Earthquake Ground Motion Matching on a Small Electric Shaking Table Using a Combined NN-PDFF Controller

Selma H. Larbi,1 Nouredine Bourahla,2 Hacine Benchoubane,3 Khireddine Choutri,3 and Mohammed Badaoui4

1LGMGC Laboratory, Civil Engineering Department, University of Saad Dahleb, Blida, Algeria
2LGSDS Laboratory, Civil Engineering Department, Ecole Nationale Polytechnique, El Harrach, Algeria
3Aeronautic Department, University of Saad Dahleb, Blida, Algeria
4LDMM Laboratory, Civil Engineering Department, University of Ziane Achor, Djelfa, Algeria

Correspondence should be addressed to Selma H. Larbi; selma.h.larbi@gmail.com

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Replicating acceleration time histories with high accuracy on shaking table platforms is still a challenging task. The complex interference between the components of the system, the inherent nonlinearities, and the coupling effect between the specimen and the shaking table are among other reasons that most affect the control performance. In this paper, a neural network- (NN-) based controller has been developed and experimentally implemented to improve the acceleration tracking performance of an electric shaking table. The latter is a biaxial shaking table driven by linear motors and controlled by a proportional-derivative-feedforward (PDFF) controller that is very efficient in reproducing displacement waveforms on the detriment of the simulation of the prescribed acceleration ground motions. In order to bypass this shortcoming, a control scheme combining the PDFF as a basic control function with a NN controller which filters the shaking table feedback signal and acts on the drive signal by compensating for acceleration distortions is proposed in this study. Several experimental tests have been carried out to build a database for offline training, validating, and testing of the proposed NN control model. Subsequently, the well-trained NN is implemented in the inner control loop of the shaking table to compensate, in parallel with the PDFF controller, the distortions during the replication of acceleration signals. Results of tests using earthquake records showed an enhancement in signal matching when integrating the NN model for both bare and loaded conditions of the shaking table. The tracking errors, estimated using the relative root-mean-square error, between the measured and the desired signal, are significantly reduced in time and frequency domains with the additional NN online controller.

1. Introduction

Shaking tables are the most outstanding dynamic tests in civil and earthquake engineering. Testing full- and reduced-scale structures, as well as individual structural components, is a powerful means to analyze their nonlinear behaviours, evaluate, and predict their seismic responses to dynamic loads similar to real earthquakes [1–3]. Therefore, the control system, which aims to replicate faithfully prescribed earthquake records and other types of acceleration signals, has become the main challenging part of the shaking table for high-precision tracking performance [4–6]. Obtaining an acceleration feedback that exactly matches the target is difficult to achieve [7]. Studies have shown that, for some shaking table tests, the acceleration signal is reproduced with errors that can exceed 100% compared to the desired signal in terms of amplitudes [8]. Multiple interdependent sources of signal distortion such as the complexity and the nonlinear behaviour of the system [9, 10], the dynamics of the base support [10], the coupling dynamics between DOFs [3, 11], the nonlinear friction effects, and the presence of external disturbances [12] require the use of robust control algorithms. Early studies have proved the sensitivity of the shaking table to
payload characteristics [13, 14]. In fact, the strong dynamic interaction between the shaking table and the payload [15–17] and the nonlinear behaviour of the test specimen [18, 19] as well as the boundary conditions between the platform and the payload [20] deteriorate considerably the acceleration tracking performance of the shaking table and even lead to the instability of the control system [21]. Improving the stability, the robustness, and the performance of the control system has been the scope of many researchers’ studies. Various advanced control algorithms have been proposed. Several control techniques for structural testing have been reviewed, and some of them are cited in an analytical framework [22]. Methods based on feedforward compensation have been investigated in controlling acceleration on a shaking table [23]. Iterative learning methods have been designed and applied to an electrohydraulic shaking table [24]. Adaptive control techniques such as the minimal control synthesis developed earlier [25] have been implemented in shaking tables which showed a remarkable improvement in the system performance [26–28]. Although these common control techniques have achieved high acceleration tracking performances, they still have many drawbacks. Recently, combining the virtues of artificial intelligence (AI) algorithms with the benefits of conventional controllers has led to new and powerful control techniques [29]. The fuzzy logic (FL), the genetic algorithms (GA), and NNs as implemented in different control schemes [30–34] have proved to be successful and achieved higher accuracy and robustness. A backpropagation NN was designed to control the DC servomotor with an embedded PID controller, and offline simulations were performed to demonstrate the efficiency of the NN in reducing nonlinear effects and coping with the variation that may occur in the system [35]. A NN-based PID controller was developed and applied for high-performance permanent magnet synchronous motor (PMSM) position control [36]. Similarly, the high potential of NNs to improve the pneumatic position control by online tuning a PID controller was demonstrated experimentally [37].

In previous works of the authors, the potential of NN algorithms to enhance the control system of shaking tables has been evaluated in different ways. At the first stage, the NN controller has been applied to a numerical model of a shaking table. The command signals predicted in the offline mode by the NN were successful in reducing delay and amplitude distortions at low amplitudes [38]. Subsequently, offline-trained NN has been incorporated with the online PID controller of the shaking table which was simulated by its total transfer function and implemented in Matlab/Simulink. The numerical results indicate that the reproduced signals matched closely the targets particularly at peak values [39].

This paper presents experimental evidence of the efficiency of the NN algorithm as an additional online controller to the PDFF in improving the acceleration tracking performance of a biaxial electric shaking table. The database is extracted experimentally and used in the offline mode to train, validate, and test the NN. The latter is implemented online in the acceleration closed-loop of the shaking table control framework. Different index performances have been used to evaluate the robustness and the capacity of the proposed control in enhancing the matching between the reference and the measured signals, for both bare and loaded conditions of the shaking table.

2. Description of the Shaking Table System

Figure 1 shows the QUANSER STIII biaxial shaking table, which is composed of two moving steel stages: a bottom stage, actuated with two linear motors along the horizontal x-axis, and a top stage, actuated by one linear motor along the transversal y-axis. The command signal is converted by QUARC real-time control software and sends to the power amplifier through the analog output channel of the DAQ device. The sliding system is composed of a pair of linear guides using ball bearings. They enable the two stages to move with a total stoke of ±21.6 cm. The peak acceleration with a maximum payload of 100 kg is 1.1 g and 1.5 g along the x-axis and y-axis, respectively. The shaking table is equipped with on-board LIDA 477/487 Heidenhain encoders for displacement measurement and dual-axis ADXL210E accelerometers for acceleration measurement in a range of ±10 g and a noise’s range of ±5.0 mg. The displacement and acceleration measured by encoders and accelerometers are acquired through a DAQ card by a control program implemented in MATLAB software on a PC. The main specifications of the shaking table are summarized in Table 1.

The control system is a Simulink-based proportional-derivative and feedforward (PDFF) controller which drives time history signals through QUARC real-time software. The block diagram used to control the stage position is depicted in Figure 2. \( A_p(s) \) is the desired acceleration, \( X_d(s) \) is the desired position, \( \dot{X}(s) \) is the measured position, \( b_d \) is the set-point velocity weight, and \( I_{ps}(s) \) and \( I_{pd}(s) \) are the command signals provided by the FF and the PD controllers, respectively.

The x-axis model of the shaking table can be represented by the transfer function which is expressed by the following equation:

\[
X(s) = \frac{1}{K_x s^2 \tau_{x}^2 s^2} I_{m,x}(s),
\]

where \( X(s) = L[x(t)] \) is the Laplace transform of the stage position, \( I_{m,x}(s) \) is the Laplace transform of the applied motor current, and \( K_{f,x} \) is the feedforward control gain along the x-axis.

The PDFF control used to regulate the stage position along the horizontal x-axis is represented in the following equation:

\[
I_m(t) = K_p(x_d(t) - x(t)) + K_d(\dot{x}_d(t) - \dot{x}(t)) + K_{f,x}(\ddot{x}_d(t) - \ddot{x}(t)),
\]

where \( K_p \) is the proportional control gain and \( K_d \) is the derivative control gain. The PD gains are obtained allowing the two following expressions:
Using artificial neural networks (ANNs) in control applications has been considerably increased due to their high capabilities in learning and compensating for nonlinearity and disturbances [36, 37, 46, 48, 53, 54]. The optimal scheme of the NN to be employed in various dynamic systems based on the loss function $f$ given in the following equation:

$$f = \sum_{i=1}^{m} e_i^2,$$

where $e_i$ is the acceleration tracking error to be minimized and $m$ is the number of data points.

The Jacobian matrix of the loss function is given as follows:

$$J_{i,j} = \frac{\partial e_i}{\partial W_i}, \quad i = 1, \ldots, m, j = 1, \ldots, n,$$

where $m$ is the number of data points and $n$ is the number of parameters in the NN.

The gradient vector of the loss function is given by the following equation:

$$\nabla f = 2J^T e.$$

The parameters of the NN are updated as follows:

$$W_{i+1} = W_i - (J^{(0)T}J^{(0)} + \lambda I)^{-1} (2J^{(0)T}e^{(0)}),$$

where $\lambda$ is a damping factor and $I$ is the identity matrix.

The database for training, testing, and validating the NN is real-time acquired acceleration signals from shaking table tests using real earthquake records, with the existing PDFF controller on QUANSER STIII. The NN input is the measured signal, and the target is the prescribed earthquake record. Signals are sampled at 0.2 ms which provide around 70,000 points: 70% of the data is used for training, 15% for validation, and 15% for test.

The performance of the NN is represented in Figure 4 in terms of mean square error (MSE) between the predicted signal and the target that reached the value of $10^{-4}$ in about 666 epochs (Figure 4(a)), and a linear regression is performed between the desired signal and the NN output (Figure 4(b)). The fitting line demonstrates that the prediction of the desired signal by the NN is achieved with an accuracy of 97%.

Based on equations (4)–(7), the optimal tuned weights and biases of the designed NN, which generate the most accurate prediction, are given in Table 4.

### 4. Neural Network-Based Control Scheme

The implementation of NNs in the control loops is widely employed in various dynamic systems. Based on the literature, different topologies of implementing the NN in the control framework have been attempted. Several works combine the high performances of the NN with the benefits of traditional controllers such as the PID [36, 37, 46, 48, 53, 54]. The optimal scheme of the NN to be
implemented in the shaking table control system is determined, first, by performing several numerical simulations. For this purpose, a realistic model of the shaking table has been developed in Simulink reproducing the measured acceleration with an estimated relative root-mean-square error that does not exceed 8%. Figure 5 shows the degree of accuracy of the numerical model to reproduce an acceleration response close to the acceleration measured experimentally.

The overall principle of the proposed control methodology is schematically represented in Figure 6. The combined controller is composed of an initially existing PD controller for displacement control, a FF controller for acceleration control to stabilize the shaking table system, and a NN-based control algorithm to enhance the acceleration replication accuracy. The aim of the designed neural controller is to compensate for the distortions measured in the feedback signals by acting on the drive signal to produce reference signals with small tracking errors.

The implementation of the NN-based PDFF controller on the Simulink model of QUANSER STIII incorporating the trained NN to perform an online correction in parallel with the existing PDFF controller is presented in Figure 7. The implementation of the combined control system in QUANSER STIII is depicted in Figure 8, where the parameters of the model are defined in Table 5.

For a comparison purpose, the experimental acceleration closed-loop frequency response of QUANSER STIII with and without the NN is depicted in Figure 9. As can be seen from the figure, the implementation of the NN block extended the frequency bandwidth of the acceleration closed-loop system from approximately 5 Hz with the PDFF controller to 55 Hz with the NN-PDFF controller.

Table 1: Specifications of QUANSER STIII.

| Description                      | Value         |
|----------------------------------|---------------|
| Stroke                           | ±10.8 cm      |
| Velocity                         |               |
| X-axis maximum velocity          | 1.55 m/s      |
| Y-axis maximum velocity          | 1.29 m/s      |
| Acceleration                     |               |
| X-axis maximum acceleration      | 1.92 g        |
| Y-axis maximum acceleration      | 4.69 g        |
| X-axis maximum acceleration with  | 1.12 g        |
| 100 kg payload                   | 1.51 g        |

Stage specifications

| Dimensions of the top stage      | 71.1 × 71.1 cm² |
| Total top stage mass             | 95.22 kg       |
| Total bottom axis mass           | 175.48 kg      |
| Moving bottom axis mass          | 139.21 kg      |
| Maximum payload                  | 100 kg         |

Table 2: Controller gain values.

| DOF | $K_p$  | $K_d$  | $K_f$  |
|-----|--------|--------|--------|
| $X$ | 7,533 A/m | 191.8 A-s/m | 1.91 A/(m/s)² |
| $Y$ | 2,577 A/m | 191.8 A-s/m | 0.653 A/(m/s)² |
5. Performance Assessment of the NN-Based PDFF Controller

Several shake table tests have been performed to evaluate the reliability of the platform to reproduce faithfully prescribed acceleration signals with the proposed control technique. For this purpose, three ground motions were applied on QUANSER STIII: the 1940 El Centro, the 1994 Northridge, and the 1995 Kobe earthquakes as they represent far-field and near-field earthquake records.

### Table 3: Performance of the NN with variation in the number of the hidden neurons.

| Number of hidden neurons | Number of epochs | MSE values | Coefficient of correlation |
|--------------------------|-----------------|------------|--------------------------|
| 5                        | 15              | $1.16 \times 10^{-3}$ | 0.80                     |
| 8                        | 300             | $1.35 \times 10^{-4}$ | 0.96                     |
| 10                       | 489             | $1.83 \times 10^{-4}$ | 0.96                     |
| 15                       | 613             | $4.54 \times 10^{-4}$ | 0.95                     |
| 25                       | 236             | $5.41 \times 10^{-4}$ | 0.88                     |
| 35                       | 833             | $4.20 \times 10^{-4}$ | 0.91                     |

### Table 4: Optimal set of weights and biases of the NN.

| Weights | Biases |
|---------|--------|
| $W_{11} = 11.3957$ | $b_1 = -10.9272$ |
| $W_{12} = -11.9247$ | $b_2 = 6.7960$ |
| $W_{13} = 11.1771$ | $b_3 = -3.6481$ |
| $W_{14} = -10.3101$ | $b_4 = 1.2071$ |
| $W_{15} = 10.9930$ | $b_5 = 2.2965$ |
| $W_{16} = -11.0828$ | $b_6 = -4.4926$ |
| $W_{17} = -10.6369$ | $b_7 = -8.9798$ |
| $W_{18} = 11.0298$ | $b_8 = 11.3982$ |
In the first stage, the potential of the NN control algorithm to reduce acceleration distortion is evaluated for an unloaded table. In the second stage, a 69 Kg single story steel specimen representing 70% of the payload, having a frequency of 3.5 Hz, is mounted on the platform. Feedback accelerations are filtered using a Kalman filter to reduce noise measurements without causing time delay.

The root-mean-square error (RMSE) is used as a quantitative evaluation index to assess, objectively, the capability of the NN controller to enhance the acceleration matching between the achieved and desired acceleration time histories. The RMSE is computed for the achieved and the desired acceleration in both time and frequency domains using the following equations:
Figure 8: Simulink diagram of QUANSER STIII with the online NN-PDFF controller.

Table 5: Parameters of the QUANSER STIII Simulink diagram.

| Parameters | Definitions | Units |
|------------|-------------|-------|
| \(X_d, Y_d\) | Desired table position along \(X-\) and \(Y\)-axis | m |
| \(X, Y\) | Measured table position along \(X\)- and \(Y\)-axis | m |
| \(a_{tbl_x}, a_{tbl_y}\) | Measured table acceleration along \(X\)- and \(Y\)-axis | g |
| \(X_{ddot}, Y_{ddot}\) | Computed table acceleration from measured position along \(X\)- and \(Y\)-axis | g |
| \(a_{f1}, a_{f2}\) | Measured acceleration of the specimen floor 1 and 2 | g |
| \(Tc_x, Tc_y\) | Scaled command time array | s |
| \(Xc, Yc\) | Scaled table position command array | cm |
| \(Id_x, Id_y\) or \(I_{ref_x}, I_{ref_y}\) | Current reference along \(X\)- and \(Y\)-axis | A |
| \(Im_x, Im_y\) or \(I_{meas_x}, I_{meas_y}\) | Measured current on linear motor along \(X\)- and \(Y\)-axis | A |
| \(Amp_en_x, Amp_en_y\) | Current amplifier along \(X\)- and \(Y\)-axis | A |
RMSET(\%) = \sqrt{\frac{\sum_{k=1}^{N} (a_d(k) - a_m(k))^2}{\sum_{k=1}^{N} a_d(k)^2}}, \hspace{1cm} (8)

RMSE_F(\%) = \sqrt{\frac{\sum_{k=1}^{N_F} (S_d(k) - S_m(k))^2}{\sum_{k=1}^{N_F} S_d(k)}} \times 100\%, \hspace{1cm} (9)

where \(a_d(k)\) and \(a_m(k)\) are the desired and the measured acceleration at the step \(k\), respectively, \(N\) is the number of data points, \(S_d(k)\) and \(S_m(k)\) are the desired and measured Fourier magnitude at the \(k\)-th frequency, respectively, and \(N_F\) is the number of frequencies in Fourier transform that cover the frequencies of interest. In this study, the frequency range of 0–100 Hz is adopted.

Another important index assessment for tracking performance of shaking tables is the fidelity in matching the PGA. In fact, the shaking table test could be totally controversial with a reproduced PGA at the base of the specimen different from the PGA of the real earthquake record [55]. In this study, the error in signal reproduction is calculated according to the following equation:

\[ \epsilon(\text{PGA}) = \frac{|\text{achieved PGA} - \text{desired PGA}|}{\text{desired PGA}} \times 100\% \] \hspace{1cm} (10)

6. Test Results

6.1. Unloaded Table Testing. In order to assess the efficiency and the robustness of the proposed control scheme, experimental tests have been carried out on an unloaded table, in the first stage of this study. A number of comparisons were performed to evaluate the fidelity in signal reproduction of the shaking table in terms of intended and achieved responses in time and frequency domains as well as attained and desired PGA. Figures 10 and 11 show a comparison between the reproduced and the desired
acceleration time histories as well as spectral accelerations under El Centro ground motion, respectively. With the additional NN controller block, an improved accuracy in the reproduced signals has been achieved as illustrated by an acceleration feedback getting closer to the target signal especially in the vicinity of the peak magnitudes and a decrease in the time delay. The frequency response amplification of the system around a critical frequency of 45 Hz has been significantly attenuated by the additional neural control function. This prominent advantage provided by the implementation of the NN control algorithm demonstrates the high capacity of the NN to cope with nonlinear aspects and resonance frequencies of the shaking table system.

Being an important index assessment for shaking table performance, the RMSE between the output and the reference signals has been computed, in both time and frequency domains, according to the above described equations (8) and (9) [3, 23, 40]. The value of RMSE_T and RMSE_F for El Centro decreased significantly from 63.62% to 16.33% and from 35.33% to 09.90%, respectively, after the implementation of the additional NN control algorithm. In Table 6, a summary of the computed RMSE of both acceleration time histories and Fourier magnitudes, for the three earthquake records that were used, is provided.

To further assess the enhancement provided by the hybrid controller presented in this study, a comparison between the reproduced PGA and the desired PGA has been carried out. Results showed that the PGA is reproduced within 10% error in the presence of the additional neural controller. The values of the errors obtained using both the PDFF and the NN-PDFF controllers are listed in Table 7.

6.2. Loaded Table Testing. As demonstrated in a number of works, the nonlinear interaction between the shaking table and the mounted specimen significantly deteriorates the performance of the acceleration reproducibility and can lead to the instability of the control system. Developing a robust controller that can minimize signal distortions measured at the base of the specimen is required. In order to further evaluate the robustness of the proposed NN-PDFF controller, a second experimental test program has been performed on a loaded table. The specimen described in Section 5 is mounted on the top stage of the shaking table, and the same earthquake records were applied. The same comparisons, as for the unloaded table, in both time and frequency domains, are performed with the existing controller and the proposed one. Figures 12 and 13 represent the comparison of acceleration time histories and spectral accelerations, respectively, between the system response and the target under the El Centro earthquake record. The proposed hybrid control achieves a better accuracy in reproducing desired accelerations on the platform. Also, it suppressed the system resonant frequencies around 45 Hz and enhanced the spectral amplitudes in the frequency range of interest.

To quantify this enhancement, the RMSE index performance assessment was used. The computed RMSE_T
between the measured and the desired acceleration for El Centro as well as the computed RMSE between the achieved and the desired spectral acceleration decreased significantly when using the proposed tracking strategy from 68.02% to 18.07% and from 53.62% to 11.61%, respectively. The computed RMSE of the acceleration time histories and spectral acceleration responses for the three earthquake records is summarized in Table 8.

The fidelity in the reproduction of the PGA on the table with a specimen has been evaluated using the index assessment given in equation (10). The PGA reproduced at the base of the specimen was in the range of 12% error maximum, for the three earthquake records that have been used. The computed errors between the desired and the achieved PGA with the PDFF and with the NN-PDFF controller are listed in Table 9.

**Table 6: RMSE relative error values for different earthquake records in time and frequency domain analysis (unloaded table).**

| Ground motion | RMSE_T % (time domain) | RMSE_F % (frequency domain) |
|---------------|-------------------------|-----------------------------|
|               | PDFF                    | Proposed                    | PDFF                      | Proposed|
| El Centro     | 63.62                   | 16.33                       | 35.33                     | 9.90     |
| Kobe          | 66.87                   | 18.07                       | 59.26                     | 18.30    |
| Northridge    | 54.31                   | 12.9                        | 22.78                     | 06.87    |

**Table 7: Error in PGA reproduction for different earthquake records (unloaded table).**

| Ground motion | Desired PGA (g) | Reproduced PGA (g) | ε (PGA) % | Reproduced PGA (g) | ε (PGA) % |
|---------------|-----------------|--------------------|----------|--------------------|----------|
| El Centro     | 0.3311          | 0.3227             | 02.56    | 0.2962             | 10.56    |
| Kobe          | 0.1243          | 0.1743             | 40.15    | 0.1360             | 09.34    |
| Northridge    | 0.6044          | 0.6617             | 09.48    | 0.5556             | 08.06    |

**Figure 11: FFT comparison between the measured and the desired signal for the El Centro earthquake record (unloaded table).**
Figure 12: Time history comparison between the measured and the desired acceleration for the El Centro earthquake record (loaded table).

Figure 13: Continued.
Based on these result analyses, a remarkable enhancement in reducing the acceleration errors between the reference input and the closed-loop system output was achieved when implementing the NN block. In fact, the NN control algorithm demonstrated the same level of efficiency to deal with the dynamic interaction between the shaking table and the specimen as well as system’s nonlinearities.

### 7. Conclusion

In order to improve the acceleration tracking performance of shaking tables, several control techniques have been recently developed, analyzed, and compared. This paper proposes a new shaking table control methodology which combines the powerful artificial neural networks and a traditional controller. A three-layer feedforward NN has been designed and integrated online in the control system of a biaxial electric shaking table to achieve further enhancement of the acceleration replication fidelity. At the first stage, experimental data were acquired in real time using the existing PDFF controller to constitute a database to train the feedforward NN offline using the Levenberg–Marquardt algorithm. Afterwards, the NN is implemented online in the outer acceleration closed-loop of the Simulink-based PDFF control system of QUANSER STIII. This enables the acceleration feedback to be shaped by the NN block before being introduced into the FF controller.

To experimentally assess the robustness and performance of the proposed NN tracking control, several tests have been conducted using three real earthquake records on both unloaded and loaded tables using the same NN model. A comparative analysis was carried out for the two testing conditions, and the results clearly proved that the NN-PDFF controller has a higher acceleration tracking accuracy over the original PDFF controller by addressing the high amplitude distortions and time delays. In fact, the reproduced accelerations matched closely the target time histories and the spectral acceleration amplitudes with an RMSE of 7% to 20% and the PGA within a range of 8% to 12% errors. The reduction in acceleration tracking errors due to the new neural control strategy proved the high capabilities of the NN to enhance the existing PDFF acceleration control accuracy and to cope with inherent nonlinearities and resonant frequencies of the system as well as the coupling effect due to the interaction between the shaking table system and the specimen, which represent an important source of classic control defiance.

**Table 8: RMSE relative error values for different earthquake records in time and frequency domain analysis (loaded table).**

| Ground motion | RMSE\(_T\)% (time domain) | RMSE\(_F\)% (frequency domain) |
|---------------|--------------------------|-------------------------------|
|               | PDFF                     | Proposed                      | PDFF                  | Proposed |
| El Centro     | 68.02                    | 18.07                         | 53.62                 | 11.61    |
| Kobe          | 75.15                    | 20.75                         | 77.60                 | 18.96    |
| Northridge    | 63.04                    | 16.61                         | 55.86                 | 09.34    |

**Table 9: Error in PGA reproduction for different earthquake records (loaded table).**

| Ground motion | Desired PGA (g) | Reproduced PGA (g) | \(\epsilon\) (PGA) % | Reproduced PGA (g) | \(\epsilon\) (PGA) % |
|---------------|----------------|--------------------|----------------------|---------------------|----------------------|
| El Centro     | 0.3311         | 0.2843             | 14.14                | 0.3002              | 09.34                |
| Kobe          | 0.1243         | 0.1758             | 41.41                | 0.1397              | 12.34                |
| Northridge    | 0.6044         | 0.7319             | 22.30                | 0.5531              | 08.48                |
The proposed shaking table control methodology is particularly useful in seismic testing on the shaking table to bypass performing preliminary signal-matching testing and iterative control tuning that would damage fragile specimens. Moreover, the neural controller has proved to be able to add to a conventional controller, robustness and efficiency against the time-varying parameter effects, the nonlinearities, and the changes in specimens’ conditions during testing. Further investigations are needed to generalize this procedure for different types of shaking tables with different types of control systems.

Data Availability
The recorded shaking table accelerations, collected as time series files, and the trained NN used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest
The authors declare that they have no conflicts of interest regarding the publication of this paper.

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