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ARTIFICIAL NEURAL NETWORK BASED SYSTEM IDENTIFICATION USAGE FOR STEEL SHEDS

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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 0.99 using steel shed 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, Regression, Steel Sheds, Levenberg-Marquardt Algorithm.

INTRODUCTION:

Sheds are typically used as storage, workshop, etc. They are single-storey roof structures with a simple structural system. From simple open sided designed for hangars, warehouses or workshops, to large span, fully enclosed, etc. There are types that differ significantly in terms of sizes and construction up to structures. Sheds used in farms or industry can be larger structures. The construction types used in the sheds can be manufactured as metal or plastic coating on a metal frame, wooden, metal or plastic covered sheds on a completely wooden frame. Small sheds are built on a wooden or plastic floor, while the more permanent ones are built on a concrete floor or foundation. Depending on the region and type of use, a shed can also be called an outbuilding. Sheds can be classified as "auxiliary buildings" in the municipal statute, which can regulate their size, appearance, and distance to the main building and border lines. As mentioned, sheds are used for storage, agricultural, tool and equipment protection, etc. They are manufactured for the purposes. In addition to being small buildings in terms of overall dimensions, those built for the purpose of protecting tools and equipment have larger dimensions. As explained, it is possible to produce a shed type structure in many different material combinations. So, each type has several advantages and disadvantages that should be taken into account by the user. For example, although metal sheds are fire and termite resistant, they may rust over time or be severely damaged by strong winds or heavy snow loads. On the other hand, wooden sheds are easier to replace or repair than plastic or metal because the woodworking tools and woodworking are easier to access. Plastic-coated, wood-framed sheds offer a better use by combining the advantage of a wooden frame with the maintenance-free aspect of plastic cladding. Metal sheds made of thin sheet metal with a metal frame (galvanized steel, aluminum, etc.) are a very good choice when long-term durability and resistance to fire, rot or termites are required. However, metal hangars can corrode over time, especially if they are made of non-galvanized steel. Therefore, it is necessary to be very careful during assembly. Also, some types of metal sheds with thin coatings can collapse easily, so wind, snow, etc. It can make thin-coated metal sheds a poor choice where external influences are intense. In cold climates, it is necessary to clear snow and ice from the roof of thin-walled metal sheds because the thin metal can be damaged by heavy accumulation. Thin metal sheds are much lighter than wooden or plastic sheds, so they are more at risk of damage from strong winds. Thin metal hangars must be attached to the concrete foundation with screws to prevent wind damage. Corrugated metal hangars are better able to withstand wind and snow loads as the corrugated shape makes the metal stronger than plain cladding. Plastic sheds using heavily molded plastics such as PVC and polyethylene are less expensive than sheet metal sheds. PVC resins and high-impact, UV-resistant polyethylene make plastic outdoor sheds lighter, more durable and more resistant to external influences than wood. Plastic kennels with plastic lining are typically among the least expensive types of construction. UV resistant plastic and metal frames are used in higher quality sheds. Plastic kennels are extremely resistant to termite or insect damage; they do not need a protector because they are resistant to rotting. This makes plastic sheds preferred in climates where the weather can be variable. Wooden sheds have a natural look that can adapt well to outdoor environments. Despite the durability of wood, untreated and untreated wood may decay, crumble, deform or mold over time. Therefore, wooden sheds should be protected with varnish or similar preservatives. Fire and, in some areas, termite attack are also potential problems. Timber sheds should be under constant care to prevent exposure to rain, damp floors, UV light, harsh climatic conditions, fungal attack and wood bugs from damaging the wood. Wooden sheds are the most useful type for repair. Deformed parts can be changed easily. These operations are more difficult in plastic and metal shed types.

The deformation of the steel huts must be obtained numerically due to these and similar negative effects. The way to create a mathematical model is possible with the system identification method. The system identification method, on the other hand, is divided into many branches, together with the methods used within and between them. In addition, the system identification method is an extremely open method. The basic logic of system definition is to make a mathematical model estimation by processing the inputs and outputs from the structure with various parameters. With the mathematical model, how the building will react to different inputs can be predicted very easily beforehand. The authors have many studies [9], [10], [11], [12], [13], [14], [21], [22], [23], [24], [25], [26], [27] on system identification given in the sources. It is aimed to observe the applicability of system definition to all types of structures by making each study with different models. In case of a possible error, it is aimed to present an innovative approach by evaluating the situation separately. There are studies that also mention newly developed system identification methods. In this study, the system identification method with ANN (Artificial Neural Network), which is formed by the integration of artificial intelligence and system identification methods, which is still popular today, was carried out with steel sheds, which is an example model. This study aimed to predict the deformations that occur and may occur on steel sheds and to examine the ANN (Artificial Neural Network) application.

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.

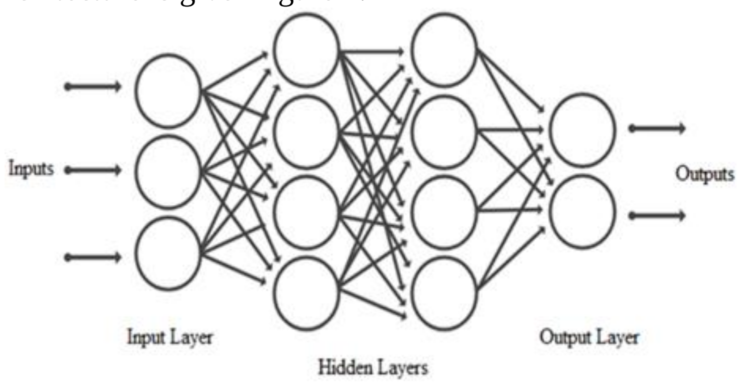

Fig. 1. Typical neural network architecture

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

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

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

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

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 STEEL SHEDS

Steel shed wall thickness is 1.5 mm. Steel shed is single storey. Floor height is 180 cm. Floor area 120 * 240 cm^2. The steel shed is given in figure 2.

Fig. 2. View of concrete steel sheds

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

Fig. 3. Layout of the accelerometers on the steel sheds

ANALYSIS RESULTS

Levenberg- Marquardt algorithm is used for the process of the training. Epoch showing in the progress goes up to 7 iterations. Validation checks also done for the 7 iterations. In the figure 4 it shows the training progress of the neural network.

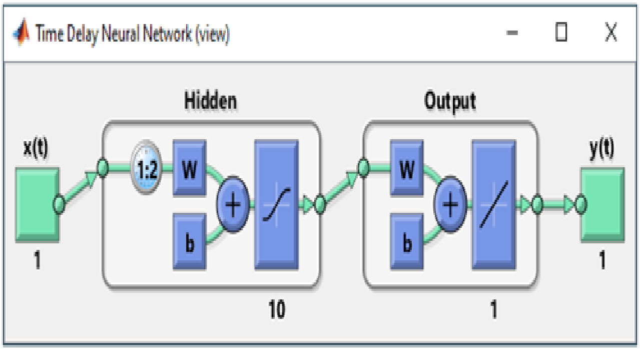

Fig. 4. Neural network diagram

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.

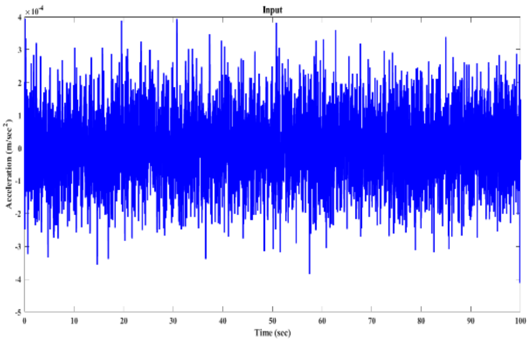

Fig. 5. Input

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.

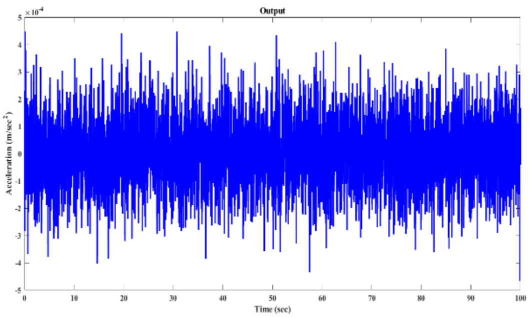

Fig. 6. Output

Output acceleration values are between about $4.5*10^{-4}$ and $-5*10^{-4}$.

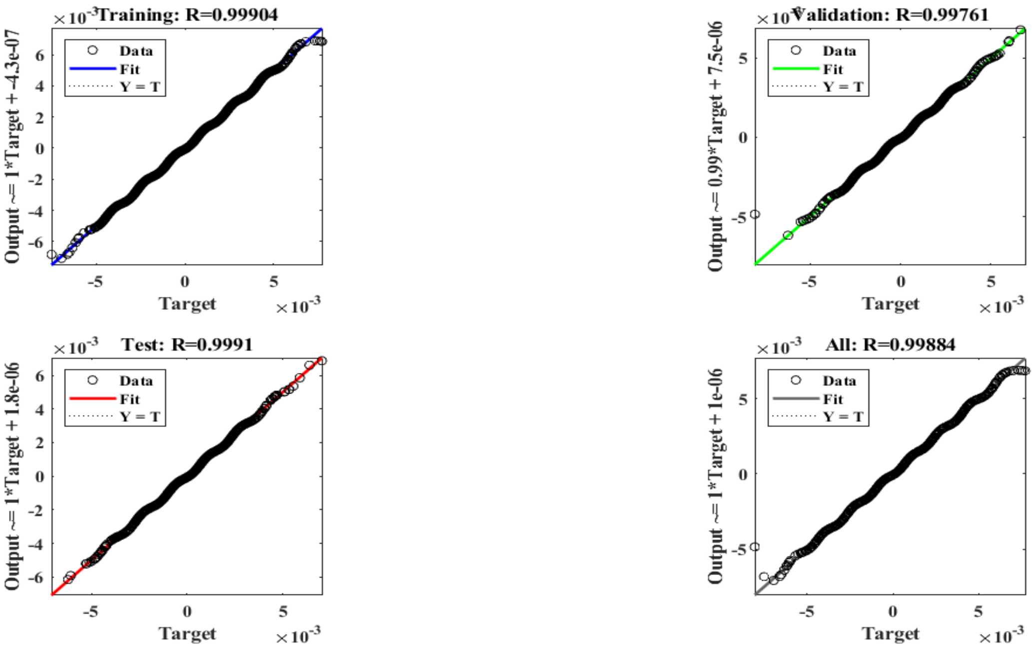

Fig. 7. Neural network training regression

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 0.99764 and 0.99910 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.

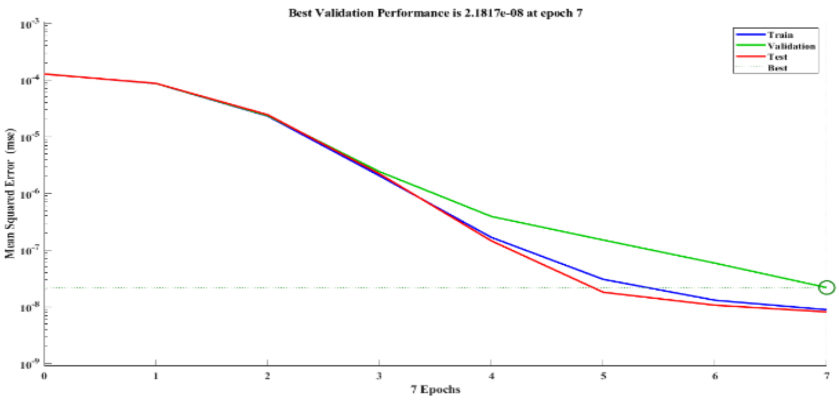

Fig. 8. Neural Network training performance

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 2.1817 e-08. 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.

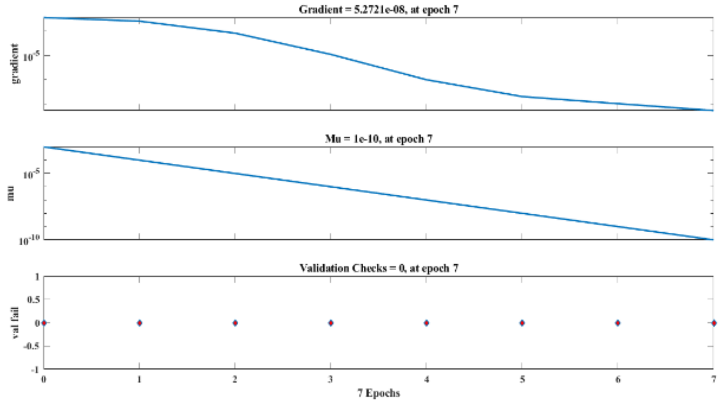

Fig. 9. Neural network training state

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 7 epochs. Mu values 1.00e-10. Validation check for 7 epochs. Gradient values 5.2721e-08.

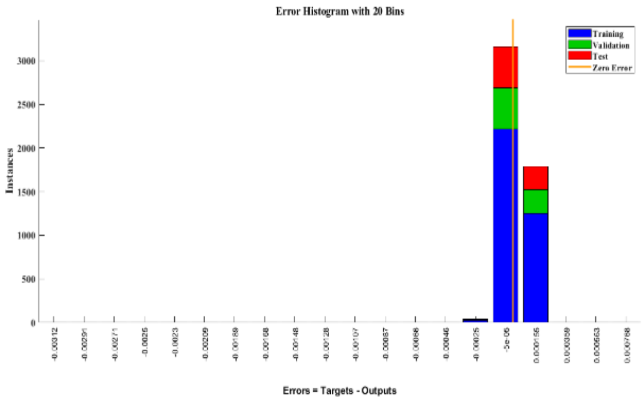

Fig. 10. Neural network training error histogram

Neural network training error histogram is given in figure 10.

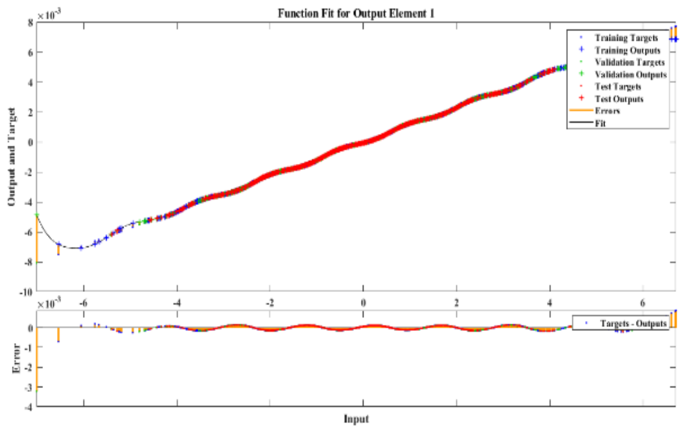

Fig. 11. Function fit for output element 1

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 0.99884.
- The best validation performance is 2.1817 e-08.
- Mu values 1.00e-10.
- Gradient values 5.2721e-08.

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.

Sample model steel shed mathematical model was created with high accuracy (99.8%). Thus, the way has been opened to reveal the current situation under the dynamic effects of steel shed. 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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