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MECSOL 2019 - Layup Optimization of CFRP Prosthetic Tubes Using ANN and Tsai-Wu Criterion

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Abstract: The use of composite materials has increased lately and the need to know the behavior of these materials is very important once these materials are subjects to suffer from damage as cracks and delamination. Normally, to analyze failure problems in composite materials, the following steps are necessary: i) structure geometry design, ii) numerical and/or experimental analysis and iii) use of failure criteria (Tsai-Wu criterion). If the used composite material has a non-expected failure criterion, the procedure must be repeated. In order to eliminate the procedure above, this study proposes the use of an Artificial Neural Networks (ANN) inversion which can be used to determine an adequate configuration for the layers of the composite material from the desired failure criteria value. Numerical simulations, based on the Finite Element Method (FEM), were made in order to create a database for ANN training and validation. After the inversion of the ANN, satisfactory results were obtained and this procedure could be used to minimize the high number of numerical simulations normally used in the design of a composite structures.

Keywords: Artificial Neural Networks, Tsai-Wu Criterion, Composite tubes, Structural optimization, Safety margin.

INTRODUCTION

Composite material has numerous benefits as low weight, high strength and stiffness. There are many industries using this type of material, thus, are important previous studies of the behavior of this material mainly about the possible failures that can occur due the conditions which these types of materials are submitted.

About failure analysis, there are some criteria that are used to verify if the material has or not failure. One of the most used is the Tsai-Wu failure criterion for anisotropic materials which can distinguish the tensile and compression strength using the concept of strength tensor (Daniel and Ishai, 1994).

The use of neural networks for analysis of composite materials has been applied over the last years with good results encouraging further study of this important topic (Haykin, 2009). As examples of use of artificial neural networks (ANN) in composite materials analysis, Brito *et al.* (2007) used the technique of neural networks to predict the dynamic-mechanical behavior in a composite material used in the aviation industry and compared the numerical results with experimental ones. In the study presented by Selva *et al.* (2013), the researches created a structural integrity monitoring method of composite plates reinforced with carbon fibers using the technique of neural networks to locate damage. In the study proposed by Velmurugan *et al.* (2014), the technique of artificial neural networks is used to predict the loss of volume in the heat treatment of a metal matrix composite material. The research presented by Fenza, Sorrentino and Vitiello (2015) shows the use of artificial neural networks together with methods probability for detect damage in composite plates using lamb waves. The authors Mallela and Upadhyay (2016) developed neural networks to predict the shear buckling load of laminated composite stiffened panels.

Gomes *et al.* (2017) used the technique of neural networks together with the genetic algorithm to analyze the failures in the carbon/epoxy composite material searching minimizes the maximum value of Tsai-Wu failure criterion. The authors Stojanovic *et al.* (2017) used the ANN with Taguchi Method for predicting the specific wear rate of a composite materials, the results showed that neural networks was more efficient than the Taguchi Method. Albanesi *et al.* (2018) developed a method using the ANN and Genetic Algorithm in order to reduce the computational cost of the optimization procedure the composite laminate of wind turbine blades. Hassan, Mohammed and Abdulsamad (2018) performed an investigation of bending fatigue behavior of composite materials using ANN and comparing with experimental part. The authors concluded that ANN is a good prediction tool for fatigue life of composite materials.

In order to contribute with researches in the composite materials technology, this study presents numerical simulations, using finite element method (FEM), for a hollow tubular structure formed from a carbon/epoxy composite material. After the simulations, it was created a database, used in the ANN training and validation, which relates the layers orientation of the composite structure with the Tsai-Wu failure criterion. Using the database, an ANN inversion was proposed which relates the desired inputs (Tsai-Wu failure criterion) according with safety margin with the networks outputs (final configuration of the laminate). This configuration can resist the load applied. Using this procedure, an ANN inversion, is hoped to reduce the design time of a carbon/epoxy composite material with adequate configuration that can resist the load applied and show a safety margin suitable.

To the author's best knowledge, there are no (or very scarce) studies in the literature investigating use of ANN applied in CFRP tubes in order to optimize the layup as well reduce the index of failure (Tsai-Wu). This paper is the first to do so. CFRP structures are vastly used in aerospace field and in high performance prosthetic applications, so it can be seen that a deep study of those structures are very important for the scientific and industrial organizations.

This manuscript is organized as follows: Section 2 the methodological procedure is presented. Section 3 presents the main results and discussion. Finally, Section 4 draws the conclusions.

MATERIAL AND METHOD

Tsai-Wu Failure Criterion for Composite Materials

The occurrence of a failure, due to various factors such as load, type of material, fibers orientation, etc., is sometimes dangerous and a diagnose of the composite material before its production can generates many benefits.

Since that the composite materials are anisotropic and their property depends of the fibers orientation, the Tsai-Wu failure criterion is totally applied to analyze this material. According to Voyiadjis and Kattan (2005), this failure criterion is based on the total strain energy failure theory, where the failure occurs in the material if the following Eq. 1 is violated:

$$F_{11}\sigma_1^2 + F_{22}\sigma_2^2 + F_{66}\tau_{12}^2 + F_1\sigma_1 + F_2\sigma_2 + F_{12}\sigma_1\sigma_2 \leq 1 \quad (1)$$

Where $F_{11}, F_{22}, F_{66}, F_1, F_2, F_{12}$ are the strength tensors and $\sigma_1, \sigma_2, \tau_{12}$ are the normal stresses. According to Voyiadjis and Kattan (2005), the strength tensors are obtained as follows:

$$F_{11} = \frac{1}{\sigma_1^T \sigma_1^C} \quad (2) \qquad F_{22} = \frac{1}{\sigma_2^T \sigma_2^C} \quad (3) \qquad F_1 = \frac{1}{\sigma_1^T} - \frac{1}{\sigma_1^C} \quad (4) \qquad F_2 = \frac{1}{\sigma_2^T} - \frac{1}{\sigma_2^C} \quad (5)$$

$$F_{66} = \frac{1}{\left(\tau_{12}^F\right)^2} \quad (6) \qquad F_{12} \approx -\frac{1}{2}\sqrt{F_{11}F_{22}} \quad (7)$$

As an important characteristic of this failure theory in relation to other theories as Tsai-Hill failure criterion, is that the Tsai-Wu failure criterion can distinguish between the tensile and compressive strengths, but is considered more complex (Kaw, 2006).

The Tsai-Wu failure criterion is one of the most used in research because of its simple computational implementation. According to Costa (2011), it is considered as a relatively easy method of calculating the loads on the composite material structure.

The authors Debski and Jonak (2015) developed a study comparing the experimental and numerical results of thin-walled composite materials in relation the problems of stability and the capacity to non-linear loads. In numerical analysis were considered the Tsai-Wu Failure Criterion and the finite elements method. The results proved the efficiency of the Tsai-Wu failure criterion for failure analysis of a composite material.

In the search proposed by Koc *et al.* (2016) an investigation about the behavior of the composite material under four-point bending was analyzed. In theirs work, some experiments and numerical analysis using the finite element method were made looking for a comparison in between supported rupture load in the simulations with the generated ones in the experiments. The authors report that the Tsai-Wu failure criterion demonstrated success in predicting the failure of the structure.

A composite structure is designed to support a given load, the safety margin is considered the capacity of the structure must support a given additional loading. When the structure is able to support this additional load its safety margin is positive (Campbell, 2010).

The safety margin used for the Tsai-Wu failure criterion according to Kolios and Proia (2012) is obtained by the Eq. 8:

$$\text{MoS} = \text{SR-1} \quad (8)$$

The SR as failure rate of the composite material is obtained by Tsai-Wu failure criterion using the Eq. 9 (Kolios and Proia, 2012).

$$SR = \frac{(-b + \sqrt{b^2 + 4 \times a})}{2 \times a} \tag{9}$$

Where a and b are calculated according to the strength tensors and the normal stresses are obtained through calculation Tsai-Wu failure criterion. A negative safety margin indicates that the material will suffer failure. A positive number indicates that material proves to be safe and reliable.

Artificial Neural Networks

Since ANN are well fitted to reproduce causal relations, we can use these devices to map the desired output with the inputs of the system. Then, an ANN is developed to perform an inversion in the composite material design where the input of the neural network is the desired failure criteria, in this case the Tsai-Wu criterion, and its output is an adequate configuration for the layers of the composite material. According to Fig. 1 check a sketching of the ANN inversion.

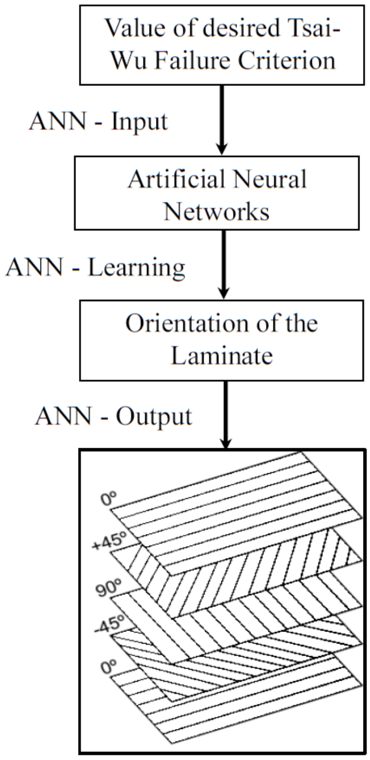

Figure 1 – The artificial neural network inversion procedure.

The theory of neural network was firstly presented in 1940 by McCulloch and Pitts and over the years this theory has been refined and began to gain prominence due to the advancement of technology (Kovàcs, 1996). According to Chong and Zak (2001), artificial neural networks resemble the human brain, they are formed by simple circuits constituted of interconnected neurons layers to each other by synaptic connections that have the function of spread information. Normally the neural network consists of input layer that has the function of receive information from the external environment, hidden layers that are responsible for extract the information provided by the input layers and do the processing and the output layer that transmits the processed response the hidden layers. The neurons in those layers have several inputs and only one output. The Neurons are housed in groups according to the learning algorithm that has the function to identify the appropriate weights and make the necessary adjustment for the network to behave appropriately and can learn from examples (Yegnanarayana, 2005).

In this study was used a multilayer feedforward network with backpropagation training algorithm that has a supervised learning. The network is trained and generated errors are transmitted to the previous layers until reach negligible values (Haykin, 2009). In addition, it was used the optimization techniques how Levenberg Marquardt and Gradient Descent Method (GDX) to contribute to the training of neural networks in order to obtain a faster convergence. There is no defined rule for choosing the numbers of hidden layers and neurons, thus, the trial and error method is used. The learning rate is normally set to a value less than one, with a learning rate high the network become unstable (Yegnanarayana, 2005; Braga, Carvalho and Ludemir, 2000).

Numerical Simulation

As there is the possibility of the appearance of failures in composite materials, it is essential to have some mechanism to predict these drawbacks before the material to be produced. Normally some tries are required in order to determine the final topology (e.g. layers orientations) in a composite material that determines the security requirements and reliability of the material.

In this study, was used the finite element method (FEM) as a tool in the numerical simulations. The analyzed composite system is a hollow tubular cross section beam used in transtibial prostheses built of prepreg carbon/epoxy composite material. According to Tab. 1 check the beam dimensions.

Table 1 – Dimensions of analyzed composite system.

Length	External diameter	External diameter composite 03 layers	External diameter composite 06 layers
0.3000 m	0.0300 m	0.0540 m	0.00108 m

In the structural analyzes were used the following properties of carbon / epoxy composite as is provided to Tab. 2.

Table 2 – Properties of composite materials carbon / epoxy.

E_1 (GPa)	E_2 (GPa)	G_{12} (GPa)	υ_{12}	ρ (kg/m³)
101.86	3.41	7.56	0.30	1550.00

In order to analyze the failure criterion by FEM, it is necessary to have other important properties of the composite material. The average values used were obtained by Martins (2015) according to Tab. 3.

Table 3 – Properties of composite materials carbon / epoxy for failure criteria.

σ_1^T (MPa)	σ_1^C (MPa)	σ_2^T (MPa)	σ_2^C (MPa)	τ_{12} (MPa)
1363.49	572.27	5.86	102.00	200.61

Using the data above, it was created a free-clamped tubular beam using finite elements according shown in Fig. 2. It Was used a shell element type and the beam was exposed to distributed compressive loads. The following intensity loads were applied (3000N, 4480N, 7500 N, 9000 N and 12000 N), the fibers orientation in each layer varied in three values (0°, 45° and 90°) and it was considered laminates with three and six layers. The structure topology of composite material is changed relative to fibers orientation and amount of layers.

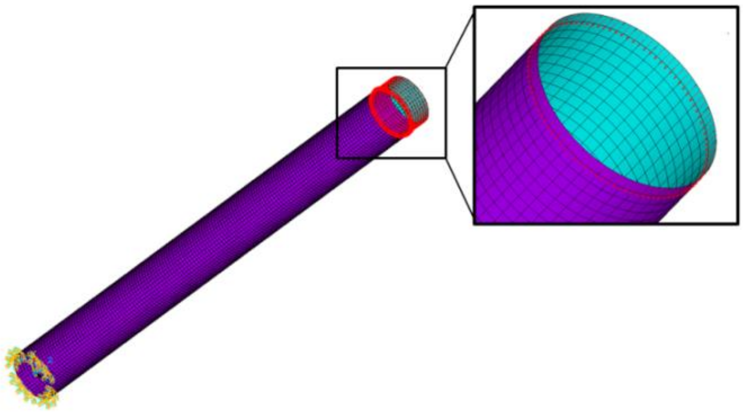

Figure 2 – The free-clamped Tubular beam analyzed.

After the structural analyzes were selected the maximum value of failure criteria to each orientation and databases were created for artificial neural network training and validation.

Using the database, an ANN inversion was done allowing a fast and sensible analyzes of the behavior of the composite material in a certain environment with adjustment in the laminate configuration.

RESULTS AND DISCUSSION

In this study was separated approximately 5% of the values of each database for network validation and the remaining data were used for training and test it. The amount of values used for training was upper than test. This amount was established by authors.

The backpropagation was used as a training method and the stopping criterion for the networks are considered in relation to the algorithm complete the proposed number of steps, the algorithm reaches the desired minimum error or when the minimum gradient recommended is found.

After a few tries, the consistent neural network parameters (number of layers, number of neurons, etc.) were found and used in the numerical simulations. The next subsection presents the main results.

Composite material with three layers

In this first numerical simulation was used an ANN with one input and one output. The input data was the value of the Tsai-Wu failure criterion and output the orientation for a three layer laminate. The general configuration of neural network is shown according Tab. 4.

Table 4 – Configuration of neural network for composite material with three layers.

Learning algorithm	Levenberg-Marquardt
Activation function (hidden layers)	Hyperbolic Tangente
Activation function (output layers)	Linear
Mean square error	1^{-15}
Number of hidden layers	2
Number of neurons in hidden layers	[7 10]
Learning rate	0.02
Number of iterations	15000

After the training, the neural network presented a good consistence in the results and a small error in the failure criterion analyzed. These good results are seen according to Tab. 5.

Table 5 – Results generated by the network of three layers considered as input the Tsai- Wu failure criterion.

Failure criterion (input)	Networks output (orientations)	Failure criterion validated	Safety margin
0.1519	89.07/89.25/3.40	0.1519	5.583
0.2850	38.76/-3.46/47.32	0.2835	2.527
0.4735	85.83/44.73/45.26	0.4737	1.111

According to Tab. 5, the orientations generated by the ANN were close to proposed ones (0°, 45° and 90°) and the obtained Tsai-Wu failure criterion from neural network was validated from a finite element commercial program shown consistency in the neural network results. Showing a positive safety margin, where the structure will support the applied load.

The Fig. 3 shows the value of Tsai-Wu failure criterion for a material composite with three layers using numerical simulation.

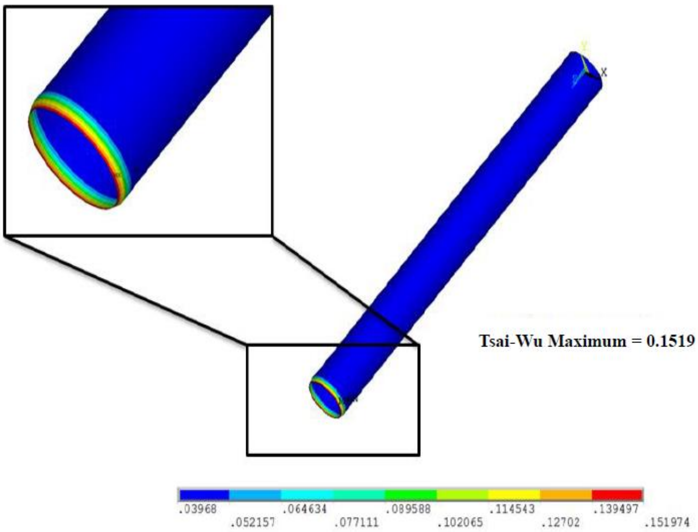

Figure 3 – Results Tsai-Wu failure criterion for a three layers laminate.

The next application is about the use as input in the neural network both failure criterion and variable applied strength (3000N, 4480N, 7500N, 9000N and 12000N). As neural network output were considered the layers orientation. The general configuration of neural network is seen according to Tab. 6:

Table 6 – Configuration of neural network for composite material with three layers.

Learning algorithm	Levenberg-Marquardt
Activation function (hidden layers)	Hyperbolic Tangente
Activation function (output layers)	Linear
Mean square error	1^{-4}
Number of hidden layers	2
Number of neurons in hidden layers	[8 23]
Learning rate	0.001
Number of iterations	20000

The results generated by the ANN are shown according to Tab. 7. As shown in the last simulation, the results from neural network with two inputs were very consistent with values so close of ones obtained from finite element commercial program. With more information, how two inputs, the ANN found more accurate results for layers orientations.

Table 7 – Results generated by the network of three layers considered as input the failure criterion and strength variation.

Failure criterion (input)	Strength variation (input)	Networks output (orientations)	Failure criterion validated	Safety Margin
0.1908	3000	1.00/44.18/45.01	0.1908	5.2410
0.1519	4480	88.26/89.40/-1.14	0.1519	6.5832
0.4746	7500	44.93/-0.16/44.94	0.4746	2.1070
0.8874	9000	42.06/44.52/1.06	0.8874	1.1268
0.4278	12000	91.60/89.12/46.54	0.4278	2.3375

The Fig. 4 shows the maximum value of Tsai-Wu failure criterion for a material composite with three layers and strength 7500N using numerical simulation.

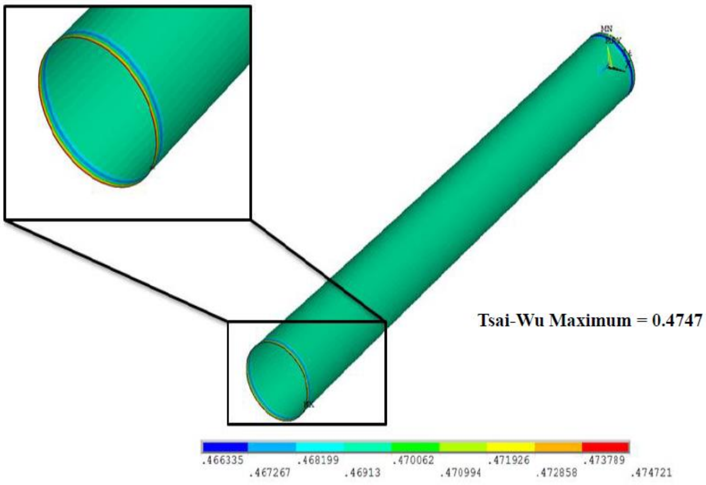

Figure 4 – Results Tsai-Wu failure criterion for a three layers laminate with strength 7500N.

Composite material with six layers

Neural networks for six layers were made considering one input and one output. The ANN had as input the value of the failure criterion and output the orientation for a six layer laminate. It is configured as follows:

Table 8 – Configuration of neural network for composite material with six layers.

Learning algorithm	GDX
Activation function (hidden layers)	Hyperbolic Tangente
Activation function (output layers)	Linear
Mean square error	1^{-2}
Number of hidden layers	2
Number of neurons in hidden layers	[350 200]
Learning rate	0.1
Number of iterations	15000

According to Tab. 9 shown the results of simulations. We can see that the results from neural network were close to the expected Tsai-Wu failure criterion values, obtained from a finite element commercial program, shown the robustness of the adopted methodology.

Table 9 – Results from the neural network of six layers considered as input the failure criteria.

Failure criterion (input)	Networks output (orientations)	Failure criterion validated	Safety Margin
0.3886	2.99/1.49/94.33/ -4.77/96.22/90.98	0.3902	1.5628
0.1933	0.93/-0.34/88.76/ 90.56/91.21/0.97	0.1933	4.1733
0.1076	91.07/-1.59/90.31/ 45.88/89.89/90.78	0.1077	8.2850

The Fig. 5 shows the value of Tsai-Wu failure criterion for a material composite with six layers using numerical simulation.

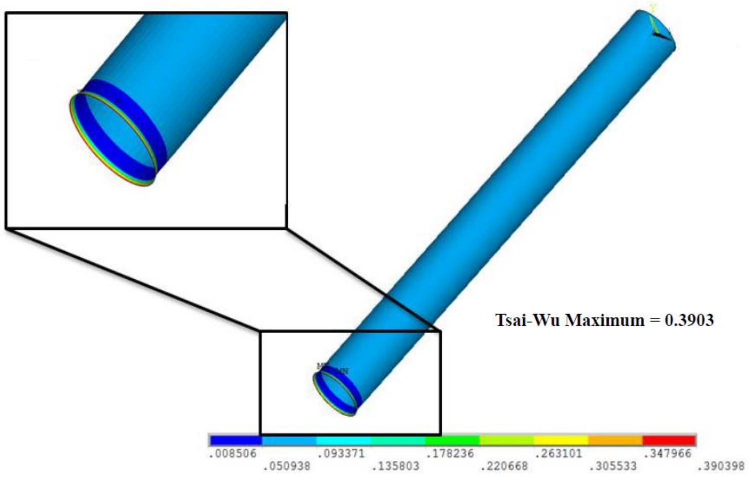

Figure 5 – Results Tsai-Wu failure criterion for a six layers laminate.

It is possible to see according to Tab. 9 that the layers orientations obtained from neural network were very close to the expected values (0°, 45° and 90°).

Studies were performed about linear regression analysis of the data used in ANN in order to explore the relationship between the responses generated by the neural network with the data used for training and validation. The results showed consistency in relation to results ANN and data used for training and validation. Linear regression analysis is detailed in the appendix.

CONCLUSION

In this study the artificial neural network were used in order to generate the appropriate hollow tubular structure formed from a carbon/epoxy composite material according to Tsai-Wu failure criterion. This failure criterion was used as input of the neural network and the orientations of the final laminate were the output of the neural network. In this sense, the artificial neural network is developed to perform an inversion in the composite material design where the input of the neural network is the desired failure criterion.

The final orientations generated by neural networks were validated using a finite element commercial program in order to certify the robustness of the adopted methodology. Then, comparing these values of the failure criterion generated by the finite element commercial program with ones used as input in the neural network, it was possible to see that the values shown very close generating a similar safety margin.

This study showed the feasibility of using neural networks for the study of composite materials. Presenting satisfactory and coherent results of the layers orientations of laminated composite materials that comply with the ideal safety margin and do not fail.

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APPENDIX

In order to verify the correlation between the data used in the ANN training and validation, it was proposed a linear regression analyzes. In this study were considered independent variables that are known orientations and the dependent variables are the orientation generated by the network. The quality of fit is measured by coefficient of determination (R^2), that has its values, nearer on one the coefficient demonstrates that the variables clarify the regression model (Montgomery *et al*., 2012).

Regression analyzes were made for the neural network with three layers and an input, three layers and two inputs and to network with six layers and one input. As shown in figures below:

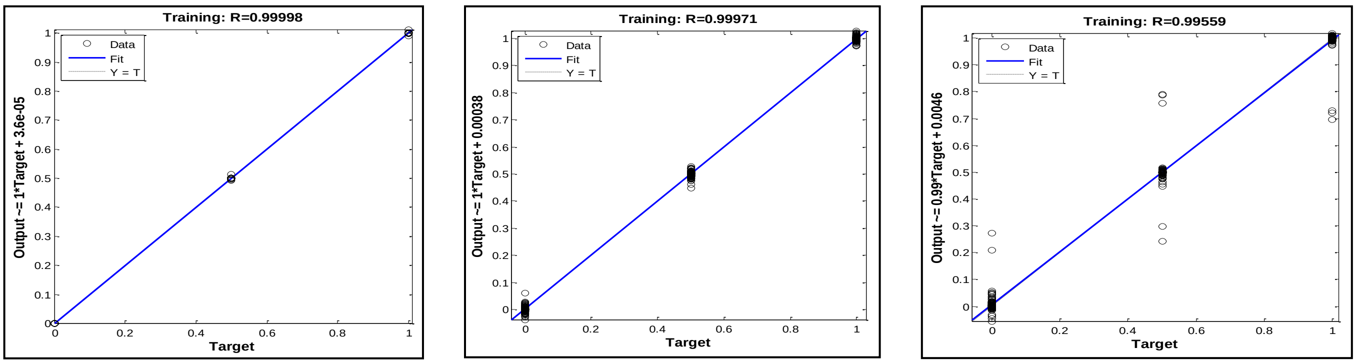

Figure 6 – Regression analysis of three layers, regression analysis of three layer neural network with two inputs and regression analysis of six layers, respectively.