

## Prediction of Deflection and Stresses of Laminated Composite Plate with Artificial Neural Network Aid

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**Abstract:** This paper discusses the use of D-optimal designs in the design of experiments (DOE) and artificial neural networks (ANN) in predicting the deflection and stresses of carbon fibre reinforced plastic (CFRP) square laminated composite plate subjected to uniformly distributed load. For training and testing of the ANN model, a number of finite element analyses have been carried out using D-optimal designs by varying the fiber orientations and thickness of each lamina. The composite plate is modeled using shell 99 elements. The ANN model has been developed using multilayer perceptron (MLP) back propagation algorithm. The adequacy of the developed model is verified by root mean square error and regression coefficient. The results showed that the training algorithm of back propagation was sufficient enough in predicting the deflection and stresses.

**Keywords:** D-Optimal designs, Finite Element Method, Artificial neural network, Multilayer perception.

### I. Introduction

Composite materials are particularly attractive to aviation and aerospace applications because of their exceptional strength and stiffness-to-density ratios and superior physical properties. The mechanical behavior of a laminate is strongly dependent on the fiber directions and because of that; the laminate should be designed to meet the specific requirements of each particular application in order to obtain the maximum advantages of such materials. Usually, laminated composite materials are fabricated from unidirectional plies of giving thickness and with fiber orientations limited to a small set of angles, eg., 0o, 45o, -45o and 90o.

A true understanding of their structural behaviour is required, such as the deflections, buckling loads and modal characteristics, the through thickness distributions of stresses and strains, the large deflection behaviour and, of extreme importance for obtaining strong, reliable multi-layered structures, the failure characteristics. In the past, the structural behaviour of plates and shells using the finite element method has been studied by a variety of approaches. Choudhary and Tungikaranalyzed the geometrically nonlinear behavior of laminated composite plates using the finite element analysis.

They studied the effect of number of layers, effect of degree of orthotropy (both symmetric and antisymmetric) and different fibre orientations on central deflections. Ganapathi *et al.* presented an eight-node C<sup>0</sup> membrane-plate quadrilateral finite element-based on the Reissner-Mindlin plate theory to analyse moderately large deflection, static and dynamic problems of moderately thick laminates including buckling analysis and membrane-plate coupling effects. Han *et al.* used the hierarchical finite element method to carry out the geometrically nonlinear analysis of laminated composite rectangular plates. Based on the first-order shear deformation theory and Timoshenko's laminated composite beam functions, the current authors developed a unified formulation of a simple displacement based 3-node, 18degree-of-freedom flat triangular plate/shell element and two simple, accurate, shear-flexible displacement based 4-node quadrilateral elements and for linear and geometrically nonlinear analysis of thin to moderately thick laminated composite plates.

The deflection and rotation functions of the element boundary were obtained from Timoshenko's laminated composite beam functions. Raja Sekhara Reddy *et al.* applied the artificial neural networks (ANN) in predicting the natural frequency of laminated composite plates under clamped boundary condition. They used the D-optimal design in the design of experiments to carry out the finite element analysis. WEN *etal.* used the finite element method to predict the damage level of the materials.

They studied the prediction of the elastic-plastic damage and creep damage using Gurson model and creep damage model, which is based on the Kachanov-Rabothov continuum creep damage law. They also studied the creep damage properties of thin film/substrate systems by bending creep tests and carried the Simulation of the interface characterization of thin film/substrate systems.

Reddy *et al* employed a distance-based optimal design in the design of experimental techniques and artificial neural networks to optimize the stacking sequence for a sixteen ply simply supported square laminated composite plate under uniformly distributed load (UDL) for minimizing the deflections and stresses using finite element method. Therefore the finite element method is especially versatile and efficient for the analysis of complex structural behavior of the composite laminated structures.

The present study proposes a new experimental design method for selection of practical laminates and thickness of each ply for a criterion of a response. This method employs *D*-optimality for selections from a set of feasible laminates. This method is applied to a 10 layer laminate to predict the deflection and stresses of a composite plate subjected to a uniform distributed load under simply supported boundary condition and an artificial neural network model has been developed to predict the same.

## II. Material and Methods

The material used to model the physical structure of the laminated composite plate is carbon fibre reinforced plastic (CFRP). The material properties are as follows:

$$E1=220GPa, E2=6.9GPa, E3=6.9GPa, G12=G23=G13=4.8GPa, \nu12=0.25, Vf=0.6.$$

The methodology adopted in predicting the deflections and stresses using the integrated approach.

### 2.1. Geometry of the shell 99 element

In this study to model the laminated composite plate the finite element analysis software ANSYS has been used. In ANSYS software, there are many element types available to model layered composite materials. In our FE analysis, the linear layered structural shell element (Shell 99) is used. It is designed to model thin to moderately thick plate and shell structures with a side-to-thickness ratio of roughly 10 or greater.

The linear layered structural shell element allows a total of 250 uniform-thickness layers. Alternatively, the element allows 125 layers with thicknesses that may vary bilinearly over the area of the layer. An accurate representation of irregular domains (i.e. domains with curved boundaries) can be accomplished by the use of refined meshes and/or irregularly shaped elements.

For example, a non-rectangular region cannot be represented using only rectangular elements; however, it can be represented by triangular and quadrilateral elements. Since, it is easy to derive the interpolation functions for a rectangular element, and it is much easier to evaluate the integrals over rectangular geometries than over irregular geometries, it is practical to use quadrilateral elements with straight or curved side assuming you have a means to generate interpolation functions and evaluate their integrals over the quadrilateral elements. The linear layered structural shell element is shown in Figure. 2.1 Nodes are represented by I, J, K, L, M, N, O, and P.

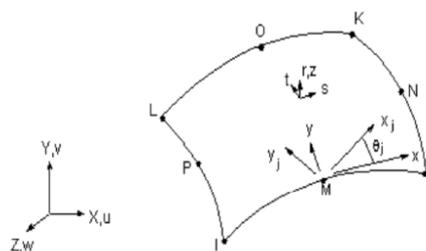


Figure 2.1 Geometry of 8-node element with six degrees of freedom

### 2.2 Design of experiments

Design of Experiments (DOE) is a mathematical methodology that defines an optimal set of experiments in the design space, in order to obtain the most relevant information possible with the highest accuracy at the lowest cost. This scientific exploration of the design space replaces a tedious, manual, trial-and-error process, and is the fastest way to acquire the most relevant information with minimum computational effort.

Traditional experimental designs (Full Factorial Designs, Fractional Factorial Designs, and Response Surface Designs) are appropriate for calibrating linear models in experimental settings where factors are relatively unconstrained in the region of interest. In some cases, however, models are necessarily nonlinear.

In other cases, certain treatments (combinations of factor levels) may be expensive or infeasible to measure. *D*-optimal designs are model-specific designs that address these limitations of traditional designs. The *D*-optimality criterion states that the best set of points in the experiment maximizes the determinant  $|X^T X|$ . "D" stands for the determinant of the X matrix associated with the model.

A *D-optimal* design is generated by an iterative search algorithm and seeks to minimize the covariance of the parameter estimates for a specified model. This is equivalent to maximizing the determinant  $D=|XTX|$ , where  $X$  is the design matrix of model terms (the columns) evaluated at specific treatments in the design space (the rows).

Unlike traditional designs, *D-optimal* designs do not require orthogonal design matrices, and as a result, parameter estimates may be correlated. Parameter estimates may also be locally, but not globally, *D-optimal*. The *D-optimal* design uses the row-exchange and Co-ordinate exchange algorithms to generate the optimal designs [16]. A related measure of the moment matrix ( $X^T X/k$ ) is the D-efficiency and can be calculated by using the following expression:

$$D - efficiency = 100 \left( \frac{1}{N_D} |X^T X|^{1/p} \right)$$

where

$N_D$  is the number of points in the design and  $p$  is the number of effects in the model including the intercept. If all variables are normalized so that they vary from -1 to 1, then the maximum value of the *Deff* is 1. Furthermore, the quality of the set of points can then be measured by *Deff*.

### 2.3 Artificial neural networks

An Artificial Neural Network (ANN) is an information processing paradigm that is inspired by the way biological nervous systems, such as the brain, process information. It resembles the human brain in two aspects: the knowledge is acquired by the network through a learning process, and inter neuron connection strengths known as synaptic weights are used to store the knowledge.

A typical biological neuron collects signals from others through a host of fine structures called dendrites. The neuron sends out spikes of electrical activity through a long, thin strand known as an axon, which splits into thousands of branches. At the end of each branch, a structure called a synapse converts the activity from the axon into electrical effects that inhibit or excite activity from the axon into electrical effects that inhibit or excite activity in the connected neurons.

When a neuron receives excitatory input that is sufficiently large compared with its inhibitory input, it sends a spike of electrical activity down its axon. Learning occurs by changing the effectiveness of the synapses so that the influence of one neuron on other changes. A biological neuron and artificial neuron are shown in figure 2.3.1 and figure 2.3.2.

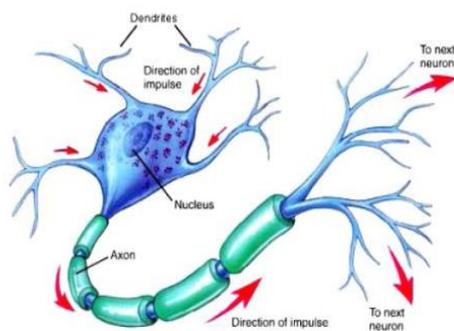


Figure2. 3.1 Simplified model of a biological Neuron

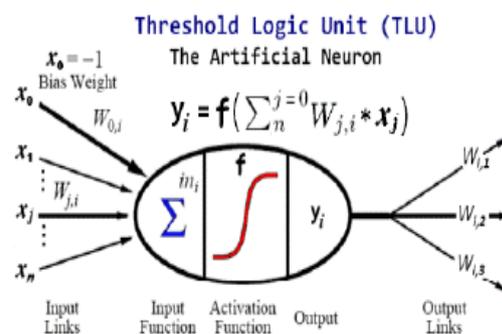


Figure 2.3.2 artificial neuron model

## III. Finite Element Analysis

### 3.1. Validation of linear layered structural shell element-a case study

In order to validate the usage of the linear layered structural shell element, a numerical example is solved in static analysis. The boundary condition is simply supported and the geometry and material properties are as follows:

$$E1/E2=40, G12=G13=0.6E2, G23=0.5E2, \nu_{12}= 0.25, a/h=10, a=1, q=1.0.$$

The center deflection and stresses are presented here in non-dimensional form using the following:

$$\bar{w} = w \times \frac{E_2 h^3}{q a^4} \times 10^3, \quad \bar{\sigma}_x = \sigma_x \times \frac{h}{a q}, \quad \bar{\sigma}_y = \sigma_y \times \frac{h}{a q} \quad \text{and} \quad \bar{\tau}_{xy} = \tau_{xy} \times \frac{h}{a q}$$

Table 3.1 and Table3.2 represents the mesh convergence study and comparison of results of non-dimensional displacement obtained from Reddy and the ANSYS computer program.The results using a free mesh show an excellent correlation to the results given by Reddy.

**Table 3.1** Nondimensional displacement of composite plates (cross- ply)

Mesh	0/90	0/90/0	0/90/90/0	0/90/0/90
2 × 2	14.222	6.8178	6.5423	6.7762
4 × 4	14.478	6.9848	6.7402	6.9897
10×10	14.488	6.9904	-	6.9965
20×20	14.488	6.9905	6.7459	6.9966
40 × 40	14.475	6.9857	6.7405	6.9904
FSDT (Reddy)	14.069	6.919	6.682	6.9260
Difference (%)	2.907	0.951	0.870	0.919

**Table 3.2** Nondimensional displacement of composite plates (θ/- θ/ θ/- θ)

Mesh	5	15
2 × 2	6.7716	6.3811
4 × 4	-	6.6625
10×10	6.9652	-
20×20	-	6.6668
40 × 40	6.9623	6.6631
FSDT (Reddy)	6.741	6.086
Difference (%)	3.2828	9.4824

## IV. Results and Discussion

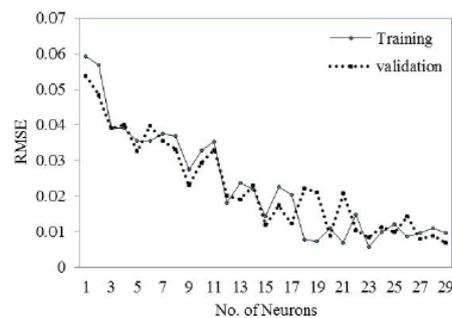
### 4.1. Development of ANN model

One of the key issues when designing a particular neural network is to calculate proper weights for neuronal activities. These are obtained from the training process applied to the given neural network. To that end, a training sample is provided, i.e. A sample of observations consisting of inputs and their respective outputs. The observations are fed to the network. In the training process the algorithm is used to calculate neuronal weights, so that the root mean squared error between the calculated outputs and observed outputs from the training set is minimized.

### 4.2. Neural network training

To calculate the connection weights, a set of desired network output values is needed. Desired output values are called the training data set. The training data set in this study was selected based on a *D-optimal design* in the design of experiments. In this study, 322 data sets were used for training, 80 data set were for validation and 20data set were used for testing the network respectively.

For calculation of weight variables, often referred to as network training. To get the best prediction by the network, several architectures were evaluated and trained using the finite element analyses data. A network with one hidden layer and 30 neurons provided to be an optimum ANN. The performance of the network (RMSE and Regression coefficient (R<sup>2</sup>)) with the number of neurons is shown in Figure.4.1.



**Figure 4.1** Root-mean square vs. number of neurons for nondimensional displacement

## V. Neural Network Validation

Once the weights are adjusted the performance of the trained network was validated and tested with the finite element analyses which were never used in the training process. Validation set is a part of the data used to tune the network topology or network parameters other than weights. It is used to define the number of hidden units to detect the moment when the predictive ability of neural network started to deteriorate.

One method, *k*-fold cross validation, is used to determine the best model complexity, such as the depth of a decision tree or the number of hidden units in a neural network. The method of *k*-fold cross validation partitions the training set into *k* sets. For each model complexity, the learner trains *k* times, each time using one

of the sets as the validation set and the remaining sets as the training set. It then selects the model complexity that has the smallest average error on the validation set (averaging over the  $k$  runs).

**5.1 Neural network testing**

The ANN predicted results are in very good agreement with experimental results and the network can be used for testing. Hence the test data sets are applied to the network, which were never used in the training process and is presented in Table. 5.1.

The test set is a part of the input data set used only to test how well the neural network will predict on new data. The results predicted by the network were compared with the finite element results and shown in Figure. The regression coefficients for deflection and stresses ( $S_x$ ,  $S_y$ ,  $S_{xy}$ ) were found to be 0.882, 0.983, 0.993 and 0.999 respectively.

Table. 5.1. ANN predicted results

S. No	First Ply angle	Second Ply angle	Third Ply angle	Fourth Ply angle	Fifth Ply angle	First Ply thickness	Second Ply thickness	Third Ply thickness	Fourth Ply thickness	Fifth Ply thickness
1	45	-45	45	0	-45	0.2	0.2	0.2	0.2	0.2
2	90	0	45	0	-45	0.2	0.2	0.2	0.2	0.2
3	0	90	45	0	-45	0.2	0.2	0.2	0.2	0.2
4	90	90	45	0	-45	0.2	0.2	0.2	0.2	0.2
5	45	0	90	0	-45	0.2	0.2	0.2	0.2	0.2
6	0	45	90	0	-45	0.2	0.2	0.2	0.2	0.2
7	90	45	90	0	-45	0.2	0.2	0.2	0.2	0.2
8	45	90	90	0	-45	0.2	0.2	0.2	0.2	0.2
9	45	0	-45	45	-45	0.2	0.2	0.2	0.2	0.2
10	0	45	-45	45	-45	0.2	0.2	0.2	0.2	0.2
11	45	-45	0	45	-45	0.2	0.2	0.2	0.2	0.2
12	45	90	90	0	-45	0.2	0.2	0.2	0.2	0.2
13	45	0	-45	45	-45	0.2	0.2	0.2	0.2	0.2
14	45	-45	90	45	-45	0.4	0.5	0.4	0.3	0.2
15	0	45	-45	90	90	0.4	0.5	0.4	0.2	0.2
16	0	45	-45	90	90	0.5	0.2	0.5	0.2	0.4
17	45	-45	90	0	90	0.4	0.2	0.5	0.5	0.4
18	45	0	-45	90	90	0.5	0.5	0.5	0.5	0.5
19	0	45	-45	90	90	0.3	0.4	0.5	0.3	0.4
20	45	90	-45	90	90	0.2	0.5	0.5	0.2	0.5

**VI. Ansys Analysis Report**

The laminated plate is subjected to deflection and stresses and analysed using ANSYS. The ANSYS analysis report are shown from figure 6.1 to 6.7.

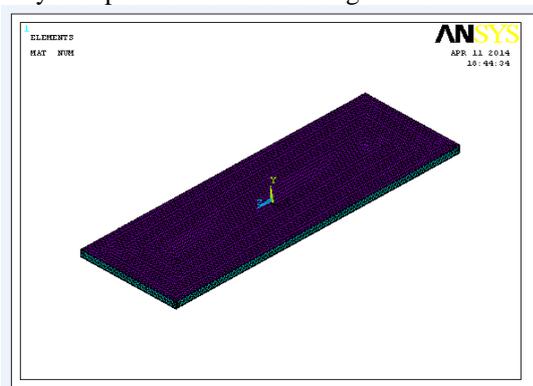


Figure 6.1 Meshed Element

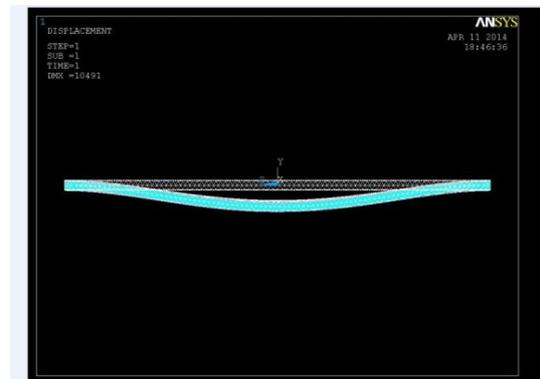


Figure 6.2 laminated plate deformed shape

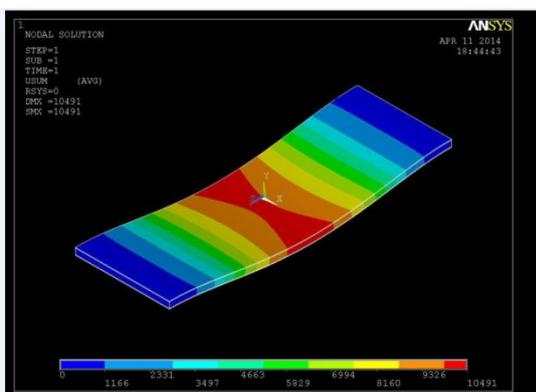


Figure 6.3 laminated plate DOF

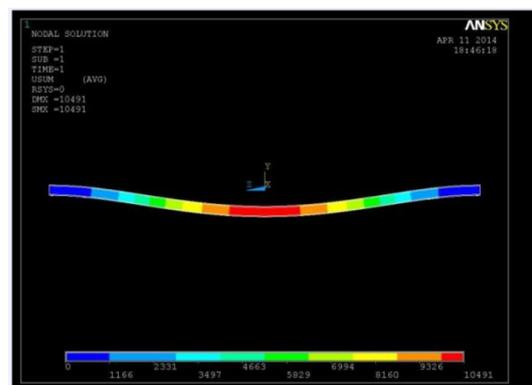


Figure 6.4 laminated plate DOF 1

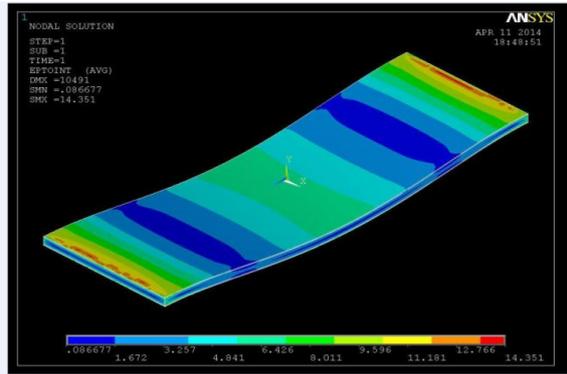


Figure 6.5 laminated plate strain intensity

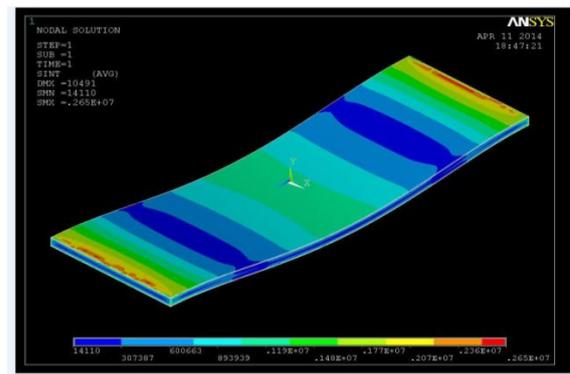


Figure 6.6 laminated plate stress intensity

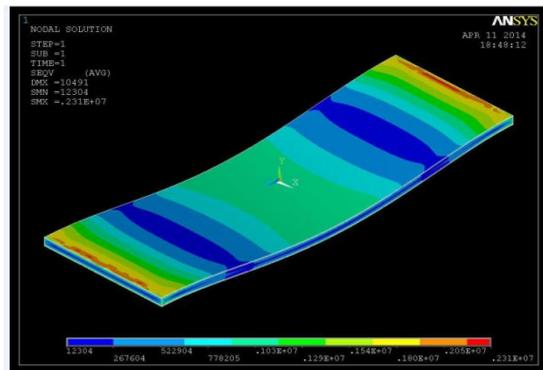


Figure 6.7 laminated plate von mises stress intensity

**STEEL PLATE**

The steel plate is subjected to deflection and stresses and analysed using ANSYS. The ANSYS analysis report are shown from figure 6.8 to 6.14 .

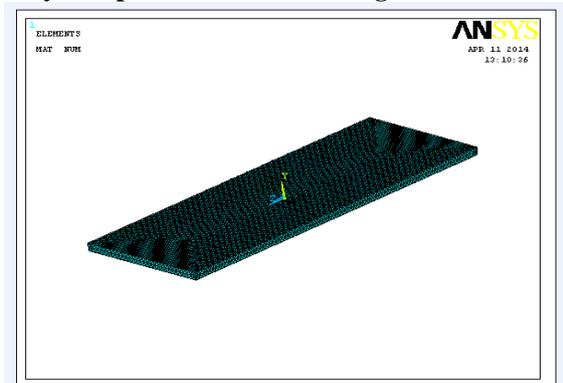


Figure 6.8 meshed element

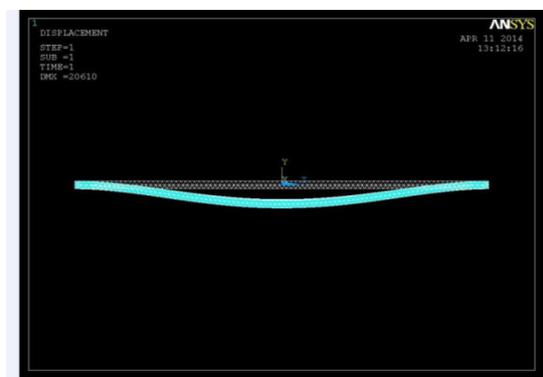


Figure 6.9 steel plate deform shape

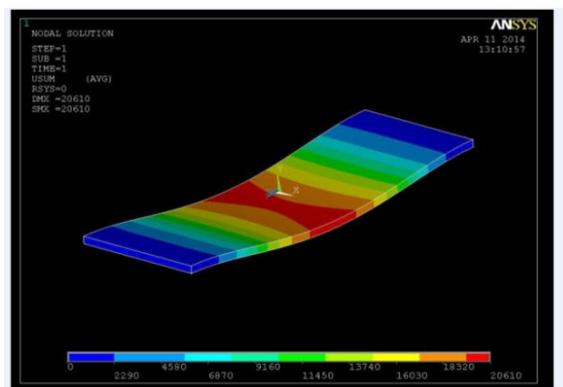


Figure 6.10 steel plate DOF

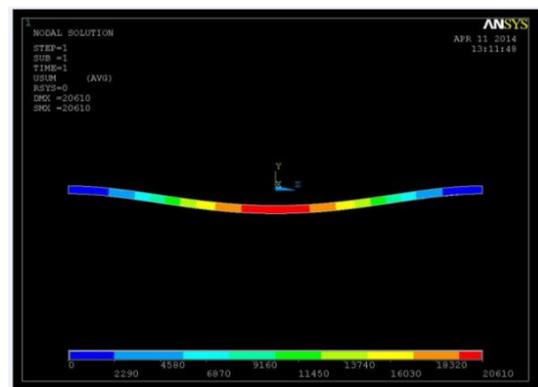


Figure 6.11 steel plate DOF 1

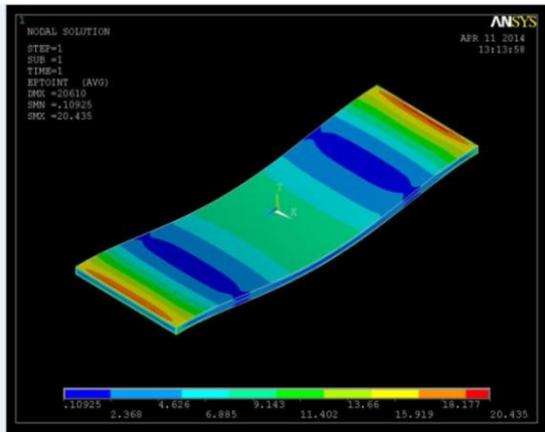


Figure 6.12 steel plate strain intensity

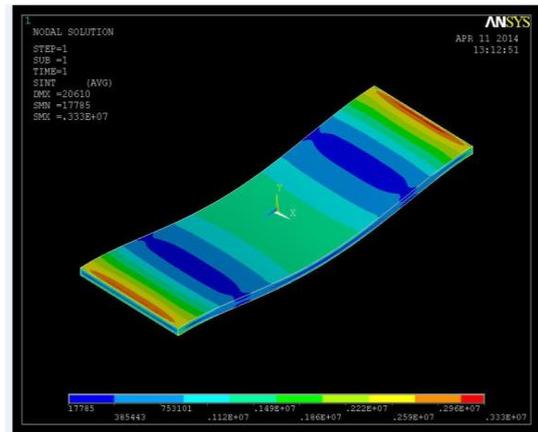


Figure 6.13 steel plate stress intensity

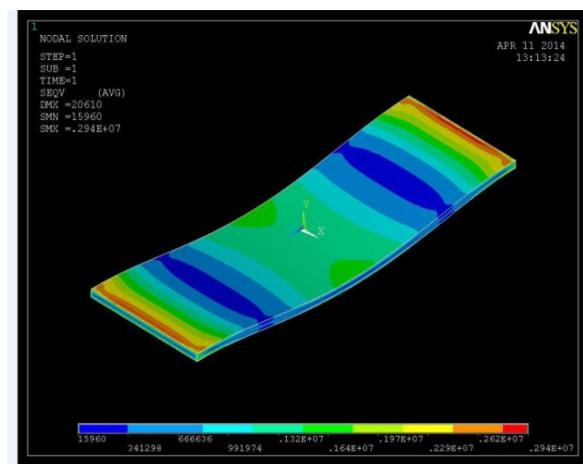


Figure 6.14 steel plate von mises stress

## VII. Conclusion

This study presented a new D-optimal set of laminates to model the artificial neural networks for predicting the deflection and stresses. The ANN predicted results are in very good agreement with the finite element results. Hence, the D-optimal design of experiments can be applied to any structural analysis.

The D-optimal set of laminates is not limited to 10 ply laminates for changing the ply thickness. It is applicable to laminates of any number of plies by changing the ply thickness. The effectiveness of the method is shown with predicting capability to deflection and stresses of laminated composite plates subjected to uniformly distributed load under simply supported boundary condition.

The two stage effort of obtaining the optimal stacking sequence by a new distance-based optimal design in design of experiments and artificial neural networks has resulted in fairly useful method for laminated composite plates. The following conclusions are drawn from the results for laminated composite material plates:

- The developed ANN model could predict the deflections and stresses ( $S_x$ ,  $S_y$ , and  $S_{xy}$ ) with an average percentage deviation of 0.028875%, 1.587178%, 2.119705% and 3.018923% respectively from training data set.
- The ANN model could predict the deflections and stresses ( $S_x$ ,  $S_y$ , and  $S_{xy}$ ) with an average percentage deviation of 6.132743%, 1.3096766%, 0.0945797% and 5.7492823% respectively from test data set.
- The ANN predicted results are very good agreement with the finite element results.
- For anti-symmetric laminated composite plates [45/-45]<sub>8</sub>, the non-dimensional deflection and transverse shear stress are lower compared to the symmetrical one.
- For anti-symmetric laminated composite plates [0/90]<sub>8</sub>, the Normal stress in x-direction is lower compared to the symmetrical one.

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