*Article*

# The influence of composite laminate stacking sequence on failure load of bonding joints using experimental and artificial neural networks methods

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**Abstract:** The objective of this article was to forecast the ultimate failure load laminate stacking sequence combination on bonding joints which are exposed to tensile strength by using artificial neural networks. We have glass fiber composite materials with three different sequence combinations ([0°/90°], [±45°], [0°/90°/±45°]). Various adherend thicknesses and also ductile type adhesive was used in the experiment. The bonding geometry is a single lap and has four types of overlap angles 30°, 45°, 60°, 75° respectively. The experimental results demonstrate that composite laminate stacking sequence profoundly affects the bonding joints of failure load. Taking experimental results into account, Levenberg–Marquardt learning algorithm model was used by preferring a three layer forward on ANN so as to discipline network. In order to procure a precise ANN tool, an integrate methodology of experimental method has been used. The outcomes are used to ensure the experimental data's to the ANN. The method of ANN permits surveying much adequately the probabilities of composite laminate stacking sequence combination using the prevalent ones which are [0°/90°], [±45°] and [0°/90°/±45°]. Testing data and training results were quite well 0.998, 0.997 and 0.998 in turn. Consequences acquired can be used by engineers who are interested in the composite material design to enhance failure load.

**Keywords:** experimental tests; composite laminates; tensile strength; artificial neural networks

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## 1. Introduction

Usage of adhesively bonded lap joints with composite materials used in aviation, aerospace and automotive industry is on the rise day by day [1]. Different bonded geometry for adhesive joints have been used by most of researchers. Accordingly the strength of joint performance by varying the input parameters is of vital importance [2]. Bonded geometry, adhesive area and sample thickness have shown remarkable influence on this improvement for joint strength. By designing extreme interface geometry which is overlap angle has contributed to cut down on stress concentrations [2].

Processes of artificial neural networks (ANNs) arouse curiosity for anticipating brings about profound develop for concerning about research areas lately [3]. As a popular technique, the ANNs are broadly used by many researchers as an alternative method to get over some troubles in experimental studies.

L. Filippis and et al. [4] a model was improved for optimization of the Friction Stir Welding (FSW) process. This process, via FSW method, shows the correlation both input variable of process and mechanical properties of welded aluminum plates. Joint quality was estimated tensile tests. Artificial Neural Networks (ANNs) identified by various algorithm, ability to provide for great reliability the FSW process for welding plates in Butt-Joint. S. Her and C. Huang [5] is experimental tests were applied to verify the theoretical guess among the fiber sensor and test sample. Sample of strain truly transmitted to fiber is based on adhesive length. The strain goes up from 56% to 82%

when the bonding distance rises from 5 cm to 12 cm. Theoretical and experimental data's indicate that harder the adhesive and greater the bonding distance. H. Majidi and et al. [6] steel/carbon fiber reinforced polymer was investigated both theoretically and experimentally on double lap bonding joints with various lengths expose to axial tensile load to find out failure. The novel method which is called point stress is developed fast and reliable to estimate the failure loads of the specimens. Ultimately, a great conformity obtains among both theoretical and experimental results depend on the novel method. J. Hwang and et al. [7] the bonding strength of carbon fiber reinforced polymer was used. The adhesion strength of mixed composite started to increase with the rises of surface roughness. I. Konovalenko and et al. [8] proposed a method for fracto-graphic image, which is relied on via artificial neural network. ANN considerably decreases the amount of parameters for accurate results. The results are quite similar and ANN bring out properties correctly compare to other methods. M. Rucka and et al. [9] the experimental test of single lap adhesive nine joints with various faults were conceived. The outcomes indicated that 2-D weighted root mean square values enabled for real faults in adhesive layer film and identified model of geometry. K. Luwei and et al. [10] sorted out a fusion process in condition monitoring (CM) of rotation machines. Artificial neural network (ANN) method is able to capability for automatic denotation of rotating machine errors. ANN algorithm offered great results as well as shows potential for enhanced these machines. Tosun and Çalık [11] figure out that failure load via ANN in single lap bonding joints exposed to axial tensile load. They demonstrated that ANN has perfect prediction capability and convenient with experimental data. Tiryaki and Aydın [12] designed an ANN pattern to predict compression strength for heat treated woods. In ANN model, extensive experiments will not be required. They showed that via ANN many satisfactory data's could be acquired which would minimize cost and time. Zghoul [13] utilized an ANN in single lap adhesive joints for rating dependent output of adhesives in order to extend the method installed to model the output of adhesive structures. Tiryaki et al. [14] examined the bonding strength of the beech, relied on the pressing time and pressure. They brought a different approach via ANN for adhesion strength on wood then accomplished the approach is a useful purpose for characterizing impacts of the quantity of pressing time and pressure on bonding strength of the beech. Kovan and Sekercioglu [15] fostered a method via ANN to predict fatigue life and shear force of bonded cylindrical joints. The outcome indicated that related model was quite powerful and viable tool for fatigue life and shear force of bonded joints. Apalak and Ekici [16] examined 3-D stresses in tension for bonding double cantilever joint. Moreover, the impacts of joint dimensions were detected via ANN model also detected composite gradient. The rules of layout were submitted for joint design. Balcıoğlu et al. [17] analyzed that via ANN the effects of single-sided and double-sided of bonding angle, patch structure and patch type for composite materials of bonded joints on failure load. Dominczuka and Kaczmarzewski [18] analyzed that via ANN for the processing of experimental data's associated to strength of bonding joints. They contrasted the ability of ANN with the capacity of typical statistical analysis methods like polynomial and linear regression. Tiryaki et al. [19] researched an ANN model which takes in multiple linear regressions for heat treated wood material to estimate ideal bonding joint strength. Guneyisi et al. [20] presented an ANN formulation relied on explicit formulation to estimate the shear capacity of single lap adhesive joint mounted on reinforced concrete elements. Gunes et al. [21] using the finite element analysis, performed a 3-D vibration analysis of bonding joint, helpfully graded circular bonding joint. Using both genetic algorithms and ANN method, he investigated the optimum parameters of bonding joints. Naderpour et al. [22] called for the compression stress of FRP concrete in via ANN method. Kalhor et al. [23] studied the effects of FRP thickness and laminate stacking order and estimated the response of FRP square pipes exposed to axial load. The ANN model is also used to see the effect of velocity impact over composite plates. Malik et al. [24] projected the energy absorbed in effects by via ANN model which was gotten data obtained by finite element method. It should be noted that the former articles supply to the velocity impacts or static exposed to the composite laminates. Nevertheless it has been determine that the estimation of composites exposed to velocity impacts is rather low. D. Fernández et al. [25] ANN is used to estimate the ballistic effect of composite materials that analyze the impact orbit. ANN is an effective

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way for estimating the effect of laminates as exposed to low velocity impact load. Dilik and Hiziroglu [26] carried out research about heat treated wood underneath bond strength. Wood specimen indicates only 23.6 % decreases in shear forces when exposed to 120 °C temperature. Loss of strength in the specimens subjected to temperatures of 160 °C and 190 ° C were found out to be 44.4% and 64.1%, in turn. Kasemsiri et al. [27] stated that the bond strength of the heat treated wood decreased from 25.12 % to 52.67 % compare with the untreated species. Bakaretal et al. [28] introduced a decline in bond strength rates from 52.7 % to 69.4 % based on the treatment cases in the heat treatment applied to various wood species. Cook and Chui [29] estimated the adhesive joint of the particle plate use radial based ANN method at precision of 87.5%. Estebanetal [30] estimated the bond quality of wood samples via ANN method with 93 % precisely. Demirkir et al. [31] worked on optimization about fabrication parameters in order to estimate the most viable bonding joint of wood. They estimated bonding joint of wood via ANN of 98.0 % precisely.

In this study, the effect of laminate stacking sequence for adhesive joints on failure load exposed to axial tensile strength via ANN method. The results revealed that the ANN method had a reliable predictive ability that the results were in great agreement with finite elements and experimental data.

## 2. Materials and Methods

### *2.1. Experimental Detail*

We have glass fiber composite materials with three different laminate stacking sequence ([0°/90°], [±45°], [0°/90°/±45°]) in Figure 1 and various adherend thicknesses (3 mm, 5 mm, 7 mm) also ductile type adhesive DP460 made by 3M firm was used in the experiment Table 1. Adhesive thickness was held constant to be 0.20 mm. The bonding geometry has four types of overlap angles 30°, 45°, 60°, 75° respectively. The model and parameters are shown in Figure 2 and Table 2. Failure load on the mechanical behaviors exposed to tensile strength was investigated then results used for artificial neural network. The mechanical properties of the composite material were determined by Dokuz Eylul University Composite Research and Testing Laboratory with Shimadzu AG-X models tensile test machine Table 1. The machine has a capacity of 100 kN is equipped with integrated video extensometer for more accurate results are obtained Figure 3. 0,10 MPa is given for pre-load and also 1 mm/min. is set for pulling speed during tensile tests. Experimental values were taken from PhD thesis of Birecikli [32].

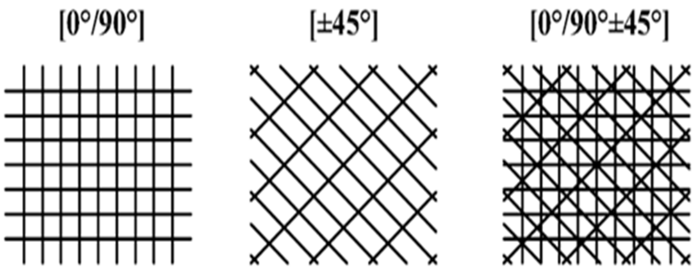


**Figure 1.** Composite laminate stacking sequence [32]

**Table 1.** Material properties of the adherend and adhesive [33].

| | Composite Material | Adhesive DP460 |
|---|---|---|
| E (Mpa) | 28,250 | 2077.10 |
| υ (-) | 0.13 | 0.38 |
| $\sigma_t$ (Mpa) | 379.232 | 44.615 |

E: Young's modulus; υ: Poisson's ratio; $\sigma_t$: Ultimate tensile strength

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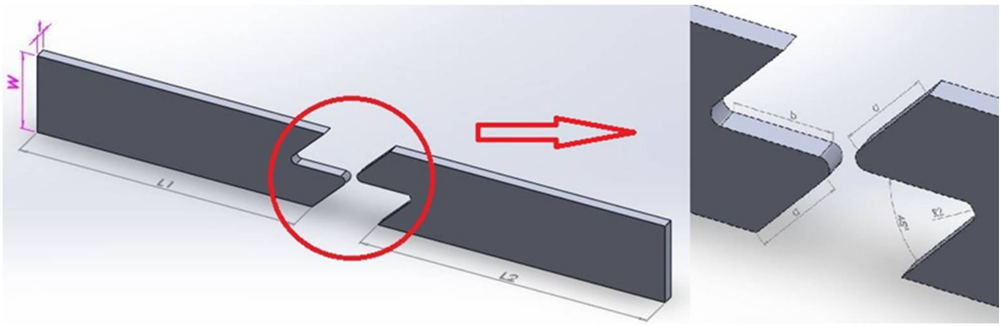

**Figure 2.** Geometry of model [33]

**Table 2.** Geometric parameters for adhesively-bonded joints [33].

| Overlap angle (°) | Width {w} (mm) | Thickness {t} (mm) | Overlap length (a), (b) (mm) | L1 (mm) | L2 (mm) |
|---|---|---|---|---|---|
| 30 | 27.46 | 3 | 20 | 118.68 | 131.32 |
| 45 | 35.12 | 3 | 20 | 122.27 | 127.73 |
| 60 | 40.64 | 3 | 20 | 126.73 | 123.27 |
| 75 | 43.66 | 3 | 20 | 131.75 | 118.25 |

**Figure 3.** Test machine [33]

### 2.2. *Artificial Neural Network*

Artificial neural networks (ANN) are inspired from biological neural networks in our brain. Brain of human is consisting of about 100 billion neurons which have about 100 trillion interconnections among them. Every neuron for input is given either closed or open on state. Interconnections work on the notion of positive empowerment, a number of inputs pave the way for an exact output and the "brain" remembers this way accurately and "learns" that way to relate. [34].

Many engineering problems can be solved easily by using ANN instead of complex mathematical rules [35]. The simplest ANN come out of three layers that input, output and hidden. The link between all layers is provided by weights, determining how strong the link is between the other layers. As can be seen in Figure 4, all inputs are multiplied by these weights and collected in a center.

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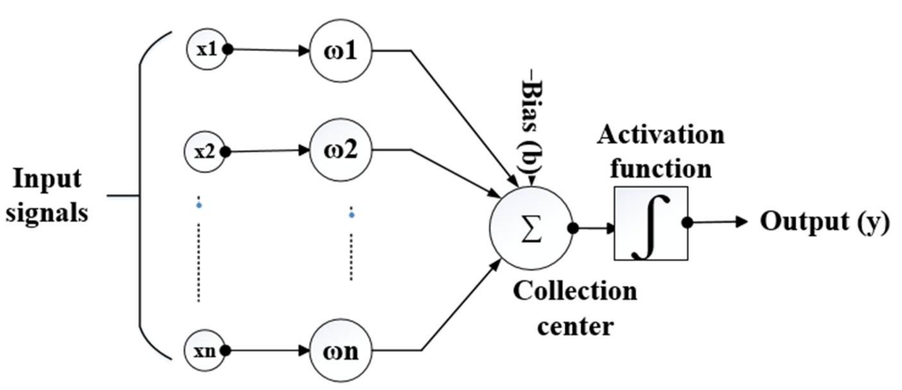


**Figure 4.** Block diagram model of a neuron

The first step of learning can be described as activation. The sum of the signals entering the nerve cell does it have a value that can activate the cell or not? The answer is as follows: if the total signal is high enough to ignite the cell and exceed the threshold value then it is the cell active (y = 1) otherwise in that case the cell is passive (y = 0). ANN has several activation functions. The most widely used "multi-layer perceptron" model in the present day generally uses the "Sigmoid function" as the activation function. The sigmoid activation function is a continuous and derivable function. This function generates a value between 0 and 1 for each of the input values. Sigmoid function is defined by the formula:

$$F\ (Net) = \frac{1}{1+e^{-Net}} \tag{1}$$

In biological systems, learning occurs through synaptic connections between neurons. In other words, people start to learning process by living from their birth. In this process, the brain is continuously developing. As experience increases, synaptic connections are established and even new connections occur. In this way, learning occurs and this also applies to ANN. Learning happens by using examples through training. In other words, by processing the input / output data, that is, by using these data's, the training algorithm repeatedly adjusts the weights of the synapses until a convergence is achieved. The selected training algorithm is important to get a good result. A large number of training algorithms exist in the literature. With regard to the training algorithm put accounted, the error among the network output and the wanted output is propagated backwards to alter the weights of the network until the error is decreased. It can be defined a neuron by the following equations:

$$o = f(wx + b)F \tag{2}$$

where w and x defines weights and inputs. Where b is bias. The intention of bias entries is to balance the origin of the activation function to provide better learning [36]. Transfer function can have described by the following equation:

$$net = \sum_{i=1}^{n} w_i . x_i + b \tag{3}$$

In this study, proposed ANN model was designed as an input layer with 4 neurons, an output layer with one neuron and a hidden layer with 10 neurons. Overlap angle (°), thickness (mm), laminate stacking sequence angle (°) and adhesion area ($mm^2$) were used as the input variables while failure load (N) was used as the output variable in this ANN model. The Levenberg - Marquardt algorithm, which is a kind of backpropagation algorithm, is used to train the modeled network. Data obtained from experiment were divided into three parts: training, validation and testing. Matlab – Neural Network Toolbox was used for design, train and simulate. A neural network model was established, trained and tested using the present test data from 48 different samples collected from the experimental tests.

The data used in neural network model are composed in a format of four input parameters that include lap angle, thickness, and laminate stacking sequence angle and adhesion area. A neural model where consist of 4 inputs and an output used in this study as shown in Figure 5.

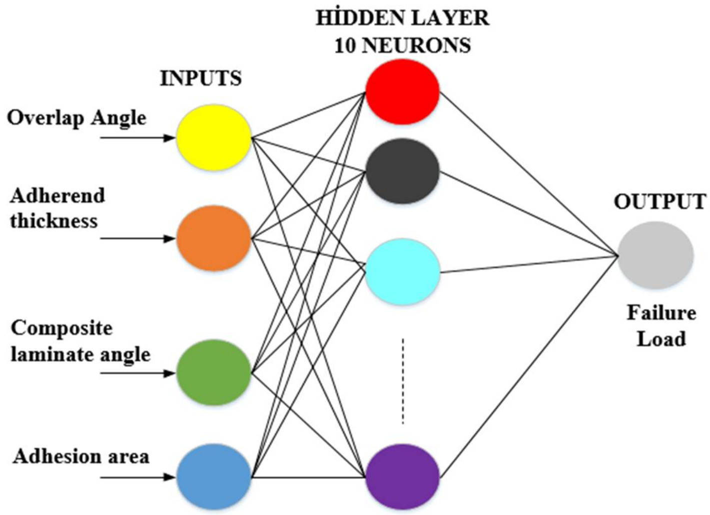


**Figure 5.** Structure of ANN model

## 3. Results and Discussion

In this study, 34 of the 48 values were used for training. 7 values are used for validation and testing respectively. The mean square error (MSE) was put accounted to evaluate the productivity of ANN estimation model. MSE is defined as the average of squares of "Errors". The mean square error was calculated by following equation:

$$MSE = \frac{1}{N}\sum_{i=1}^{N}\binom{n}{k}(t_i - td_i)^2 \tag{4}$$

where $t_i$ is the measured value of the experiment, $td_i$ is the estimated value, and N is the total number of samples. The mean square error (MSE) depending on iteration of the ANN is shown in Figure 6. The training of the ANN was turned off after 10 epochs due to the targeted MSE value was achieve.

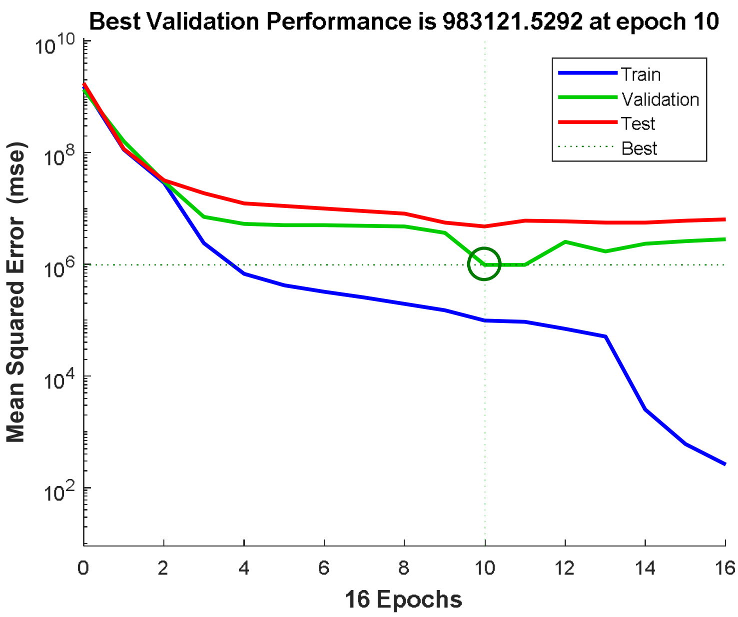


**Figure 6.** The graphic of the mean square error (MSE) depending on iteration of the ANN.

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Artificial neural networks using the Levenberg-Marquardt algorithm are estimated the failure load. The values estimated by using the ANN model for the testing, validation and training data, percentage error ratios and the measured values are shown in Table 3. When Table 3 is shown, it is seen that the estimated values obtained by ANN are found with very low percentage errors. These ratios of errors are very satisfactory for estimating failure load values. These values show that the ANN efficaciously produces sensible results and has a reasonable reliability and accuracy ratio in the model of failure load [19].

**Table 3.** The relationship between the estimated values obtained by using the ANN model and the experimental results is shown in Figure 6 [32].

| **Overlap Angle** (°) | **Adherend Thickness** (mm) | **Composite Laminate Angle** (°) | **Adhesion Area** ($mm^2$) | **Failure Load** (N) | **Estimated Failure Load** (N) | **(%) Error** |
|---|---|---|---|---|---|---|
| 30 | 3 | [0/90] | 180 | 8136 | 7972,5 | 2,01 |
| 45 | 3 | [0/90] | 180 | 7531,2 | 7289,87 | 3,20 |
| 60 | 3 | [0/90] | 180 | 9091,8 | 9428,88 | -3,71 |
| 75 | 3 | [0/90] | 180 | 14900,4 | 15399,99 | -3,35 |
| 30 | 3 | [±45] | 180 | 9811,8 | 10259,35 | -4,56 |
| 45 | 3 | [±45] | 180 | 8593,2 | 8854,74 | -3,04 |
| 60 | 3 | [±45] | 180 | 10292,4 | 10384,22 | -0,89 |
| 75 | 3 | [±45] | 180 | 15390 | 15271,52 | 0,77 |
| 30 | 3 | [0/90/±45] | 180 | 10472,4 | 10599,79 | -1,22 |
| 45 | 3 | [0/90/±45] | 180 | 9433,8 | 9381,31 | 0,56 |
| 60 | 3 | [0/90/±45] | 180 | 10645,2 | 10576,01 | 0,65 |
| 75 | 3 | [0/90/±45] | 180 | 15885 | 15775,31 | 0,69 |
| 30 | 5 | [0/90] | 300 | 13560 | 13697,65 | -1,02 |
| 45 | 5 | [0/90] | 300 | 12552 | 13071,58 | -4,14 |
| 60 | 5 | [0/90] | 300 | 15153 | 15475,20 | -2,13 |
| 75 | 5 | [0/90] | 300 | 24834 | 24977,38 | -0,58 |
| 30 | 5 | [±45] | 300 | 18330 | 18544,52 | -1,17 |
| 45 | 5 | [±45] | 300 | 14853 | 15019,08 | -1,12 |
| 60 | 5 | [±45] | 300 | 17154 | 17220,69 | -0,39 |
| 75 | 5 | [±45] | 300 | 25650 | 25607,17 | 0,17 |
| 30 | 5 | [0/90/±45] | 300 | 17454 | 17520,01 | -0,38 |
| 45 | 5 | [0/90/±45] | 300 | 15900 | 15905,74 | -0,04 |
| 60 | 5 | [0/90/±45] | 300 | 18000 | 17884,51 | 0,64 |
| 75 | 5 | [0/90/±45] | 300 | 26475 | 26930,73 | -1,72 |
| 30 | 7 | [0/90] | 420 | 18984 | 19177,89 | -1,02 |
| 45 | 7 | [0/90] | 420 | 17572 | 18000,39 | -2,44 |
| 60 | 7 | [0/90] | 420 | 21214 | 20907,30 | 1,45 |
| 75 | 7 | [0/90] | 420 | 34767 | 34853,51 | -0,25 |
| 30 | 7 | [±45] | 420 | 26964 | 26964,01 | 0,00 |
| 45 | 7 | [±45] | 420 | 21592,2 | 21658,05 | -0,30 |
| 60 | 7 | [±45] | 420 | 24015,6 | 24165,40 | -0,62 |

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| | | | | | | |
|---|---|---|---|---|---|---|
| 75 | 7 | [±45] | 420 | 35910 | 37243,21 | -3,71 |
| 30 | 7 | [0/90/±45] | 420 | 24435,6 | 24546,26 | -0,45 |
| 45 | 7 | [0/90/±45] | 420 | 22012,2 | 22019,05 | -0,03 |
| 60 | 7 | [0/90/±45] | 420 | 24838,8 | 24727,82 | 0,45 |
| 75 | 7 | [0/90/±45] | 420 | 37065 | 36764,81 | 0,81 |
| 30 | 10 | [0/90] | 600 | 27120 | 26922,72 | 0,73 |
| 45 | 10 | [0/90] | 600 | 25104 | 27000,31 | -7,55 |
| 60 | 10 | [0/90] | 600 | 30306 | 30339,61 | -0,11 |
| 75 | 10 | [0/90] | 600 | 49668 | 49351,75 | 0,64 |
| 30 | 10 | [±45] | 600 | 38520 | 38473,11 | 0,12 |
| 45 | 10 | [±45] | 600 | 30846 | 30866,89 | -0,07 |
| 60 | 10 | [±45] | 600 | 34308 | 34308,09 | 0,00 |
| 75 | 10 | [±45] | 600 | 51600 | 51488,09 | 0,22 |
| 30 | 10 | [0/90/±45] | 600 | 34908 | 34895,56 | 0,04 |
| 45 | 10 | [0/90/±45] | 600 | 31446 | 31422,59 | 0,07 |
| 60 | 10 | [0/90/±45] | 600 | 35484 | 36236,69 | -2,12 |
| 75 | 10 | [0/90/±45] | 600 | 52950 | 52728,77 | 0,42 |

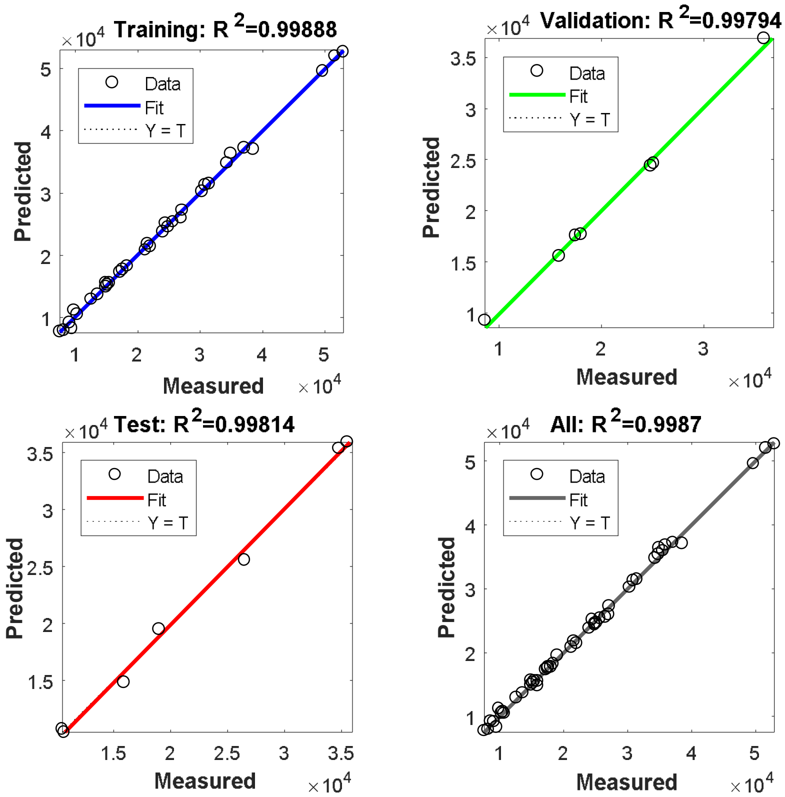


**Figure 7.** Relationship between the experimental values and estimated values

## 4. Conclusion

The experimental results in Table 3 tried to explain that, failure load value increases when overlap angle from 30° to 75° in geometry. Composites laminate stacking sequence can be said to affect tensile strength remarkably. [±45°] instead of [0°/90°] showed an average 10% increase in failure load. When using multi-directional fabric [0°/90°/±45°], the value increased by an average of 15%.

In a similar manner as shown in Figure 7, $R^2$ values for training data set, validation data set and testing data set in the prediction of failure load by ANN are 0.998, 0.997 and 0.998, respectively. These results mean that the designed model is ability of explaining at least 0.99 % for the training and 0.98% for the testing of obtained data by experiment. The estimated values show that the error is in acceptable limits. The actual experimental results were compared with the estimated values, ANN estimation is quite good and can strongly be suggested to decrease time wastage and support laboratory experiment.

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