership functions. Similarly, the FLC output is described by nine membership functions. The triangular membership functions have been employed because of their simplicity and their excellent potential for being tune *d*.

Let's study a rule, e.g. the one for which both displacement and velocity errors are negative big implying a big error and a strong tendency toward a bigger one. In this case, a big reverse control command, i.e. PB, is required to counteract this big error. The other rules have also been written in the same manner. Furthermore, the membership functions for the FLC inputs and output are illustrated as Figures (11) and (12).

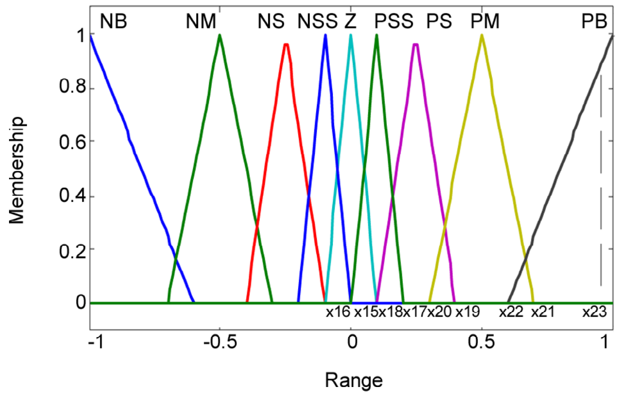

Figure 11. Membership function for the FLC output.

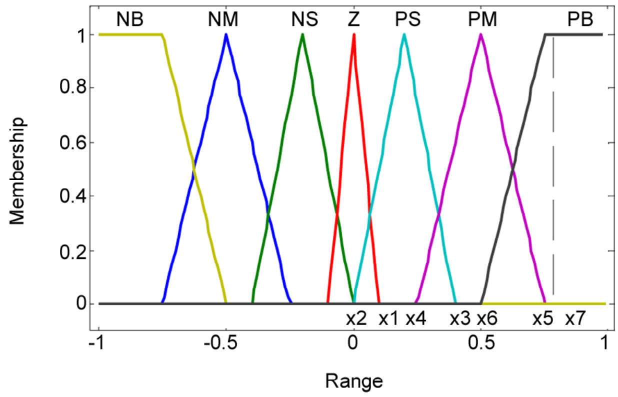

Figure 12. Membership function for the FLC inputs.

Table 2. Fuzzy rule base for FLC.

$Err'_{displacement}$ / $Err_{displacement}$	PB	PM	PS	Z	NS	NM	NB
NB	PM	PM	PB	PB	PB	PB	PB
NM	PSS	PS	PS	PM	PM	PM	PB
NS	PSS	PSS	PS	PS	PS	PS	PS
Z	NSS	NSS	Z	Z	Z	PSS	PSS
PS	NS	NS	NS	NS	NS	NSS	NSS
PM	NB	NS	NM	NM	NS	NS	NS
PB	NB	NB	NB	NB	NB	NM	NM

As seen in these figures, the membership functions have been distributed uniformly over the Universe of discourse. This can be considered as a defeat for the fuzzy controller, as in this case the, fuzzy controller will not necessarily work optimally in confrontation with a specific disturbance. In order to boost the performance of the fuzzy supervisor controller, a genetic optimization algorithm is employed to tune the fuzzy controller.

3.2. Genetic Optimization

It is believed, in the tracking control problem of the shake table, the proper tracking of the acceleration signal is a key requirement that should be met. Moreover, displacement tracking is very important, due to its impact on the test structure estimated displacements. Therefore, tuning of the fuzzy supervisor controller is formulated as a multi-objective optimization problem whose objectives are shown as equations [9] and [10].

$$Y(1) = \sqrt{\frac{\left(Acc[i] - Acc_{ref}[i]\right)^2}{N}} \tag{9}$$

$$Y(2) = \sqrt{\frac{\left(Disp[i] - Disp_{ref}[i]\right)^2}{N}} \tag{10}$$

In these equations, N is the number of samples, Acc is the achieved acceleration response, Acc_{ref} is the acceleration reference signal, $Disp$ is the achieved displacement response, and $Disp_{ref}$ is the displacement reference signal. The reference signals are the scaled version of the earthquakes mentioned in Table (3). The scaling factor for all the reference signals is 0.5.

The optimization variables are the constituent parameters of the membership function shown in Figures (11) and (12). As it is believed, the rule base is devised based on an authentic justification, the rule base parameters are excluded from the optimization procedure. The GA parameters are also depicted as Table (3).

Table 3. Genetic algorithm parameters.

Parameter	Specification/ Value
Population Size	150
Crossover Function	Two Point
Mutation	Adaptive Feasible
Number of Generations	100
Migration Direction	Both Sides
Selection Function	Tournament

Figure (13) depicts the pareto front for the multi-objective optimization results. The selected solution is also identified in this figure.

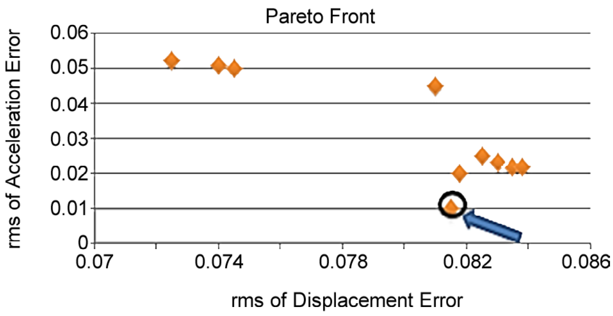

Figure 13. Pareto front for the multi-objective geneti optimization.

4. Controller Implementation and Test Results

The supervisor controller is implemented in the shake table using Lab View software. The control system acquires displacement and acceleration feedbacks from the sensors via a PCI DAQ card connected to the PC. The DAQ card is also an interface for sending back the control output to the controller that is connected to the AC motor drive. The supervisor controller consists of three loops that acquire data from sensors and calculate the control command based the estimated errors. There are also two limit sensors located at the stage stroke border to avoid the stage from over-travelling.

Performance of the controllers is evaluated via shake table test. Kobe and Chalfant earthquakes have been considered as reference signal. Specifications for the earthquakes are shown in Table (4).

Displacement response history for the shake table with the fuzzy-supervisory and genetic-fuzzy supervisory controllers are shown as Figures (14) and (15) respectively. For the simulations, a scaled version of the earthquakes introduced in Table (4) is employed.

Figure (16) also compares the normalized values calculated for the root mean square (rms) of the displacement tracking errors for the Kobe and Chalfant earthquakes with various controllers. In

Table 4. Genetic algorithm parameters.

	Magnitude	Date	Time	Station	Data Source
Kobe	M (6.9)	1995/01/16	20:46	0Nishi-Akashi	CUE
Chalfant Valley	Ml (5.9)	1986/07/20	14:29	54428 Zack Brothers Ranch	CDMG

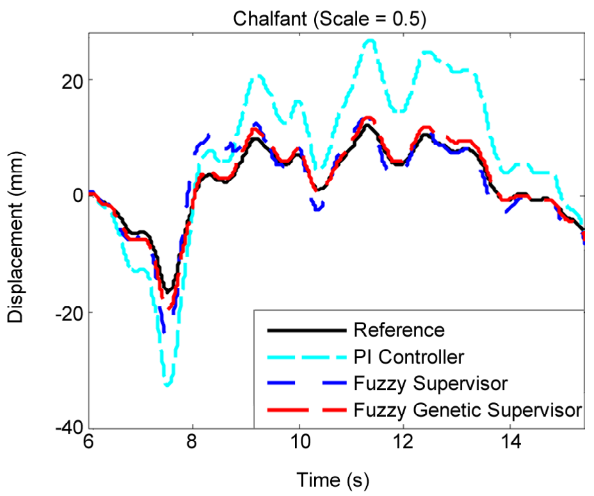

Figure 14. Displacement history for Chalfant earthquake.

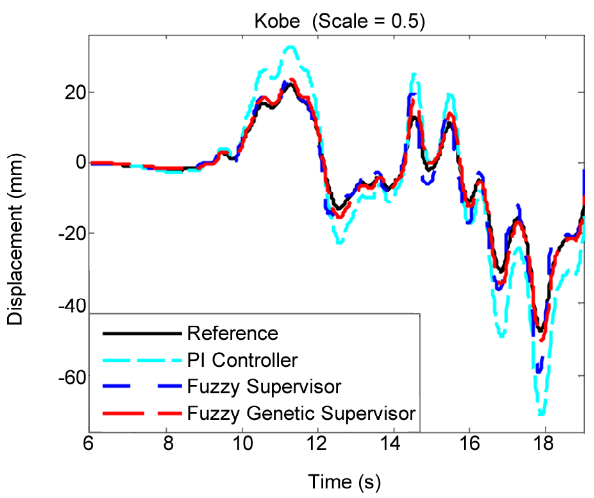

Figure 15. Displacement response history for Kobe earthquake.

order to normalize the responses in the mentioned figures, the responses with the PI controller are considered as unity. The other responses are then calculated in accordance with this value.

As it is seen in this figure, the fuzzy supervisor controller causes a considerable decrease in the displacement tracking error. Furthermore, optimization of the fuzzy controller has caused a further decrease in the tracking error, where a total 80 percent reduction in the displacement tracking error is attained using the genetic-fuzzy supervisory controller.

Figure (17) compares the velocity tracking response history errors via rms index. As shown in this figure, the application of fuzzy supervisory controller yields a 20, 30 drop in the rms errors calculated for Kobe and Chalfant respectively. The genetic-fuzzy supervisor controller, on the other hand, causes a further decrease in the velocity tracking error, which sums up the overall velocity tracking errors to 62 and 50 percent for the Kobe and Chalfant earthquakes respectively.

Finally, performance of the supervisor controllers at acceleration tracking is evaluated in Figure (18). As seen in this figure, the fuzzy-genetic supervisor controller could decrease the acceleration tracking errors by 61 and 70 percent for Kobe and Chalfant earthquakes respectively, implying effectiveness of the proposed controller at tracking the acceleration profiles.

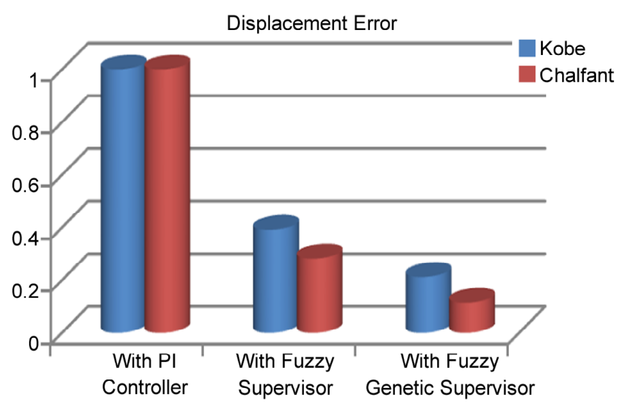

Figure 16. Normalized RMS displacement tracking error.

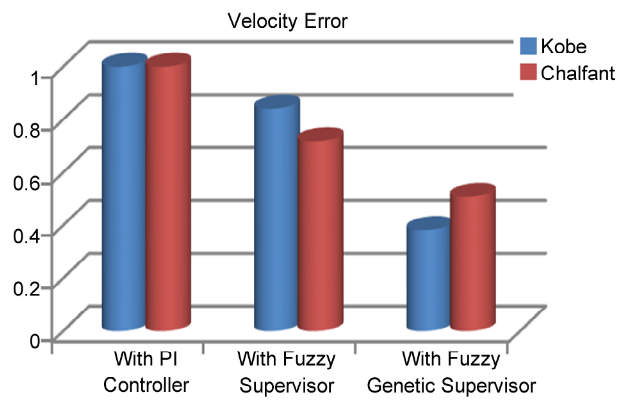

Figure 17. Normalized RMS Velocity tracking error.

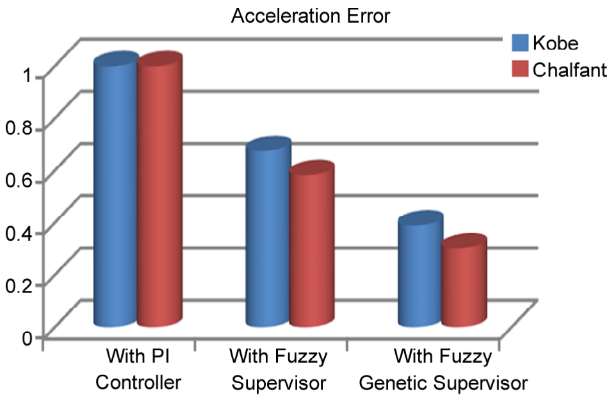

Figure 18. Normalized RMS acceleration tracking error.

5. Conclusion

Design and implementation of genetic-fuzzy supervisory controller in order to enhance tracking performance in an electric seismic shake table was addressed in this work. A double loop controller was proposed for this purpose. A fuzzy controller was devised as the supervisor controller for the inner loop, the PI controller. The parameters of the fuzzy controller were then optimized using a multi-objective genetic optimization approach. For this purpose, a model was developed and validated for the shake table using test data. The proposed controller was then implemented in the shake table and its performance is compared with that of primary fuzzy supervisor controller. Test results prove effectiveness of the proposed controller in enhancing displacement and acceleration tracking performance of the shake table.

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