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IDENTIFICATION OF DYNAMIC SYSTEM USING NEURAL NETWORK

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Abstract. *Field of system identification have become important discipline. Identification is basically the process of developing or improving a mathematical representation of a physical system using experimental data. The artificial neural network is a newly developed technique among the identification methods. Dynamic function mapping, including the structural dynamic model is still a challenging topic in neural network applications. In this paper is presented a neural network approach for structural dynamic model identification. The neural network is trained and tested by using the responses recorded in a real frame during earthquakes. The obtained results show the great potential of using neural networks in structural dynamic model identification.*

1. INTRODUCTION

The modeling and identification of linear and nonlinear dynamic systems through the use of measured experimental data is a problem of considerable importance in engineering. System identification, which is based on the method of least square fit to identify system parameters, may be classified into two categories: one in a deterministic manner and the other in a statistical manner. These techniques can be used to identify some system parameters, such as a damping and modal frequencies of the system. Among the nonparametric identification methods, the artificial neural network is a newly developed technique for the purposes of identification. Due to its attributes, such as massive parallelism, adaptability, robustness and the inherent capability to handle nonlinear systems, this technique have been widely used in complex nonlinear function mapping, image processing [1,2], pattern recognition and classification. A static function mapping can be determined empirically without knowing any fundamental physics of the

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system by using the neural network technique. However, the dynamic function mapping including dynamic model identification is still a challenging topic in neural network applications.

Approach for identification of nonlinear dynamic system using neural networks is to involve the dynamic differential equation into each of the neural network processing elements to create a new type of neuron called a dynamic neuron. Since differential equations are involved in the processing, these approaches cannot take full advantage of the neural network operation. For structural dynamic model identification, the knowledge of system dynamics is useful. In the present paper, a neural network approach for dynamic model identification is developed based on the knowledge of the system physics. This neural network is trained, tested and verified by using the responses recorded in a real frame during earthquakes.

2. ARTIFICIAL NEURAL NETWORK

Neural networks are powerful tool for the identification of systems typically encountered in the structural dynamics fields. Neural network were originally developed simulate the function of the human brain or neural system. Artificial neural network is basically a massive parallel computational model that imitates the human brain. This method do not really solve problems in a strictly mathematical sense, but they are one method of relaxation that gives an approximate solution to problems. A number of neural network techniques have been used in system identification such as backpropagation network, Hopfield network and Kohonen network. In the present paper, the most widely used technique, the backpropagation neural network, is adapted for the identification of a structural dynamic model. The principles of the backpropagation neural network are shown in the following.

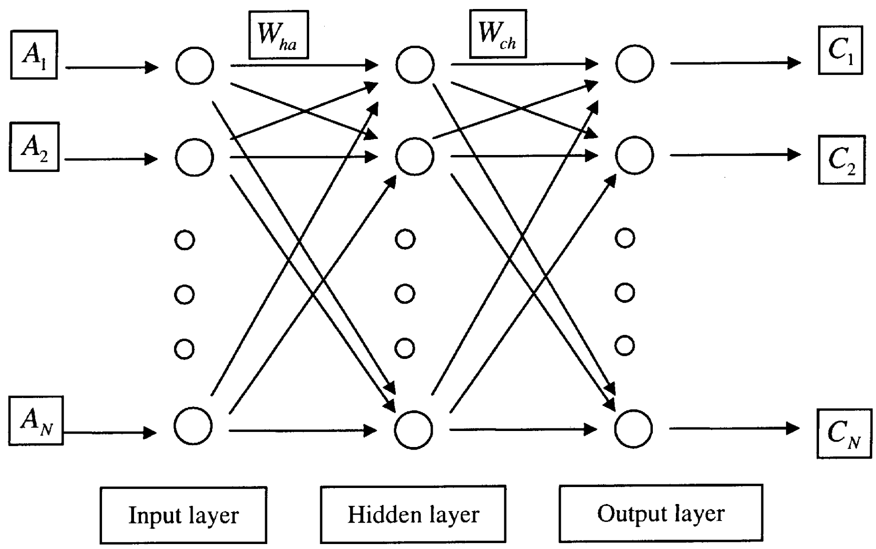

Fig.1. Three layer Backpropagation Neurel Network

A typical three-layer backpropagation neural network is shown in Fig.1 and consisted of the next: the input layer with *a* nodes, the hidden layer with *b* nodes and output layer with *c* nodes. Between layers there are weights W_{ha} and W_{ch} representing the strength of connections of the nodes in the network. The first type of operation of backpropagation neural network is called feedforward and is shown as solid lines with arrow in Fig.1. For this operation, the output vector C(t) is calculated by feeding the input vector A(t) through the hidden layer of the neural network. The output of the node h in the hidden layer $H_h(t)$ for the given input layer A(t) is

$$H_h(t) = F(Net_h(t))$$

$$H_h(t) = F(\sum_i W_{hi} A_i(t))$$

where Net_h represents the total input to the node h in the hidden layer; and F(x) is the activation function, which has to be differentiable. In this paper the activation function function is the sigmoid function

$$\text{F(x)} = \frac{1}{1+e^{-x}}.$$

The output of the node *c* in the output layer $C_c(t)$ is

$$C_c(t) = F(Net_c(t))$$
$$C_c(t) = F(\sum_h W_{ch} F(\sum_i W_{hi} A_i(t)))$$

where Net_c represents the total input to the node *c* in the output layer.

The second type of operation of the backpropagation neural network is called error backpropagation, which is marked by dashed lines in Fig.1. The sum of the square of the differences between the desired output $L_c(t)$ and neural network outputs $C_c(t)$ is

$$E = \frac{1}{2}\Sigma(L_c(t) - C_c(t))^2 \tag{1}$$

The adaptive rule for the weight W_{ch} as the connections between the hidden layer and output layer, can be determined as

$$W_{ch}(t+\Delta t) = W_{ch}(t) + \Delta W_{ch}$$
$$\Delta W_{ch} = -\eta \frac{\partial E}{\partial W_{ch}} \tag{2}$$

$$\Delta W_{ch} = -\eta \sum_t \Delta_c(t) H_h(t)$$

$$\Delta_c(t) = \frac{dF(Net_c)}{dNet_c}(L_c(t) - C_c(t))$$

The adaptive rule for connections between the input layer and the hidden layer W_{hc} as

$$\Delta W_{ha} = -\eta \frac{\partial E}{\partial W_{ha}}$$

$$\Delta W_{ha} = -\eta \sum_t \Delta_h(t) A_a(t)$$

$$\Delta_h(t) = \frac{dF(Net_h)}{dNet_h} \sum_c W_{hc} \Delta_c(t) \tag{3}$$

The coefficient η is called the learning rate. The error backpropagation rules shown in the equations (2) and (3) with applying the differentiation process successively can be expanded to the networks with any number of hidden layers. The weights in the network are continuously adjusted until the inputs and outputs reach the desired relationship.

3. IDENTIFICATION OF STRUCTURAL DYNAMICS MODEL

The backpropagation neural network can be used to empirically map any function using measured experimental data. However, the dynamic function mapping is still a challenging topic in neural network applications. Knowledge of the dynamics of the system is useful in the determination of the neural network architecture, its inputs, outputs and training process for dynamic model identification purposes.

The general concept of structural dynamics for demonstrate how to successfully use the knowledge of structural dynamics in neural network application is discussed in the following.

The outputs of a structure subjected of ground acceleration $\ddot{G}(t)$ can be described by:

$$M\ddot{X}(t) + C\dot{X}(t) + KX(t) = M\ddot{G}(t) + Hu(t) \tag{4}$$

where M, C and K - mass, damping and stiffness matrices and $X(t)$ displacement with respect to the ground.

This equation can be written as

$$\dot{Y}(t) = AY(t) + Bu(t) + Pf(t) \tag{5}$$

$$Y(t) = \begin{bmatrix} \dot{X}(t) \\ X(t) \end{bmatrix}$$

Matrices A, B, P and f can be determined as follows:

$$A = \begin{bmatrix} -M^{-1}C & -M^{-1}K \\ I & 0 \end{bmatrix},\ B = \begin{bmatrix} -M^{-1}H \\ 0 \end{bmatrix},\ P = \begin{bmatrix} I \\ 0 \end{bmatrix} \text{ and } f(t) = \ddot{G}(t).$$

Equation (5) can be written in the discrete state equation as

$$Y(k+1) = e^{A\Delta t}(Y(k) + Bu(k) + Pf(k)) \tag{6}$$

where k - an integer number, $k = 0,1,2,...N$; $Y(k+1)$ is response at time $t = (k+1)\Delta t$ where

Δt is sampling period.

In the present paper, a backpropagation neural network is chosen as the neural network to model the dynamic behaviors of the structure described by (6) through the training process. This equation shows that given the state variables $Y(k)$ and the dynamic loading $f(k)$ can be determined the response at the next step $Y(k+1)$ completely. It means the next: if the inputs of the network are chosen as $Y(k)$ and $f(k)$ than the output of the neural network should convergence to $Y(k+1)$ through the training process and is shown on Fig 2. The weight of the neural network are initialized with small random numbers first. The outputs of neural network are computed by feeding forward the inputs through the network.

The error function $E_m(k+1)$ is calculated from the difference between the outputs of the neural network $Y_n(k+1)$ and measured responses of the structure $Y_m(k+1)$. By backpropagation the error function $E_m(k+1)$ to adjust the weights, the neural network can be trained to reach a desired accuracy for modeling the dynamic behavior of the structure.

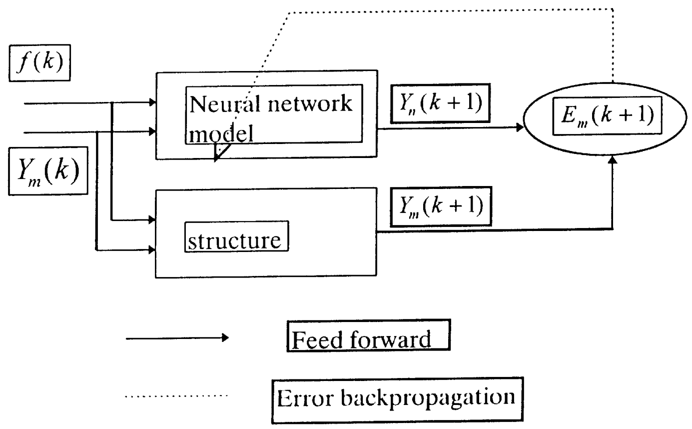

Fig.2 Training and architecture of neural network model

As shown in Fig.2, in principle, the on-line training of the neural network dynamic model can be achieved. However, the back propagation neural network is not suitable to perform the on-line training due to its slow convergence. In practice, the convergence of the backpropagation neural network can be sped up for the on-line training if the off-line trained network is used as the initial model of the backpropagation neural network.

To demonstrate the performance of the neural network in the structural dynamic model identification, a five-story steel frame, was chosen as structure to be identified. In earthquake engineering the response of the physical systems can be obtained by experimental investigations of the systems using various test procedures, such as shaking table test, full scale tests of structures, etc. All these test provide various experimental results which, depending on the model concept, are used for the determination of the model directly or after filtering. This experimental program was planed in a way to ensure the collection of maximum useful experimental data. So, the displacement and acceleration time histories were recorded for various set of earthquakes [3] of different excitation levels on each floor. As shown in Fig. 3 our test model is a five-story steel frame, mounted on two heavy base floor girders and puts on the shaking table. The experimental model was instrumented by 30 channels which measured the accelerations, displacements and stresses. The displacement were recorded by linear potentiometers with respect to a reference beam located on the foundation block.

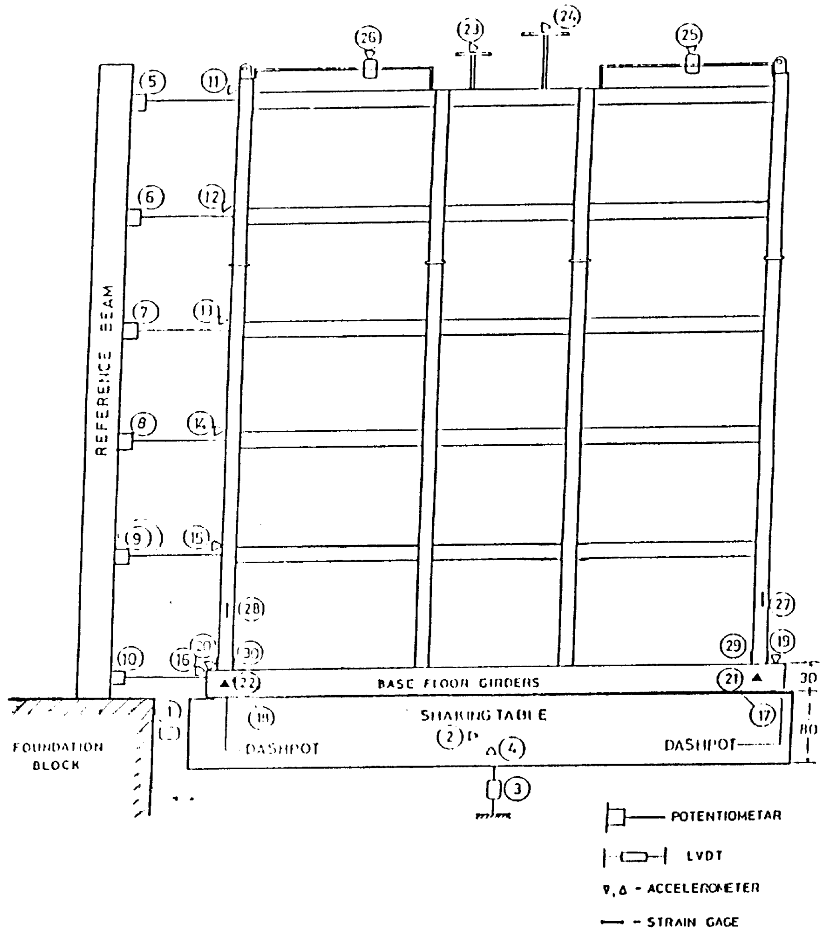

Fig.3 Structural model on the shaking table

Two earthquakes used for the dynamic model identification were recorded in the frame.They are the Petrovac 1979, component N-S and El Centro 1940, component N-S. The seismic data, including the displacement velocity and acceleration were processed by the IZIIS (Institute of Earthquake Engineering and Engineering Seismology, Skopje, Macedonia), having a uniform time interval of 0.01s and a total of 1,000 points (10.0s).

4. Discussion of the results

The data set, used for training of the neural network dynamic model, is the first 500 points taken from 1,000 points record [4] of the Petrovac 1979 earthquake. The weight are adjusted based on the error function E_m, with a learning rate $\eta = 0,7$. The whole of line training process takes 47 cycles and the root-mean-square error is reduced to 0.0068(cm).

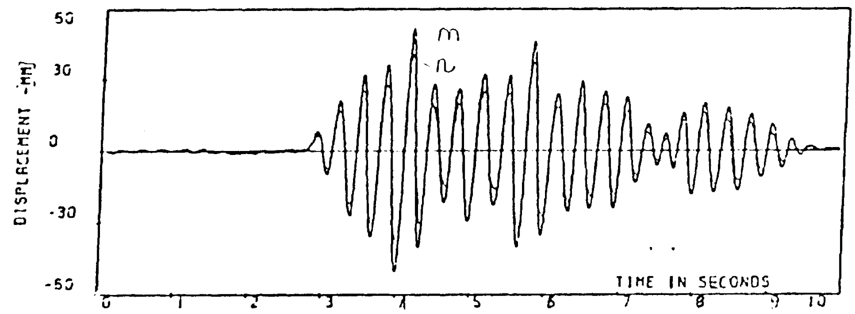

Fig. 4 Comparison of experimental (m) and neural network (n) responses of steel frame subjected to earthquake Petrovac 1979.

In the Fig. 4 is the comparison of the responses observed of the fifth floor of the frame and the responses generated from the trained neural network dynamic model. This figure shows that the training neural network model represents the real frame very well, not only in the first 500 points used for training, but also in the remaining 500 points. The root-mean-square error of the generated responses from the model network for the entire record of 10s reaches 0.0429 cm. The weighs are adjusted once according to the training the neural network. The weighs adjusted according to the error computed from (6) after the entire 500 time steps had been fed through the network, were also examined. Increasing the size of the network is likely to improve the representative capabilities of the network for the data set used in the training. However, network over fitting not only increases the training time, but it may also lose the generalization to the new inputs. The neural network model presented here in this paper can represent the dynamic behavior including its nonlinearity through just training processing using the collected sample data without the formulation of the structural model.

5. Conclusion

The application of the neural network technique in the field of earthquake engineering, in the case where experimental results are available for the considered physical systems, is a very powerful tool for an objective definition of structural dynamic model. Based on the knowledge of the system dynamics, the inputs and outputs of the neural network are chosen properly so that the structural model can be identified efficiently. Results from the study of the responses of a real frame subjected to earthquakes show great promise in structural dynamic model identification by using the neural network.

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IDENTIFIKACIJA DINAMIČKOG SISTEMA KORIŠĆENJEM NEURALNE MREŽE

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Identifikacija sistema, kao veoma aktuelna naučna oblast, u osnovi predstavlja proces razvijanja ili poboljšanja matematičkog predstavljanja fizičkog sistema uz korišćenje eksperimentalnih podataka. Među mnogim identifikacionim metodama nalazi se i novorazvijena metoda vještačke neuralne mreže. Funkcija dinamičkog mapiranja, uključujući dinamički model, predstavlja izazovnu temu u nizu aplikacija neuralne mreže. U ovom radu je prezentirana identifikacija konstruktivnog dinamičkog sistema uz korišćenje neuralne mreže. Neuralna mreža je trenirana i testirana korišćenjem zapisa odgovora realne konstrukcije za vrijeme zemljotresa. Dobijeni rezultati potvrđuju ovu metodu kao veoma efikasnu i moćnu u oblasti identifikacije dinamičkog modela.