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METAMODELLING USING SIMULATION TRAINED ARTIFICIAL NEURAL NETWORK FOR STRUCTURE APPLICATIONS

K. Mahboob[1, 2,*], A. Khan[1], M.N. Khan[3], Q. Awais[4], K.A. Khan[3] and T. Azid[1]

[1]Department of Mechanical Engineering, University of Engineering and Technology Lahore, Pakistan
[2]Department of Mechanical Engineering, Chenab College of Engineering and Technology Gujranwala, Pakistan
[3]Department of Electrical Engineering, The University of Lahore, Lahore, Pakistan
[4]Department of Electrical Engineering, Chenab College of Engineering and Technology Gujranwala, Pakistan
[*]Corresponding author's E-mail: mahboobccet@gmail.com ,

ABSTRACT: Usage of neural network for metamodeling is quite common in different fields of engineering. Engineering simulations' cost directed us to replace it with some metamodel. In this paper neural network is used for predictions and an optimal ANN structure is predicted and modeled. A truss structure is modeled and simulations are carried out with different variations. Neural network is trained and verified for data derived from non linear truss analysis. It is observed that neural network results are in conformance with the simulation results and simulation result base metamodel was formed successfully.

Keywords: Artificial Neural Network, FEM, Non linear Truss structure, Simulation

INTRODUCTION

Metamodelling are considered as one of the emerging field in modern science used in different fields (Kroetz *et al.,* 2017; Zeinali *et al.*, 2015; Fienen *et al.*, 2016; Ghiasi *et al.*, 2018; Ryberg *et al.*, 2015). Neural Networks (NN) are also used to develop metamodels (Wang *et al.*, 2018; Dai and Cao, 2017) and its history goes back to 1940 with origins from neurobiology. In this era researchers studying the brain function, tried to copy the brain function and use to solve different problems. Later in 1950 and 1960, group of researchers modeled the first Artificial Neural Network (ANN) on the basis of these biological and psychological insights. ANN was initially used in hard and later in soft computing. It is used for past several years in computer simulation behavior (Jain *et al.*, 1996; Mahboob *et al.*, 2018). Due to its flexibility and effectiveness these are used in a number of applications like, pattern recognition, control systems, vision and predictions (Khosravi *et al.*, 2010; Chambers and Mount-Campbell, 2002; Zhu *et al.*, 2009; Domeij *et al.*, 2017).

Biological model of a neuron: The human brain is the central unit of the human nervous system. It takes information from the outer sources routed through the sensing system. It consists of more than 1000 neurons connected to each other to form networks. These neurons are of different types like sensory neurons, motor neurons. Neuron is the basic unit of human nervous system and it consists of three components that are body, dendrites and axon. Dendrites arise from the cell body and are branched multiple times to form the dendrite tree. They are connected with the other neurons to form the NN. There may be many dendrites in cell body of neuron but only one axon. The function of the neuron is as follows,

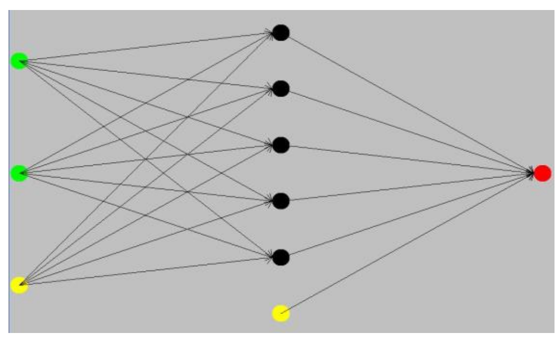

Figure 1: Artificial Neural Network

It receives signals from dendrites and sends them to cell body which processes these signals. If sufficient signal received that stimulate the neuron to threshold level, it send them to other neurons via axons. If signal is less than threshold level then it decays gradually (Hopfield and Tank, 1986; Yao and Freeman, 1990; Izhikevich, 2004).

Mathematical model of a neuron: Inspired from the biological neuron, a mathematical model was created which works on the same principal.

Neuron consists of followings three components

1 Weights
2 Threshold
3 Activation function

Weights: Weights are the values associated with input node and determine the strength of the input. The input of the neurons is multiplied by the weights of the connection before adding. Weights may be positive or negative. Values of weights vary in the training process to get the output.

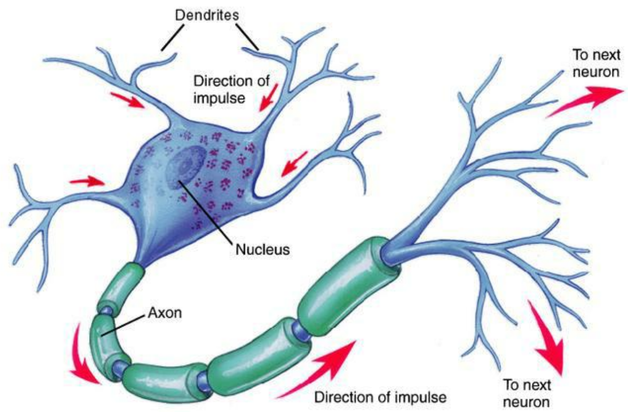

Figure 2: Neuron.

Threshold: Threshold determines the activation of the neuron. Output is affected by the threshold.
Activation function: There exist different forms of activation function. Most common are as follows,

a) Linear function
b) Threshold function
c) Piecewise linear function
d) Sigmoidal function
e) Tangent hyperbolic function

Multi-layer perceptron: Multi-layer perceptron (MLP) is used for the complex nonlinear problems (Shahin *et al.*, 2008). It consists of multilayers of nodes and neurons. A single layer perceptron can only form a half plane decision region whereas MLP form complex decision region. MLP is popular because of its flexibility and ability to be trained for complex shape of patterns in the data. As shown in the figure 4, it consists of the 3 layers (Lightbody and Irwin, 1996).

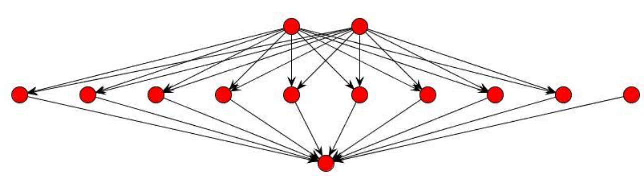

Figure 3: Multilayer Perceptron

First layer known as input layer consists of neurons which passes information from external source to network. The number of input layer neurons depends on the number of inputs we want our network to get. The second layer which is not in contact with external input or output is known as hidden layer. Hidden layer receives the information from input layer and sum the corresponding weights. This summing is similar to a linear neuron but it passes the sum through a nonlinear transfer function. There may be more than one hidden layers. It is already proven that one hidden layer of MLP can approximate any function that connects its input with its outputs if such a function exists. The information processed through these hidden layers comes to output layer which sends the output signal. For the input and hidden layer, an additional node containing the value 1 is considered this is known as bias. It provides the threshold for the activation neuron. Bias input is connected to all neurons in the hidden or output layers.

MATERIALS AND METHODS

Section sketch: A truss of circular cross section is used. An assembly of two trusses is formed to make non linear truss structure. In zero load condition the y distance of the truss is 0.78 m. The horizontal value changes with the change of truss length. The calculation are done using ABAQUS Finite Element (FE) program.

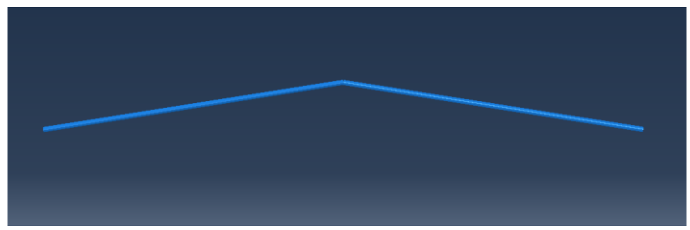

Figure 4: Model of nonlinear truss structure

Boundary conditions: The model is bounded on the right, left and bottom side with roller supports. Force is applied on the assembly junction of both trusses.

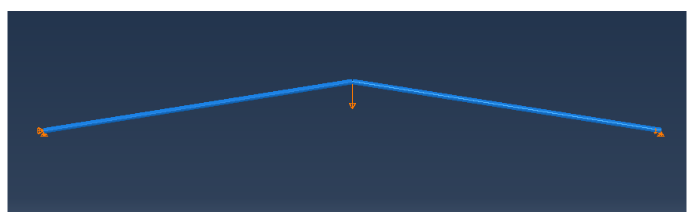

Figure 5: Boundary condition

Element and mesh type: A non linear 2D type truss element type is used for the truss structure. Each truss consists of 2 nodes truss element.

Truss element: Truss elements are structural members considered as long and slender. Axial force can be transmitted but moments cannot be transmitted and are presented in one-dimensional solid. At the start it does not have any stiffness perpendicular to their axis to resist loading. If it is loaded in Abaqus/Standard perpendicular to its axis, lack of convergence and numerical singularities can result. But in case of large displacement implicit analysis it develops stiffness perpendicular to its axis after the first iteration, sometimes allowing overcome numerical problems of an analysis.

Application in nonlinear truss analysis: A truss structure consists of two trusses as shown in the figure 6 is considered, fixed at one end and having force on the other. A distance based criteria is used because with the increase of force it shows non linear pattern which is not possible if load based criteria is used.

Parameters in nonlinear truss analysis: Followings are the input parameters used for the analysis.

1 Area
2 Length
3 Displacement

Load is the output parameters.

Material parameters: Young modulus (E) is kept constant and has a value $210e^9$ and Poisson ratio (v) is 0.4. Both of these constant does not show any influence on the output.

Types of loading criterion: Analyses are carried out based on three types of input parameters. Firstly, analysis is carried out by varying the cross-sectional area of the truss and keeping length constant. Secondly length of the truss is varied while keeping cross sectional area constant. Finally, simulations are carried out by varying both length and cross-sectional area of the truss.

Post processing: Built in post processor of Abaqus is used for post processing the results. Figure 6 shows the deformation of the structure. Deformation scale is visible on the legend and corresponding color contours can be seen on the truss structure.

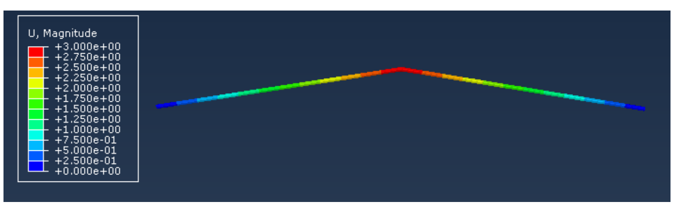

Figure 6: Deformation of the structure

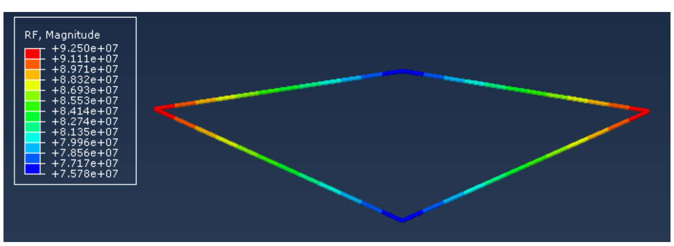

Figure 7: Reaction forces in the structure

Figure 7 shows the reaction force magnitude of the structure. RF scale is visible on the legend and corresponding color contours can be seen on the truss structure.

Training of Neural Network: A two-layer multi-layer perceptron (MLP) is used for training and prediction of results. Number of neurons can be varied in first and second layer to get optimum number of neurons in both layers. To achieve this different NN with different number of hidden layer neurons are trained to get an optimum structure.

Figure 8 shows a multi-layer perceptron consist of two hidden layers. There are 3 input neurons same as number of inputs. Three neurons are placed in 1st hidden layer and two neurons in 2nd hidden layer. Output layer consist of 1 neuron same as number of outputs. Based on the result obtained from the above-mentioned analysis, NN was trained. Only 10% data is used for training.

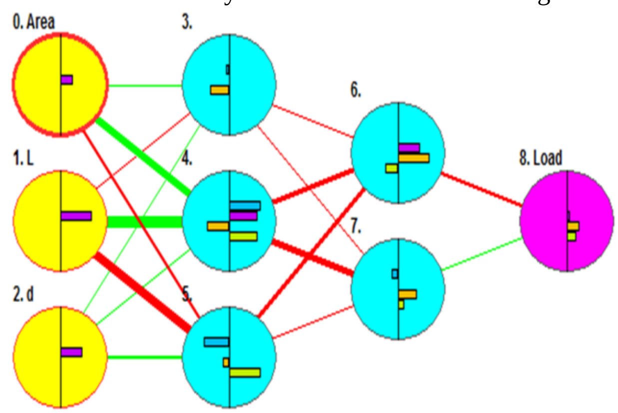

Figure 8: MLP trained on given input and output

RESULTS AND DISCUSSION

Different analyses are carried out for combination of variation of these parameters. Figure 9 shows the structural analysis is carried out with variation in the area keeping the other parameters constant.

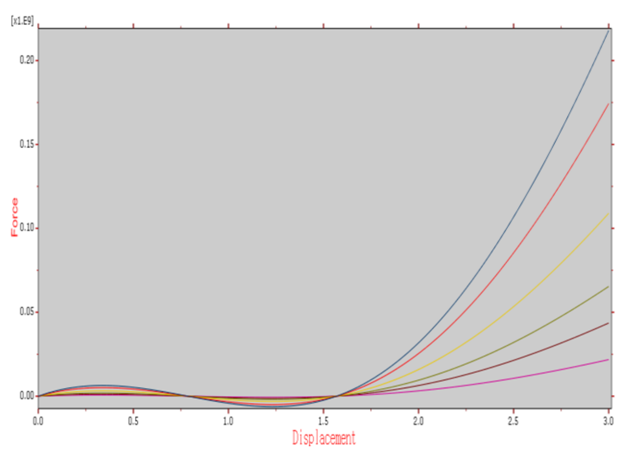

Figure 9: Results from area variations

Curves show the change in the value of area from 0.001 to 0.01.

Figure 10 shows the structural analysis carried out with variation in the length keeping other parameters constant.

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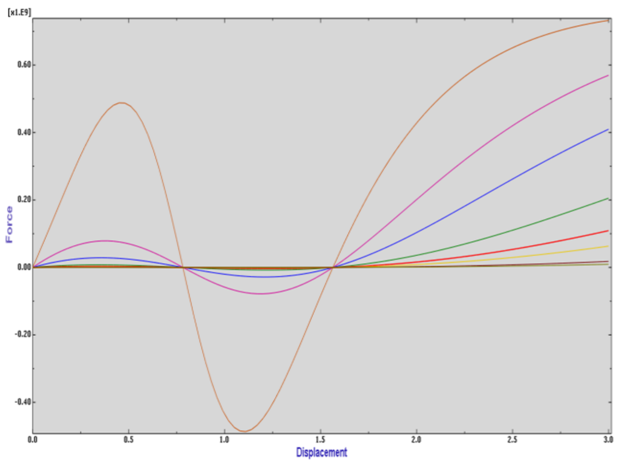

Figure 10: Results from length variation

Curves show the change in the value of length from 1 to 10.

Figure 11 shows the combination of above mentioned structural analysis carried out with variation in the length and area keeping the other parameters constant.

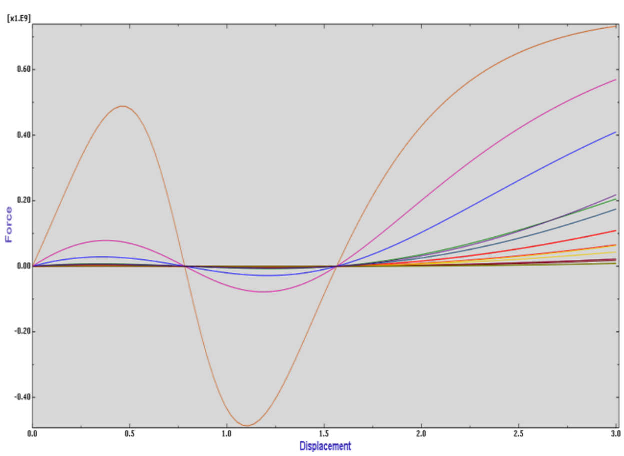

Figure 11: Results from area and length variation

Figure 11 shows a plot of different values obtained from NN prediction using different number of hidden neurons along with simulation value. On the horizontal axis displacement is plotted and load is plotted on the vertical axis.

It is important to note that notation H3HH3 is used, where H shows the number of neurons in 1st hidden layer and HH shows the number of neurons in the 2nd hidden layer. O is the value obtained from the simulation. It is revealed from the results that with varying the number of the hidden layers neurons, behavior of NN is changed. It is also observed that with certain combination of neurons in NN it is possible to maps the results within desired error range.

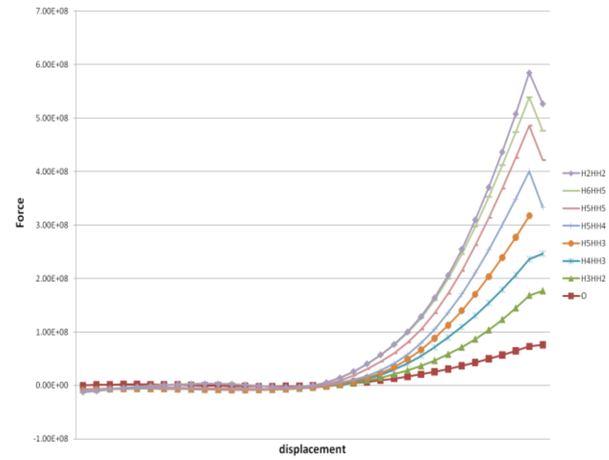

Figure 12: Comparison of results obtained from different hidden layer neurons

It is clear from the results that H3HH2 shows the closely mapped results

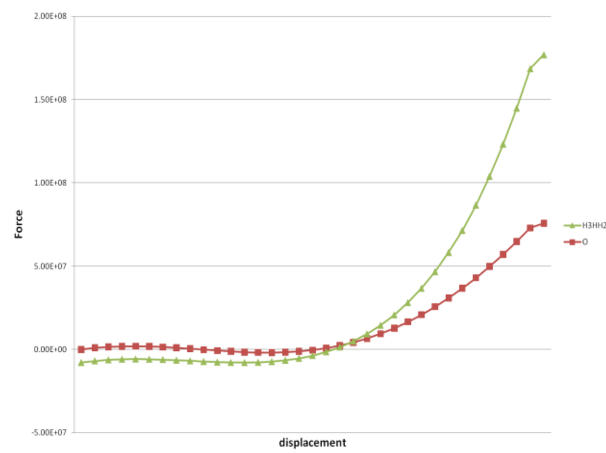

Figure 13: Comparison of results obtained from NN vs simulation

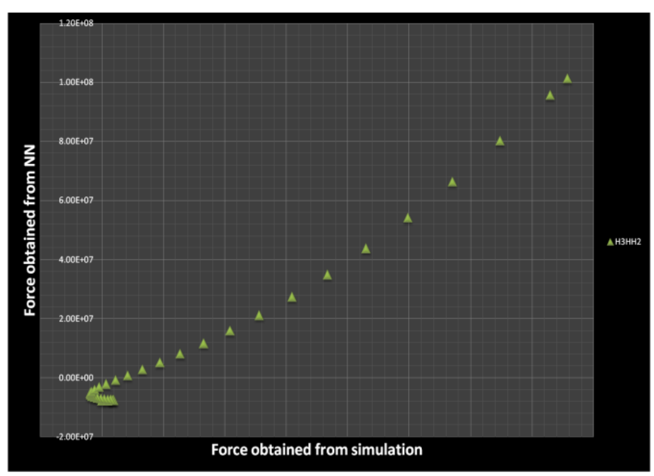

Figure 14: Plots of results from H3HH2

Figure 13 shows the plot of H3HH2 against simulation value. There are some variations but this is due to the fact that only small amount of data is used for training.

Figure 14 shows the plot of H3HH2 against simulation value. A line parallel to 45-degree angle will be best fitting of this curve and we see most of the plotted points lie around 45-degree line.

Conclusion: It is evident from the results; both Length and diameter have greater influence over the output By varying the number of neurons in the hidden layers, over fitting can be seen in the results. Smaller training data is enough to predict the result closely. This study revealed the capability of neural network for non linear analysis and it satisfies its compatibility. It is clear from the above-mentioned analysis that we can use our neural network model for non linear problem.

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