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Determination of Lateral load Capacity of Steel Shear Walls Based on Artificial Neural Network Models

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Abstract

In this paper, load-carrying capacity of steel shear wall (SSW) was estimated using artificial neural networks (ANNs). The SSW parameters including load-carrying capacity (as ANN's target), plate thickness, thickness of stiffener, diagonal stiffener distance, horizontal stiffener distance and gravity load (as ANN's inputs) are used in this paper to train the ANNs. 144 samples data of each of these parameters was calculated using SSW simulation in ABAQUS. Load-carrying capacity of SSW was estimated using radial basic function (RBF) and multi-layer perceptron (MLP) neural networks. Spread parameter in RBF and number of hidden layer, number of neurons in this layers and activation function in MLP optimized using a trial and error method. The results showed that the load-carrying capacity of SSW could estimate using RBF and ANN by 84 and 96 percent of precision respectively.

Key words:*Load-carrying capacity of SSW, RBF neural network, MLP neural networks.*

1. Introduction

In the current seismic resistant design, building structures are allowed to exceed their elastic limit under severe earthquake excitation. However, brittle collapse of a building should be prevented. Besides strength requirements, stiffness is another concern in a structural design. With high strength and high stiffness, the steel plate shear wall (SPSW) has drawn many engineers' attention. Many research works have been carried out on the steel plate shear walls. One of the attractions of steel plate shear walls, SPSWs, is the easiness of opening application in the infill plate, sometimes required for passing the utilities, architectural purposes, or structural reasons.

Experimental studies have been carried out on the thin steel plate shear walls by Caccese et al. [1], Driver et al. [2], and Lubell et al. [3]. Analytical studies on the shear buckling behavior of steel plate wall and the behavior of a multistory steel wall system were conducted by Elgaaly et al. [4, 5], Driver et al.[6], Berman and Bruneau [7], and Sabouri-Ghomi et al. [8].Design rules of the thin steel plate shear wall are also specified in the design specifications, such as AISC [9] and CSA [10]. In[11], several experiments have been performed on the behavior and energy absorption coefficients of ductile SPSW with stiffeners and without stiffeners. The obtained results in this approach show that behavior coefficients of the SPSW with stiffeners and without stiffeners are 11.5 and 12.2, respectively. Energy absorption of the SPSW without stiffeners is 36%lower than that of SPSW with stiffeners. Another experiment has been carried out on the SPSW with and without opening. So the stiffeners are affected the SSW performance.

AlHamaydeh and Sagher[12] investigated the key parameters influencing the behavior of steel plate shear walls. The complex behavior of steel plate shear walls was investigated in their paper through nonlinear finite element (FE) simulations. A 3d detailed FE model was developed and validated utilizing experimental results available in the literature. They investigated the influence of key parameters on the structural behavior. The parameters that they considered were: the infill

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plate thickness, the beam size, the column size, the infill plate material grade and the frame material grade. Several structural response used in their research as criteria to quantify their influence on the SPSW behavior. The evaluated structural responses was: yield strength, yield displacement, ultimate strength, initial stiffness and secondary stiffness. Their obtained results show that overall the most influential parameter is the infill plate thickness followed by the beam size. Also, it was found that the least influential parameter is the frame material grade. Songzhi et al studied seismic behavior of SPSW using finite element method.

In this paper according to evaluated results provided by Delnavaz et al. an artificial neural network modeling has been done to estimate the load-carrying capacity of SPSW. The load-carrying capacity of SPSW is predicted using multi-layer perceptron and radial basis function neural networks. To ANN modeling six parameter containing load-carrying capacity (as ANN's target), plate thickness, thickness of stiffener, diagonal stiffener distance, horizontal stiffener distance and gravity load (as ANN's inputs) are used that have the most influence on SPSW performance.

2. ANNs modeling

To load-carrying capacity estimation using RBF neural network, the MATLAB R2016a is used. 15 % of total data are selected randomly as testing data and others as training data. Then the RBF was coded with six inputs including training matrix, target matrix. Goal, SPREAD, MN, and DF Goal is the mean square error goal that its default value is 0. That's means that the network trained until its error goes to zero. Spread is spread of radial basis functions, default = 1.0.MN is maximum number of neurons, and default is number of input vectors. This process returns a new radial basis network that can get new inputs and estimate the output. The larger that SPREAD is the smoother the function approximation will be. Too large a spread means a lot of neurons will be required to fit a fast changing function. Too small a spread means many neurons will be required to fit a smooth function, and the network may not generalize well. Call NEWRB with different spreads to find the best value for a given problem.

To MLP optimized modeling to estimate load-carrying capacity of SPSW, the algorithm showing in fig. 1 must be conducted. MLP neural network modeling with back propagation algorithm is done using MATLAB R2016a. The data was randomly divided into training (70% of all dataset, testing (15% of all dataset) and validation (15% of all dataset) subset to model the MLP neural network. The network use mean square error parameter to assess the performance. The training data points were used to approximate the network weights and biases, and the test data points and validation data points were used to assess the prediction capability of the developed model against new data.

In the next step, the input and output variables were normalized according to the following equation to increase the network prediction speed and precision, generalization capability.

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}} \quad (1)$$

WhereX_{norm}, X_{min} and X_{max} represent the values of normalized, minimum, and maximum of the variable X, respectively. It is obvious that all variables have been scaled between 0 and 1after normalization. Variable normalization is a common practice in ANN modeling; especially when the range of variation is very wide and different.

Determination of the number of hidden layers, neurons in each hidden layer, the neuron activation function are important in MLP neural network modeling. These parameters are normally determined through a trial and error procedure via comparing the performance of different network architecture after training the network. During the training process, the performance function which is usually the mean squared error (MSE) of the network prediction should be minimized in each iteration in order to find the appropriate values of ANN parameters.

In the present study, various neuron activation functions were tested and subsequently the logistic sigmoid (equation (2)) and purelin transfer functions (equation (3)) were selected for hidden and output layers, respectively.

$$f(x) = \frac{1}{(1 + e^{-cx})} \quad (2)$$

$$f(x) = x \quad (3)$$

The activation functions of hidden layers should introduce nonlinearity into the network in order to enhance network prediction capability in comparison with plain perception. Moreover, a linear activation function, such as purelin, could be selected for the output neuron since it is appropriate for continuous valued targets.

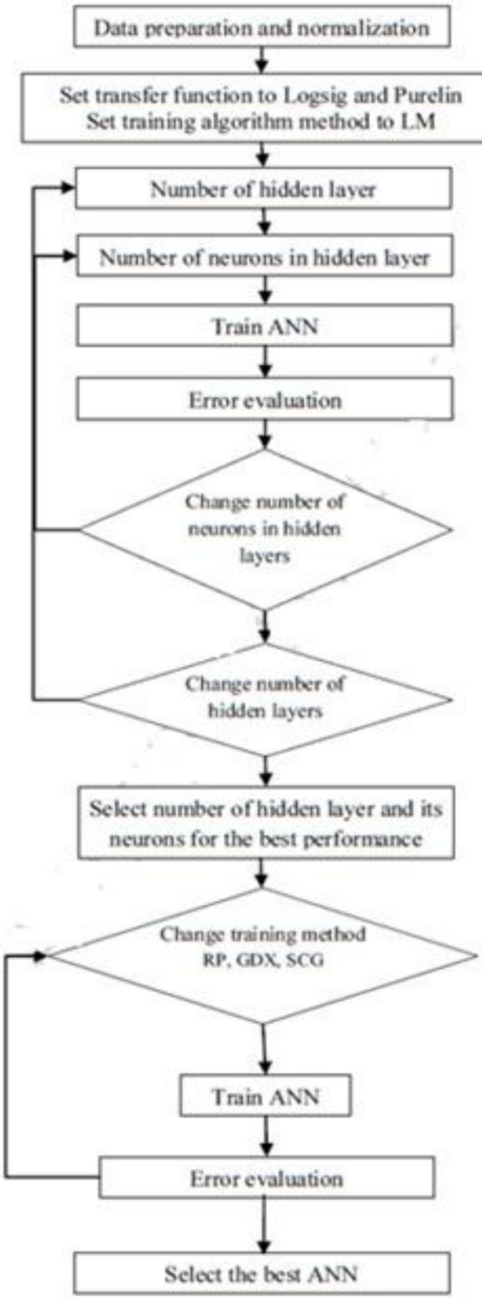

Figure 1. The applied algorithm to create an optimized MLP neural network model.

The predictive performance of ANN networks were compared by changing the number of hidden layers, number of neurons in each hidden layer, and also different back propagation training algorithm such as scaled conjugate gradient (SCG), Levenberg Marquardt(LM), gradient descent with variable learning rate back propagation (GDX), and Resilient back propagation(RP).The best network architecture is selected based on several statistical criteria, including regression (coefficient of determinationR^2), error histogram, and mean squared error (MSE).

AS mentioned above, several configurations were tested for ANN using a trial and error method to find the best architecture for the network to estimate the load-carrying capacity of SSW. A feed forward neural network generally has one or more hidden layer that enables the network to model nonlinear and complicated functions. The network performance is not satisfied if the number of neurons in hidden layers was smaller. On the other hand, if the larger number of neurons was selected for this layer then the training phase was long and boring and the network may over fitted and get in local minimum. Therefore, there is no generalized rule to select the optimum number of hidden layers and neurons in them. These ANN parameters depend on the complication of the system to be modeled.

3. Data

To load-carrying capacity estimation through effective parameters on the SSW performance using neural networks, first several SSW modeling have been done in abaqus software to obtain the neural networks inputs and targets dataset. This obtaining datasets have been validated using experimental results provided in [12]. 144 samples data obtained from abaqus. The effective parameters on the load-carrying capacity are plate thickness, thickness of stiffener, diagonal stiffener distance, horizontal stiffener distance and gravity load.

4. Results and discussion

In this section, firs the RBF neural network result are presented. After determine RBF inputs, the network was trained and the regression, performance and the targets and inputs comparison plot are explored.

RBF configuration is shown in fig.2. As can be seen in this figure, the number of input, first and second hidden layers neurons are 6, 124 and 1 respectively. The output layer has one neuron.

RBF neural network estimation performance is shown in fig.3. In this figure the horizontal axis represent mean square error of estimated data (output) and the vertical axis represent the epoch number. An epoch is a measure of the number of times all of the training vectors are used once to update the weights. For batch training all of the training samples pass through the learning algorithm simultaneously in one epoch before weights are updated. As seen from fig.3, in the first epochs, the network estimation error is high that this error over 125 epochs arrived the minimum error value of about zero.

Outputs and targets data of the RBF neural network compared in the plot showing in fig.4. In fact the network outputs and targets are the load-carrying capacity of SSW. From the fig.4.a it can be seen that the network outputs and targets are in accordance completely. It should mentioned that the networks use training data as new inputs after completing training process and estimated new outputs that this new outputs compared with the targets in this figure. The fig.4.b showed the regression of the network outputs and targets. In the regression plot shown in fig.4.b, the horizontal and vertical axis shows the outputs and targets respectively. If the fitting line pass through all data (outputs and targets) then it can be said that the estimation precision is 100% that happened here.

Fig.5 and fig.6 has the similar interpretation represented for the fig.4. The only difference is in the phase of the network modeling which the fig.4 is for training data while fig.5 and fig.6 are for testing and all data respectively. The network accuracy for testing and all data are 36% and 94% respectively. So the RBF neural network that modeled in this paper can predict the load-carrying capacity with total precision of 94%.

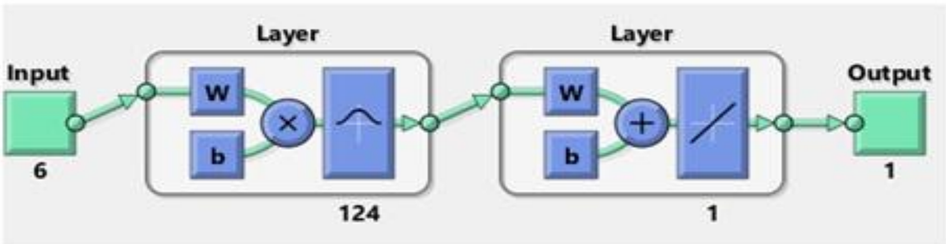

Figure 2. RBF neural network optimum configuration

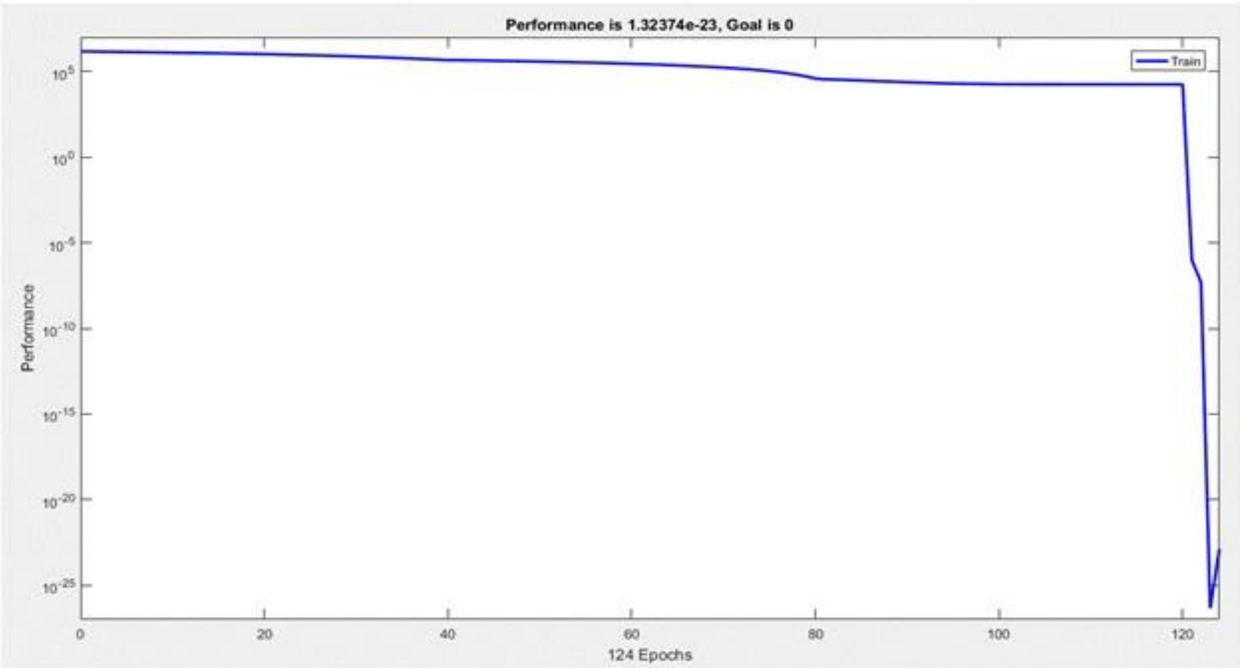

Figure 3. RBF neural network performance

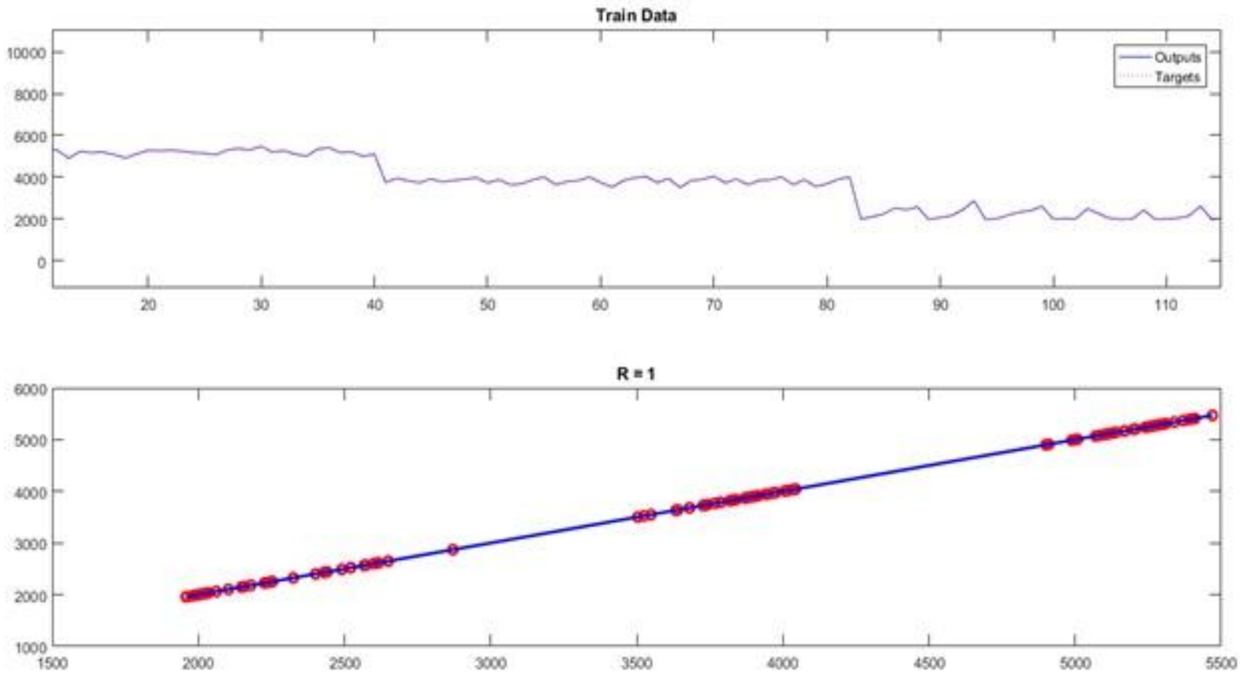

Figure 4. RBF neural network outputs and targets comparison for training data

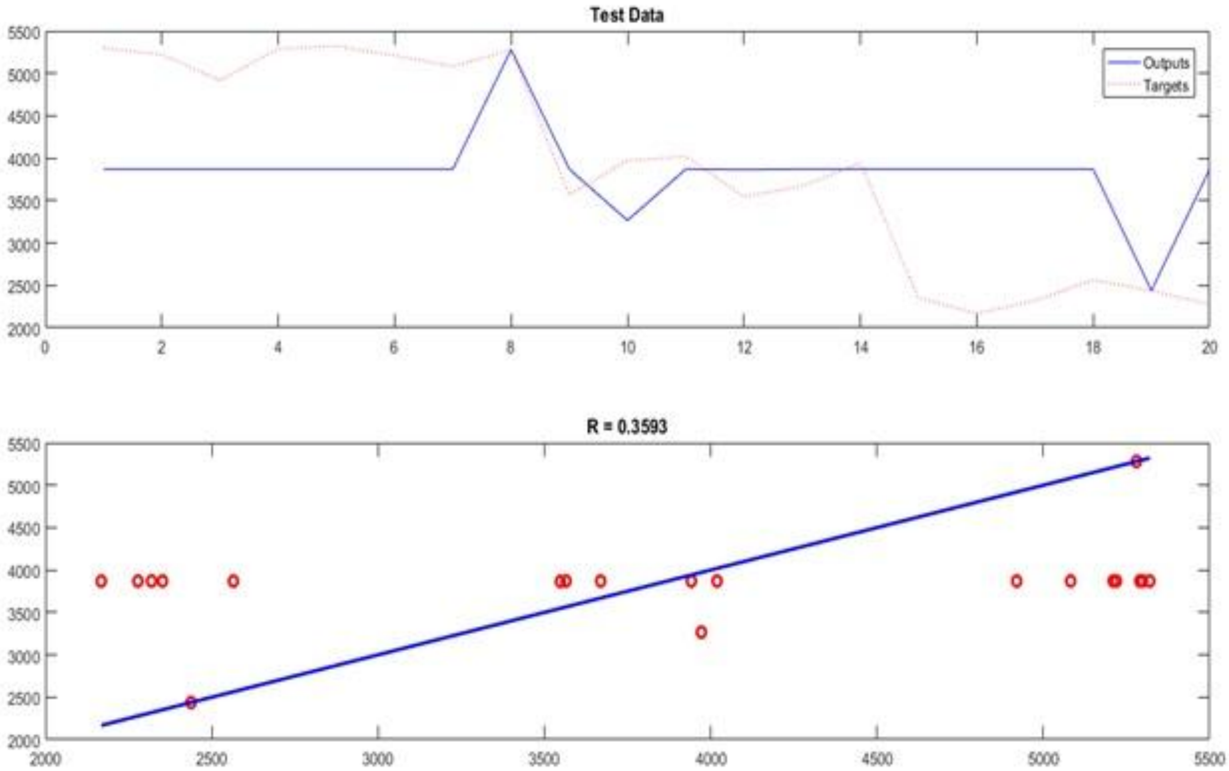

Figure 5. RBF neural network outputs and targets comparison for testing data

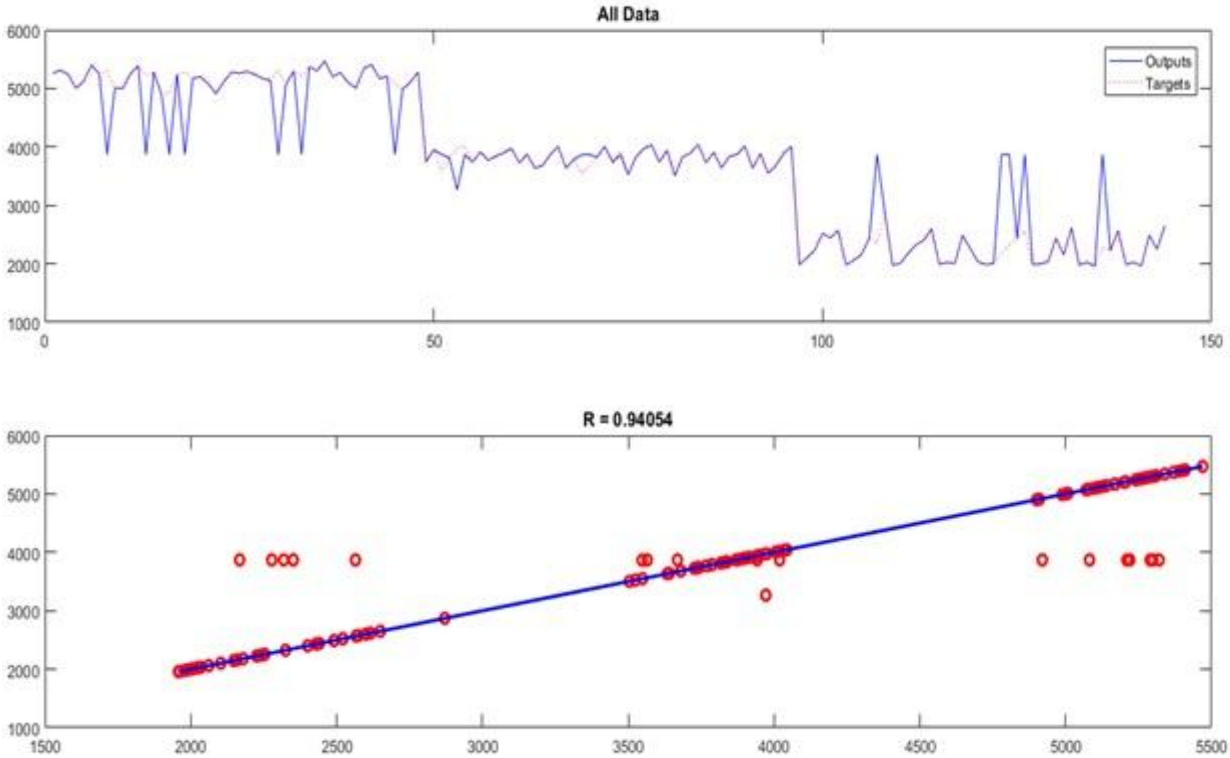

Figure 6. RBF neural network outputs and targets comparison for all data

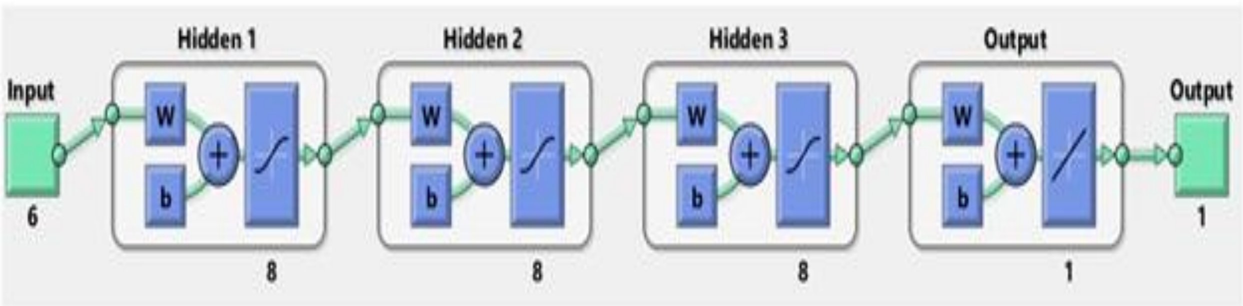

Figure 7. MLP optimum architecture

The estimation results for MLP neural network are presented in the following. As previously mentioned, the optimum configuration of ANN find using a trial and error method. By testing different architecture for the MLP neural network, it is shown that the best network is that with three hidden layers and eight neurons in each, sigmoid transfer function and Levenberg Marquardt as training algorithm (see fig.7). As shown in fig.7, this network has 6 and 1 neurons in the input and output layer respectively that this number of neurons are selected by the network respected to the number of the rows in the inputs and outputs matrix.

Network convergence and performance in training, testing and validation phase shown in fig.8. As shown in this figure, the network is converged over 121 epochs and gains the optimum results. It should mentioned that, network converging means that the network goes to minimum mean square error as the training, testing and validation plot not getting away from each other.

The error histogram of predicted data is shown in fig.9 that this plot compute the error values as a difference between target values and predicted values for training, testing and validation data. The error values presented in this figure are relatively high due to large number of targets and output data.

Another plot that could present for result assessment is the regression of the data (see fig.10). It is obvious from this figure that the network prediction accuracy for prediction of training, testing, validation and all data are 99.91%, 99.96%, 99.80 and 99.84 respectively that are good precisions. Therefore the network mean error for all data is about 1.16%.

The last plot presented here for evaluating MLP prediction results is comparison between network targets (real load-carrying capacity values) and outputs (predicted load-carrying capacity values). It is clearly seen that the targets and outputs data are in good accordance.

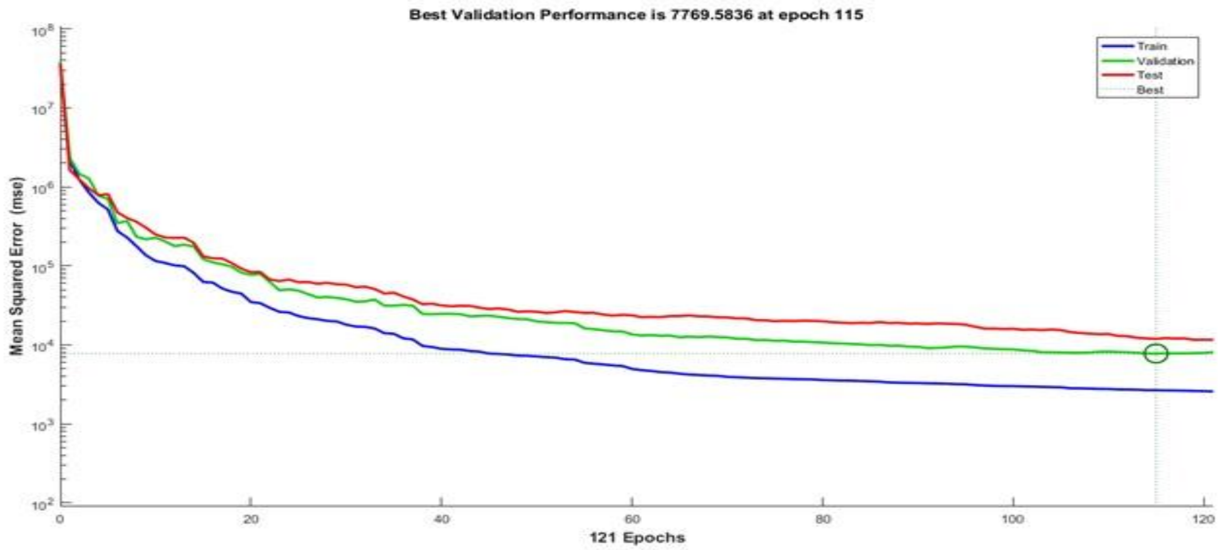

Figure 8. MLP neural network performance

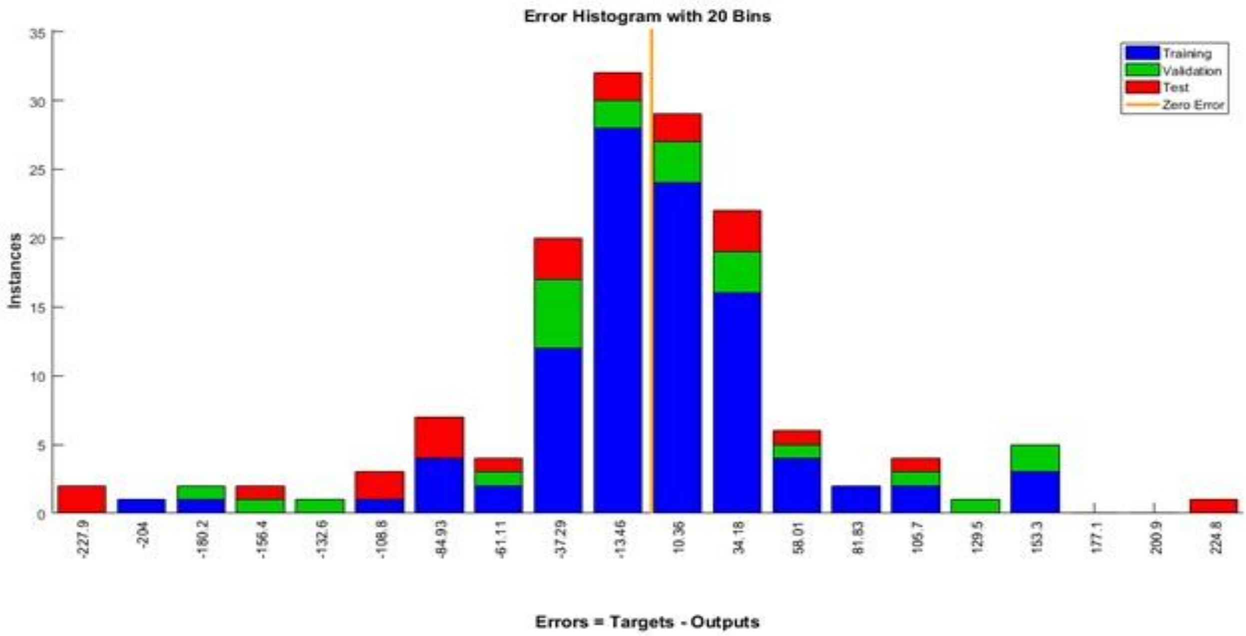

Figure 9. Error histogram for MLP neural network

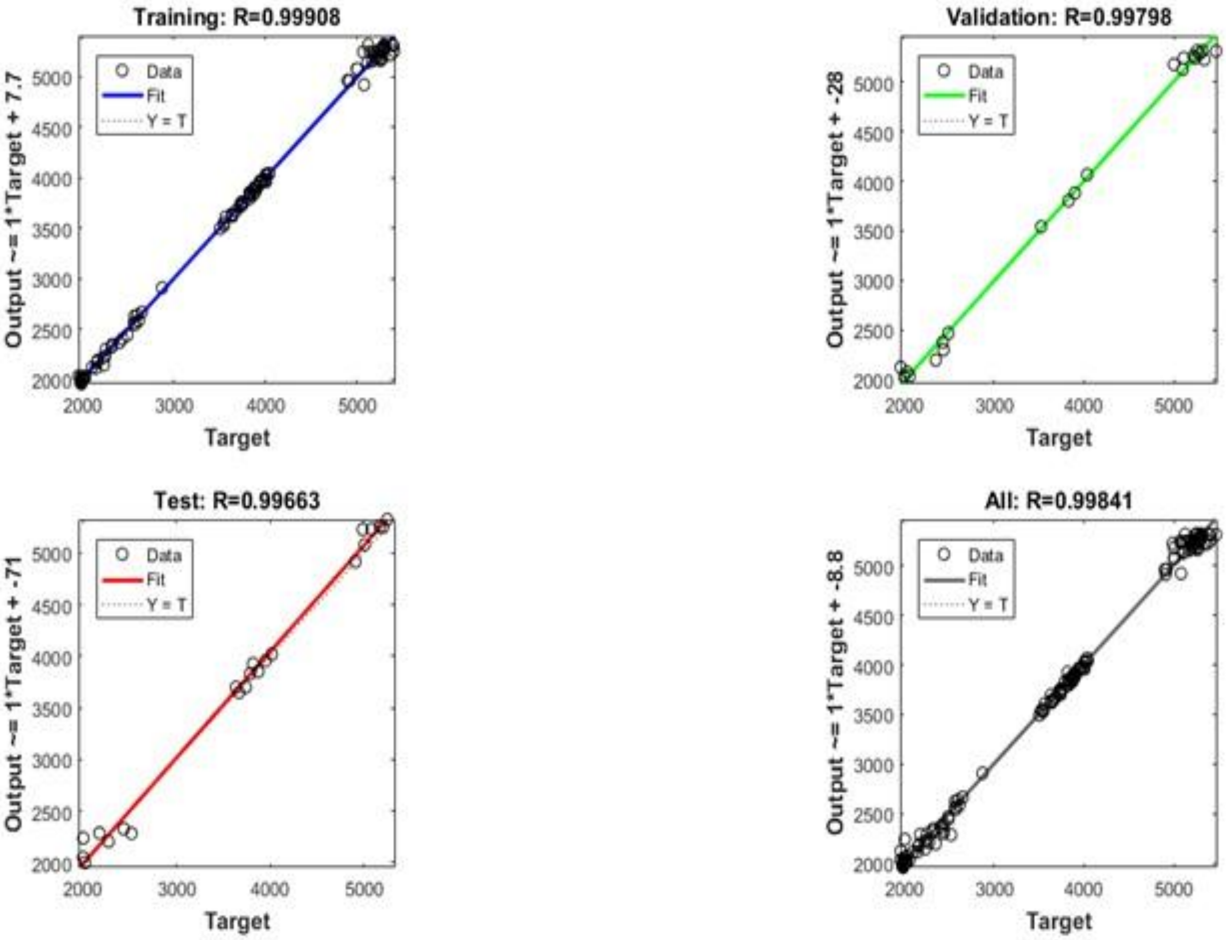

Figure 10. Linear regression between MLP neural network targets and outputs

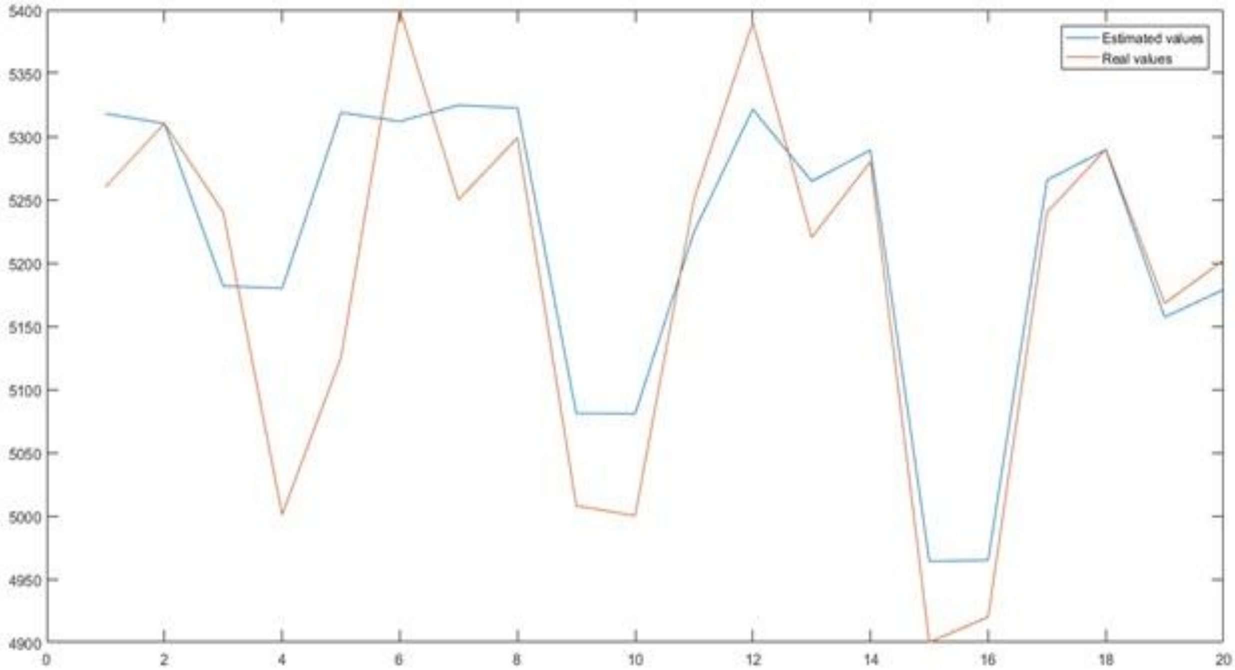

Figure 11. The MLPNN targets and outputs data comparison

5. Conclusion

In this paper two different artificial neural network (RBF and MLP) approaches have been developed for prediction the load-carrying capacity of steel plate shear walls. The load-carrying capacity as ANN target and the plate thickness, thickness of stiffener, diagonal stiffener distance, horizontal stiffener distance and gravity load as ANN inputs used to model the neural networks. The used data for ANN modeling are obtained using 144 sample of SPSW with different geometries and loading conditions modeled and validated through experimental results. This obtained data divided randomly into training, testing and validation sets. Optimum configuration for this two type of ANNs obtained by testing different training algorithms and different architectures. This study indicate that the optimum configuration for RBF neural network is that with one input layer, two hidden layer and one output layer with 6, 124, 1 and 1 neurons in each of them respectively and the best model for MLP neural network is that with one input layer and 6 neurons in it, three hidden layers and eight neurons in each of them, one output layer and one neuron in it, LM as training algorithm and sigmoid transfer function. The results show that the RBF and MLP neural networks can predict the load-carrying capacity of SPSW with correlation coefficient of 0.94 and 0.99 respectively.

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