EXPERIMENTAL STUDY OF THE PARAMETRIC AND NON-PARAMETRIC SYSTEM IDENTIFICATION USING NEURAL NETWORKS

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SUMMARY

In this paper, experimental verification of a non-parametric system identification method using the neural networks capabilities is presented and evaluated. This method has been developed as a prelude for a comprehensive experimental verification of a recently developed structural control method using neural networks. The experimental program has been carried out on the earthquake simulator at the University of Illinois at Urbana-Champaign. The test specimen was a 1/4 scale model of a three storey steel frame. The control system consisted of a tendon/pulley system controlled by a single electro-hydraulic actuator. The structure had three distinct lightly damped fundamental modes of vibration plus two higher modes representing the structure–control interaction and the actuator dynamics. The system identification and parameter estimation have been achieved using two approaches of experimental nature. The first approach, described as a parametric system identification method, is used to describe the structure by set of first order differential equations using experimentally generated data. In the second approach, the structure was described by non-parametric models using the learning capabilities of the artificial neural networks. In this case, six neural network models were developed and trained to represent and simulate the system response with different time delays and prediction ranges. These models were referred to as the emulator neural networks. The prediction capabilities of the emulators were employed in developing and training the controllers. In this paper, full description of the test setup, the specimen, the instrumentations, and the hardware/software implementations are presented. Additionally, experimental validations of the parametric and the non-parametric models are presented and outlined. The evaluation was conducted experimentally for different loading cases. The results showed that the neural networks are suitable for system identification and their performance are very comprehensive in representing the system models with different time delays, noises and uncertainties.

INTRODUCTION

The effectiveness, robustness and stability of the controllers depends on the accuracy of the dynamic system models. In conventional control methods the control design is highly dependent on the parametric construction of the dynamic system models. Therefore, in conventional control methods, such as the optimal control method the designer must identify the controlled system accurately. In actuality control systems are inherently nonlinear, and therefore it is difficult, if not impossible, to build the real parametric nonlinear system models. Consequently, in conventional control methods the nonlinear systems is approximated by linear dynamic models. This paper presents a new neural network based method to enhance the system identification techniques. This methodology enables the neurocontroller to include non-parametric neural network identifiers to represent the nonlinear behavior.
The identification experiments were organized in two successive phases. The first phase was a series of experiments for parametric system identification. A mathematical parametric state space model was developed. The validation results of the simulation and the experiments are presented and compared. The second phase contained four shaking table tests, that were used for the training of the multiple emulator neural networks which identify the system transfer functions and predict the structure response to produce non-para-

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works which identify the system transfer functions and predict the structure response to produce non-parametric models. The effectiveness of theses emulator neural networks were evaluated and presented experimentally.

EXPERIMENTAL SETUP

The experiments were conducted on the earthquake simulator at the University of Illinois at Urbana–Champaign as shown in Figure 1. The earthquake simulator provides dynamic base excitation in one horizontal direction, and its platform area is 3.66 x 3.66 m^2 (12 x 12 ft^2). The shake table is connected to a 333.6 KN (75 kips) hydraulic actuator capacity with a 10.16 cm (4 in) piston stroke length.
The test specimen is a three story steel frame as shown in Figure 2. The specimen was design to approximate similar structural models tested in different studies (Miller *et. al*). The structural system was an approximate 1/4 scale model of a prototype structure which has been introduced by Clough and Tang[3] for seismic testing. This model has become the standard for structural control problems (Soong *et. al*), and has been used in many structural control tests (Chung *et. al*; Dyke *et. al*). The structure has three distinct lightly damped fundamental modes of vibration plus two higher modes that represent the building-control system interaction and the actuator dynamics. A detailed description of the model is presented in an earlier papers by the authors (Bani-Hani *et. all*). The model was mounted on the earthquake simulator such that the two moment–resisting frames were parallel to the axis of the motion of the table.
The control system consists of four 0.635 cm (1/4") Φ 6X37 IWRC wire rope tendons with average yielding capacity of 20,000 N (4,500 lb) and the average stiffness of 9,631 N/cm (5,500 lb/in). The four tendons were pre-tensioned to 8,896 N (2,000 lb) force to ensure the continuity of tension force in the tendons during the tests. Four pulleys of 10.478 cm (4 1/8 ") diameter each and service strength of 11,1200 N(2,500 lb) were bolted at the base plates to direct the control force to the first floor. The tendons are connected to the first floor through a set of steel brackets. A computer controlled hydraulic actuator of 9,785 N (2,200lb) capacity is connected to the loading yoke. Consequently, the hydraulic actuator at the base coupled with the tendon–pulley system controlled the motion of the first floor of the structure. A detailed photo illustrating these elements is shown in Figure 2. The stucture was fully instrumented to provide an accurate representation of the structure motion. Six LVDTs with 4 accelerometers as well as five load cells were used in structural monitoring (Figure 2).
The control actuator has been regulated through a Power PC computer and an INSTRON Plus 8500 digital unit through a high-performance multifunction analog, digital and timing input/output (I/O) board for Macintosh NuBus computers.

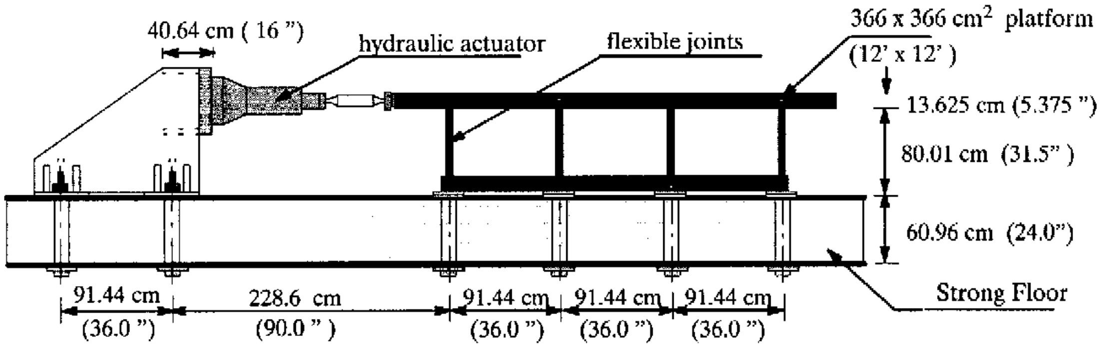
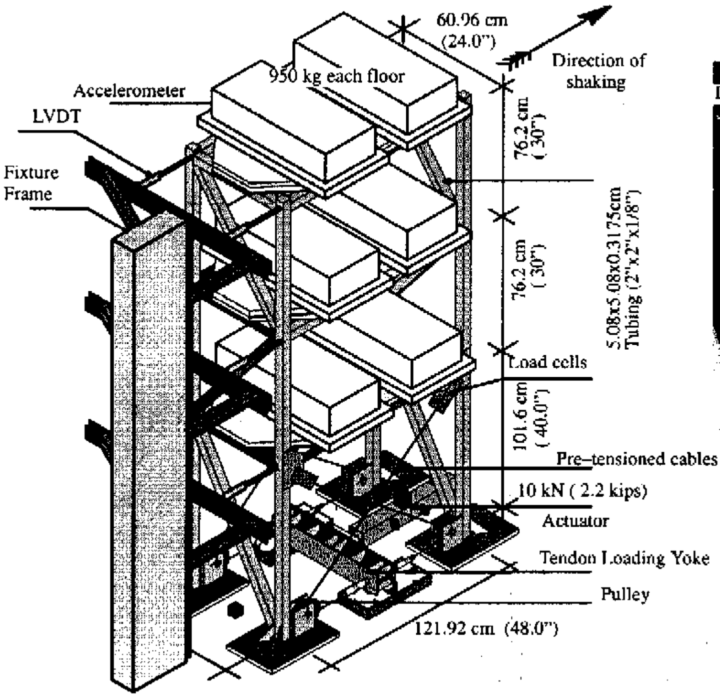


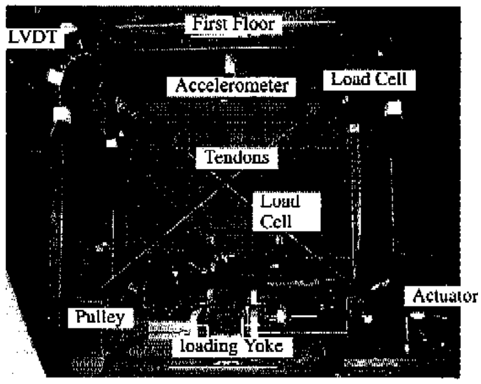
Figure 1. The Earthquake Simulator at the University of Illinois at Urbana–Champaign

PARAMETRIC SYSTEM IDENTIFICATION

Generally, the mathematical model of the structural system can be obtained by two different methods. The first method is to generate a model based on the physical properties of the system. These analytical finite element models can be developed using mass and stiffness characteristics of the structure. However, this leads to an approximate, incomplete system model which may be adequate for analysis and design purpose but not for structural control. A more accurate and reliable method, known as the system identification technique, is to develop the model based on experimental data that possess the real system behavior. In this study parametric modelling of the test system has been achieved in the time domain[6] and the frequency domain[4, 8]. First, the modelling was performed in the time domain. Next the estimated parameters and the system model were employed to produce a more accurate system model using the frequency domain methods.
One important issue in the system identification is the generation of the experimental data used in the parameter estimation approach. This task can be achieved by exciting the system with signals that can produce

the system output in the desired range of frequencies. In designing the excitation signal and recording the output signals different concepts and issues have to be controlled and observed: *aliasing, window functions, digital filters, sampling time, and filter leakage.* These concepts are discussed in many vibration testing books, such as Kenneth[7].





The Control System Elements

Figure 2. The Test Specimen used in This Study. Three Story Steel Frame with Active Tendons.

In this study the experimental data generated for the system identification was collected in two separate tests conducted at 200 kHz sampling rate. In the first test, the system was only excited with white noise ground motion of (0−60 Hz). The identified transfer functions were used to build a linear subsystem with one input (ground excitation) and many outputs (system response). In the second test, the system was excited by band−limited white noise (0−60Hz) control signal to determine the relationship between the control signal and the system response. This resulted in a second linear subsystem with the different input (the control signal) and the system response output. The previous concepts mentioned in developing the excitation signal were observed and satisfied. Moreover the developed experimental data were digitally processed and filtered using a Butterworth digital lowpass *anti−aliasing* filter with 60 Hz cutoff frequency.

In the discrete-time domain, the input-output model can be described in the form of the general Nonlinear AutoRegressive Moving Average (NARMA) model, where the new system output can be predicted using the past input and output samples of the system. In general, the input-output system can be described as follows:

$$y(k) = f(y(k-1),\ y(k-2),\ldots,\ y(k-n),\ u(k),\quad u(k-1),\ldots,\ u(k-m)) \tag{1}$$

where $y(k)$ and $u(k)$ represent the input−output pair of the system at discrete time step k, and the positive integers n and m are the order of the system. If the system is assumed to be linear, the function f is linear. Thus, the system can be described as follows:

$$y(k) = \sum_{i=1}^{n} a_i\, y(k-i) \quad + \sum_{j=0}^{m} b_j\, u(k-i), \tag{2}$$

So the best least−squares fit of the parameter vector can be estimated over the experimental input−output data.

A MATLAB code was used to fit the strategic relationships of the input−output system.

In the frequency domain identification method, the experimental transfer functions of the input-output relationships were estimated, empirically, from ten experiments on the shake table for the two different cases; the ground excitation and the actuator command. These transfer functions were obtained as the average over the ten experiments. A least−squares routine is used to determine the best fit of these transfer functions making use of the estimated parameters in the previous step in the time domain identifications.

Once all the desired transfer functions were identified, the zeros, poles and gains of each transfer function were computed. Then, the transfer functions have been transformed into state space form. The system identification process and the state space realization resulted in high−fidelity model of 25 poles corresponding to system model up to 100 Hz. However, ten of these poles represent the lightly−damped fundamental poles of the system: six poles represent the structural fundamental poles, $-0.0321 \pm 23j$, $-1.18 \pm 71.5j$, $-0.0754 \pm 129j$ (in rad/sec), and four poles that represent the control system and the actuator dynamics, $-1.48 \pm 288j$, and $-2.17 \pm 314j$ (in rad/sec).

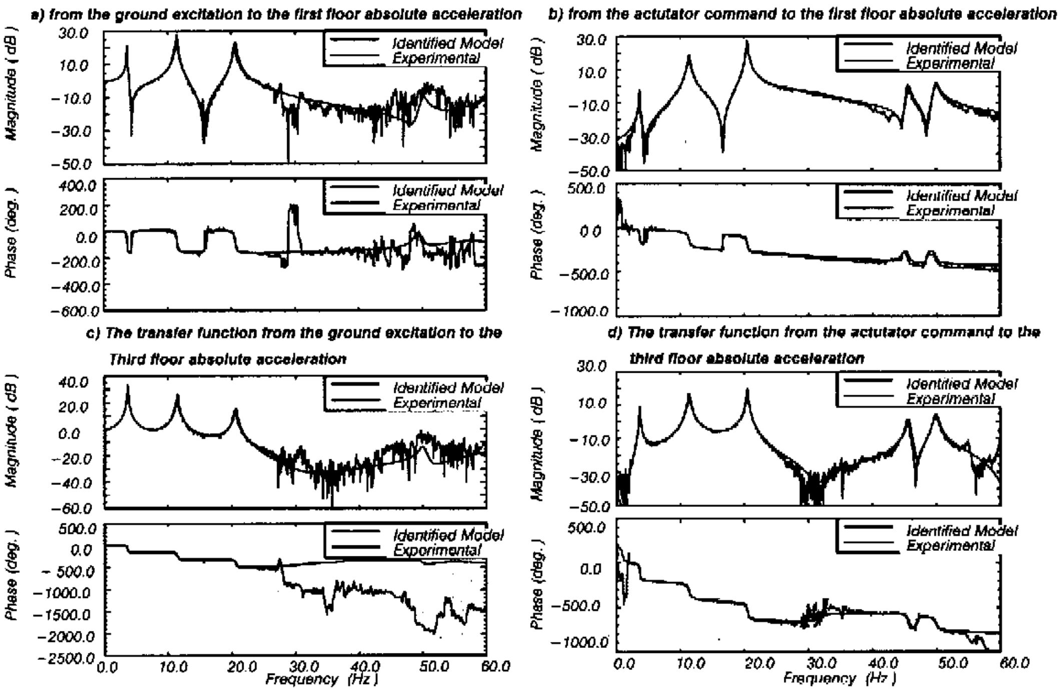


Figure 3. Sample Comparison Between the Transfer Functions

The validity of the identified model is illustrated by presenting sample comparisons of experimental and analytical results of the transfer functions. Figure 3 shows a comparison between the transfer functions from the ground excitation $\ddot{x}_g$ to the first and the third floor absolute accelerations as well as sample comparison between thetransfer functions from the actuator command u to the first and the third floor absolute accelerations. It can be seen that the analytical model successfully represented the needed transfer functions.

NON-PARAMETRIC IDENTIFICATIONS: SYSTEM EMULATION USING NEURAL NETRWORKS

Modeling the dynamical systems by using neural networks has been increasingly recognized as one of the system identification paradigms. The application of neural networks in system identification is due to their generalization ability and their capability to describing the system model accurately, specially when they are trained from experimentally generated data containing the system model uncertainties, time delays, and the structure-environment interaction. The neural network modeling problem in system identification is to develop a neural network model that is capable of learning and predicting the functional mapping between the inputs and the outputs of an unknown linear or nonlinear discrete-time multivariable dynamic system.

In this study, three independent neural network identifiers called emulator neural networks are trained. (Bani−Hani *et. al*). In addition to aiding in training a neurocontroller, the emulator neural network corresponds to the identification of the system dynamics where it identifies the transfer functions of the structural model in a non-parametric manner (black-box). The emulator neural network is expected to learn the functional mapping between the inputs and outputs of a system. This can be described in the following function.

$$y_{k+1} = f(\, y_k,\ y_{k-1}, \ldots,\ y_{k-n},\ u_{k-r+1},\ u_{k-r},\ u_{k-r-1}, \ldots,\ u_{k-r-m}) \qquad (3)$$

Where y_{k+1} represents the system response at time step $k+1$, u_k represents the present control command and r is a non-negative integer number controls the prediction capabilities of the emulator. Generally, the training process and the performance of the emulator degrades with larger values of r. The integers m and n are related to the degree of complexity and nonlinearity of the underlying process represented by the function. A trial and error process usually produces reasonable values for n and m. It is important to note that the function in Eq. (3), which must be learned by the emulator neural network also includes the effects of the actuator dynamics, actuator saturation, time delays and the sampling period. It is, therefore, a nonlinear function, even if the structure itself behaves linearly.

The emulator neural network learns the relationships represented by Eq. (3). However, neural network representation is not exactly the same as the functions they learn. For this reason we use a different symbol to represent the trained neural networks.

$$y_{k+1} = NN_e(y_k,\ y_{k-1},\ldots,\ y_{k-n},\ u_{k-r+1},\ u_{k-r},\ u_{k-r-1},\ldots,\ u_{k-r-m}) \tag{4}$$

Two sets of three emulator neural networks have been developed and trained These emulator neural networks differ in their prediction capabilities, architecture and their sampling rates. In the first set, three emulators were trained. The first emulator of this set, referred to as *EU3AI*, was trained to learn a direct relationship between the system response and the present control command including the time delays, where the value of r in Eq. (4) is zero. With this emulator it was possible to predict the response from the past history of the response and the present control command and part of its past history. The second emulator, referred to as *EU3AII*, was trained to predict the system response from the past history of the system response and the past history of the control command, where r=1. This emulator allowed the prediction of the system response one time step ahead. The third emulator, referred to as *EU3AIII*, had two time step prediction capabilities, where r=2. The three emulators of the first set can be represented using the following notation.

$$Output\ field\ =\ output\ field\ \mathbf{NN}\ [\{input\ field\};\ \{Neural\ Network\ architecture\}] \tag{5}$$

Hence, the three emulators can be represented symbolically using this notation as follows:

Emulator *EU3AI:*

$$\ddot{x}_k = \ddot{x}_k^P\,\mathbf{NN}\left[\ u_k,\ u_{k-1},\ u_{k-2},\ \ddot{x}_{k-1},\ \ddot{x}_{k-2},\ \ddot{x}_{k-3};\ 12,7,7,3\right] \tag{6}$$

Emulator *EU3AII:*

$$\ddot{x}_k = \ddot{x}_k^P\,\mathbf{NN}\left[u_{k-1},\ u_{k-2},\ u_{k-3},\ \ddot{x}_{k-1},\ \ddot{x}_{k-2},\ \ddot{x}_{k-3};\ 12,9,9,3\right] \tag{7}$$

Emulator *EU3AIII:*

$$\ddot{x}_k = \ddot{x}_k^P\,\mathbf{NN}\left[\ u_{k-2},\ u_{k-3},\ u_{k-4},\ \ddot{x}_{k-1},\ \ddot{x}_{k-2},\ \ddot{x}_{k-3};\ 12,11,11,3\right] \tag{8}$$

This representation describes the input and output field of the neural network model. The neural network symbol **NN** indicates that the output vector $\ddot{x}_k^P$ is predicted from neural network model. The information in the square brackets describes the neural network input and its architecture. The numbers following the semicolon describe the neural network architecture, i.e., number of layers and units in each layer.

In the second set, three emulators were trained. The first emulator of this set, is referred to as *EUAI*. The second emulator of this set is referred to as *EUAII.* The third emulator of this set is referred to as *EUAIII*. Similar to the first set of emulators, emulator *EUAI* learns the direct relationship between the control signal and the response. Whereas, emulator *EUAII* and *EUAIII* learn to predict the system response one time step ahead and two time steps ahead, consecutively. These three emulators are symbolically represented by the following equations.

Emulator *EUAI:*

$$\ddot{x}_{3_k} = \ddot{x}_{3_k}^P\ \mathbf{NN}\ \left[\ u_k,\ u_{k-1},\ u_{k-2},\ \ddot{x}_{3_{k-1}},\ \ddot{x}_{3_{k-2}},\ldots,\ \ddot{x}_{3_{k-6}}, 9, 5, 5, 1\right] \tag{9}$$

Emulator *EUAII:*

$$\ddot{x}_{3_k} = \ddot{x}_{3_k}^P\ \mathbf{NN}\ \left[u_{k-1},\ u_{k-2},\ u_{k-3},\ \ddot{x}_{3_{k-1}},\ \ddot{x}_{3_{k-2}},\ldots,\ \ddot{x}_{3_{k-6}}, 9, 6, 6, 1\right] \tag{10}$$

Emulator *EUAIII:*

$$\ddot{x}_{3_k} = \ddot{x}_{3_k}^P\ \mathbf{NN}\ \left[u_{k-2},\ u_{k-3},\ u_{k-4},\ \ddot{x}_{3_{k-1}},\ \ddot{x}_{3_{k-2}},\ldots,\ \ddot{x}_{3_{k-6}}, 9, 8, 8, 1\right] \tag{11}$$

The three emulators in each of the two sets were chosen to have the same m and n parameters given in Eq. (4).

The number of the nodes in each hidden layer of the emulator neural networks were adaptively determined during the training method. The difference in the number of nodes in the hidden layers in the adaptive architecture determination reflects the degree of difficulty in learning the various prediction capabilities for the emulator neural networks.

Training of the six emulator neural networks has been performed on experimentally–generated data from four earthquake simulator tests. The training data was collected when the system was set in motion with the following: 1) 25 seconds of 25% of the amplitude of El Centro Earthquake record with time compressed factor of two; 2) 50 seconds of 0–50 Hz band limited white noise ground excitation; 3) 50 seconds of 0–50 Hz band limited white noise actuator command; and finally 4) 25 seconds of 25% of the amplitude of El Centro earthquake record with time compressed factor of two and 25 seconds of 0–50 Hz band limited white noise actuator command. Neurocontroller *U3A* has a sampling period of 10 msec. and neurocontroller *UA* has a sampling period of 5 msec. Consequently, the first set of the three emulators(*EU3AI, EU3AII,* and *EU3AIII*), associated with neurocontroller *U3A*, have a 10 msec. sampling period therefore, 15,000 training cases were used in this set. The second set of the emulators (*EUAI, EUAII,* and *EUAIII*) associated with neurocontroller *UA* have a 5 msec. sampling period, and hence, 30,000 cases were used in their training.

Emulator Neural Networks Evaluation

Evaluation of the prediction capabilities of the trained emulator neural networks have been presented in frequency and time domain. In the frequency domain, the effectiveness of the emulators in reproducing and predicting the system transfer functions have been investigated and studied. The six emulators (*EU3AI, EUAI, EU3AII, EUAII, EU3AIII* and *EUAIII*) have been employed to reproduce the transfer functions from experimentally generated data, where the inputs to each emulator have been collected directly from the instrumented sensors on the specimen. Figure 4 shows the procedure to produce the system transfer functions using the three emulator neural networks in parallel–series fashion with a control signal of 0–50Hz band–limited white noise.

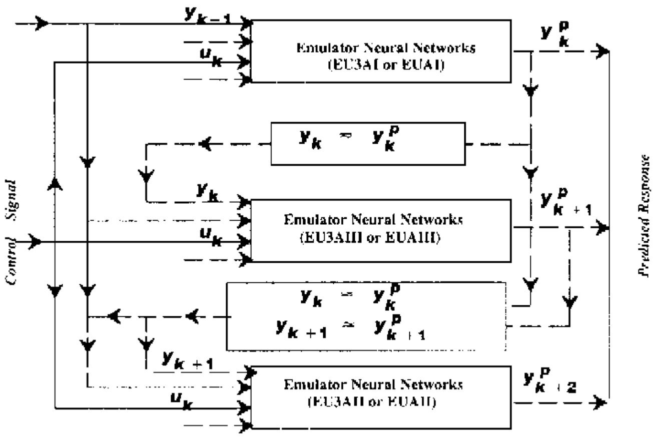


Figure 4. The Emulators Neural Networks in Parallel–Series Fashion.

Clearly, the sample illustration in Figure 5 show that the emulators are able to predict the transfer functions very well. However, as mentioned earlier, the performance of the emulators are slightly degraded with the increase of the values of *r* in Eq. (4). This is likely due to two reasons: 1) as *r* increases, the uncertainty in predicting further into the future increases, 2) and the input information in the second and the third emulators contain the output of the first and the second emulators which already have some small prediction error, therefore, the predicted response compounds the accumulated error.

In time domain, the performance of the emulator neural networks were evaluated by comparing their response with the experimental results. This evaluation was performed for three different cases: (1) 50% of 1952 Taft earthquake record with zero control command for the six emulators ; 2) 20% of 1994 Northridge earthquake record at Santa Monica–City Halll, with zero control command for the first set of emulators (*EU3AI, EU3AII* and *EU3AIII*) ; and 3) 50 seconds period 0–50Hz of band–limited white noise actuator command for the second set of emulators (*EUAI, EUAII* and *EUAIII*). The first case is shown in Figures 6 as one sample of these three cases. The same phenomenon of performance degredations with the increase in the value of the *r* is noticed, for the same reasons as stated before. Clearly, the emulator neural networks have been able to learn the transfer functions from the control command to the system response very well.

and to reproduce the structural response under different seismic excitations very accurately. In the evaluation of the emulator neural networks it has been intended to use validation experimental data different than the experimental training data. Clearly, as evidenced from the experimental results, the emulators were capable of predicting the response for novel cases that were not included in the training cases of the neural networks. This is always true when the neural networks are used, which makes the emulator neural networks independent of the training cases and generalized model for the system under study.

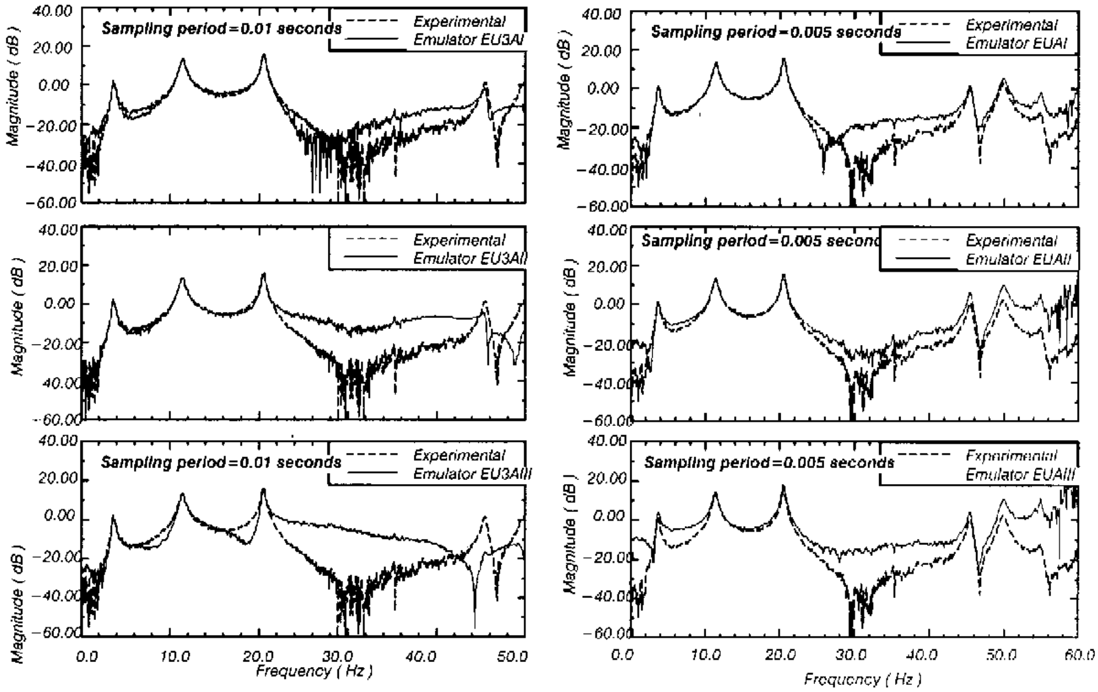


Figure 5. Comparison of the Experimental Transfer Function of the Actuator Command to the *Third Floor* Absolute Accelerations Using both set of the Emulator Neural Networks (*EU3AI, EU3AII EU3AIII, EUAI, EUAII* and *EUAII*).

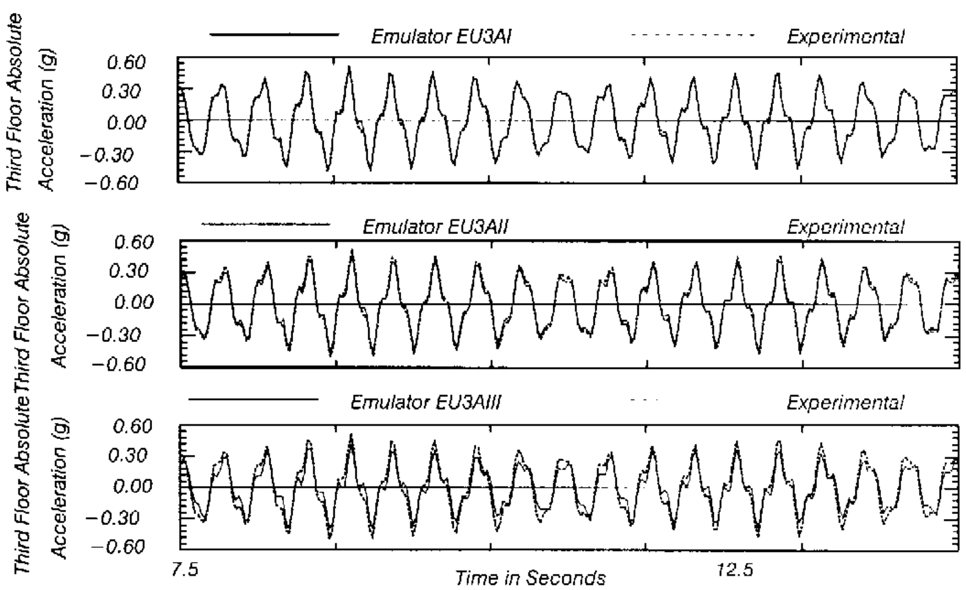


Figure 6. Comparison of the Experimental and Emulators response (using *EU3AI, EU3AII* and *EU3AIII*). The Structure has been Excited by 50% of Taft Earthquake Record.

CONCLUDING REMARKS

Experimental verifications of a neural networks based system identification has been presented and evaluated. The neural network models used for the system identification were called emulator neural networks. These emulators were developed for use in an experimental study of a recently developed structural control method using neural networks. Six different emulators were trained and verified. These emulators have different architectures, prediction capabilities and sampling rates. The experiments were performed on the earthquake simulator at the University of Illinois at Urbana–Champaign. First, the system was identified in the time domain and the estimated parameters were used in the frequency domain methods in a parametric identification method. In a second method, the system was modeled and identified using multiple emulator neural networks, intended for use in the neurocontrol design. The experimental validation of the mathematical model has been established in the time and frequency domains. The multiple emulator neural networks performance was demonstrated experimentally and shown to be independent of the training data.

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