International Journal of Trend in Scientific Research and Development (IJTSRD)
Volume 4 Issue 2, February 2020 Available Online: www.ijtsrd.com e-ISSN: 2456 – 6470

Obtaining Modal Parameters in Steel Model Bridge by System Identification using Artificial Neural Networks

Hakan Aydin

Department of Civil Engineering, Ondokuz Mayis University, Faculty of Engineering, Atakum, Samsun, Turkey

ABSTRACT

Artificial Neural Networks are easy to build and take good care of large amounts of noisy data. They are especially suitable for the solution of nonlinear problems. They work well for problems where domain experts aren't available or there are no known rules. Artificial Neural Networks can also be adapted to civil engineering structures and suffer from dynamic effects. Structures around the world were badly damaged by the earthquake. Thus, loss of life and property was experienced. This particularly affected countries on active fault lines. Pre and post-earthquake precautions have been developed in the world. For these reasons, it is necessary to determine the dynamic performance of structures in the world. There are several methods to determine dynamic performance. System identification is one of these methods. The mathematical model of the structural system is obtained by system identification method. Artificial Neural Networks (ANN) is a system identification method. ANN can adapt to their environment, work with incomplete information, make decisions under uncertainties and tolerate errors. Steel Model Bridge was used in this study. The system identification of the steel model bridge with the ANN method of 0.90 was made successfully. As a result of this study, ANN approach can provide a very useful and accurate tool to solve the problem in modal identification studies.

KEYWORDS: *Steel Model Bridge, System Identification, Artificial Neural Networks, Modal Parameters, Input-Output dimensions*

How to cite this paper: Hakan Aydin "Obtaining Modal Parameters in Steel Model Bridge by System Identification using Artificial Neural Networks" Published in International Journal of Trend in Scientific Research and Development (ijtsrd), ISSN: 2456-6470, Volume-4 | Issue-2, February 2020, pp.438-443, URL: www.ijtsrd.com/papers/ijtsrd30013.pdf

IJTSRD30013

INTRODUCTION

Most of the structures located in areas prone to earthquake hazard suffer from various types of destruction caused by seismic loads. They occur under such an earthquake. [5]. There are many studies taking this into consideration [24]. In regions with seismic hazards, structures are expected to have vibrations due to seismic loads [15]. There are currently many types of structural and architectural structures in the field of civil engineering. These structures can effectively resist both static and dynamic loads [16].

So many studies should be done to clarify the performance of structures under seismic loads [13]. Further research is being carried out to obtain the required performance of structures under seismic loading by looking at different perspectives and directions [14]. In recent years, it has become very important to determine the impact of vibrations on structures and structural behavior in the world and in our country [17]. Buildings located in seismically active areas are at risk of serious damage from harmful earthquake loads [6]. Civil engineering structures are exposed to various 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 dimensions of these systems, it is necessary to determine and measure the sizes affecting the structures in order to obtain a behavioral model. Model identification uses the system's prior knowledge based on physical laws and the size of the system (input size or input signal) from the system's response (output size or output signal). Physical laws are defined by differential or algebraic equations. In this way, the model is expressed not only by the relationship between input and output dimensions, but also by determining the model structure. On the other hand, the lack of any prior knowledge about the system or system is very complex. If available, identification methods (such as parametric definition) are used to determine the system model. In this case, the model is obtained using the input and output dimensions. This technique can be applied by making some preliminary assumptions about system quality, selection of input and output dimensions [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].

Methodology

The models of the computing for the perform the pattern recognition methods by the performance and the structure of the biological neural network. A network consists of computing units which can display the features of the biological network. The features of the neural network that motivate the study of the neural computing are discussed and the differences in processing by the brain and a computer presented, historical development of neural network principle, Artificial Neural Network (ANN) terminology, neuron models and topology were discussed.[1]

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 [22].

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 [23].

A typical neural network topology is given in figure 1.

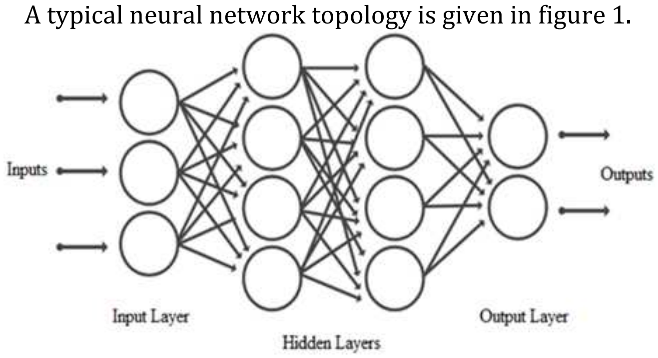

Fig.1. Typical neural network topology

The values of the connections connecting the artificial neural networks are called weight values. Process elements are collected in 3 layers parallel to each other 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. First the weights of the web have been determined, it is not known what the weight means. Therefore, artificial neural networks are "black boxes". Although it is not known what each weight means, the network makes a decision about the inputs that use these weights. It can be said that intelligence is stored at these weights. Find out an event for that event by choosing the right neural network model for the network. Many artificial neural network models have been developed. The most common models developed as single and multilayer, where the 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 feed forward networks), then the Hessian matrix, approximately

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

and can be calculated as gradient

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

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

$$x_{k+1} = x_k - [J^T J + \mu I]^{-1} J^T e \qquad (3)$$

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 [25]. [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 Steel Model Bridge

In this study, a steel model bridge with a width of 6.10 m and a height of 1.88 m. The profiles, which continue along the axis of the deck, are made of 2.5x5cm box profile with a thickness of 3mm. Round lattices with 4 cm diameter and 3 mm thickness were used in trusses. In the Diagonal and Cross Connection elements, 10 mm steel elements are used. The bridge model has deformed belt geometry. The feet tilted inward in the direction of the long axis of the deck, provided the cantilevering of the end sections of the deck. 45 degree bending of the feet is provided. The structure and the geometric information of the structure are given in figures 2, 3.

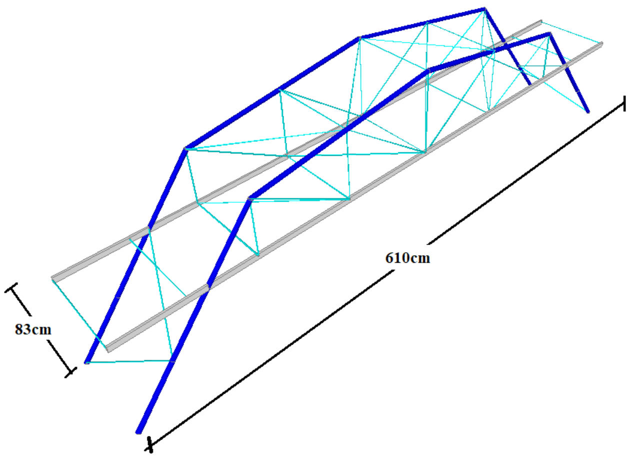

Fig.2. Front view of steel model bridge

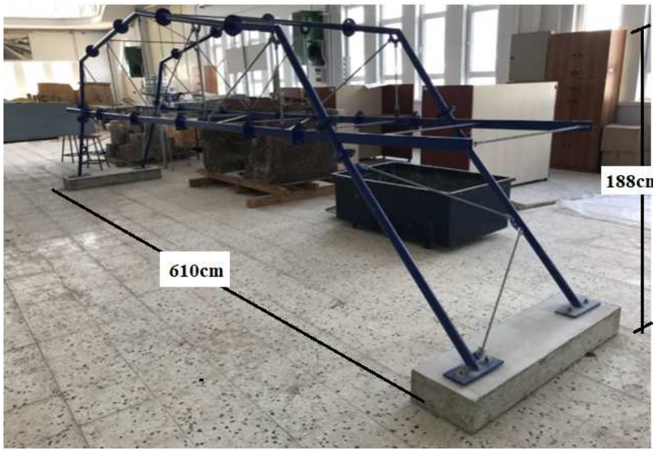

Fig.3. View of steel model bridge

Analysis Results

Levenberg-Marquardt algorithm is used for the training process. The progress period is up to 1000 iterations. Validation checks were carried out for 1000 iterations. Figure 4 shows the educational progression of the neural network.

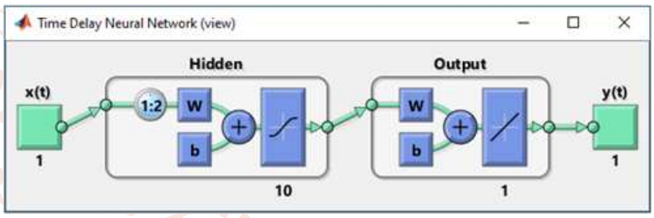

Fig.4. Neural network diagram

The Gradient Landing algorithm changes the weight and tendencies according to the subsidiaries of the system, taking into account the ultimate goal to minimize the error. This is a clear disadvantage, as the Gradient Landing algorithm requires a smaller preparation rate for more moderate learning, as it is a moderately moderate and currently accurate time spending procedure.

Both Leven berg-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.

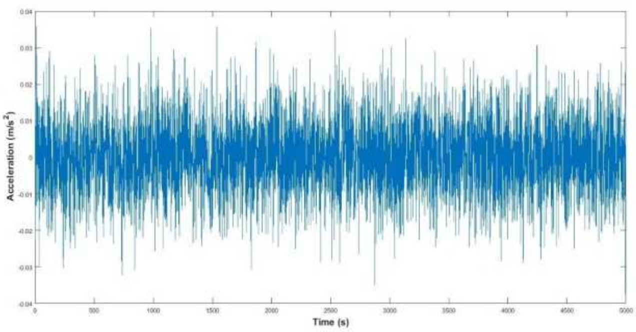

Fig.5. Input

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

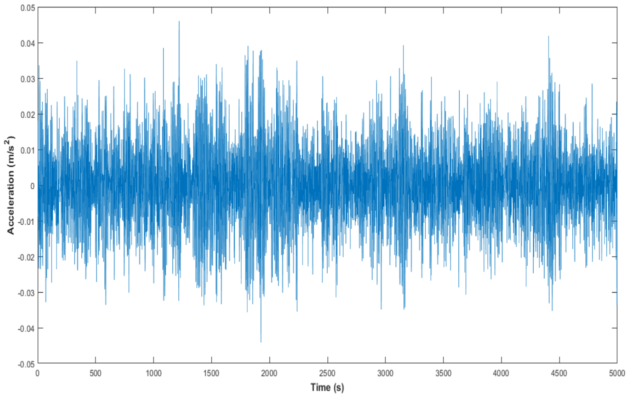

Fig.6. Output

Output acceleration values are between about 0.05 and -0.4.

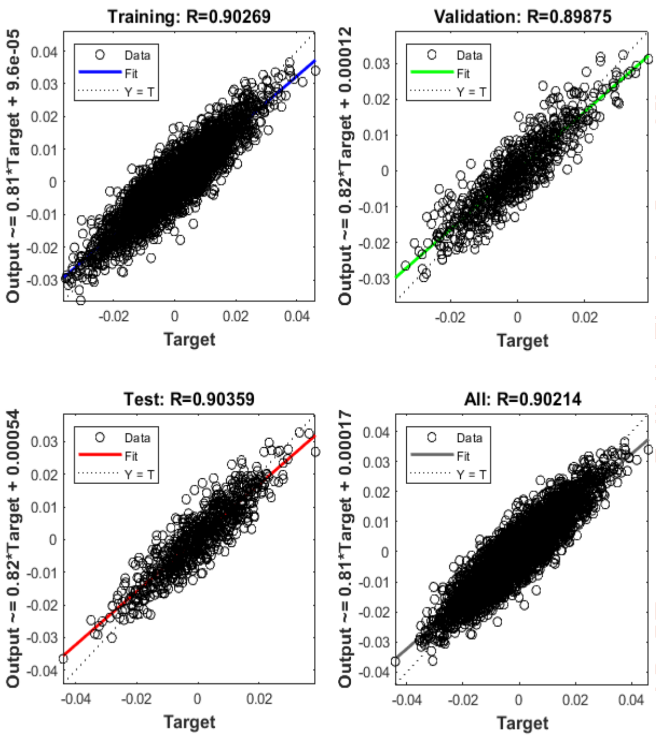

Fig.7. Neural network testing regression

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

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

The regression values for the exercise plot are 0.90. If the regression values are 1, there is a full linear relationship between the output and the target, and if the regression value is 0, there is a full nonlinear relationship between the output and the target. Similarly, the regression values for validation and testing are 0.89875 and 0.90359, respectively. The straight line represents the optimal linear regression plot between output and target data. The dashed line represents the best result between the output and the target. Performance curve plot for training, validation and testing along the no of epochs.

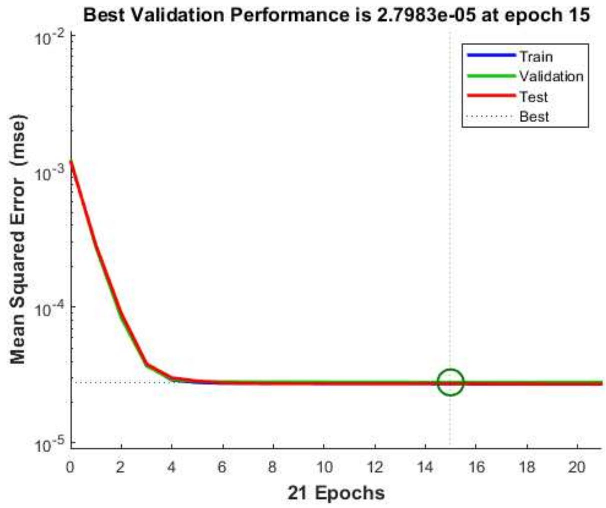

Fig.8. Neural Network test performance

Neural network test performance is given in figure 8. Figure 8 shows the performance curve for training, testing and validation. The best verification performance is 2.7983e-05. The blue lines indicate the variation of the training curve over the periods; green for verification and red for test curve. The dotted line shows the best verification performance curve. Mean Frame Error is the average square difference between outputs and targets. Low values are best. Zero means no error.

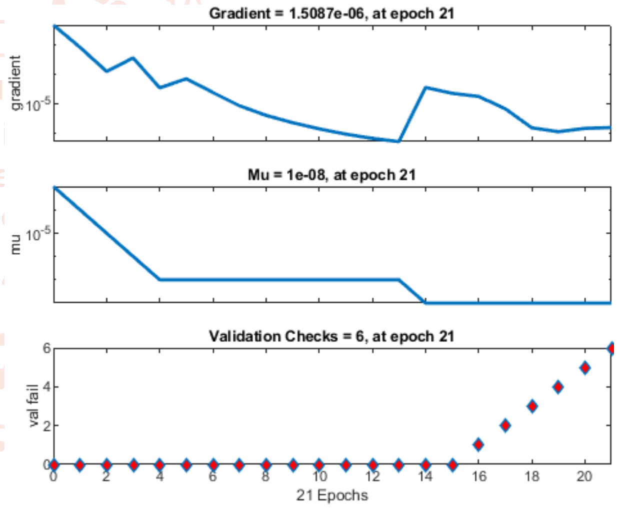

Fig.9. Neural network training state

Neural network test is given in figure 9. This curve shows the training status when training performance is complete. 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 1.5087e-06.

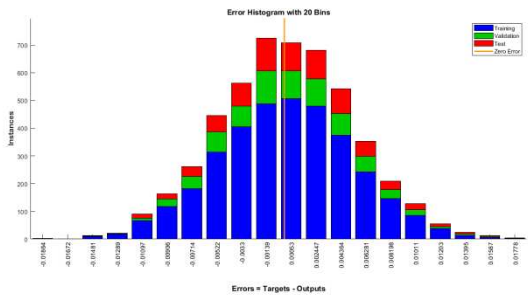

Fig.10. Neural network training error histogram

Neural network training error histogram is given in figure 10.

Conclusions

In the conclusion of the study, the following numerical data were obtained.

- The regression values for training plot are 0.90.
- The best validation performance is 2.7983 e-05.
- Mu values 1.00e-08.
- Gradient values 1.5087e-06.

Artificial Neural Network (ANN) shows a good ability to model the dynamic process. Levenberg-Marquardt is the best model for this work. They are useful and powerful tools for solving complex problems. The result obtained in this study clearly shows that artificial neural networks can model the stage discharge relationship in the region where the level of the indicator is irregular, thereby confirming the overall increase using artificial neural network in many other civil engineering fields.

The results show that the artificial neural network is more suitable than other traditional methods to estimate the phase discharge relationship. ANN approach can provide a very useful and accurate tool to solve the problem in modal identification studies.

References

[1] Rajesh CVS | M. Padmanabham "Basics and Features of Artificial Neural Networks" Published in International Journal of Trend in Scientific Research and Development (ijtsrd), ISSN: 2456-6470, Volume-2 | Issue-2, February 2018, pp.1065-1069, URL: https://www.ijtsrd.com/papers/ijtsrd9578.pdf

[2] Hagan, M. T., Demuth, H. B., & Beale, M. H. (1996). Neural network design, PWS Pub. Co., Boston, 3632.

[3] Hagan, M. T., & Menhaj, M. B. (1994). Training feed forward networks with the Marquardt algorithm. IEEE transactions on Neural Networks, 5(6), 989-993.

[4] MATLAB. (2010). version 7.10.0 (R2010a). Natick, Massachusetts: The MathWorks Inc.

[5] Tuhta.S., Gunday F., Aydin H., Dynamic Analysis of Model Steel Structures Retrofitted with GFRP Composites under Micro tremor Vibration International Journal of Trend in Scientific Research and Development (IJTSRD)Volume: 3 | Issue: 2 | Jan-Feb 2019.

[6] Tuhta. S., Abrar O., Gunday F., Experimental Study on Behavior of Bench-Scale Steel Structure Retrofitted with CFRP Composites under Ambient Vibration, European Journal of Engineering Research and Science, 2019.

[7] J. Kim, System Identification of Civil Engineering Structures through Wireless Structural Monitoring and Subspace System Identification Methods, PhD thesis, University of Michigan, 2011.

[8] G.F. Sirca Jr., H. Adeli, System identification in structural engineering, Scientia Iranica A (2012) 19 (6), 1355–1364.

[9] Tuhta, S., & Günday, F. (2019). Multi Input Multi Output System Identification of Concrete Pavement Using N4SID. International Journal of Interdisciplinary Innovative Research Development, 4(1).

[10] Tuhta, S., Alameri, I., & Günday, F. (2019). Numerical Algorithms N4SID for System Identification of Buildings. International Journal of Advanced Research in Engineering Technology Science, 1(6).

[11] Tuhta, S., Günday, F., Aydin, H., & Alalou, M. (2019). MIMO System Identification of MachineFoundation Using N4SID. International Journal of Interdisciplinary Innovative Research Development

[12] Tuhta, S., & Günday, F. (2019). Mimo System İdentification of İndustrial Building Using N4sid with Ambient Vibration. International Journal of Innovations in Engineering Research and Technology.

[13] Gunday. F., "OMA of RC Industrial Building Retrofitted with CFRP using SSI" International Journal of Advance Engineering and Research Development, 2018.

[14] Gunday. F., "GFRP Retrofitting Effect on the Dynamic Characteristics of Model Steel Structure Using SSI" International Journal of Advance Engineering and Research Development, 2018.

[15] Dushimimana, A., Günday, F., & Tuhta, S. (2018). Operational Modal Analysis of Aluminum Model Structures Using Earthquake Simulator. Presented at the International Conference on Innovative Engineering Applications.

[16] Günday, F., Dushimimana, A., & Tuhta, S. (2018). Analytical and Experimental Modal Analysis of a Model Steel Structure Using Blast Excitation. Presented at the International Conference on Innovative Engineering Applications.

[17] Tuhta, S., & Günday, F. (2019). Application of Oma on The Bench scale Aluminum Bridge Using Micro Tremor Data. İnternational Journal of Advance Research and Innovative İdeas in Education, 5(5), 912–923.

[18] Kasimzade, A., Tuhta, S., Günday, F., & Aydin, H. (2019). Investigation of Modal Parameters on Steel Structure Using FDD from Ambient Vibration. Presented at the 8th International Steel Structures Symposium, Konya.

[19] Kasimzade, A., Tuhta, S., Aydin, H., & Günday, F. (2019). Determination of Modal Parameters on Steel Model Bridge Using Operational Modal Analysis. Presented at the 8th International Steel Structures Symposium, Konya.

[20] Tuhta, S., Günday, F., & Abrar, O. (2019). Experimental Study on Effect of Seismic Damper to Reduce the Dynamic Response of Bench Scale Steel Structure Model. International Journal of Advance Research and Innovative İdeas in Education, 5(5), 901–911.

[21] Tuhta, S., Günday, F., & Aydin, H. (2019). Numerical Algorithms for System Identification of Benchmark Steel Structure. Presented at the iSTE-CE'xx2019-International Conference on Innovation,

Sustainability, Technology and Education in Civil Engineering.

[22] Tuhta, S., Günday, F (2019). Modal Parameters Determination of Steel Benchmark Warehouse by System Identification Using ANN. International Journal of Research and Innovation in Applied Science (IJRIAS) | Volume IV, Issue XII, December 2019|ISSN 2454-6194

[23] Tuhta, S., Günday, F., Alalou M. (2019). Determination of System Parameters on Model Lighting Pole Using ANN by Ambient Vibration. International Journal of Research and Scientific Innovation (IJRSI) | Volume VI, Issue XI, November 2019 | ISSN 2321–2705

[24] Tuhta, S., "GFRP retrofitting effect on the dynamic characteristics of model steel structure," STEEL AND COMPOSITE STRUCTURES, vol. 28, no. 2, pp. 223–231, Jul. 2018.

[25] Marquardt, D. W. (1963). An algorithm for least-squares estimation of nonlinear parameters. Journal of the society for Industrial and Applied Mathematics, 11(2), 431-441.