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Buckling optimization of laminated composite plate with elliptical cutout using ANN and GA

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Abstract. Buckling optimization of laminated composite plates is significant as they fail because of buckling under in-plane compressive loading. The plate is usually modeled without cutout so that the buckling strength is found analytically using classical laminate plate theory (CLPT). However in real world applications, the composite plates are modeled with cutouts for getting them assembled and to offer the provisions like windows, doors and control system. Finite element analysis (FEA) is used to analyze the buckling strength of the plate with cutouts and it leads to high computational cost when the plate is optimized. In this article, a genetic algorithm based optimization technique is used to optimize the composite plate with cutout. The computational time is highly reduced by replacing FEA with artificial neural network (ANN). The effectiveness of the proposed method is explored with two numerical examples.

Keywords: sacking sequence optimization; artificial neural network; genetic algorithm; finite element analysis

1. Introduction

Fiber reinforced laminated composite plates are used in aerospace industries, automobile industries and other applications for their high stiffness to weight ratio and strength to weight ratio. They are generally subjected to in-plane compressive loading and fail due to buckling. The buckling strength of the rectangular composite plate are analytically computed using classical laminate plate theory and increased by optimally varying the ply angle, thickness, stacking sequence and loading conditions. In the last three decades various optimization techniques were used to obtain the optimum buckling strength of the rectangular composite plate without any cutout. Aymerich and Serra (2008) performed stacking sequence optimization to increase the buckling strength of the composite plate where conventional ply angles are used as the design variable and ant colony optimization is used as the optimization tool. Soremekun *et al*. (2001) carried out buckling optimization of the laminated plate using genetic algorithm. Ozgur and Sonmez (2005) implemented direct simulated annealing based buckling optimization to maximize the buckling strength of the composite plate. Topal and Uzman (2007) used MFD method to

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maximize the buckling strength of laminated plates. Rao and Arvind (2005) carried out thermal buckling optimization of laminated composite plates using scatter search algorithm. Sebaey *et al*. (2011), Nicholas *et al*. (2012) have increased the design space by replacing the conventional ply angle with dispersed layer angle and proved that the buckling strength can be highly increased. In all these works the rectangular laminated plate without any cutout is chosen and the buckling strength is analytically calculated using classical laminate plate theory.

In real world applications it is indispensable to design the composite plate with holes in order to assemble them and to function as doors, windows, or access ports. Qablan *et al*. (2009) stated that cutouts are necessary for accessibility reasons and to reduce the weight of the structure. Liu *et al*. (2006) indicated that the design of interior cutouts in laminated composite panels is of great importance in aerospace, automobile and structural engineering. Lopes *et al*. (2010) mentioned that cutouts on composite panels are required to accommodate windows, doors, and bolted joints. If the plates are modeled with cutouts, then finite element analysis is required to analyze them. Komur *et al*. (2010) referred that cutouts are generally used in composites as design necessities and used finite element method to study the effect of cutout shape on buckling strength. He observed that the elliptical cutout is the best and square cutout is the worst cutout type. Ahmet Erklig *et al*. (2013) used finite element analysis and studied the effects of various cutout shapes on the lateral buckling behavior of composite beams. Qablan *et al*. (2009) assessed the influence of several factors like size and location of cutout, fiber orientation angle and loading type on the buckling load of cross-ply laminated plates with cutouts using FEM.

Even though many works were done on buckling analysis of composite structure with cutouts, very few works were done on optimization of plates with cutout for finite element analysis is to be inserted in optimization procedure. These works are also limited with less design space due to the high computational time. Iyengar and Vyas (2011) carried out optimization to obtain maximum buckling load by varying design variables ply thickness, ply angle and stacking sequences. The design space is restricted with the ply angles ±60°, ±45°, ±30°, 0°/90°. Yi Liu *et al*. (2006) performed fixed grid optimization for the shape optimization of multiple interior cutouts. The work was limited with $[\theta/-\theta]_{2s}$ stacking sequences. Rocha *et al*. (2014) optimized the laminated composite structure using FEA and hybrid distributed memory parallel genetic algorithm. Lopes *et al*. (2010) optimized composite panels with cutout where the work is limited with the stacking sequence consists $[\theta/-\theta]_{6s}$. Hu and Wang (1992) optimized for buckling resistance of laminated shells with or without cutouts. Sivakumar *et al*. (1998) found the optimum design of the laminated composite plate in the presence of elliptical cutouts using FEM. In all these works, FEA is used to find the fitness value and this leads to high computational cost. This computational cost can be reduced by using neural network as the prediction tool. Zheng *et al*. (2009) used wavelet neural network to estimate the delamination locality. Mahmut (2011) used artificial neural network (ANN) for the buckling analysis of slender prismatic columns.

1.1 Research gap and problem identification

It is observed from the literature review that many research works were done on stacking sequence optimization of composite laminated plate without cutout in order to increase the buckling strength of the structure. However the cutout must be made on composite plate when they are used for the real world applications. Further it is revealed that the cutout shape, dimension and location have the impact on buckling strength of the plate. It is also exposed that the analysis of plate with cutout requires FEA and it consumes more time. Due to this, very less amount of work

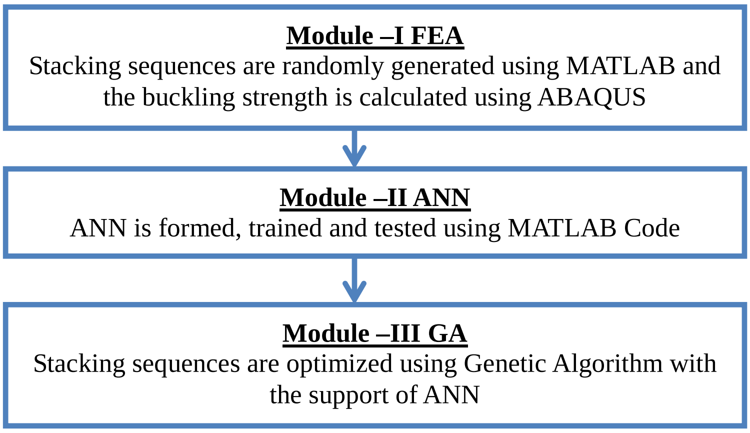


Fig. 1 Proposed method

was done on buckling optimization of composite plate with cutouts and those works were also limited with less design space due to the computational cost. It has been proved that the buckling strength of the plate can be increased without violating the weight of the structure by increasing the design space. Therefore this paper applies an efficient and less time consuming method to optimize the composite plate with cutout.

The method comprises three modules as shown in Fig. 1. In the first module, the stacking sequences of laminated plate with elliptical cutout are randomly generated from the available design space with the help of MATLAB code and the buckling strength of each configuration is evaluated using the commercial FEA software ABAQUS 6.12. In the second module, the neural network (ANN) structure is formed using MATLAB code and is trained and tested by the samples generated in the first module. Finally, genetic algorithm is used as the optimization tool where the trained ANN is used to predict the fitness value.

2. Problem definition and solution methodology

2.1 Problem definition

In real world applications the laminated composite plates are made with cutouts. The cutout location, shape and size will affect the buckling strength of the plate. With this in mind, the rectangular composite plate with central elliptical cutout is chosen to maximize the buckling strength. The simply supported boundary conditions and equal magnitude compressive loads are applied on all the four sides of the plate. The symmetric assumption of the plate reduces half of the design variables. The ply angle, stacking sequence and cutout orientation are chosen as the design variables and the in-plane strength of the structure is set as design constraint. With the intention of obtaining the superior design, the design space of the optimization is increased by reducing the ply angle interval. The objective function of the problem is defined as given in Eq. (1).

$$\textit{Maximize the buckling strength, } \lambda = f(\theta, \alpha)$$
$$\textit{such that } \theta = \{\theta_1, \theta_2, \theta_3, \ldots, \theta_n\}$$

$$-90^\circ \le \theta_i \le 90^\circ, i = 1,2,3,...n$$
$$0^\circ \le \alpha \le 90^\circ \quad (1)$$

2.2 Finite element analysis and data generation

When the geometry of a structure is irregular or made with cutout arbitrarily then the structure must be analyzed using FEA. The commercial FEA software ABAQUS is used here to find the buckling strength of the plate. The plate is modeled with four nodes shell element S4R as shown in Fig. 3. Each node of the element has six degrees of freedom. The bi-axial compressive load is applied along the edges. The training and testing data for ANN are equipped by randomly generating the stacking sequences and the cutout orientations form the given design space. The buckling strength of each configuration is computed using ABAQUS. MATLAB code is used to generate the stacking sequences randomly and python script is used to interface ABAQUS with MATLAB.

2.3 Artificial neural network

Artificial neural network is generally used as a prediction tool in the applications where the

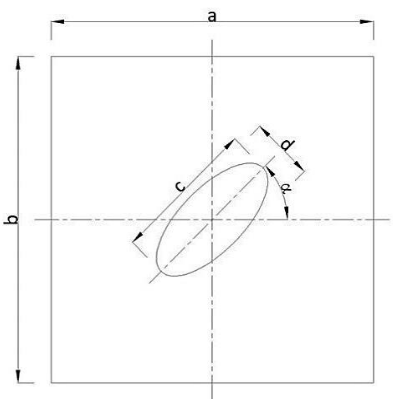


Fig. 2 Geometry of the model

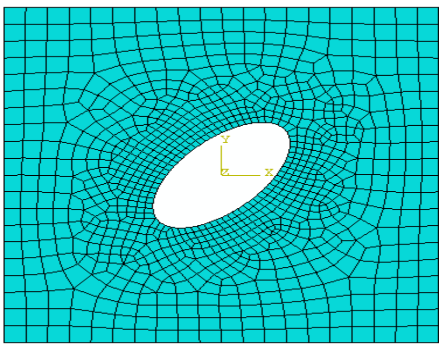


Fig. 3 Finite element model of the composite plate

opportunities to analyze the actual target are time consuming or not available. As the design space of this work is enlarged and FEA is required to analyze the structure, ANN is used here to predict the fitness value in genetic algorithm based optimization. A multilayer feed-forward back-propagation neural network is used. The neural network is built in four stages. In the first stage, the sample data with their targets are collected. The network object with suitable neuron in each layer, number of layers, transfer function for each layer and the training algorithm of the network are chosen in the second stage. The created network is trained in stage three with the samples generated in stage one. The network is tested in stage four with the remaining samples and after the satisfaction of the performance of the network with these test samples, the network is simulated for the new inputs.

The performance of neural network during the training and after the training depends upon the choice of numbers of hidden layers, neurons, training algorithm and transfer function. Yuen and Lam (2006) mentioned that these parameters have to be decided based on the experience or rule of thumb only. Tomislav *et al*. (2014) have obtained the network structure by optimally varying these parameters. In this paper, the network objects are decided by trial and error method as Kermanshashi and Iwamiya (2002), Chakraborty (2005) have done in their work. The network is constructed with three layers in which the first layer is an input layer followed by a hidden layer and an output layer. The inputs and the targets are normalized between −1 to 1. Tan-sigmoid transfer function is used for the first two layers and linear transfer function is used for the last layer. Fletcher-Reeves conjugate gradient training algorithm is used for this network which updates weight and bias values based on conjugate gradient back-propagation. Usually the network will memorize the training and testing samples and function well during the training but when the same network is used for the newly generated data, there may be possibilities of over fitting. Demuth *et al*. (2000) has suggested a method called regularization in order to improve the generalization of the network. In this method, the mean square error performance function is modified and added with the mean squared weights and biases of the network. This modified performance function suggested by Demuth *et al*. (2000) is given in Eq. (2). It permits the network to have smaller weights and biases and reduces the possibilities of over fitting. The performance ratio (γ) varies from 0 to 1 and has to be chosen by trial and error method. When performance ratio is closer to one, the performance function behaves like the mean square error performance function and it leads to over fitting. When it is reduced to very small, it ignores the mean square error so that the network may not effectively fit the training samples. The various objects of network obtained by trial and error method are shown in Table 1.

$$msereg = \gamma\ (mse) + (1-\gamma)\ msw \tag{2}$$

2.4 Genetic algorithm

Genetic algorithm, which has been proved as the preeminent optimization tool by many researchers in the field of optimization of laminated composite, is chosen for this work. The genetic algorithm develops the optimal design with the operators known as selection, crossover, and mutation. At first, the initial population of size '*N*' is generated randomly and their fitness values are evaluated. The succeeding generations are fashioned by picking the parents from the current population based on their ranks and subsequently applying the genetic operators. Roulette wheel selection is used as the selection operator to pick the healthy chromosomes to accomplish crossover and mutation in order to yield the offspring. The crossover operator is used to combine

Table 1 Architecture of ANN

α	Neurons in Each layer	Transfer function	Training Algorithm	Performance function	γ
15°	15-25-1	Tansig-Tansig-Linear	Fletcher-Reeves conjugate gradient algorithm	msereg	0.1
30°	15-25-1	Tansig-Tansig-Linear	Fletcher-Reeves conjugate gradient algorithm	msereg	0.1
45°	15-25-1	Tansig-Tansig-Linear	Fletcher-Reeves conjugate gradient algorithm	msereg	0.1
60°	15-25-1	Tansig-Tansig-Linear	Fletcher-Reeves conjugate gradient algorithm	msereg	0.1
75°	15-25-1	Tansig-Tansig-Linear	Fletcher-Reeves conjugate gradient algorithm	msereg	0.1
90°	15-25-1	Tansig-Tansig-Linear	Fletcher-Reeves conjugate gradient algorithm	msereg	0.1

Table 2 Material properties of the carbon/epoxy composite

Property	Values
E_1	133.86 GPa
E_2=E_3	7.706 GPa
G_{12}=G_{13}	4.306 GPa
G_{23}	2.76 GPa
$\upsilon_{12} = \upsilon_{13}$	0.301
υ_{23}	0.396

two parent chromosomes to produce the new chromosomes called offspring. After the crossover, mutation takes place to avoid the population from stagnating at any local optima. Since the design variable is a discrete one in this work, a real coded genetic algorithm is used. The uniform crossover and mutation operators are applied. The uniform crossover operator permits the parent chromosomes, to be mixed at gene level rather than the segment level. The uniform mutation operator used here interchanges the value of the selected gene with a uniform random value selected between the upper and lower limits for that gene. The stacking sequence and the orientation of the cutout of the plate are taken as design variables and are optimized to maximize the buckling strength which is the objective function of the problem.

3. Numerical results and discussion

In order to show the efficacy of the suggested method two numerical examples are considered. The carbon/epoxy composite (AS4D/9310) of size 1000 mm×1000 mm with the material properties listed in Table 2 is used for this work. The plate is assumed made up of 24 layers of uniform thickness 1.25 mm.

3.1 Validation of finite element analysis

As the structure is divided into small elements in FEA, only the approximate solution shall be obtained and the accuracy of this approximate solution can be increased in various ways like increasing the number of elements or the polynomial order. When the size of element is decreased, the number of nodes are increased and also the computational time. Therefore it is important in FEA to find the optimum number of elements to be used for a specific problem. This is done here with the graph shown in Fig. 4 where the result is converged by increasing the number of elements and it is observed that the optimum number of elements for this problem is 5000. After fixing the number of elements, it is essential to verify the entire procedure of FEA including the boundary conditions. It is accomplished by obtaining the solutions for 50 samples using ABAQUS and also the analytical method. The buckling strength formula is analytically derived using CLPT as given in Eq. (3).

$$\lambda(m,n)=\frac{D_{11}p^4+2(D_{12}+2D_{66})p^2q^2+D_{22}q^4}{p^2+kq^2} \tag{3}$$

where $p=\frac{m\pi}{a}, q=\frac{n\pi}{b}$.

The results obtained analytically and using FEA are plotted in Fig. 5 and it shows that the FEA results are very close to the actual results.

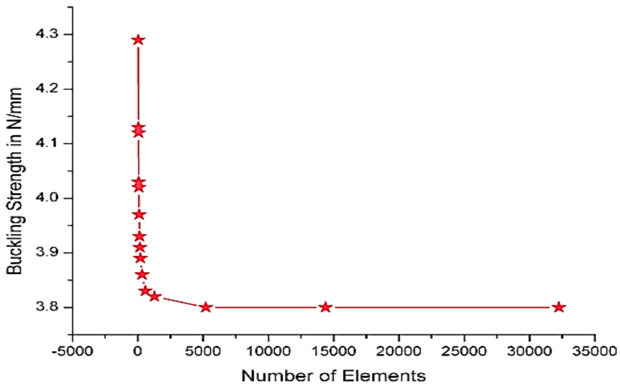


Fig. 4 Convergence of number of elements

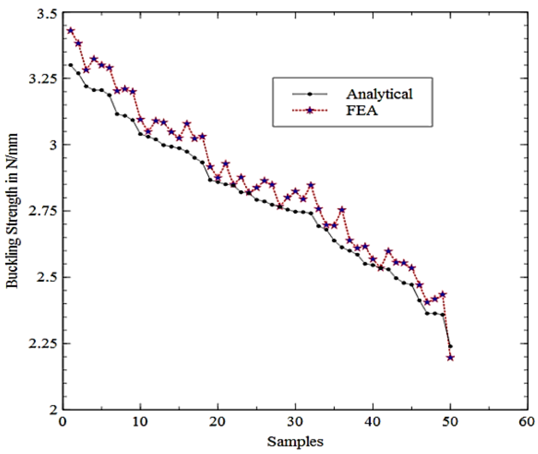


Fig. 5 Validation of FEA

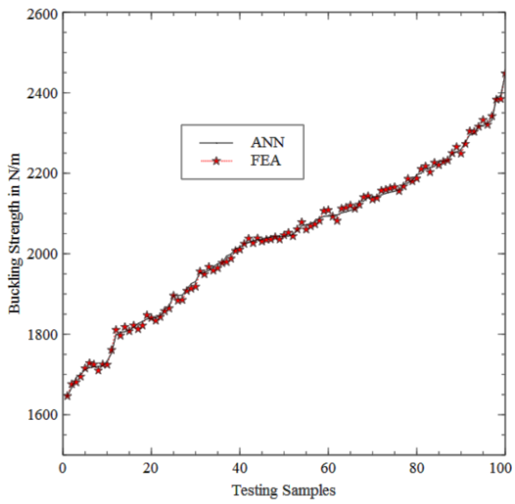


Fig. 6 Predicted values Vs. Actual targets

Table 3 Validation of GA

Ply angle interval	Stacking Sequence		Buckling Strength in N/mm	
	SA (Ozgur 2005)	GA	SA	GA
45°	$[90_{10}/\pm 45_2/90_2/\pm 45_3/90_2/\pm 45_4]_s$	$[90_6/\pm45/90_4/\pm45/(90_2/\pm45)_3/90_4/\pm45]_s$	3973.01	3976.5
30°	$[90_5/60/90/60/90/60/90/60_6/90_2/60_8/90/60_2/90/60]_s$	$[90_3/-60_3/90/60/-60/90_4/60/-60/90_2/60_2/-60/90/-60/60/90/60_4/90_3]_s$	4080.08	4083.8
15°	$[75_3/60/75_3/60/75_{10}/60/75_8/60/75_2/60_2]_s$	$[75/-75/75_3/-75_2/60/-75_2/75_2/-60/-75_2/75_2/-60/75/90/60/-60/60_3/-75_2/90/75/-60_2/-45]_s$	4114.81	4114.3
10°	$[70/80/70_4/80/70_2/80/70_3/80/70_4/80_4/70_2/80_2/70/80/70/90/70/60]_s$	$[-70_2/70/80/70/-70_2/70_2/-70/80/-80/70/-80_2/90/-80/80/-70/60/80/-70_2/80/-70/70/-60/-80/60/70/50/-70]_s$	4123.28	4125.3
5°	-	$[75/-70/-65/-75/-70/90/-75/-70/-75_2/-70/-80/-70/-80/-65_2/70/-70/-80/85/-85/-70/-60/55/85/-70/65/85/-30/-60/85/70]_s$	-	4126.2

3.2 Validation of neural network

Now the plate is modeled with elliptical cutout and the sample data are generated randomly using MATLAB code. The ANN is structured using MATLAB with the details given in Table 4 and is trained with 85% of sample data. The network is tested with the remaining samples and a graph is plot in Fig. 6 between the predicted values and actual targets. The results show that the prediction of output is nearer to the actual targets.

Table 4 GA control parameters

GA Control Parameters	
Population size	60
Number of generations	300
Crossover probability	0.85
Mutation probability	0.03
Mixing ratio in crossover	0.6

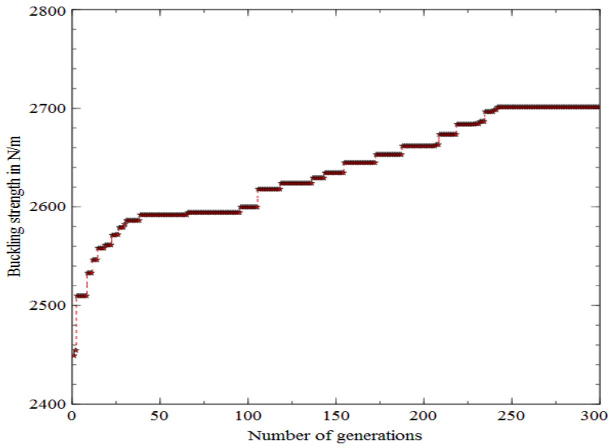


Fig. 7 Optimum results for stacking sequence optimization

3.3 Validation of genetic algorithm

The work done by Ozgur (2005) is taken and the same problem is optimized here using genetic algorithm and the results obtained for various ply angle interval are compared in Table 3. The results show that the proposed algorithm is able to find the optimum design even in a large design space. It is also found that the buckling strength can be increased significantly by reducing the ply angle interval. The control parameters used for the genetic algorithm is listed in Table 4.

3.4 Stacking sequence optimization

In the first example, an elliptical cutout of size 400 mm×200 mm is made at the center of the plate with the orientation of 60°. The buckling strength of the plate is maximized by optimally varying the stacking sequences. Due to symmetry, the ply angles of the first 12 layers are chosen as the design variables. The ply angle interval is kept 5° which makes the design space with 3712 possible designs. MATLAB code is used to generate stacking sequences randomly and the buckling strength of those configurations is found using the python script written for ABAQUS. ANN is trained by 85% of the samples and tested by the remaining 15% of the samples. The correlation coefficient (R) between the predicted values and actual targets is 0.998 and this shows that the prediction of ANN is very close to actual outputs. Now the ANN is used as a prediction tool to evaluate the fitness value in genetic algorithm based optimization. A graph is plotted in Fig. 7 between the optimum results obtained and number of generations. It is observed that the results

Table 5 Comparison of results obtained for 5° ply interval

Optimum stacking sequences	Buckling strength in N/m		Percentage of error
	ANN prediction	Actual target	
$[40/-45/40/-50/50/65/-70/-55/-45/-5/-5/25]_s$	2701.18	2601.7	3.68
$[45/-45/40/-50/50/65/-70/-55/-45/-5/-5/60]_s$	2698.42	2598.5	3.70
$[45/-45/40/-50/50/65/-70/-55/-45/-5/-5/65]_s$	2696.467	2600.7	3.55
$[45/-45/45/-45/45/60/-80/-60/-65/85/-80/-15]_s$	2668.526	2574.7	3.51
$[45/-45/40/-50/50/65/-80/-55/-45/-5/-40/-50]_s$	2661.437	2560.7	3.78

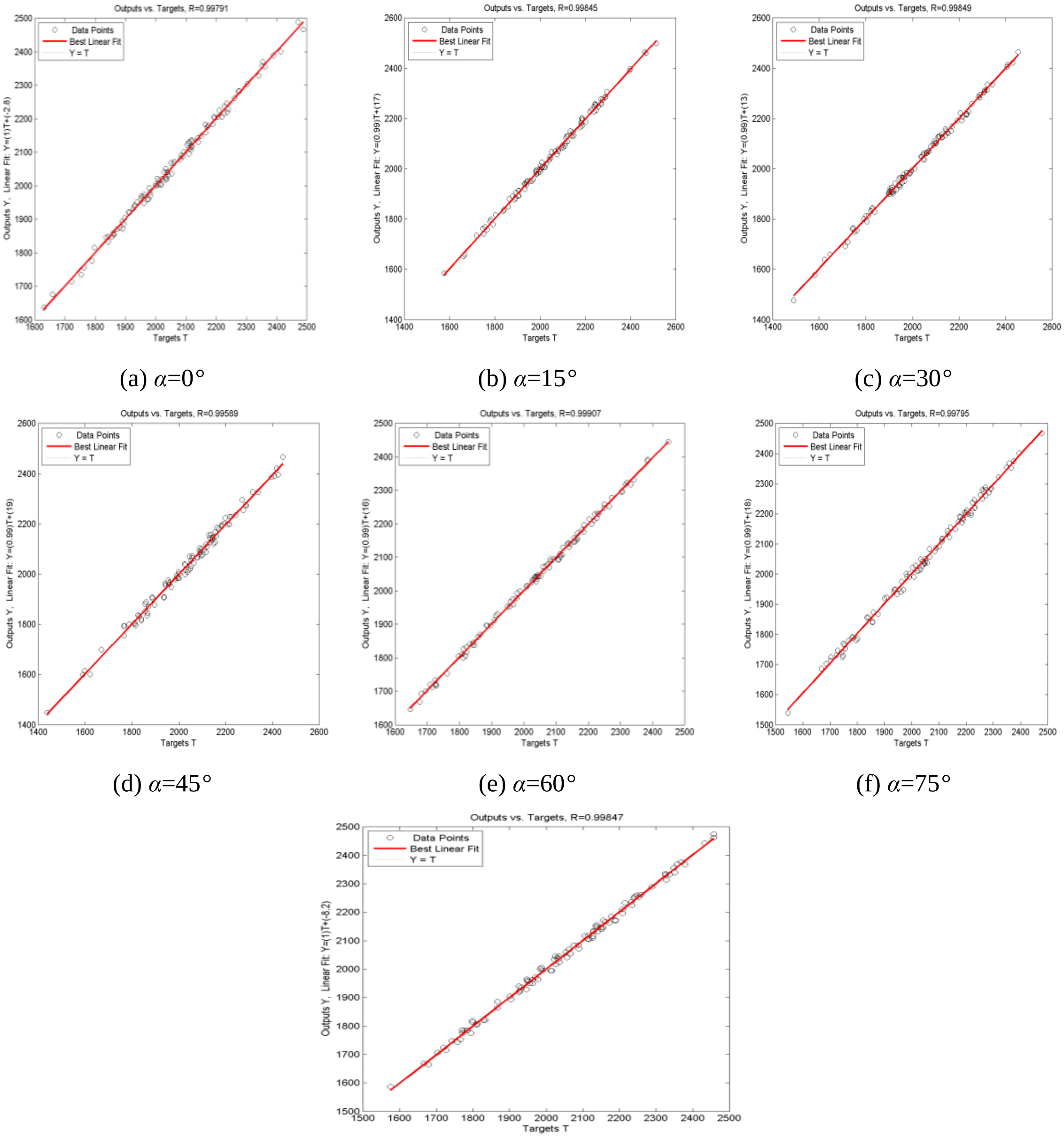
Table 7 Cutout orientation and stacking sequence optimization results

Cutout orientation	Optimum Stacking Sequence	Buckling Strength in N/mm
0°	[45,40,-45,40,-45,-45,-45,50,-40,-5,0,85]s	2640
15°	[35,45,-30,55,-35,-40,-40,50,-30,-25,35,-80]s	2645
30°	[35,45,-30,55,-35,-40,-40,50,-30,-25,35,-40]s	2653
45°	[40,-45,55,50,-25,-45,40,-15,85,30,-70,55]s	2659
60°	$[40/-45/40/-50/50/65/-70/-55/-45/-5/-5/25]_s$	2701
75°	[-60,45,-50,45,70,-50,45,25,5,85,-55,-50]s	2679
90°	[-45,45,-50,45,45,-50,50,55,-55,70,5,0]s	2681

are converged after 250 generations and each generation works with 60 populations. If FEA is used to find the fitness value, ABAQUS might be called more than 15,000 times and each run will consume approximately 9 seconds. Therefore more than 37 hours are needed to carry out this optimization process with the help of FEA. However the same work is finished here with the support of trained ANN which takes less than 15 minutes. Though the building of ANN takes around 4 hours as the training samples are to be generated using FEA, the weighs and biases of the trained network can be saved and will be used in future without any further training. The optimum designs are listed in Table 5 and are verified by FEA so as to find the error in ANN prediction. It is found that ANN prediction is very close to the actual values and the percentage of error is less than 4%.

3.4 Cutout orientation and stacking sequence optimization

Orientation of the cutout is also included as the design variable in the second example as it has the effect on buckling strength (Qablan 2009). The orientation of the cutout is varied from 0° to 90° with the increment of 15°. ANN structure is segmented into seven different networks and is trained by the data of seven different cutout orientations. The performance of ANN in testing period for each cutout orientation is shown in Fig. 8. The results show that the correlation factor between predicted values and actual target (R value) ranges from 0.996 to 0.999 so that the predicted outputs are very close to the actual targets in each network. The genetic algorithm uses the appropriate network to predict the fitness value based on the cutout orientation generated during the optimization process. The optimum stacking sequences obtained in each cutout orientation with their buckling strength are listed in Table 7. It is observed from the results that the optimum results are obtained in all cutout orientations with the same buckling strength. The stacking sequences are altered based on the cutout orientation of the plate.



(a) α=0° (b) α=15° (c) α=30°

(d) α=45° (e) α=60° (f) α=75°

(g) α=90°

Fig. 8 Performance of ANN in testing period

4. Conclusions

Cutouts are indispensable when the laminated composite plates are used for the real world applications and finite element analysis is required to compute the buckling strength of the structure with cutouts. The design variables stacking sequence, ply angle and cutout orientation are optimized to maximize the buckling strength. Inclusion of FEA in optimization procedure increases the computational cost and this problem has been resolved in this article by replacing FEA with artificial neural network. MATLAB code has been used to build ANN structure and python script for ABAQUS was used to interface ABAQUS with MATLAB. The trained ANN structure has been used to model the buckling strength of the composite plate in genetic algorithm based optimization. Numerical examples were used to validate the performance of FEA, ANN and GA. The results have shown that the correlation factor of ANN (R-value) was above 0.996 and the predictions of ANN were very close to actual targets. It has also been proved that the buckling strength of the structure can be increased about 5% by replacing the conventional ply angle with the reduced ply angle interval. Further the computational cost of the optimization process is reduced from several hours to few minutes with this proposed methodology.

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PL

Nomenclature

a, b - major and minor dimensions of the plate
α - orientation of cutout with major reference axis
λ - buckling strength of the plate
θ - stacking sequence of the plate
θ_i - angle of layer i from mid-plane
l - number of layers
m,n - number of half waves along major and minor axes
D_{ij} - bending stiffness matrix
N_{xx} - compressive load along major axis
N_{yy} - compressive load along minor axis
k - load ratio, $k = \frac{N_{yy}}{N_{xx}}$
A - population size
N - maximum number of generations
mse - mean square error, $mse = \frac{1}{N}\sum_{i=1}^{N}(t_i - a_i)^2$
msw - mean of the sum of squares of the network weights and biases, $msw = \frac{1}{n}\sum_{k=1}^{n} w_k^2$
γ - performance ratio