Determination of System Parameters on Model Lighting Pole Using ANN by Ambient Vibration

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***Abstract*—Today, civil engineering structures have dynamic effects. The land in the buildings has been severely damaged by the earthquake. Thus, loss of life and property was experienced. These countries are particularly affected in active fault lines. The pre- and post-earthquake measures were developed in the world. For these reasons, it is necessary to determine the dynamic performance of structures in the world. There are several ways to determine dynamic performance. System definition is one of these methods. The mathematical model of the structural system was obtained by the system identification method. Artificial neural networks (ANN) are a method of identifying the system. Artificial neural networks (ANN) can adapt to their environment, adapt and work with incomplete information and make decisions under uncertainty and tolerate errors. In this study, a steel model lighting pole was used. The system identification of the model lighting pole using the 0.999 ANN method was successfully performed. As a result of this study, the ANN approach can provide a very useful and accurate tool for problem solving in media identification studies.**

***Keywords*—System Identification, ANN, Modal Parameters, Ambient Vibrations**

I. INTRODUCTION

Most buildings located in earthquake-prone areas suffer various damage caused by seismic loads. [5] There are many studies that take this into consideration. In seismic danger zones, structures are expected to vibrate due to seismic loads [15]. In the field of civil engineering, there are currently many types of structural and architectural structures. These structures can be managed by effective resistance to static and dynamic loads [16], and further studies are needed to clarify the performance of structures under seismic loads [13]. Further research is conducted to obtain the necessary performance for seismic loading structures by considering different perspectives and trends [14]. In recent years, determining the impact of vibrations on structures and structural behavior has become very important in the world and in our country [17]. Buildings located in seismically active areas are at risk of severe damage from harmful seismic loads. [6] Civil engineering structures are subjected to various natural and artificial impacts throughout their lives. These effects are forces that may affect the dynamic characteristics of the structure and hence the service life [18]. In all building systems, damage begins at the level of materials. The greater the damage in the system, the greater the value known as degradation [19]. In general, forced and environmental vibration methods are used to test vibrations in structures [20]. The authors emphasized the reasons for their work. The authors also noted the need to focus on this point. This study was conducted considering these negative attitudes.

System definition (SI) is a modeling process for an unknown system based on a series of inputs and outputs and is used in different engineering fields [8], [9]. The definition of a space space system is presented as a powerful tool for the definition of a black box system. Structures [21]. In particular, the implementation of the method of supporting erotic structures was emphasized. Black box case models derived from the definition of subspace systems are used to estimate the conditional properties of structures (such as genetic damping, frequency and pattern forms) [7], [10].

Depending on the input and output dimensions of these systems, it is necessary to identify and measure metrics that affect structures in order to obtain a behavioral model. The model definition is used based on physical laws based on the system's predefined definition, system size (input size or input signal), and system response to these quantities (output size or output signal). Depending on the input and output dimensions of these systems, it is necessary to identify and measure the metrics that effect on structures in order to obtain a behavioral model. The model definition is used based on physical laws based on the system's predefined definition, system size (input size or input signal), and system response to these quantities (output size or output signal).

Stable adaptive control designs are one of the most important research topics in recent years because they can produce effective solutions against time-varying system parameters and disturbing effects on the problem of system output control required [11].

II. METHODS

Artificial neural networks (ANNs) are computer-based systems that perform the function of learning, a key feature of the human brain. Performs the learning process with the help of existing examples. These networks then form elements of the connected process (artificial neurons). Each link has its own weight value. This is information that indicates that the artificial neural network has values for weight and spreads on the network.

Artificial neural networks are different from other known calculation methods. They can adapt to their environment, adapt, work with incomplete information, make decisions under uncertainty and tolerate mistakes. Successful applications of this calculation method can be seen in almost all areas of life.

Typical neural network architecture is given figure 1.

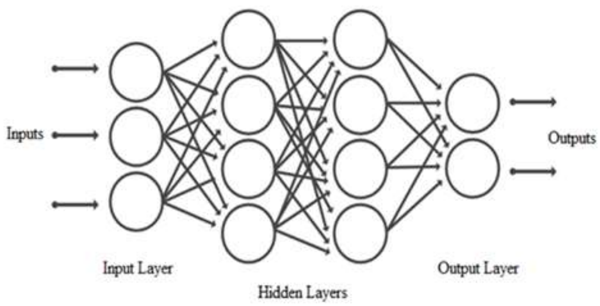

Fig. 1Typical neural network architecture

The values of the connections that connect artificial neural networks are called weight values. The process elements are grouped into 3 layers parallel to each other and forming a mesh. and this is:

- Input layer
- Hidden layers
- Output layer

The information is transferred from the input layer to the network. The intermediate layers are processed and sent to the output layer. Values weigh the information that comes to the network without processing the information using the output. The grid can produce the correct output of the input. Weights must contain the correct values.

The process of finding the correct weights is called network training. These values are initially set randomly. Then, where each sample is displayed on the grid during training, weights change. Then another sample is presented to the grid and weights are changed again and attempts to find the most accurate values. These processes are repeated until the correct output of all samples in the network training package is produced. Once this is achieved, the samples in the test group are displayed on the grid. If the samples in the network test set respond correctly, the network is trained. Once we determine web weights, the meaning of each is not known by weight. So artificial neural networks are "black boxes." Although it is not known what individual weights mean, the grid determines the inputs that use these weights. It can be said that the information is stored in these weights. Learn about an event for this event by choosing the appropriate artificial neural network model for the network.

Many models of artificial neural networks were developed. The most commonly used models developed by single and multi-layer sensors are LVQ, ART, SOM and Elman network.

The artificial neural network (ANN) shows good ability to model the dynamic process. In this study, Leifenberg Marquardt is the best model. They are useful and powerful tools for solving complex problems. They are useful and powerful tools for solving complex problems. The results obtained in this study clearly showed that artificial neural networks can model the phase discharge relationship in an area where the indicator level is irregular; therefore, it confirms the general evolution in many other civil engineering fields using artificial neural networks. The results showed that the artificial neural network is more appropriate than other conventional methods to predict the relationship of phase discharge. The ANN approach can provide a very useful and accurate tool for problem solving in media identification studies.

The algorithm of Markberg's Leifenberg;

Like quasi-newton methods (QNM), the Markenberg-Leifenberg algorithm is designed to approach the speed of secondary education without the need to calculate the Hsi matrix. When the performance function is in the form of total boxes (as in the training of the front feeding networks), the Hess matrix is approximate.

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

and can be calculated as gradient

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

J is a Jacobian matrix containing the first derivatives of weights and biases for network errors, and e is a vector of network errors. The Jacobite matrix can be calculated using the standard rear diffusion technique, which is much less complex than the Hsian matrix [3].

The Levenberg-Marquardt algorithm uses this approach in the Hessian matrix in an update that resembles Newton below.

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

When zero is zero, this is Newton's method, using the approximate Hsian matrix. When M is large, it changes to a small gradual descent. The Newton method is faster and more accurate near the minimum error, so the goal is to switch to the Newton method as quickly as possible. Thus, after each successful step (decrease in performance function) μ decreases and increases only when a temporary step increases the performance function. In this way, the performance function is always reduced with each iteration of the algorithm.

The original description of the Markenberg-Leifenberg algorithm is given in the following section [1]. [2] Explain the application of Levenberg-Marquardt on training in neural networks. This algorithm seems to be the fastest way to train medium-sized neural networks (up to several hundred weights). There is an effective application in MATLAB, because the solution of the matrix equation is a built-in function, so its features become more apparent in the MATLAB environment.

For a demonstration of the performance of the collective Levenberg-Marquardt algorithm, try the latest neural network design.

III. DESCRIPTION OF MODEL LIGHTING POLE

Model lightning pole wall thickness is 0.3 mm, diameter is 30 mm.One-storey steel reference tank. Height 75 cm. There is a width of 27.5 cm on the typical lighting pole.The structure and the geometric information of the structure are given in figures 2.

Fig. 2Typical neural network architecture Front view of model lightning pole

IV. ANALYSIS

The Levenberg-Marquardt algorithm was used during the training process. The era continues up to 1000 repetitions. Validations are also performed for 1000 iterations. Figure 3 shows the educational progress of the neural network.

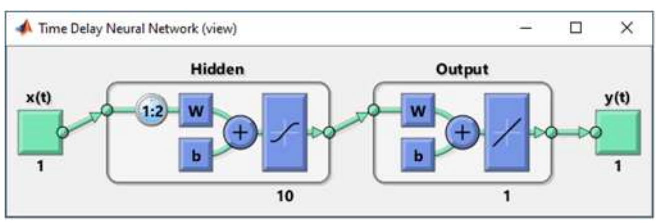

Fig. 3Neural network diagram

The color gamut algorithm changes the weights and trends related to system affiliates, taking into account the goal of error reduction. The downward algorithm is fairly mild because it requires a lower rate of preparation for more stable learning, and this is incomprehensible negativity as it is currently a time-consuming procedure. As part of this study, the Levenberg-Marquardt and Gradient Descent algorithms are used to assess the effects considered and to apply algorithms to prepare nervous system models. ANN can also be combined with many different methodologies, including key link frames, to improve prediction quality. Advance neural network model during the training process.

The inputs and outputs used in the study are given in figure 4 and figure 5.

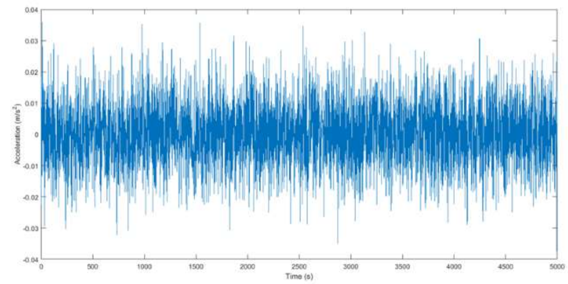

Fig. 4Input

Input acceleration values are between about 0.4 and -0.4.

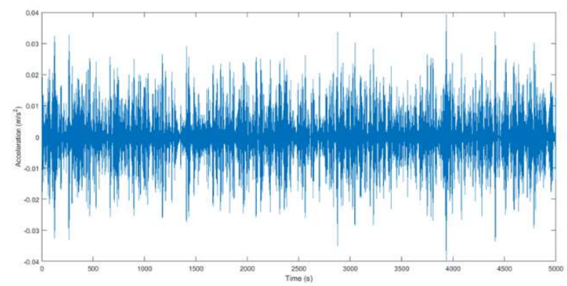

Fig. 5Output

Output acceleration values are between about 0.4 and -0.4.

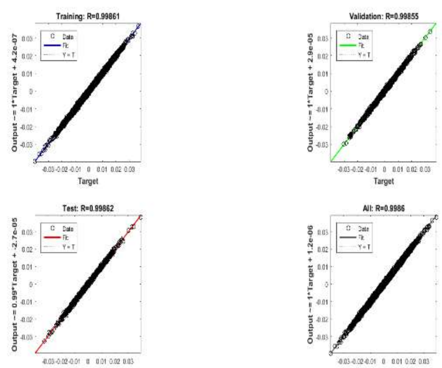

Fig. 6Neural network training regression

Neural network training regression plot is shown in the figure 6.

This is a regression graph for training, validation and testing. We received 70% data for training, 15% for verification and 15% for testing. Training data represent the number of weights and corresponding prejudices to reduce error. Verification data represents untrained network values. Data testing represents the best performance of the model. In training, 70% of the values presented on the ground were trained and 15% and 15% were validated and tested. Therefore, the necessary model was developed in three stages: the training phase (calibration stage), the verification phase and the testing phase. During the training phase, a larger part of the database was used for network training, and the rest of the data were used for verification and testing.

Measures the relationship between regression values, outputs, and objectives. An R value of 1 means a close relationship and R 0 means a random relationship.

The regression values for the training graph were 0.999. If the regression values are 1, there is an absolute linear relationship between the output and the target, and if the regression value is 0, there is an absolute nonlinear relationship between the output and the target. Similarly, regression values for validation and testing were 0.99862 and 0.99855, respectively. The straight line represents the most appropriate Linear regression plot between output and target data. The dashed line represents the best result between the output and the target. Plot the performance curve for training, validation and testing along a number of ages.

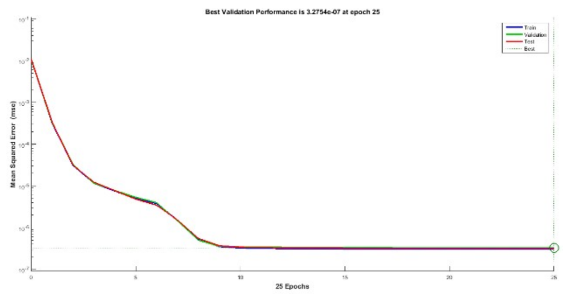

Fig. 7Neural Network training performance

The performance of artificial neural network training is shown in Figure 7. Figure 7 illustrates the performance curve for training, testing and verification. The best performance is 3.2754 e-07. Blue lines indicate that the training curve varies over the number of ages, green to check it and red to the test curve. The dotted line shows the best verification performance curve. Mean Frame Error is the average frame difference between outputs and objectives. Low values are preferable. No zero error.

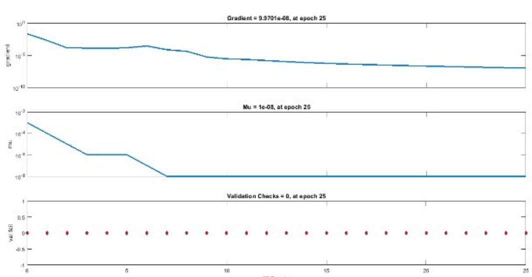

Fig. 8Neural network training state

The training case for the artificial neural network is shown in Figure 8. This curve shows the training status when training performance is complete. The verification error varies linearly across the number of ages. Verification stops when maximum speed is not reached. Validation error is valid for 1000 points. Rate mo 1.00e-08. Check 1000 conditions. Gradient values 9.9701e-08.

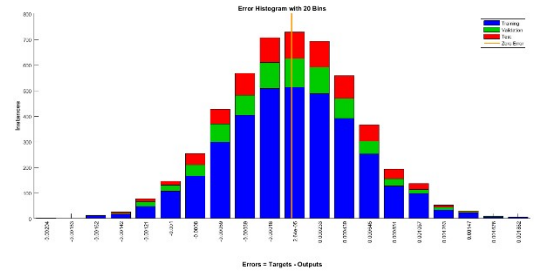

Fig. 9Neural network training error histogram

Neural network training error histogram is given in figure 9.

V. CONCLUSIONS

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

- The regression values for training plot are 0.999.
- The best validation performance is 3.2754 e-07.
- Mu values 1.00e-08.
- Gradient values 3.581e-06.

The artificial neural network (ANN) shows good ability to model the dynamic process. In this study, Leifenberg Marquardt is the best model. They are useful and powerful tools for solving complex problems. The results obtained in this study clearly showed that artificial neural networks can model the phase discharge relationship in an area where the indicator level is irregular; therefore, it confirms the general evolution in many other civil engineering fields using artificial neural networks.

The results showed that the artificial neural network is more appropriate than other conventional methods to predict the relationship of phase discharge. The ANN approach can provide a very useful and accurate tool for problem solving in media identification studies.

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