DYNAMIC PARAMETERS DETERMINATION OF CONCRETE TERRACE WALL WITH SYSTEM IDENTIFICATION USING ANN

SERTAC TUHTA,
Department of Civil Engineering, Ondokuz Mayis University, Turkey

FURKAN GUNDAY
Department of Civil Engineering, Ondokuz Mayis University, Turkey

ABSTRACT:

Civil engineering structures have been adversely affected by dynamic effects from past to present. This has always been a problem for civil engineering. Civil engineers strive to design structures to be least affected by dynamic effects. The biggest challenge in these designs is the exact and realistic calculation of the effect of dynamic effects on the structure. There are various methods for calculating the dynamic effects affecting the structures. System identification method is one of the methods used to calculate the responses of the building to the dynamic effects affecting the buildings. On the other hand, today artificial intelligence is used in many areas as well as in system identification method. For these reasons, Artificial Neural Network (ANN) has been used in the system identification method in this study. The system definition was made with a success rate of approximately 0.96 using Terrace Wall as an example model. As a result of this study, The Artificial Neural Network (ANN) approach can provide a very fast and true tool to solve problem in modal identification studies. The Artificial Neural Network (ANN) method can also be used to determine dynamic parameters of structures.

KEYWORDS: **System Identification, ANN, Dynamic Parameters, Concrete Terrace Wall, Levenberg-Marquardt Algorithm**

INTRODUCTION:

Retaining structures are elements manufactured to limit the movement of the ground under the natural slope angle. Apart from this purpose, for constructive purposes, separation of two different grounds, etc. They are used in situations. Different types of retaining structures have emerged depending on the mechanical properties of the ground. In addition to these mechanical properties, the place of use of the retaining structure to be built (coast, sea, etc.), its purpose (to ensure ground stability, to separate different soils, etc.), environmental conditions (air temperature, humidity, etc.), other nearby structures status, etc. It should be designed by considering the situations (Azarafza et al. 2017). Today, terrace walls are the most preferred retaining structures. There are many reasons why these structures are used frequently. First of all, their project is easy and fast compared to other structures. Size flexibility is unlimited compared to other building types. Many different types of materials can be used (concrete, reinforced concrete, steel, masonry, composite, etc.). They are very successful against many dynamic load types (earthquake, tsunami, blasting, etc.) apart from their main usage purposes.

Researchers have done a lot of work on terrace walls. In these studies, terrace walls for different soil types (loose sand, dense sand, clay, etc.) were analyzed using the finite element method Naseri and Behfarnia (2018). Some researchers have examined different types of terrace walls under different soil properties.

Terrace wall types used can be counted as gravity, piling, and cantilever and anchored. It is quite a lot of researchers who examine the behavior of terrace walls using finite element method under various dynamic load effects. Most of the studies on terrace walls are analytical (Tuken et al. 2017). Therefore, it has been revealed that experimental studies should be conducted to examine such structures, which are of great importance for the stability of the ground and structures. Along with the technological developments, important steps have been taken in the experimental study of terrace walls there is a limited number of studies on operational and experimental modal analysis of terrace walls. In these studies, various types of materials (concrete, reinforced concrete, masonry, etc.), type of terrace wall (gravity, cantilever, piling, etc.), boundary conditions, etc). Examinations were made according to the parameters. Some researchers have done similar studies under different environmental conditions. There are few studies in the literature for the operational modal analysis of concrete terrace walls. Studies on operational and experimental modal analysis began on the basis of system identification. There are many studies on system identification. Nowadays, researchers use genetic algorithm, artificial neural networks, fuzzy logic, etc. they moved the works in different directions. In the studies, the use of traditional tools and equipment has been replaced by more advanced technological materials. Wireless accelerometers, self-powered sensors, etc. are some of them. Many new technologies have been developed for the continuous monitoring of the dynamic parameters of the terrace walls. With these technologies, it has become possible to produce safer structures and to constantly control the structure. In order to reach the dynamic parameters correctly, it is necessary to define the parameters of the structure correctly. In most studies, it was observed that the finite element model of the terrace walls and the dynamic parameters obtained from the operational modal analysis were different. The differences between the finite element model and the operational modal analysis are at an acceptable level of 2-5%. In situations where there is more difference, it is frequently encountered that there are errors in the finite element model or measurement. Errors in the finite element model are often due to incorrect material properties, dimensional measurement errors, etc. It arises. Errors in measurement are deficiencies in fixing the accelerometers, environmental effects, etc. can be listed as. In this study, special attention was paid not to make mistakes in the finite element model and operational modal analysis measurement mentioned above, which was positively reflected in the results.

For these reasons, it has been thought that the dynamic parameters of the concrete terrace wall should be determined. It is planned to use a concrete terrace wall sample in this study. It is planned to receive inputs and outputs over the concrete terrace at the same time in the area where the concrete terrace is located. It is planned to define the system of the wall using ANN with the data obtained.

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.

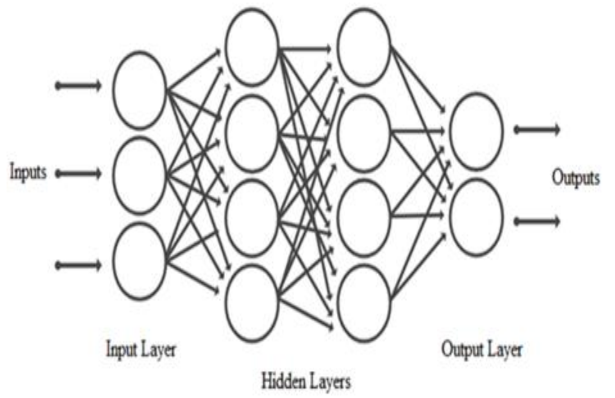

Fig. 1. Typical neural network architecture

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

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

DESCRIPTION OF CONCRETE TERRACE WALL:

A terrace wall or a terraced retaining wall is a partitioned wall, not a single wall as it is; they can be useful when building a retaining structure on steep ground. A partially terraced wall is designed so that the upper terrace and the lower terrace come together to form a higher wall. The retaining wall may still be in good condition, but it may have structural and aesthetic issues. For this purpose, terrace walls must be built. Two types of Terraced Retaining Walls are manufactured. The first of these is the independent terraced wall. It is a wall where the upper wall exerts no additional load or no load on the lower wall.

The wall should be at a distance of 1/2 from the lower wall, or the upper wall should be built twice the height of the lower wall. For example, if the lower wall is 3 meters high, the upper wall should be built 6 meters away.

The upper wall should also be less than or equal to the height of the lower wall. At the top for smooth drainage

The drain pipe of the wall should not be extended to the lower wall.

The second type of terraced wall is the dependent terraced wall. It is the wall where the upper wall transmits an additional load to the lower wall. When is the distance between the upper and lower wall

If closer than 1/2 height ratio, the walls are interconnected. In this type of terrace walls

It is important to get the help of a professional engineer, so a detailed static analysis and geotechnical investigations are carried out.

Concrete terrace wall thickness is 5 cm. The height of the concrete terrace wall is 2 m. The concrete terrace wall is 2 meters wide. The concrete terrace wall is given in figure 2.

Fig. 2. View of concrete terrace wall

Triaxial accelerometers are used for input and output measurement. Outputs were meticulously obtained by placing them on the concrete terrace wall. The outputs and inputs obtained were processed with Matlab. The layout of the accelerometers on the terrace wall is given in figure 3.

Fig. 3. Layout of the accelerometers on the terrace wall

I. ANALYSIS RESULTS

Levenberg- Marquardt algorithm is used for the process of the training. Epoch showing in the progress goes up to 6 iterations. Validation checks also done for the 6 iterations. In the figure 4 it shows the training progress of the neural network.

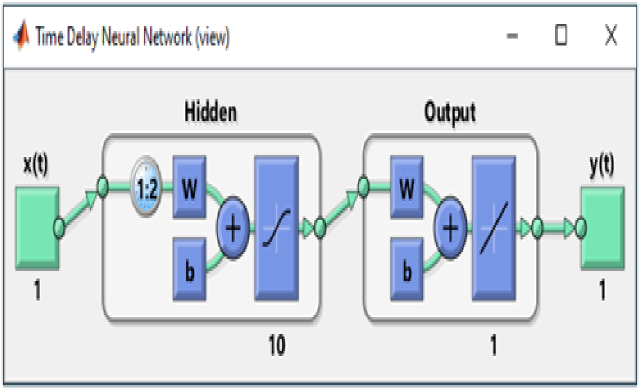

Fig. 4. Neural network diagram

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.

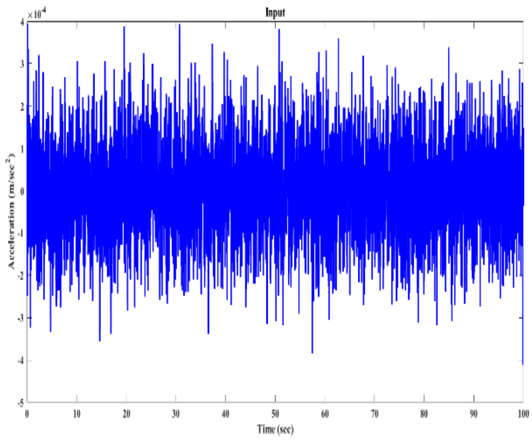

Fig. 5. Input

The inputs and outputs used in the study are given in figure 5 and figure 6. İnput acceleration values are between about 4*10-4 and -4*10-4.

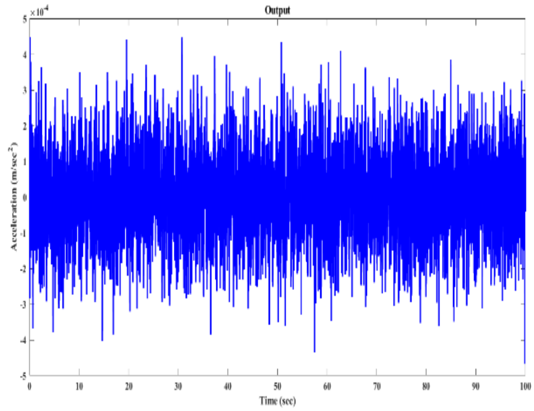

Fig. 6. Output

Output acceleration values are between about $4.5*10^{-4}$ and $-4.5*10^{-4}$.

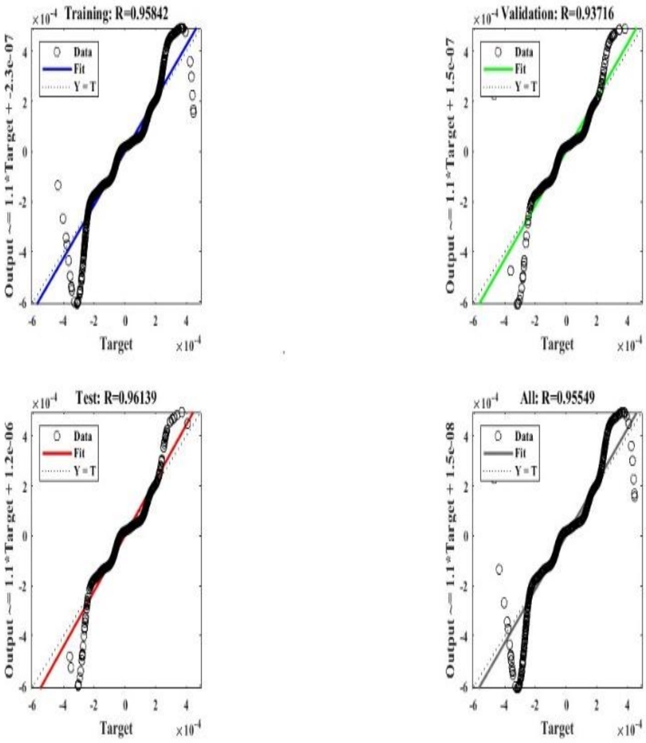

Fig. 7. Neural network training regression

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 0.96. 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 for validation and testing is 0.93716 and 0.96139 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.

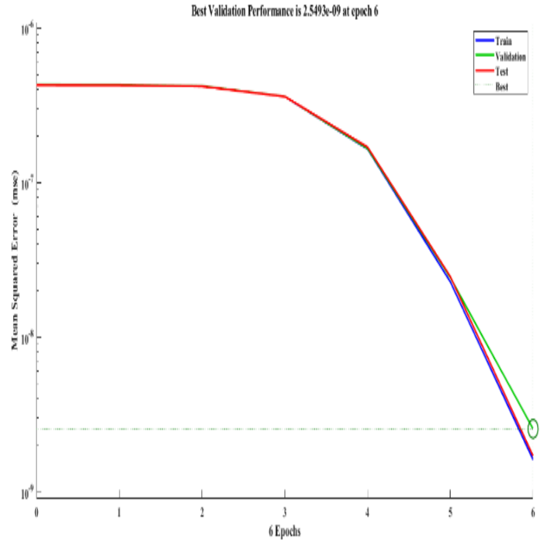

Fig. 8. Neural Network training performance

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 2.5493 e-09. 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.

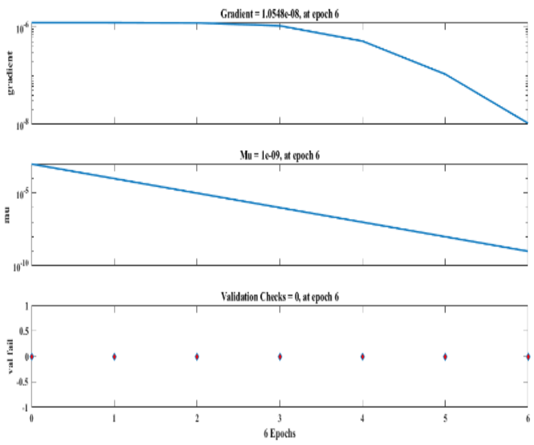

Fig. 9. Neural network training state

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 6 epochs. Mu values 1.00e-09. Validation check for 6 epochs. Gradient values 1.0548e-06.

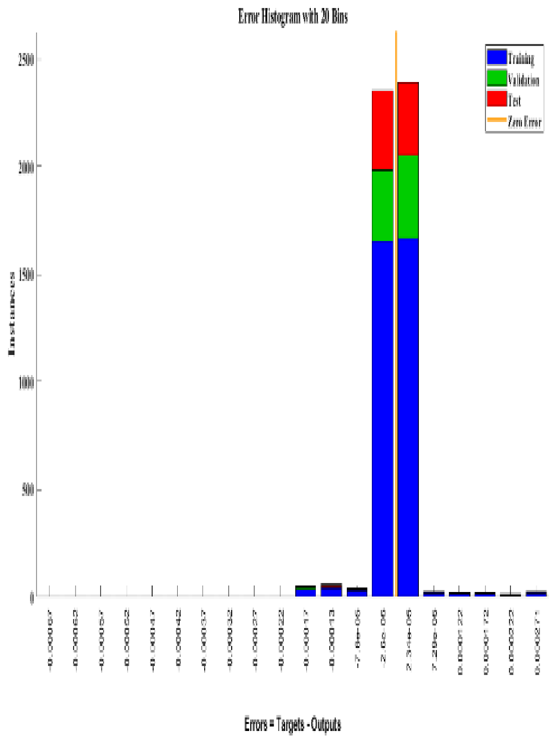

Fig. 10. Neural network training error histogram

Neural network training error histogram is given in figure 10.

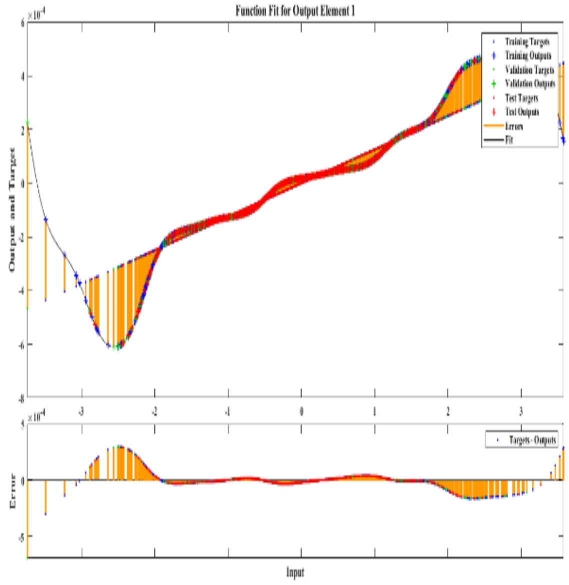

Fig. 11. Function fit for output element 1

Also, an example of function fit for output element is given in figure 11.

CONCLUSIONS

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

- The regression values for training plot are 0.96.
- The best validation performance is 2.5493 e-09.
- Mu values 1.00e-09.
- Gradient values 1.0548e-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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