CHAPTER-4

The Prediction of Buckling Load of Laminated Composite Hat-Stiffened Panels under edge Compression Load by using Neural Networks

4.1 Introduction

ANNs are parallel computing systems similar to biological neural networks. Artificial Neural Networks (ANNs) consist of large number of processing elements with their interconnections. Artificial neural networks (ANN) modeling is a nonlinear statistical technique. It can be applied to solve complex problems that are not amenable to conventional statistical and mathematical methods. In the past few years there has been constantly increasing interest in neural networks modeling in different fields of civil engineering. Usually neural networks are trained so that a particular set of inputs produces, as nearly as possible, a specific set of target outputs. Usually neural networks are trained with a particular set of inputs produces and nearly as possible as a specific target output.

The most commonly used ANN is the three-layer feed-forward back propagation ANN. In feed-forward backpropagation neural networks architecture, there are layers and nodes at each layer. Each node at input and inner layers receives input values, processes and passes it to the next layer; this process is conducted by weights. Weight is the connection strength between two nodes. The numbers of neurons in the input layer and the output layer are determined by the numbers of input and output parameters respectively. Commonly, neural network modeling follows these steps; database collection, analysis, preprocessing of the data and training of the neural network. In a neural network model, the outputs are correlated to the inputs through the neurons with weights and bias. The behavior of a neural network is defined by the way its individual computing elements are connected and by the strength of those connections or weights. The weights are automatically adjusted by training the network according to a specific learning rule until it performs with the desired error rate.

Kadi [90] presented a review on pattern estimation of the mechanical behaviour of fiber-reinforced combined materials with the help of ANN tool. Mallela and Upadhyay [91] used a computational tool (ANN) for predicting the buckling load of panel subjected to in-plane shear loading. The results of ANN were compared with FEM results of stiffened panels. Rogers [92] developed a guideline for designing and training an ANN to simulate the structural analysis program. Alqedra and Ashour [93] performed ANN to study the significant parameters on the concrete shear capacity of anchor bolts. Few researchers have used ANNs for predictions of the behaviour of laminated composite materials [94]. Multilayer feedforward networks are universally accepted and gives result in the desired accuracy with a specific sense [97-98]. Results from one hidden layer were given desired output with different weight value connection for continuous function but the selection of the second layer for the discontinuous function [99]. The hidden layer should contain a total number of neurons was equal to the one greater than twice the number of input parameters and some cases the hidden layer selection based quality and quantity of the training data [100]. Some situation the multi-hidden layer was given better result over the single hidden layer [101-102]. Chakraborty [103] developed an optimum network with application of computational tool (ANN) for predicting of the presence of a delamination of laminated composite panel at different location along with its shape and size from FE analysis generated input data (natural frequencies).

This chapter deals with the optimization of laminated composite hat-stiffened panels under in-plane compressive loading by using ANNs. The ANNs have been trained by using a generated database of FE models. Finite element (FE) models have been used to generate data set of four different parameters. The four parameters are extensional stiffness ratio of skin in the longitudinal direction to the transverse direction, orthotropy ratio of the panel, the ratio of twisting stiffness to transverse flexural stiffness and smeared extensional stiffness ratio of stiffeners to that of the plate. For training of ANN, multilayer feedforward back-propagation is used as a network function with two-hidden layers in the neural network. The good network architecture is obtained after several iterations to predict the buckling load of the laminated composite hat-stiffened panel. Artificial neural network (ANN) are used to analyze the laminated composite hat-stiffened panels and compare with finite element analysis (FEA) results. Optimum neural network architecture has been established and tested with unknown data set.

4.2 FE Modeling of the Laminated Composite Panels

Numerical studies have been carried out by analyzing hat-stiffened panel of dimension 762 mm x 762 mm as shown in Figure 4.1. FE analysis has been performed for the hat-stiffened panel under compressive loading by using ABAQUS software. The laminated composite hat-stiffened panel has been modeled carefully to define the material properties of skin and stiffeners, number of layers, thickness and fiber orientations of skin. Shell element (S4R) has been taken for FE analysis of panel in ABAQUS [124], which possesses both bending and membrane capabilities. The hat-stiffened panel has been discretized with shell element (S4R) and 820 elements is generated of the panel as shown in Figure 4.2. Uniformly distributed edge compression load of 1 kN/m has been applied to the panel in stiffeners direction. The model has been submitted for the eigenvalue buckling analysis with application of simply supported boundary conditions on the panel. The buckling load has been obtained by multiplying the edge compression load and the eigenvalue as obtained from the FE analysis.

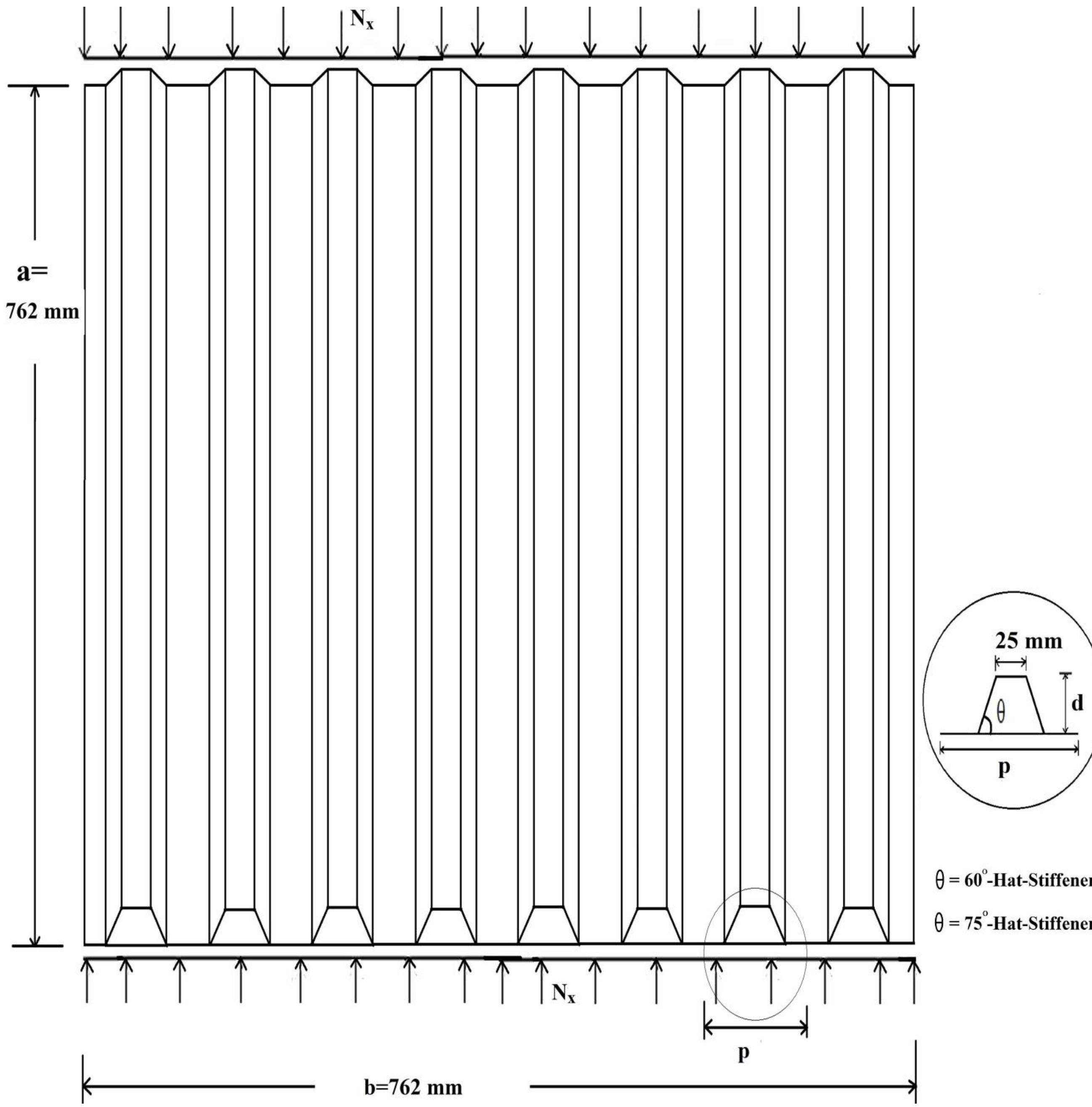


Figure 4.1 Structural geometry of the panel with 8 number of hat-stiffener.

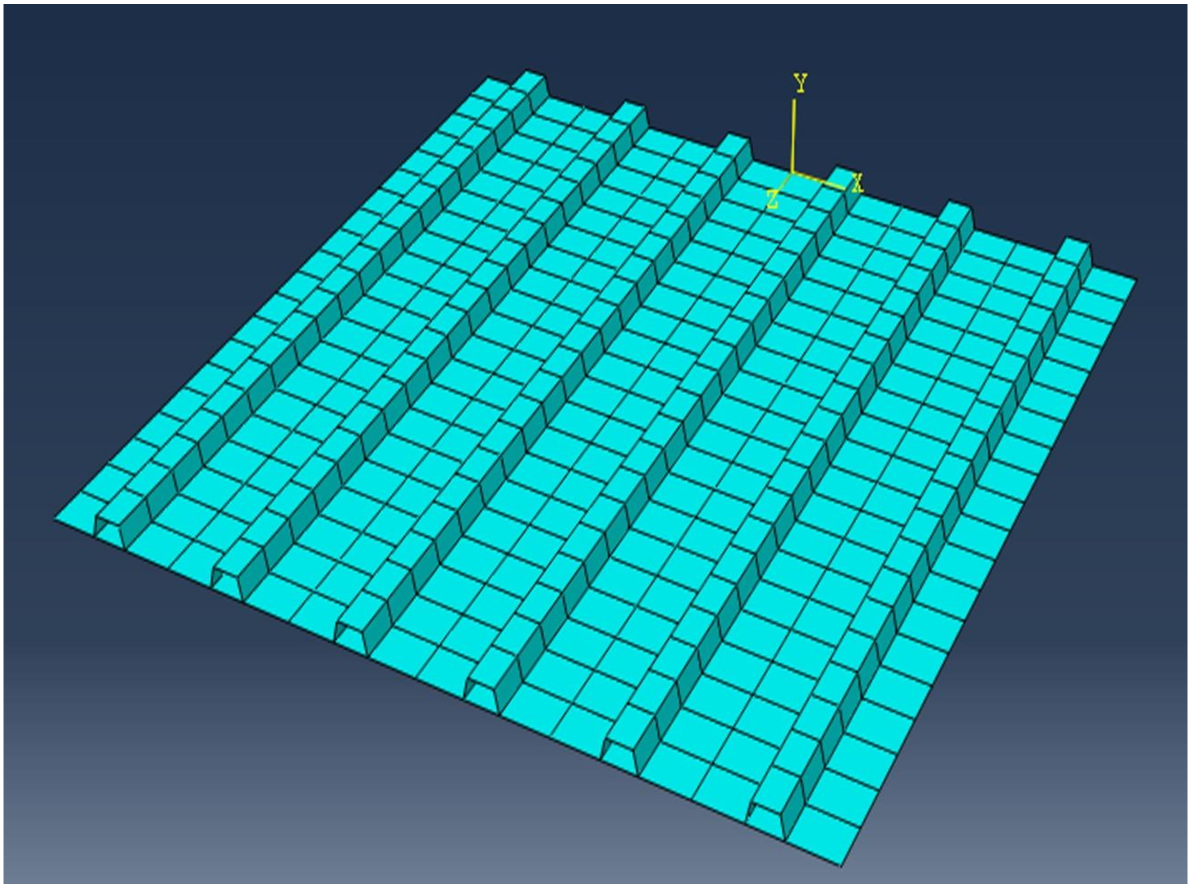
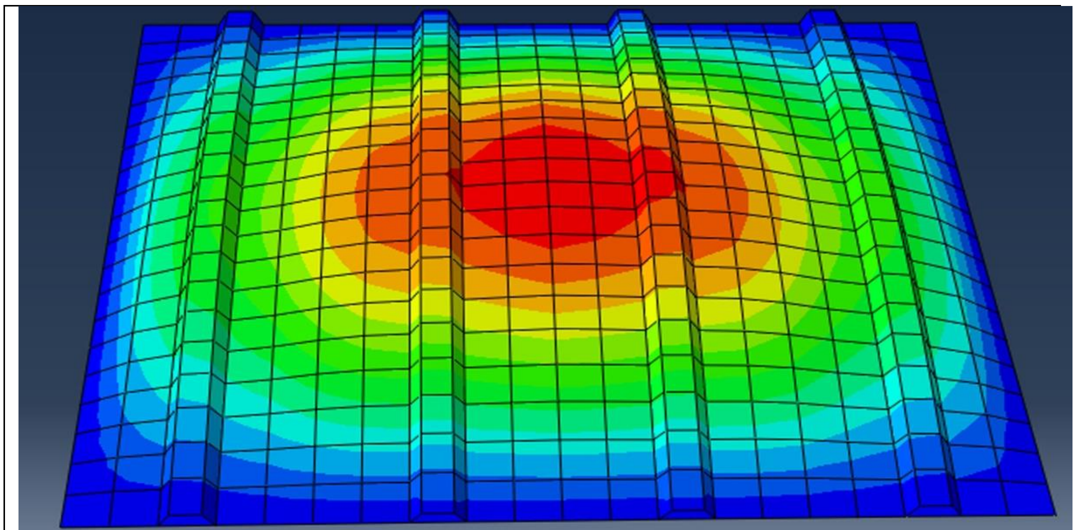


Figure 4.2 The stiffened panel discretized with shell element.

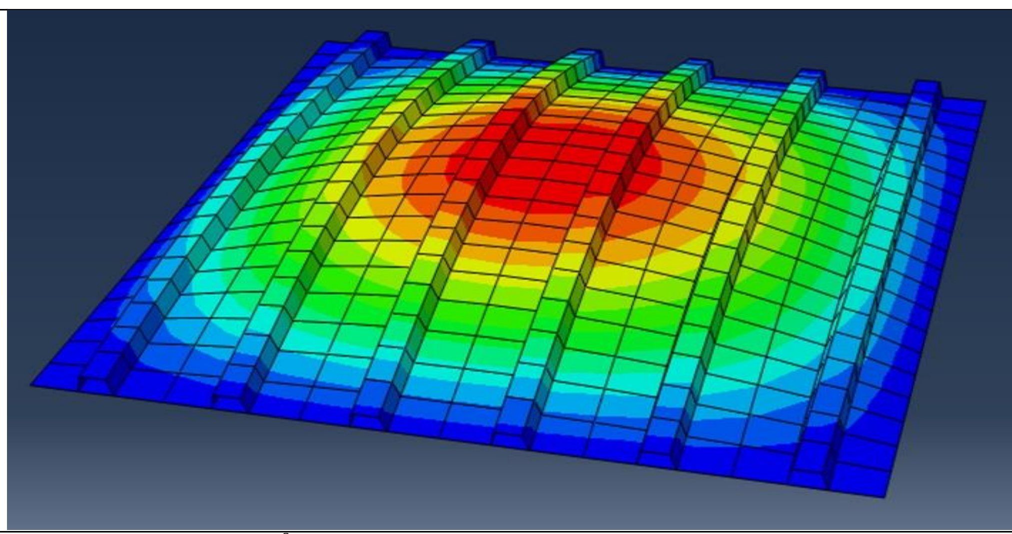
4.2.1 Numerical Studies of the Hat-Stiffened Panel

Numerical studies have been carried out by analyzing the hat-stiffened panel of dimension 762 mm x 762 mm with variation of pitch length (84.67 mm to 381 mm) and depth (25 mm to 55 mm) of the stiffener with a fixed top width of 25 mm. The carbon fiber composite (CFC) material property of each ply of thickness 0.125 mm is illustrated in Table 3.2. Three types of plies configuration of skin are used for plate element and stiffener component of the panel, which is illustrated in Table 3.3.

A program was developed on the basis of smeared stiffness approach by using equation (3.18) to (3.22) in previous chapter 3 for different pre decided orthotropy ratio. The depth of hat-stiffener is obtained by trial and error with variation of pitch length of stiffeners for three different skin considered separately, which has been used for FE modeling of the panel. The buckling analysis has been performed on the stiffened panel subjected to uniformly distributed edge compressive load with simply supported boundary condition on all edges. Input parameters of ANN are calculated from equation (3.18) to (3.22) which is given in previous chapter 3.



(a) 60^0-hat-stiffener with pitch length = 190.5 mm



(b) 75^0-hat-stiffener with pitch length = 127 mm

Figure 4.3 Global buckled mode shapes of panel for (a) skin-1 with D_1/D_2 = 200, (b) skin-3 with D_1/D_2 = 100.

Parameters have been identified by generated data, which influence the buckling load of the stiffened panel. The parameters A_{11}/A_{22} are extensional stiffness ratio of skin in the longitudinal direction to the transverse direction, D_1/D_2 gives the global flexural properties of the stiffened panel, D_3/D_2 gives the idea of the torsional rigidity of the panel and $(EA)_S/(EA)_P$ gives the knowledge about the material strength of stiffener to that plate. For given skin of the panel, the ratios D_1/D_2 and $(EA)_S/(EA)_P$ of the stiffened panel increase only by increasing pitch length and depth of stiffener. Local buckling of the panel is increased with increasing the depth of stiffener. Figure 4.3(a)-(b) shows the global buckling mode of the 60^0-hat-stiffened panel and 75^0-hat-stiffened panel under compressive loading for different pitch length and D_1/D_2.

4.3 Methodology for Prediction of Buckling Load by ANN

The neural network is a computational technique, which was inspired by the working pattern of human biological brains [95-96]. The neural network is a combination of input layer, hidden layer and output layer. The further hidden layer can be more than one layer, which is problem specific. All three-layer are connected with different nodes and nodes connection with specific weight and a bias value. There are different types of network available for prediction, but the problem will define which network is more suitable for best output. Multilayer feedforward networks were worked as a universal accepted and gave result in the desired accuracy with a specific sense [97-98]. For prediction of Civil engineering problems most widely used network is feed-forward backpropagation. Present work is divided into four steps as follows:

- Selection of training and testing data from the main datasheet
- Deciding the network type and another required parameter

- Training the network and simulation
- Evaluation of the performance of ANN

4.3.1 Selection of Training and Testing Data from the Main Data-Sheet

192 number of FE model of simulated data-set has been divided into two parts as training data set and test data set. The data have been divided as the combination of 80 % data for training purpose and 20 % data for testing purpose. Four different input variables A_{11}/A_{22}, D_1/D_2, D_3/D_2 and $(EA)_S/(EA)_P$ have been taken, which influence the buckling problem of the hat-stiffened panel under compressive loading and buckling load per unit area taken as output for preparation of networks. The parameter A_{11}/A_{22} is varied 0.59 (for skin-3) and 1.68 (for skin-1) as shown in Table 3.3. D_1/D_2 is taken in range 100-500 with a variation of depth of hat-stiffener for pitch length of 84.67 to 381 mm. D_3/D_2 is varied in the range of 7.4 - 68.1 for variation of the shaped of hat-stiffener. The parameter $(EA)_S$ $/(EA)_P$ is varied 0.14 to 1.01 with a variation of depth of stiffener for different skin.

4.3.2 Deciding the Network Type and other Required Parameters

Development of perfect network with a proper combination of the input layer, hidden layer and the output layer is necessary for good prediction of results. The input node is the combination of four different parameters A_{11}/A_{22}, D_1/D_2, D_3/D_2 and $(EA)_S$ $/(EA)_P$ to obtain the desired output. Once after deciding input and output parameter, the next step is to find the architecture of hidden layers. For finding the best suitable hidden layer, different types of combination of layers have been taken as shown in Table 4.1. Results from one hidden layer were given desired output with different weight value connection for continuous function but the selection of the second layer for the discontinuous function [99]. The hidden layer can be one or more than one, but there is no fix theory for selection of hidden layers. Some cases the hidden layer selection was based on quality and quantity of the training data [100]. Some situation the multi hidden layer was given better result over the single hidden layer [101-102]. The hidden layer should contain a total number of neurons was equal to the one greater than twice the number of input parameters [100]. It is not easy to select any fixed pattern for a selection of hidden layer; normally it is based on the trial and error method. Table 4.1 shows a reflection of the different type of hidden layer combination and plot R square after testing and validation with the help of observed and actual data. Network performance has been considered on the basis of a mean square error at the time of training and testing, where mean square error is found 0.0140 and 0.8091 at the time of training and testing respectively for the best network. Finally, a neural network architecture 4-7-2-1 has been obtained as shown in Figure 4.4, which gives the desired output for prediction of buckling load per unit area of the hat-stiffened panel.

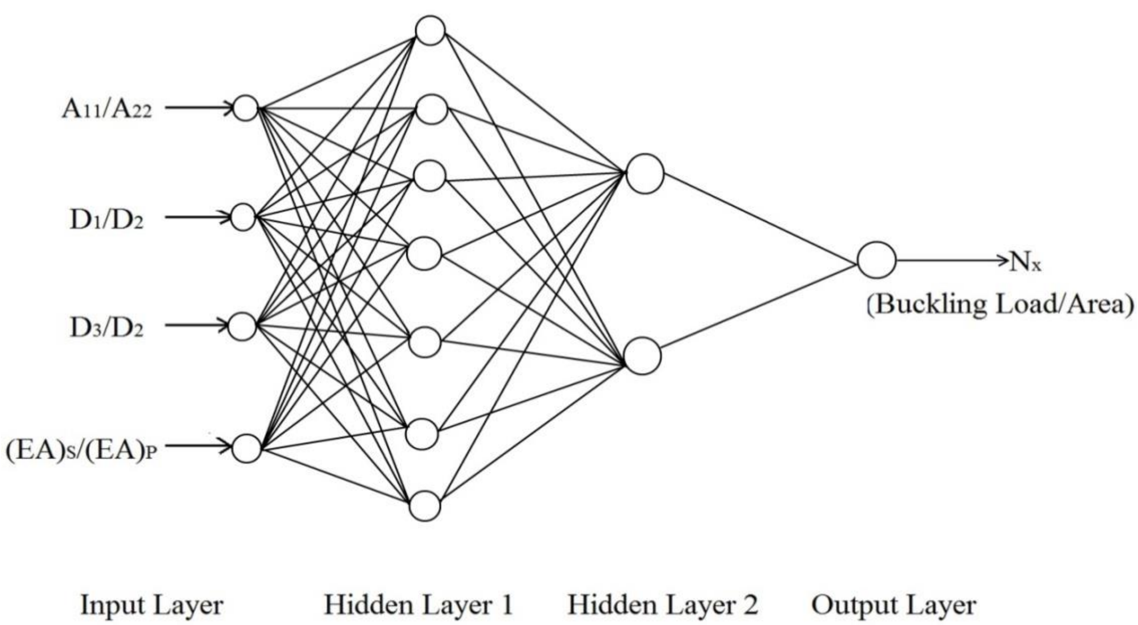


Figure 4.4 Architecture diagram of a 4-7-2-1 multi-layer feedforward back-propagation neural network.

Table 4.1 Comparative study of R-square for different number of hidden nodes and hidden layers.

Input nodes	Hidden Nodes		Output nodes	R^2
	1st Layer	2nd Layer		
4	5	0	1	0.8896
4	13	0	1	0.9167
4	15	0	1	0.9181
4	9	0	1	0.9334
4	7	3	1	0.9451
4	8	4	1	0.9574
4	5	4	1	0.9590
4	6	3	1	0.9692
4	11	0	1	0.9848
4	6	0	1	0.9848
4	4	3	1	0.9850
4	10	0	1	0.9871
4	8	0	1	0.9883
4	7	4	1	0.9896
4	8	2	1	0.9898
4	7	0	1	0.9905
4	8	3	1	0.9952
4	7	2	1	0.9983

4.3.3 Training the Network and Simulation

It is observed that ANN is the best tool for predicting the buckling load per unit area based on the good training and testing data. A neural network architecture 4-7-2-1 has been selected which is best suitable for this problem. Figure 4.5 shows the process of multilayer feedforward back-propagation as a network function in this work. There have some working steps of this network as follows:

- Feed forward in training pattern.

- Comparison and calculation of error.
- If the result is good, then draw output otherwise back propagation starts and adjust weights.
- Back-propagation work in a loop till desire output not receive.

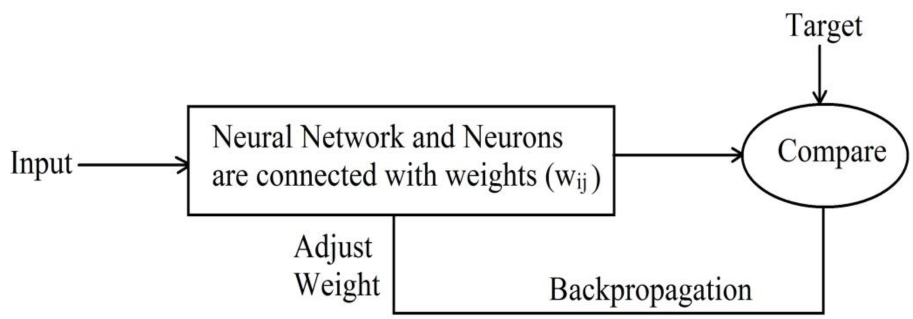


Figure 4.5 The process of feed forward back-propagation in the neural network.

There is a very high range of training function available in Matlab where TrainLM has been used for training function which function is given better results. Also, LearnGDM has been used for adaptive learning function. Two hidden layers have been used for the network creation. The tan-sigmoid transfer function has been used for the hidden layer, where the range of tan-sigmoid is -1 to 1. The pure linear transfer function has been used for the plot the output result, and this combination is given a better result.

R-squared is a statistical measurement of data, which checks the data closeness to the best-fitted regression line. R-squared is also known as the coefficient of determination. R-squared value varies from 0 to 100 present, where '0' present shows worst fitted to regression line and 100 present shows best fit to the regression line.

The suitable network has been found after many iterations of training of the network for the satisfactory prediction of buckling load. R-squared value has been estimated for every network and find out the best network for the prediction of buckling load per area of the panel. Also, a continuously checking of the performance based on mean square error has been calculated for training and testing. Continuously training and testing work have been processed until the best-trained network is not found. After the selection of best network, the next step is to note the weight value and bais value of that network for future prediction.

4.3.4 Evaluation of the Performance of ANN

The performance of the neural network has been verified by using new data set and the result of new data set is reflected the accuracy of trained network. The best prediction of results has been obtained for the new data from selected neural network model. Finally, error between the actual data and predicted output data has been found which shows good performance of the neural network.

4.4. Results and Discussion

In this chapter, multilayer feedforward back-propagation process has been used as a network function with neural network architecture 4-7-2-1 as shown in Figure 4.4. The neural network has been trained to get the suitable value of the buckling load per unit area of the panel. Weight value matrix (W_1), which is connected to four input nodes to seven 1st hidden layer nodes:

$$W_1 = \begin{bmatrix} -0.3055 & 0.8393 & -0.2013 & -2.9280 \\ 0.4546 & -0.1903 & -0.6738 & 0.3047 \\ 0.2031 & -2.1879 & 2.2828 & 0.6275 \\ -1.7214 & -0.6199 & -0.5154 & 0.3579 \\ -1.4015 & -0.5750 & -0.0214 & 0.5097 \\ 0.5592 & -0.5159 & 1.9310 & 0.2174 \\ -2.2713 & -1.3913 & 0.0685 & 0.7581 \end{bmatrix}$$

Weight value matrix (W_2), which is connected to seven 1st hidden layer nodes to two 2nd hidden layer nodes:

$$W_2 = \begin{bmatrix} 1.2617 & 0.1387 & -1.8535 & 0.2512 & -1.0811 & -1.0851 & 0.3747 \\ -0.3869 & 0.3925 & 0.1843 & 0.3254 & -0.4691 & -0.6722 & 0.1032 \end{bmatrix}$$

Weight value matrix (W_3), which is connected to two nodes of 2nd hidden layers to one node of output layer:

$$W_3 = [-1.2679 \quad -2.0134]$$

Bias for different hidden layers are given below:

$$\text{For first hidden layer: } (b_1) = \begin{bmatrix} -2.6436 \\ -0.5004 \\ -0.1125 \\ 0.1256 \\ -0.4688 \\ 2.0969 \\ -1.9752 \end{bmatrix}$$

$$\text{For second hidden layer: } (b_2) = \begin{bmatrix} -1.3818 \\ 0.74469 \end{bmatrix}$$

For output layer: (b_3) = [-0.6399]

Figure 4.6 shows the linear regression graph between the target of FEM result and ANN prediction. The regression line is obtained Y = Slope *X + Intercept, where the slope is 1.0052 and intercept is -0.1978. The standard error of slope and intercept are 0.00881and 0.52658 respectively. R-Square value is 0.9983, which is nearer to 1:1 line. This result shows that the regression line is very good fit.

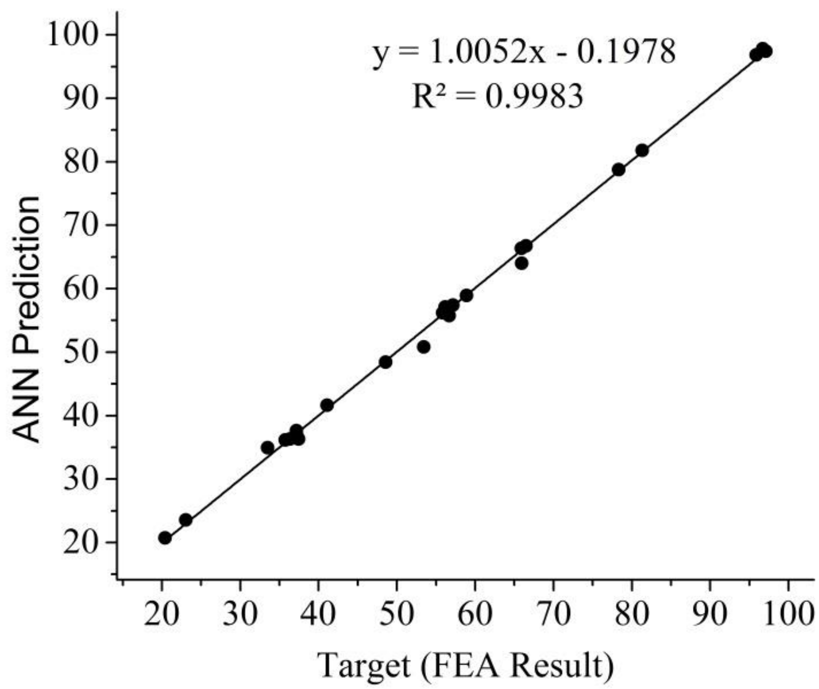


Figure 4.6 Linear regression graph between target (FEA Result) and ANN prediction.

For different D_1/D_2 and skin, variation of buckling load per unit area of the 60^0 hat-stiffened panel and 75^0 hat-stiffened panel with $(EA)_S/(EA)_P$ are shown in Figure 4.7 and Figure 4.8 respectively, which is obtained by FEA and ANN. It is observed that with the increase in $(EA)_S/(EA)_P$, buckling load per unit area increases upto certain values of $(EA)_S/(EA)_P$ for all D_1/D_2 in a different skin, after that buckling load per unit area is approximately constant. The minimum value of $(EA)_S/(EA)_P$ is obtained for all D_1/D_2 of the different skins from Figure 4.7 and Figure 4.8 at which the hat-stiffened panel has the maximum buckling load per unit area. Therefore, this minimum value is defined as optimum $(EA)_S/(EA)_P$ of the hat-stiffened panel and hence number of the stiffener and depth of the hat-stiffened panel are increased to a certain limit for efficient buckling performance of the panel without unnecessary increase in the weight of panel and the local buckling. The pitch length and depth of the hat-stiffener of efficient buckling performance of the panel can be found on the basis of obtained optimum $(EA)_S/(EA)_P$ of the hat-stiffened panel for different orthotropy ratio D_1/D_2. It is observed that the curve obtained from ANN results is similar to the pattern obtained by FEA. It is also observed that ANN prediction curve for D_1/D_2 = 150 and 250 is in-between the FEA curve for D_1/D_2 = 100 to 200 and D_1/D_2 = 200 to 300 respectively.

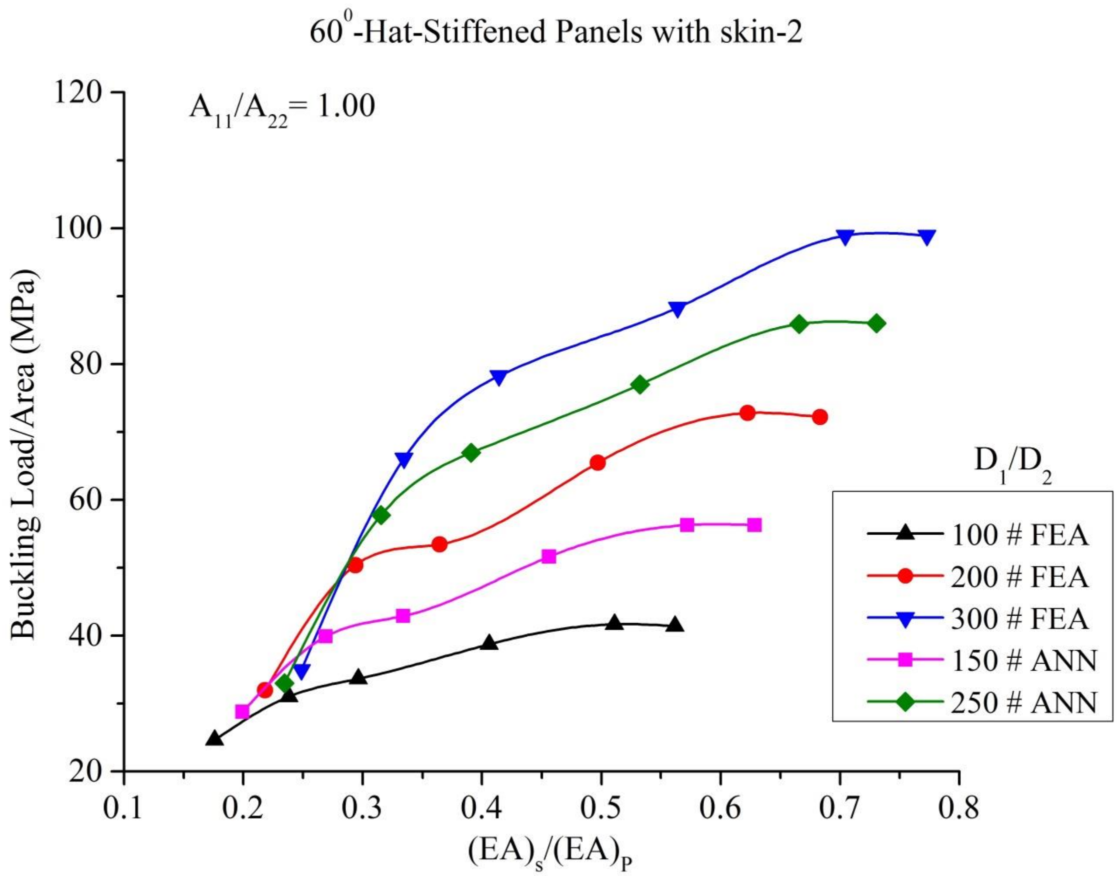


Figure 4.7 Buckling load/Area of the 60^0 hat-stiffened panel vs. $(EA)_S/(EA)_P$.

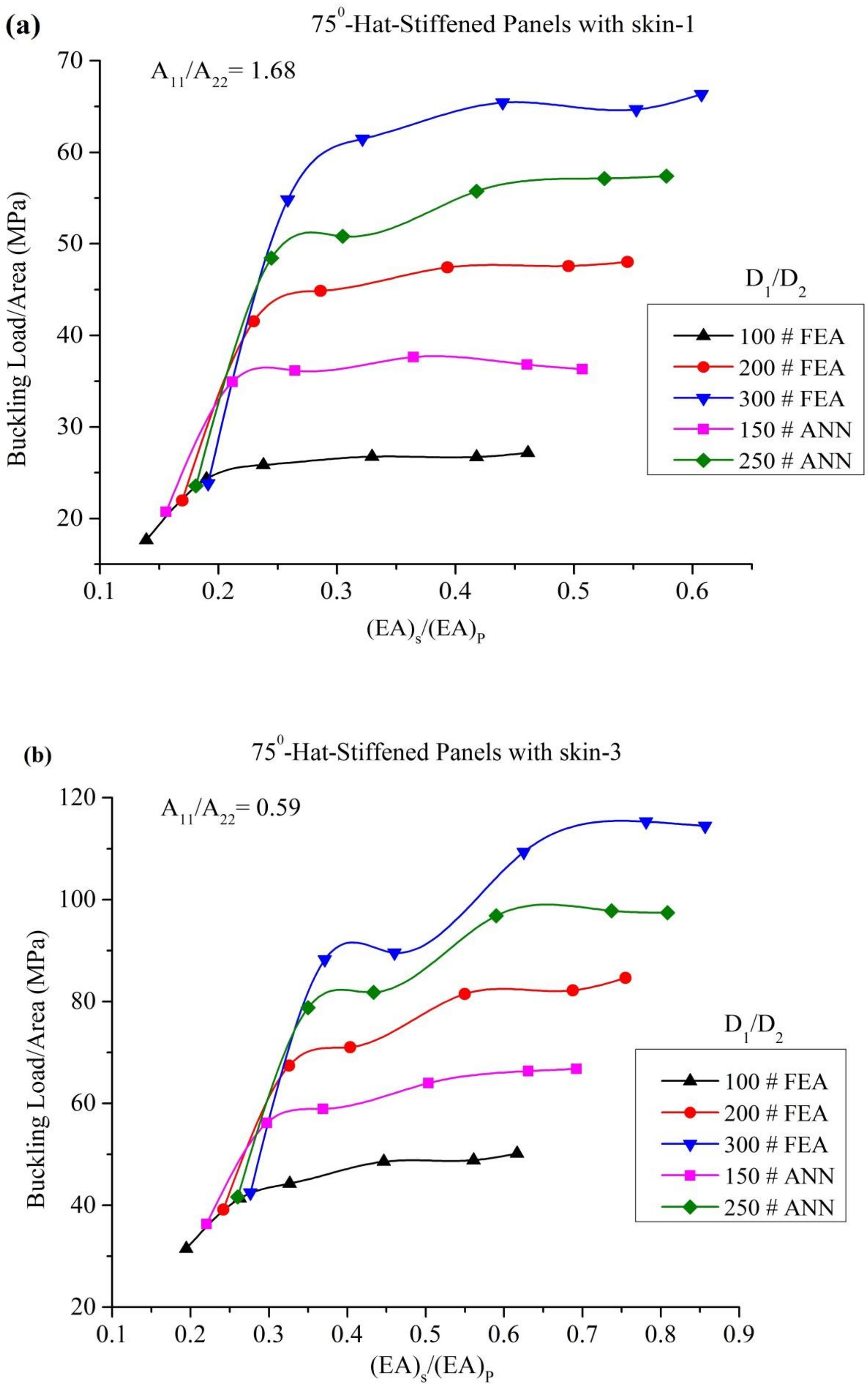


Figure 4.8 Buckling load/Area of the 75^0 hat-stiffened panel vs. $(EA)_S/(EA)_P$.

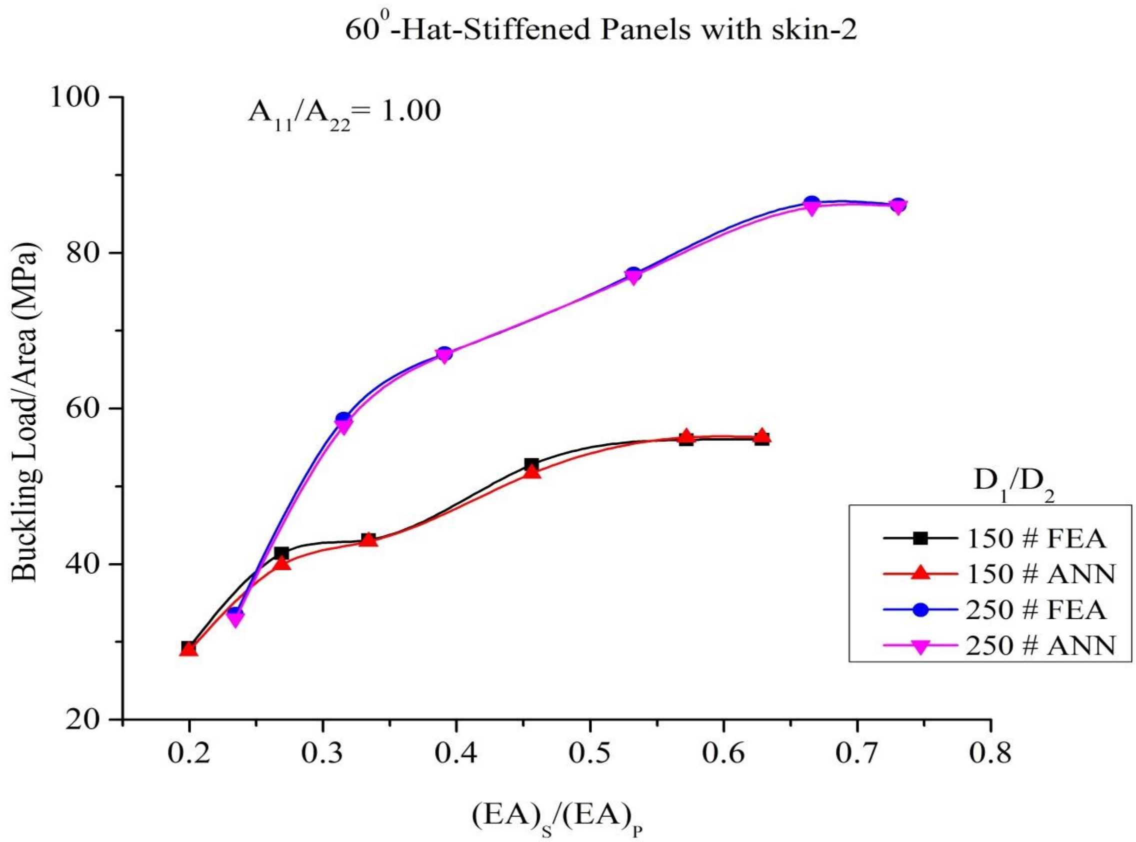


Figure 4.9 Comparing FEA results with ANN predicted results vs. $(EA)_S/(EA)_P$ for 60^0 hat-stiffened panel with skin-2.

Figure 4.9 and Figure 4.10 show the comparison the FEA results with ANN predicted results with a variation of $(EA)_S/(EA)_P$ for 60^0 hat-stiffened panel with skin-2 and 75^0 hat-stiffened panel with skin-1 and skin-3 respectively. It is observed that the results obtained from ANN is similar to the results of FEA data and sometimes it overlaps to each other for D_1/D_2 = 150 and 250 with skin-1, skin-2 and skin-3. Also, Table 4.2 and Table 4.3 show the comparison the FEA results with ANN predicted of new data with percentage difference for 60^0 hat-stiffened panel with skin-2 and 75^0 hat-stiffened panel with skin-1 and skin-3. The maximum and minimum percentage difference of ANN predicted with FEA results are found about 2.193% and 0.064% respectively.

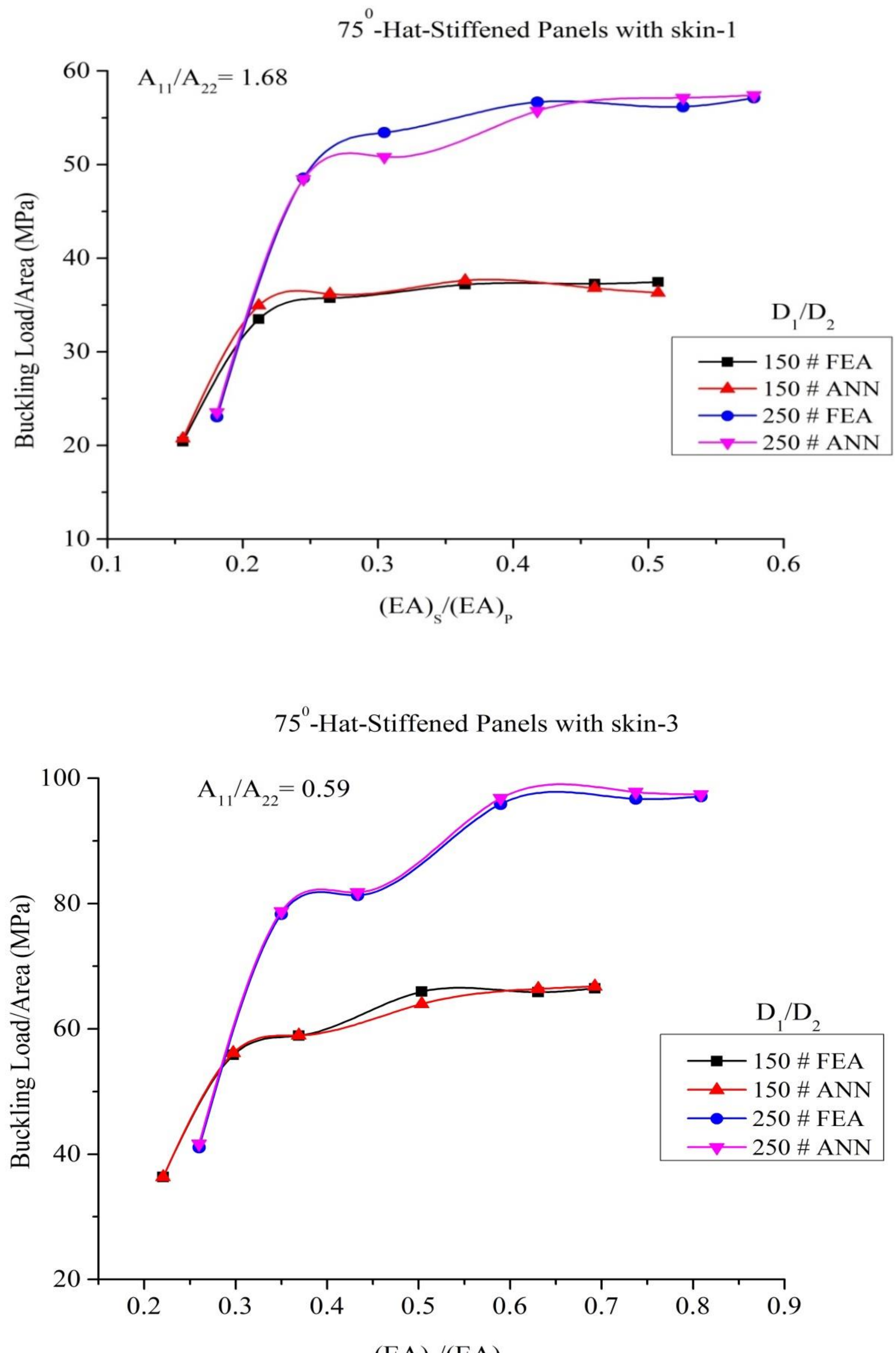


Figure 4.10 Comparing FEA results with ANN predicted results vs. $(EA)_S/(EA)_P$ for 75^0 hat-stiffened panel with skin-1 and skin-3.

Table 4.2 Comparison of FEA results with ANN predicted results of 60^0 hat-stiffened panel.

A_{11}/A_{22}	D_1/D_2	D_3/D_2	$\frac{(EA)_S}{(EA)_P}$	Buckling Load/Area (MPa) FEA results (x)	Buckling Load/Area (MPa) ANN results (y)	% Difference $\left(\frac{Y-X}{X}\right) * 100$
1.00	150	18.91	0.20	29.28	28.81	-1.61
		27.83	0.57	55.99	56.28	0.51
	250	29.40	0.23	33.56	32.99	-1.70
		44.07	0.67	86.40	85.89	-0.59

Table 4.3 Comparison of FEA results with ANN predicted results of 75^0 hat-stiffened panel.

A_{11} / A_{22}	D_1 / D_2	D_3 / D_2	$\frac{(EA)_S}{(EA)_P}$	Buckling Load/Area (MPa) FEA results (x)	Buckling Load/Area (MPa) ANN results (y)	% Difference $\left(\frac{Y-X}{X}\right) * 100$
1.68	150	10.02	0.16	20.403	20.73	1.602
		13.84	0.36	37.190	37.626	1.173
	250	14.76	0.18	23.050	23.556	2.193
		21.01	0.42	56.655	55.749	-1.599
0.59	150	12.80	0.22	36.360	36.337	-0.064
		21.03	0.63	65.875	66.364	0.743
	250	18.94	0.26	41.079	41.619	1.315
		31.89	0.74	96.720	97.810	1.126

In the above discussion, it has been found that the prediction of buckling load of the stiffened panel by ANN is in good agreement with FEA results for different cases. Therefore, ANN is good analytical computation tool for prediction of buckling capacity of the simply supported hat-stiffened panel under compressive loading. Hence, ANN tool can be used to design of complex problem of structural application in civil engineering and optimization of laminated composite structural.

4.5. Summary

Buckling of the laminated composite 75^0-hat-stiffened panel is analyzed by both finite element analysis and artificial neural network. FEA has been used both for generating the input data for training of ANN and numerical analysis of stiffened panels. Numerical studies are carried out with variation of four different parameters A_{11}/A_{22}, D_1/D_2, D_3/D_2 and $(EA)_S$ /$(EA)_P$ with 75^0-hat-stiffeners. The optimum $(EA)_S/(EA)_P$ increases with the decreasing A_{11}/A_{22} of the skin for all D_1/D_2 and it also increases with the increasing D_1/D_2 for the same skin. The well trained Neural network gives the best result with the help of network architecture 4-7-2-1. The result shows that ANN tool is good analytical computational tools for design of the complex structural problem in civil engineering and optimization of the laminated composite stiffened panel. The maximum and minimum percentage difference of ANN predicted and FEA results are obtained 2.193% and 0.064% respectively. Mean square error is 0.0140 and 0.8091 at the time of training and testing respectively for the best network. The R-Square value is 0.9983, which is nearer to 1. From above results and discussions, it is observed that ANN can be used efficiently for predicting of buckling load with different types of loading condition for better analysis and design of the stiffened panel.