Modal Parameters Determination of Steel Benchmark Warehouse by System Identification Using ANN

Sertaç TUHTA[1], Furkan GÜNDAY[2]

[1,2]*Department of Civil Engineering, Ondokuz Mayis University, Turkey*

***Abstract*—Today, civil engineering structures suffer from dynamic effects. Earth on structures have been severely damaged by the earthquake. Thus, there has been loss of life and property. This has particularly affected countries located on active fault lines. Pre- and post-earthquake measures have been developed in world. For these reasons, it is necessary to determine the dynamic performance of structures around the world. There are various methods for determine the dynamic performance. System identification is one of these methods. Mathematical model of the structural system is obtained by system identification method. Artificial Neural Networks (ANN) is a system identification method. Artificial Neural Networks (ANN) can adapt to their environment, adapt, work with incomplete information, make decisions under uncertainties and tolerate errors. Steel warehouse sample was used in this study. The system identification of the steel warehouse structure with the ANN method of 0.95 was made successfully. As a result of this study, The ANN approach can provide a very useful and accurate tool to solve problem in modal identification studies.**

***Keywords*—System Identification, ANN, Modal Parameters, Steel Warehouse**

I. INTRODUCTION

Most of structures located in regions prone to earthquake hazards suffer from various types of destruction caused by seismic loads. Under such earthquake occurring [5].There are many studies that take this into account. In the regions of seismic hazards, structures are expected to have vibrations due to seismic loads [15]. In civil engineering field, currently there are many varieties of structural and architectural structures. Such structures can be managed to resist to both static and dynamic loads effectively [16].More work should be done to clarify the performance of structures under seismic loads [13].More researches are being conducted to get required performance of structures under seismic loading, by means of looking at different point of view and directions [14].In recent years, in the world and our country, the determination of the effect of vibrations on structures and structural behavior has become very important [17].Buildings located in seismically active regions are under high risk of severe damages caused by harmful earthquake loads [6].Civil engineering structures are exposed to a variety of natural and artificial effects throughout their lifetime. These effects are the forces that can affect the dynamic characteristics of the structure and thus the service life [18].In all construction systems, damage starts at the material level. As the damage in the system increases, it reaches a value defined as deterioration [19]. Generally forced and ambient vibration methods are used in the purpose of vibration testing of structures [20].The authors pointed out the reasons for their studies.The authors also pointed out that this point should be focused on. This study was carried out considering these negative situations.

System identification (SI) is a modeling process for an unknown system based on a set of input outputs and is used in various engineering fields [8], [9].Subspace system identification is introduced as a powerful black-box system identification tool for structures [21]. The application of the method for supporting excited structures is emphasized in particular. The black- box state- space models derived from the identification of subspace systems are used to estimate the modal properties (i.e. modal damping, modal frequency and mode shapes) of the structures [7], [10].

Depending on the input and output sizes of these systems, in order to obtain a behavioral model, it is necessary to determine and measure the magnitudes affecting the structures. Model identification, system-related, based on physical laws based on the preliminary information and the size of the system (introduction magnitude or input signal) from the system's response to these magnitudes (output magnitude or output signal) It is exploited. Physical laws are defined by differential or algebraic equations. In this way model, not only the relationship between the input and output sizes, but also by determining the model structure are expressed. On the other hand, the lack of any preliminary information about the system or the system is too complex. In case of having, identification methods (such as parametric definition) are used in determining the model of the system. In this case, the model is obtained by using input and output sizes. This technique can be applied by making some preliminary assumptions regarding the choice of system grade, input and output sizes [12].

Stable adaptive controller designs have been one of the most important research topics in recent years as they can produce effective solutions against time-varying system parameters and disturbing effects in the desired system output monitoring problem [11].

II. METHODOLOGY

Artificial Neural Networks (ANN) is computer-based systems that perform the learning function which is the most basic feature of human brain. Performs the learning process with the help of existing examples. It then forms these networks from connected process elements (artificial neural cells). Each link has its own weight value. This is the information that the artificial neural network has weight values and spreads to the network.

Artificial neural networks are different from other known calculation methods. It can adapt to their environment, adapt, work with incomplete information, make decisions under uncertainties and tolerate errors. It is possible to see successful applications of this calculation method in almost all areas of life.

Typical neural network architecture is given figure 1.

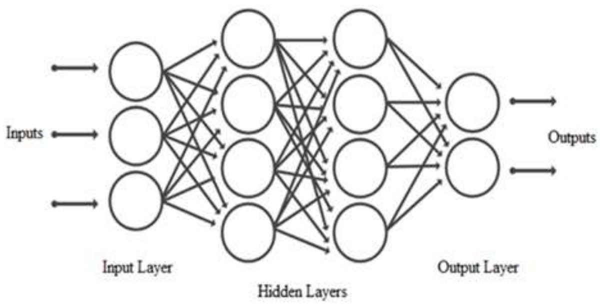

Fig. 1. Typical neural network architecture

Weight values to the values of the connections connecting the artificial neural networks it is called. Process elements are assembled in 3 layers parallel to each other come and form a network. These;

- Input layer
- Hidden layers
- Output layer

The information is transmitted from the input layer to the network. They are processed in intermediate layers and sent from there to the output layer. The weight values of the information coming to the network without information processing using output. The network can produce the right outputs for the inputs. Weights must have the correct values. The process of finding the right weights is called training the network. These values are initially assigned randomly. Then, when each sample is shown to the network during training, weights are changed. Then another sample is presented to the network and weights are changed again and the most accurate values are tried to be found. These operations are repeated until you produce the correct output for all samples in the network training set. After this has been achieved the samples in the test set are shown to the network. If the correct answers to the samples in the network test set network is considered trained. Once the weights of the web have been determined, each what weight means is unknown. Therefore, artificial neural networks “black box”. Although it is not known what the individual weights mean, the network makes a decision about the inputs using these weights. Intelligence can be said to be stored in these weights. For the network learn an event for that event choosing the right artificial neural network model. So many artificial neural network models were developed. The most widely used models developed by single and multi-layered that Sensors are LVQ, ART networks, SOM, Elman network.

The Artificial Neural Network (ANN) shows good capability to model dynamical process. For this study, Levenberg-Marquardt is the best model. They are useful and powerful tools to handle complex problems. They are useful and powerful tools to handle complex problems. In this study, the result obtained shows clearly that the artificial neural networks are capable of modeling stage discharge relationship in the region where gauge level is irregular, thus confirming the general enhancement achieved by using artificial neural network in many other civil engineering fields. The results indicate that artificial neural network is more suitable to predict stage discharge relationship than any other conventional methods. The ANN approach can provide a very useful and accurate tool to solve problem in modal identification studies.

Levenberg-Marquardt Algorithm;

Like the Quasi-Newton methods (QNM), the Levenberg-Marquardt algorithm was designed to approach second-order training speed without having to compute the Hessian matrix. When the performance function has the form of a sum of squares (as is typical in training feedforward networks), then the Hessian matrix, approximately

$$H = J^T J \quad (1)$$

and can be calculated as gradient

$$g = J^T e \quad (2)$$

J is the Jacobian matrix that contains first derivatives of the network errors with respect to the weights and biases, and e is a vector of network errors. The Jacobian matrix can be computed through a standard back propagation technique see [3] that is much less complex than computing the Hessian matrix.

The Levenberg-Marquardt algorithm uses this approximation to the Hessian matrix in the following Newton-like update

$$x_{k+1} = x_k - [J^T J + \mu I]^{-1} J^T e \quad (4)$$

When the scalar μ is zero, this is just Newton’s method, using the approximate Hessian matrix. When μ is large, this becomes gradient descent with a small step size. Newton’s method is faster and more accurate near an error minimum, so the aim is to shift toward Newton’s method as quickly as possible. Thus, μ is decreased after each successful step (reduction in performance function) and is increased only when a tentative step would increase the performance function. In this way, the performance function is always reduced at each iteration of the algorithm.

The original description of the Levenberg-Marquardt algorithm is given in the following section [1]. [2] Describes the application of Levenberg-Marquardt to neural network training that is [2]. This algorithm appears to be the fastest method for training moderate-sized feed forward neural networks (up to several hundred weights). There is an effective application in MATLAB software, because the solution of the matrix equation is a built-in function, so its attributes become even more pronounced in a MATLAB environment.

For a demonstration of the performance of the collective Levenberg-Marquardt algorithm, try the end [2] Neural Network Design.

III. DESCRIPTION OF STEEL BENCHMARK WAREHOUSE

Steel benchmark warehouse wall thickness is 0.3 mm. Steel benchmark warehouse is single storey. Floor height is 150 cm. Floor area 250 * 200 cm^2. There is a 30 cm high roof on the steel benchmark warehouse.The structure and the geometric information of the structure are given in figures 2, 3.

Fig. 2. Front view of steel benchmark warehouse

Fig. 3. View of steel benchmark warehouse

IV. ANALYSIS RESULTS

Levenberg- Marquardt algorithm is used for the process of the training. Epoch showing in the progress goes up to 1000 iterations. Validation checks also done for the 1000 iterations. In the figure 4 it shows the training progress of the neural network.

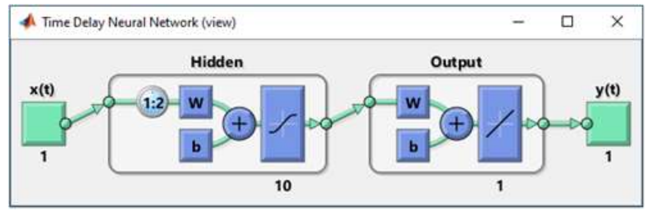

Fig. 4. Neural network diagram

Gradient Descent algorithm changes weights and predispositions relative to subsidiaries of system keeping in mind the end goal to minimize the mistake. Gradient Descent algorithm is moderately moderate as it obliges littler preparing rate for more steady learning and this is an unmistakable downside because of now is the right time expending procedure. Both Levenberg-Marquardt and Gradient Descent algorithms are utilized as a part of this study to assess conceivable impacts and execution of the preparing algorithms of neural systems models. ANN likewise can be incorporated with numerous different methodologies including connection master frameworks to enhance the forecast quality advance. Neural network model progress during training process.

The inputs and outputs used in the study are given in figure 5 and figure 6.

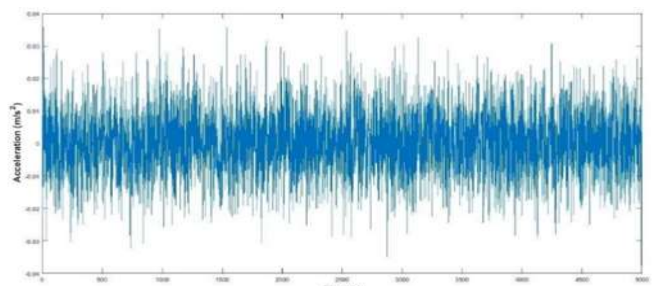

Fig. 5. Input

The inputs and outputs used in the study are given in figure 5 and figure 6.

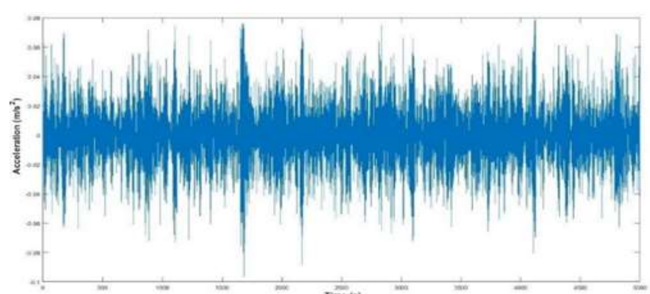

Fig. 6. Output

Output acceleration values are between about 0.08 and -0.1.

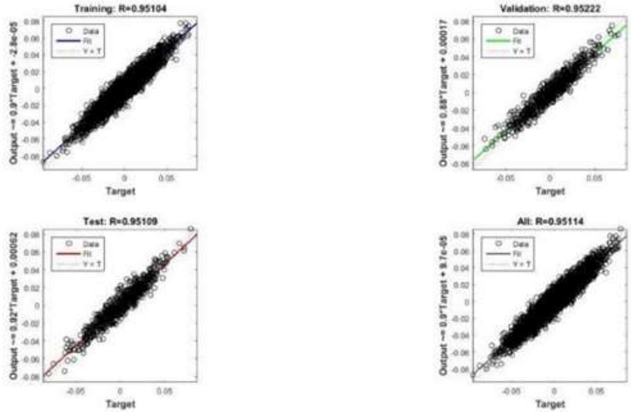

Fig. 7. Neural network training regression

Neural network training regression plot is shown in the figure 7.

Regression values measure the correlation between outputs and targets. An R value of 1 means close relationship and R value of 0 means random relationship.

The regression values for training plot are 0.95. If the regression values will be 1 then there is exact linear relationship between output and target and if the regression value is 0 then there is exact non-linear relationship between output and target. Similarly, the regression values forvalidation and testing is 0.95104 and 0.95222 respectively. Solid line represents the best fit linear regression plot between the output and target data. Dashed line represents the best result between output and target. Performance curve plot for training, validation and testing along the no of epochs.

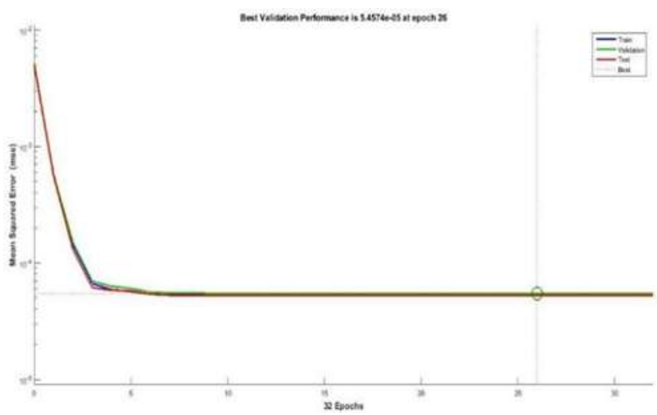

Fig. 8.Neural Network training performance

Neural network training performance is given in figure 8. Figure 8 shows the performance curve for training, testing and validation. The best validation performance is 5.4574 e-05. The blue lines show the training curve variation along the no of epochs, green is for validation and red one for testing curve. The dotted line shows the best validation performance curve. Mean Square Error is the average squared difference between outputs and targets. Lower values are best. Zero means no error.

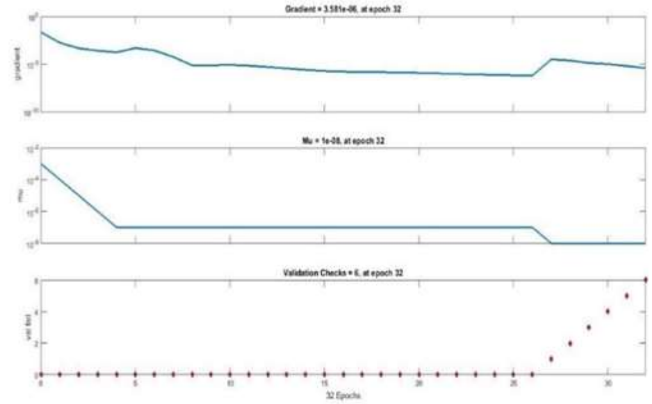

Fig. 9.Neural network training state

Neural network training state is given in figure 9. This curve shows the training state when the training performance is done. Validation failure varies linearly along the no of epochs. Validation is stop when the maximum no of epochs reached. Validation failure also run for 1000 epochs. Mu values 1.00e-08. Validation check for 1000 epochs. Gradient values 3.581e-06.

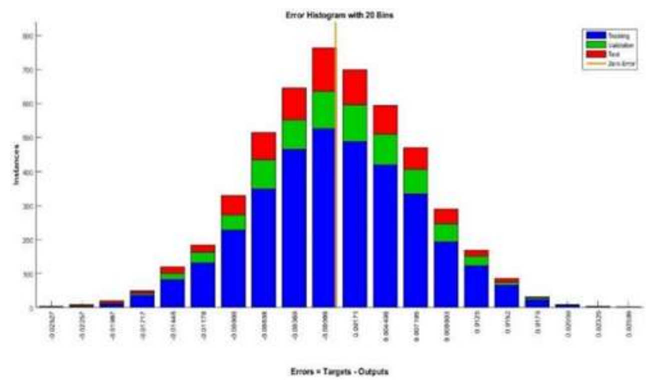

Fig. 10.Neural network training error histogram

Neural network training error histogram is given in figure 10.

V. CONCLUSIONS

As a result of this study, the following numerical data were obtained.

- The regression values for training plot are 0.95.
- The best validation performance is 5.4574 e-05.
- Mu values 1.00e-08.
- Gradient values 3.581e-06.

The Artificial Neural Network (ANN) shows good capability to model dynamical process. For this study, Levenberg-Marquardt is the best model. They are useful and powerful tools to handle complex problems. In this study, the result obtained shows clearly that the artificial neural networks are capable of modeling stage discharge relationship in the region where gauge level is irregular, thus confirming the general enhancement achieved by using artificial neural network in many other civil engineering fields.

The results indicate that artificial neural network is more suitable to predict stage discharge relationship than any other conventional methods. The ANN approach can provide a very useful and accurate tool to solve problem in modal identification studies.

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