Developing a Neural Network algorithm as an additional online controller to the PID controller.

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Abstract

The shaking table is a powerful tool in dynamic testing in which a high signal reproduction fidelity is considered as a distinguishing feature of the system. However, a precise control of the platform motions to ensure desired accelerations is still a challenging target because of the interference of the different mechanical, hydraulic and electronic parts as well as the test specimen particularly their strong inherent nonlinearities.

This study addresses the improvement of acceleration signal matching on a shaking table using an additional online controller based on a recurrent neural network algorithm. The latter is developed to provide an additional correction to the command signal produced by the actual shaking table control system, in order to reduce the signal distortion between the reproduced signal and the desired one. The shaking table is simulated by its transfer function implemented in Matlab/Simulink, including a PID online controller.

The training of the Neural Network is performed offline. The response of the transfer function of the system acceleration is used as input to the NN. The desired signal in acceleration represents the NN target.

After training, the NN is implemented in Matlab/Simulink model in order to provide an online correction to the output signal, in the same time as the PID. To evaluate the performance of the proposed control scheme i.e a PID-NN controller, a correlation coefficient R has been calculated between the target signal and the system output. Results show that the NN controller improves the signal matching in acceleration.

Key words: Shaking table; Neural Network; Elman Neural Network; control; online controller.

1. Introduction

Shaking tables are one of the most essential tools in experimental Earthquake Engineering. They are used to reproduce dynamic loads similar to real earthquake motions to test the dynamic behavior of structures or structural elements. However, the presence of inherent nonlinearities in the system, the interaction table-specimen, the complexity of the entire system and the highly nonlinear states of the specimen while testing, are known to widely deteriorate control performance. Linear controllers cannot control the shaking table in an efficient way.

Several works have been carried out to develop robust control methods and improve the traditional PID control performance, such as adding acceleration feedback, nonlinear compensations, or most recently combining the PID with Artificial Neural Networks. The latter have been introduced in different manners. In one scheme, an additional control function is given by neural network for learning and compensating the inherent nonlinearities [1]. In a different way, PIDNN controller has been developed where the PID functions are included in the hidden neurons [2, 3]. Neural networks has been also used to tune the PID and predict the appropriate PID controller parameters [4, 5].

In this paper a neural network is used as an auxiliary online corrector to enhance the PID performance.

2. The shaking table model

Modeling of the shaking table is a real complex task due to the several nonlinear parts of the system and its time varying parameters. Many studies have been done to modeling the shaking table system using experimental parameters identification [6] or linearization methods of the dynamic system to develop analytical model of the system [7].

A previous work of the authors [8] focused on modeling the general behavior of a shaking table in a realistic way, by preserving the physical parts of the system using a Finite Element (FE) model of a loaded shaking table with no controller.

In the present study, an analytical transfer function of the system is estimated by comparing the input and output relationship of the FE model. The most accurate results are produced using sine sweep simulations [9]. The 2nd order estimated transfer function of the shaking table is given by this following equation:

$$T(s) = \frac{2.8912s + 383.9521}{s^2 + 2.6485s + 524.642} \tag{1}$$

The magnitude and the phase of the shaking table transfer function are shown in Fig.1.

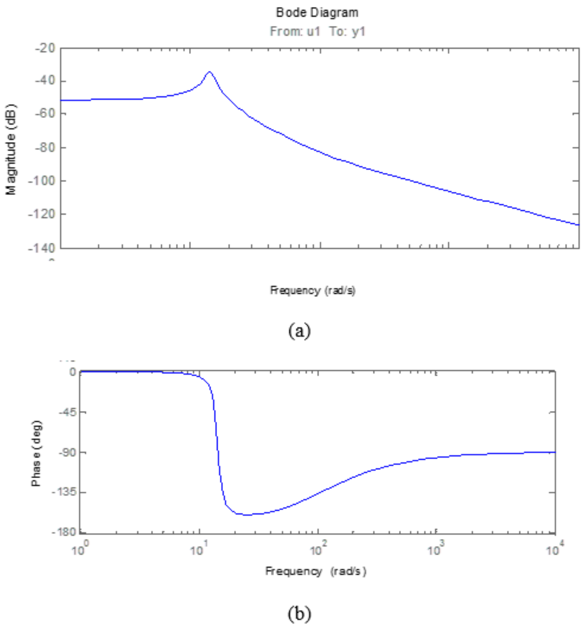

Fig. 1. Magnitude (a) and phase (b) of the shaking table transfer function

In order to model the behavior of the shaking table with an online control system, the above transfer function is implemented in Matlab/Simulink with an online PID controller. The tuned gains of the controller i.e. P, I and D parameters are equal to 0.717, 0.013 and 3.32 respectively. The model is shown in Fig.2.

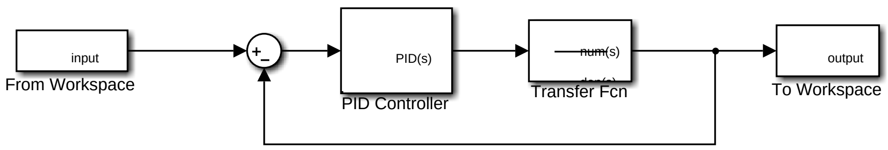

Fig.2. Schematic of the Shaking Table with a PID controller (Matlab/Simulink).

3. Neural Network-PID control strategy

The NN is used to add an additional correction to the command signal produced by the PID controller, in order to reduce the signal distortion. The schematic of the proposed matching control is shown in Fig.3.

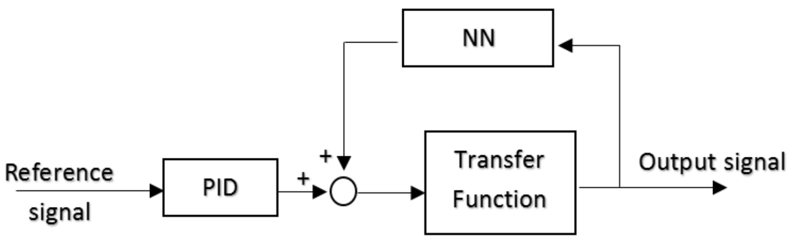

Fig.3. Schematic of the proposed control.

As in the previous work of the authors, the NN used is the Layer-Recurrent Network (LRN) which is a new version of the Elman Network. The training algorithm used is Lavenberg-Marquardt algorithm. The number of nodes and hidden layers are determined by experiments. 21 neurons with sigmoid function are implemented in the hidden layer (Fig.4).

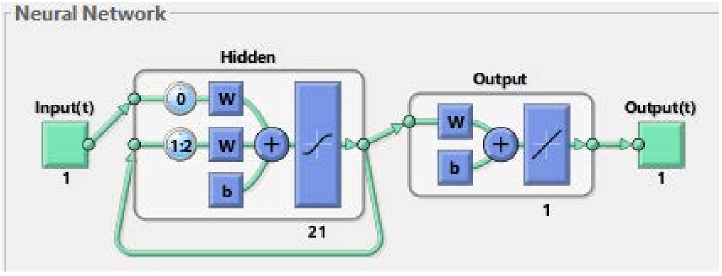

Fig.4. Structure of the proposed NN.

Several simulations are carried out to collect input/output signals of the shaking table with a PID controller and were used to constitute a database to train the NN, on offline mode.

After training, the proposed NN is implemented through a Matlab Function in the Matlab/Simulink model to add an auxiliary online control to the plant. The model of the system with both PID and NN controller is shown in Fig.5.

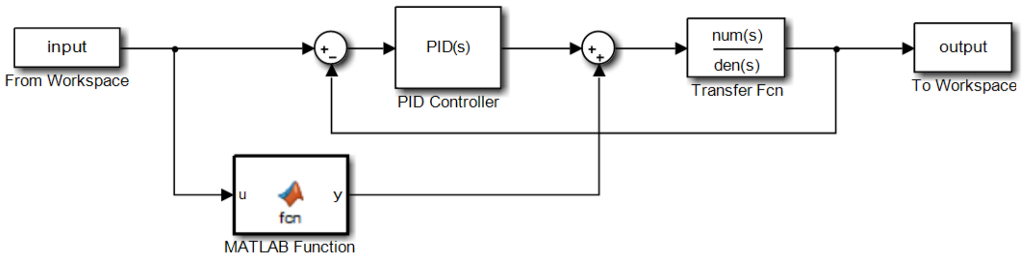

Fig.5. Structure of the proposed online NN.

4. Performance of the online correction with the NN controller

The NN is designed to achieve an additional correction to the output signal provided by the tuned PID controller. The database to train the NN is constituted using inputs and outputs from the shaking table model controlled by the PID. The error in the prediction of the target signal is estimated using the mean square error formula (MSE) with a target value around 10^{-4}. A linear regression between the network response and the target is performed and a correlation coefficient between the response and the target R is calculated. The fitting line shown in Fig.5 is practically superposed with the diagonal and the correlation coefficient R obtained is very close to unity.

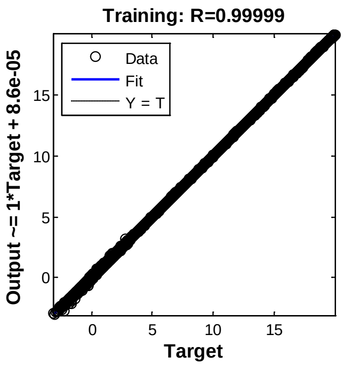

Fig.5. Linear Regression between the NN output and desired signal.

Then, the trained network is implemented in the model to perform an additional online control in conjunction with the PID controller. The performance of the total control is evaluated by comparing the system output and the target signals. The PID-NN scheme shows an enhanced behavior over the PID control.

For comparison purpose, several earthquake records are simulated using the PID controller alone and the PID-NN controller. A representative response curves shown in Fig.6 compare the response of the system table with PID controller, the response of the system with the additional NN online controller together with the desired signal. It is visible that the NN enhances the signal reproduction on the shaking table, where the signal output with the additional neural control correction follows the target signal more accurately especially the peak values.

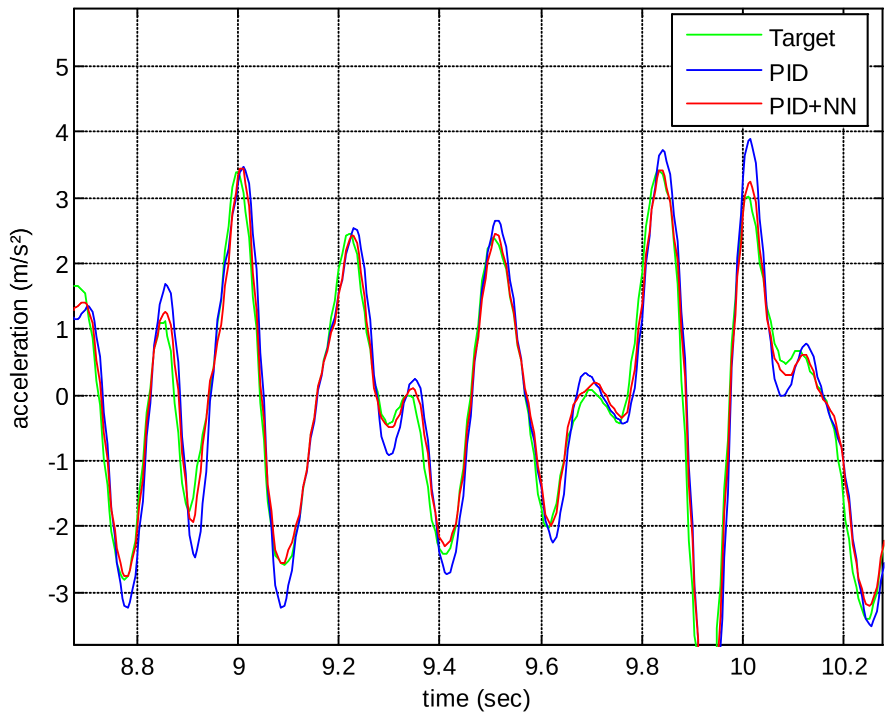

Fig.6. Desired signal, PID only controlled and PID+NN controlled responses of the shaking table under Kobe earthquake record.

5. Conclusion

The conventional PID controller is limited in some applications when the controlled plant shows a coupling or nonlinear behavior. As a complex system with inherent high nonlinearities and strong coupling with flexible specimens, shaking tables require a robust control performance to be able to reproduce the desired motion. For this purpose, a dynamic neural network is proposed to enhance the PID performance and improve the fidelity in signal reproduction. The shaking table is herein modeled by its approximated transfer function, with an online tuned PID controller. This model is used to build a database to train the NN, on offline mode. After training, the NN is implemented in the model in an online mode, in order to add a correction to the PID command signal. Results indicate that the PID-NN scheme has an enhanced behavior over the PID control alone and the reproduced signal is closer to the desired signal particularly at peak values.

6. References

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