

A Hybrid Radial-Based Neuro-GA Multiobjective Design of Laminated Composite Plates under Moisture and Thermal Actions

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Abstract—In this paper, the optimum weight and cost of a laminated composite plate is sought, while it undergoes the heaviest load prior to a complete failure. Various failure criteria are defined for such structures in the literature. In this work, the Tsai-Hill theory is used as the failure criterion. The theory of analysis was based on the Classical Lamination Theory (CLT). A newly type of Genetic Algorithm (GA) as an optimization technique with a direct use of real variables was employed. Yet, since the optimization via GAs is a long process, and the major time is consumed through the analysis, Radial Basis Function Neural Networks (RBFNN) was employed in predicting the output from the analysis. Thus, the process of optimization will be carried out through a hybrid neuro-GA environment, and the procedure will be carried out until a predicted optimum solution is achieved.

Keywords—Composite Laminates, GA, Multi-objective Optimization, Neural Networks, RBFNN.

I. INTRODUCTION

STRUCTURAL optimization is a process by which the optimum design is aimed while satisfying all the defined constraints. In recent years, using laminated composite materials in fabrication of mechanical, aerospace, marine and machine industries are of major concern, due to their high strength and light weight.

The multi-objective function introduced here consists of weight, cost and failure loading. Thus, the weight and the cost will be minimized while the failure load for all the laminated plies is to be maximized.

The design variables could be any combination of thickness, orientation of fibers and the material for each layer. The thickness of the layers could be considered continuous whereas the cost and the material type for each layer to be discrete. Software development was then aimed for the analysis and the optimum design of laminated composite plates under any combination of design parameters. The process of optimization will be carried out through a hybrid neuro-GA environment, and the procedure will continue until a predicted optimum solution is reached.

The most common basis of the RBF is a Gaussian kernel function. The name RBF comes from the fact that these Gaussian kernels are radially symmetric; that is, each node produces an identical output for inputs that lie a fixed radial

distance from the centre of the kernel. Having linked the RBFNN to the optimizer, a number of problems were then attempted, and recorded. Verification of the results indicate that composite laminates with a considerably reduced weight and cost may resist very large loads, and that neural networks have a major role in reducing time of optimization process.

II. MULTI-OBJECTIVE OPTIMISATION

Multi-objective optimization is a process by which a vector of design parameters like $x^* = [x_1^*, x_2^*, \dots, x_n^*]$ will be sought so that it satisfies m inequality constraints $g_i(x) \geq 0$ and p equality constraints $h_j(x) = 0$ while optimising an objective function $f(x) = [f(x_1), f(x_2), \dots, f(x_n)]^T$. In this paper, the goal is to minimize weight and cost of a laminated composite plate while maximizing its failure load. Therefore a multi-objective optimization process will be carried out such that $f(x) = [weight(x), cost(x), failureload(x)]$.

III. ANALYSIS OF LAMINATED COMPOSITE PLATES

Composite laminates are considered as orthotropic materials. An orthotropic body has material properties that are different in three mutually perpendicular directions at a point in the body and, further, have three mutually perpendicular planes of material symmetry. Thus, the properties are a function of orientation at a point in the body. Because of their low thickness sizes, they can be modeled as shells.

A. Strain-Stress Relations in an orthotropic material

the lamina in the 1-2 plane of Figure (1), a plane stress state is defined by setting

$$\sigma_3 = 0 \quad \tau_{23} = 0 \quad \tau_{31} = 0 \quad (1)$$

Thus, using (1), strain-stress relations can be formulated as in (2)

$$\begin{Bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \gamma_{12} \end{Bmatrix} = \begin{bmatrix} S_{11} & S_{12} & 0 \\ S_{12} & S_{22} & 0 \\ 0 & 0 & S_{66} \end{bmatrix} \begin{Bmatrix} \sigma_1 \\ \sigma_2 \\ \tau_{12} \end{Bmatrix} \quad (2)$$

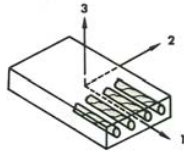


Fig. 1 Unidirectional reinforced lamina.

where

$$S_{11} = \frac{1}{E_1}; S_{22} = \frac{1}{E_2}; S_{12} = -\frac{\nu_{12}}{E_1} = -\frac{\nu_{21}}{E_2}; S_{66} = \frac{1}{G_{12}} \quad (3)$$

B. Stress-Strain Relations for a lamina of arbitrary orientation

For a set of lamina that is in x-y plane and its principal directions are in 1-2 plane as in Figure(2), using Transformation matrix, the stress relation is

$$\begin{Bmatrix} \sigma_x \\ \sigma_y \\ \tau_{xy} \end{Bmatrix} = [T]^{-1} \begin{Bmatrix} \sigma_1 \\ \sigma_2 \\ \tau_{12} \end{Bmatrix} \quad (4)$$

where $[T]$ is the Transformation Matrix.

$$[T] = \begin{bmatrix} \cos^2 \theta & \sin^2 \theta & 2 \sin \theta \cos \theta \\ \sin^2 \theta & \cos^2 \theta & -2 \sin \theta \cos \theta \\ -\sin \theta \cos \theta & \sin \theta \cos \theta & \cos^2 \theta - \sin^2 \theta \end{bmatrix} \quad (5)$$

Similarly the strain relation will be obtained as

$$\begin{Bmatrix} \epsilon_x \\ \epsilon_y \\ \frac{\gamma_{xy}}{2} \end{Bmatrix} = [T]^{-1} \begin{Bmatrix} \epsilon_1 \\ \epsilon_2 \\ \frac{\gamma_{12}}{2} \end{Bmatrix} \quad (6)$$

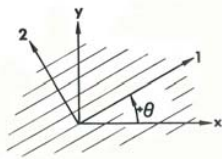


Fig. 2 Positive rotation of principal axes from arbitrary x-y axes.

However, if the matrix R is defined as

$$[R] = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 2 \end{bmatrix} \quad (7)$$

using (4) to (7), it will lead to the following relation.

$$\begin{Bmatrix} \sigma_x \\ \sigma_y \\ \tau_{xy} \end{Bmatrix} = [T]^{-1} [Q] [R] [T] [R]^{-1} \begin{Bmatrix} \epsilon_x \\ \epsilon_y \\ \gamma_{xy} \end{Bmatrix} \quad (8)$$

Assigning $[T]^{-T} = [R][T][R]^{-1}$ and $[\bar{Q}] = [T]^{-1}[Q][T]^{-T}$ it

will lead to the following relation

$$\begin{Bmatrix} \sigma_x \\ \sigma_y \\ \tau_{xy} \end{Bmatrix} = [\bar{Q}] \begin{Bmatrix} \epsilon_x \\ \epsilon_y \\ \gamma_{xy} \end{Bmatrix} \quad (9)$$

where \bar{Q} is the transformed stiffness matrix [1].

C. Strength of an Orthotropic Lamina

Strength of a lamina is depended on fiber material the matrix and its fiber angle. In composite laminates we have three principal strengths, as shown in Figure (3), namely X as the axial or longitudinal strength, Y the transverse strength and S as the shear strength.

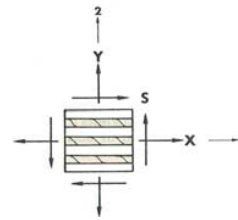


Fig. 3 Definition of fundamental strengths for unidirectional lamina.

If the material has unequal properties in tension and compression as do most composite materials, then the following strengths are required:

X_t = axial or longitudinal strength in tension, X_c = axial or longitudinal strength in compression, Y_t = transverse strength in tension, Y_c = transverse strength in compression and S = shear strength.

D. Tsai-Hill Theory

In this theory for orthotropic materials we have the relation

$$\left(\frac{\sigma_1}{X}\right)^2 - \left(\frac{\sigma_1 \sigma_2}{X^2}\right) + \left(\frac{\sigma_2}{Y}\right)^2 + \left(\frac{\tau_{12}}{S}\right)^2 = 1 \quad (10)$$

If σ is in compression, one should use X_c and Y_c , otherwise X_t and Y_t will be used.

E. Loads and Moments of Laminated Plates

Using Integration over thickness of a layer, Moments and Loads for each layer can be computed. Equation (11) shows the leading relation concluded:

$$\begin{Bmatrix} N \\ M \end{Bmatrix} = \begin{bmatrix} [A] & [B] \\ [B] & [D] \end{bmatrix} \begin{Bmatrix} \varepsilon^0 \\ \kappa \end{Bmatrix} \quad (11)$$

where $N = \{N_x, N_y, N_{xy}\}$ and $M = \{M_x, M_y, M_{xy}\}$ are loads and moments vectors. ε^0 and κ are strain and curvature of middle plane, respectively. $[A]$ is extensional stiffness matrix, $[B]$ is coupling stiffness matrix and $[D]$ is bending stiffness matrix.

F. Environmental Effects

Environmental effects change strength and stiffness of laminates and the matrix. In this paper two of the most important effects which are considered, are the thermal and moisture effects.

1. Thermal effects: If thermal changes are taken into account in layers, thermal loads and moments shown in Eq. (12) should be subtracted from (11)

$$\begin{Bmatrix} N_x^T \\ N_y^T \\ N_{xy}^T \end{Bmatrix} = \int \begin{bmatrix} \bar{Q}_{11} & \bar{Q}_{12} & \bar{Q}_{16} \\ \bar{Q}_{12} & \bar{Q}_{22} & \bar{Q}_{26} \\ \bar{Q}_{16} & \bar{Q}_{26} & \bar{Q}_{66} \end{bmatrix} \begin{Bmatrix} \alpha_x \\ \alpha_y \\ \alpha_{xy} \end{Bmatrix} \Delta T \cdot d_z$$

$$\begin{Bmatrix} M_x^T \\ M_y^T \\ M_{xy}^T \end{Bmatrix} = \int \begin{bmatrix} \bar{Q}_{11} & \bar{Q}_{12} & \bar{Q}_{16} \\ \bar{Q}_{12} & \bar{Q}_{22} & \bar{Q}_{26} \\ \bar{Q}_{16} & \bar{Q}_{26} & \bar{Q}_{66} \end{bmatrix} \begin{Bmatrix} \alpha_x \\ \alpha_y \\ \alpha_{xy} \end{Bmatrix} \Delta T \cdot z \cdot d_z \quad (12)$$

where z is the momental distance from the corresponding layer to the symmetrical plane. ΔT is temperature difference, α_x and α_y are coefficients and α_{xy} is shear coefficient of thermal expansion.

2. Moisture effects: Assigning Δc as moisture difference, similarly one can conclude that

$$\begin{Bmatrix} N_x^M \\ N_y^M \\ N_{xy}^M \end{Bmatrix} = \int \begin{bmatrix} \bar{Q} \\ \bar{Q} \\ \bar{Q} \end{bmatrix} \begin{Bmatrix} \beta_x \\ \beta_y \\ \beta_{xy} \end{Bmatrix} \Delta c \cdot d_z$$

$$\begin{Bmatrix} M_x^M \\ M_y^M \\ M_{xy}^M \end{Bmatrix} = \int \begin{bmatrix} \bar{Q} \\ \bar{Q} \\ \bar{Q} \end{bmatrix} \begin{Bmatrix} \beta_x \\ \beta_y \\ \beta_{xy} \end{Bmatrix} \Delta c \cdot z \cdot d_z \quad (13)$$

Having completed formulations for the analysis, in the next section, the optimization technique used in this study, based on Genetic Algorithm, will be defined.

G. Developed Analysis Program

In this study, the analysis program, emphasizing on the moisture and thermal effects, was developed. The validity of the developed program was also compared and well matched with the commercial program LAMINATOR.

There after, the idea was to determine the failure load by which all the layers one by one fail to respond. In this case, one can simply say that the maximum failure load is met. Figure (4) issues the above statement graphically.

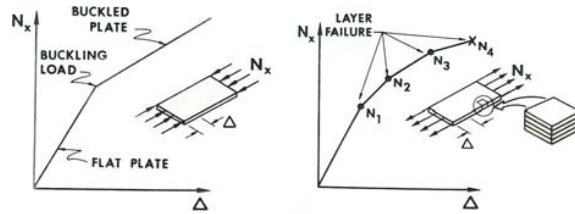


Fig. 4 Analogy between buckled plate and laminate load-deformation behavior.

IV. GENETIC ALGORITHM

In this research we use Genetic Algorithm (GA) for a multi-objective optimization of composite laminates, where weight, cost and failure loads for the laminated composite plates are interconnected. The design parameters are angle of fibers (θ), layer thickness sizes (t) and material types (M) for each layer.

A. Mathematical Model

1. Objective Function: The multi-objective function used contains three major terms as in (14):

$$\varphi = \left(1 + \frac{W}{W_{\max}}\right)^2 + \left(1 + \frac{C}{C_{\max}}\right)^2 + \frac{\left(2 - \frac{N_x}{N_{x\max}}\right)^2 + \left(2 - \frac{N_y}{N_{y\max}}\right)^2 + \dots + \left(2 - \frac{M_{xy}}{M_{xy\max}}\right)^2}{nl} \quad (14)$$

where φ is the goal function, W is weight of all layers, W_{\max} is maximum weight that layers can possess, C is cost of all layers, C_{\max} is maximum cost that layers may contain, N_x, N_y, \dots, M_{xy} are failure loads and moments for all layers, $N_{x\max}, N_{y\max}, \dots, M_{xy\max}$ are the maximum failure loads and moments, and nl is number of loads applied to the structure. For example if only N_x and M_x applied to the plate, then $nl=2$.

Computation of the fixed value W_{\max} was made by choosing maximum thickness and heaviest material for all layers. Similarly, C_{\max} was computed by assigning the maximum thickness, and relatively most expensive materials for all layers which according to the list available in Reference [5], it will be the case when $\theta=45$.

And finally calculation of $N_{x_{max}}, N_{y_{max}}, \dots, M_{xy_{max}}$, will be set by choosing maximum thickness, strongest materials and adapted θ with location of loads and moments.

2. *Constraints*: To enable a rather faster convergence to the optimum solution, some constraints are introduced. Thus, after the process of analysis of each individual belong to each generation, if any of the designs had failure loads and moments less than 15% of maximum computed loads and moments or being heavier than 45% of maximum weight or even found to be more expensive than 45% of maximum cost of the plate, they will not be allowed to breed and will automatically be replaced by another randomly generated individual which satisfies all the constrains as listed in (15):

$$\begin{aligned} (FailureLoad)_{ipop} &\geq 0.15(FailureLoad)_{max} \\ (FailureMoment)_{ipop} &\geq 0.15(FailureMoment)_{max} \\ (Weight)_{ipop} &\leq 0.45(Weight)_{max} \\ (Cost)_{ipop} &\leq 0.45(Cost)_{max} \end{aligned} \quad (15)$$

where the subscript *ipop* indicates one design of a population, and the subscript *max* refers to the maximum possible value of that parameter.

B. Genetic Operators

There are available catalogue lists of 12 fiber angles, 13 layer thicknesses and 15 material types where the three different design variables are chosen from. They are listed in the tables I, II and III.

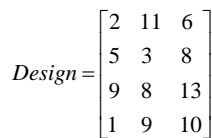


Fig. 5 sample Design

Figure (5) shows one sample design of a generation. Columns one, two and three of this design, correspond to θ , t and M , respectively. This design has 4 rows and it means that there are 8 layers available for this design. That is because of symmetry, which means there are only four layers to be shown. Numbers in this matrix must change using tables I, II and III. For example θ , t and M for layer 2 of this design is 60 deg., 0.1cm and AS4/5250-3, respectively.

TABLE I
CATALOGUE LIST OF FIBRE ANGLES

θ	1	2	3	4	5	6
deg	0	15	30	45	60	75
θ	7	8	9	10	11	12
deg	90	-15	-30	-45	-60	-75

TABLE II
CATALOGUE LIST OF LAYER THICKNESSES

t	1	2	3	4	5	6	7
cm	0.06	0.08	0.1	0.12	0.14	0.16	0.18
t	8	9	10	11	12	13	
cm	0.2	0.22	0.24	0.26	0.28	0.3	

TABLE III
CATALOGUE LIST OF MATERIAL TYPES

M	Material name
1	T300/5208
2	T300/934
3	T300/976
4	AS/3501
5	AS4/3501-6
6	AS4/3502
7	AS4/APC2
8	AS4/5250-3
9	Generic IM6
10	IM6/APC2
11	Generic E-Glass
12	Generic S-Glass
13	S2-499/SP
14	Generic Kevlar
15	GY70/934

1. *Mating Pool*: After generating the first population, and having analyzed each of the individuals, the obtained objective values will be sorted. They are then credited with respect to their validities. For the purpose of carrying the genetic operations then, a mating pool is generated. The procedure of generating the mating pool is such that *100% individuals in the mating pool = the first 50% of total + the first 20% of total + the first 10% of total + random 20% of the remaining individuals.*

Therefore there will be 100% individuals in the mating Pool. Now, in order to proceed with creation of new generations towards better designs, genetic operations take place.

2. *Selection*: Due to a specific type of creating a mating pool, selection operator is carried out quite randomly where the credits to better designs were already given in generating the mating pool. However, out of a 100% individuals in a generation there are only 10% of the new generation to be created through selection.

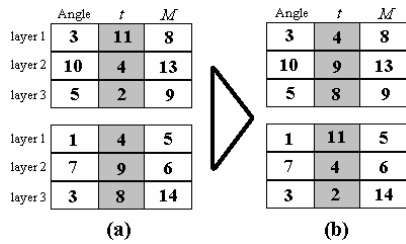


Fig. 6 Cross-over for thickness of the layers
(a): two sample parents (b): children

3. *Cross-over*: Since the algorithm introduced in this study deals with real variables, which are themselves of three different types (θ , t and M), therefore, there will only be three positions for the cross-over to take place. Thus, when two designs are selected from mating pool, they may randomly exchange their θ , t or M . Figure (6) demonstrates the exchange of the second type of the design variables, as a result of which children are created. However, out of a 100% individuals in a generation there are only 30% of the new generation to be created through cross-over.

4. *Mutation*: This type of genetic operators is carried out similar to Cross-over. However, as indicated in Figure (7), in case of the thickness of the layers to mutate, within their catalogue range they will be randomly changed, as a result of which new children are created. However, out of a 100% individuals in a generation there are 60% of the new generation to be created through mutation.

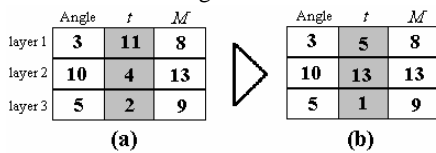


Fig. 7 Mutation for thickness
(a): before Mutation (b): after Mutation

V. ARTIFICIAL NEURAL NETWORKS

The design of Neural Network (NN) has been inspired by the biological research on how the human’s brain works. The brain is a network consisting of approximately 2.5 billion simple processors, called neurons, connected to one another through branchlike structures called axons and dendrites (see Figure8). Synapses connect the axons and dendrites of one neuron to those of another. The objective of NN is to mimic the neurons in the brain by linking together many simple processors, called Artificial Neurons or Nodes. Variable strength connections, called weights, implement the biological synapses [4], [8].

The main objective in neural model development is to find an optimal set of weight parameters w such that $y = y(x, w)$ closely approximates the original problem behavior. This is achieved through a process called training. During training, the neural network performance is evaluated by computing the difference between actual NN outputs and

desired outputs for all the training samples. The difference is also known as the error. The weight parameters w are adjusted during training, such that this error is minimized. The technique by which the training phase is processed is called back propagation, a detail of which is given in [6], [8]. However, in the following sections some detail of new type of neural network techniques namely RBF will be described.

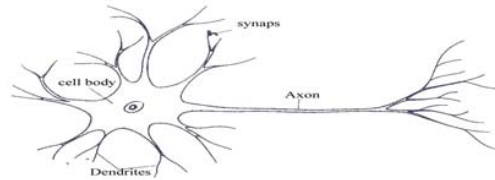


Fig. 8 The structure of a biologic neuron

A. Radial Basis Function Neural Networks

Radial Basis Function is a function which depends only on the radial distance from a point. This type of NN consists of three layers. The first layer is called the input layer. Number of neurons in this layer equates number of elements of the input vector. The second layer is known as the hidden layer. Each neuron of this layer is affected by a Gaussian activation function, results of which are transferred to the third layer, namely the output layer. Since the latter is influenced by a linear activation function, it is also referred to as the linear layer. Since the curve of Gaussian activation function in the hidden layer is radially symmetrical, neurons in the hidden layer are therefore called neurons of Radial Basis Function (RBF). Also, since the essence of this network operation is pawned to the neurons in the hidden layer, this type of artificial NN is known as RBF network.

Figure 9 shows the architecture of a simple neuron of RBF network in hidden layer.

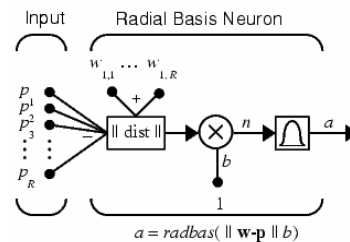


Fig. 9 RBF networks architecture and a simple neuron [9].

During the process of network training, the modifiable parameters and weight matrix of the output layer change in quantity such that the mean error between desired outputs and those of the network reach a permissible value [4], [7].

As indicated in Figure (9), a RBF neuron in hidden layer consists of three blocks:

1. $||dist||$ block. This block determines the distance between input vector P and its weight vector W , so that

$$D = \sqrt{\sum_{i=1}^R (W_i - p_i)^2} \tag{16}$$

where R is number of components of P and W. Now if P applies to a RBF network, then R would equate number of columns of weight matrix.

2. Cross Block: In this block, output of $\|dist\|$ being a value, will be multiplied by the bias of a neuron. Bias, is a weight itself which is compared with a weight that transfers a constant input value one to the cross block.

3. radbas Block: The output of cross block is used as an input to the Gaussian basis function. The maximum value of this function being equal to one, appears when its input is equal to zero. This occurs when input vector to the neuron and weight vector match very closely in value. Thus, an increase in the distance between these two vectors causes a quick reduction on the value of radbas. This function uses the following relation in its computations:

$$a = e^{-n^2} \tag{17}$$

Using bias b in cross block, adjusts the sensitivity of RBF neuron to the parameter D in (16). For instance if the bias for a RBF neuron had a value of 0.1, it would output 0.5 for any input vector P at vector distance of 8.326 ($0.8326/b$) from its weight vector W. This is because n and radbas(n) would be computed as follows:

$$n = 8.376 * b \rightarrow n = 8.326 * 0.1 = 0.8526 \rightarrow radbas = 0.5 \tag{18}$$

Therefore the major role of the bias in RBF neuron is to increase the network generalizing ability.

VI. OPTIMIZATION NETWORKS

In the present research, training of a neural network requires provision of solutions to a number of laminated plates. Note that all the individuals in generations should satisfy all the constraints. Otherwise they will be replaced by other randomly generated and valid individuals. The optimization procedure can be detailed in two stages. First, to train the RBFNN network, the best 30 percent of the total population of the analyzed first generation are transferred to the network through a linkage to the MATLAB software environment. Obviously, for each sample, the values of the design variables are considered as one set of input data to enter the NN and its corresponding loads and moments, as the reference output to the NN for that sample.

Having completed the first stage of the algorithm, the second stage is to verify the validity of the trained network. Thus, a new design of the remaining 70% individuals of the first generation is randomly chosen and is verified by the network. In case the outcome is not within the accepted range, the best 10% population of the second generation is then added as training samples to the network, for which it should be trained. This process will be continued until the error on the results is minimized to the accepted value. Thereafter, the

analysis will automatically be carried out through the trained network.

In the following section some examples will be presented, results of which involve the multi-objective optimization of composite plates using a hybrid merging of GA with RBFNN.

VII. EXAMPLES

A. Example (1)

This example is a laminated plate with 9 layers, four of which are symmetrical as shown in Table IV. The plate is under a distributed N_y loading. As stated in Section VI, the training of the network was completed in the fifth generation, after which the analysis was carried out using RBFNN and at the same time using the developed analysis software. This was made in order to enable a comparison of the two procedures as shown in Figure (10).

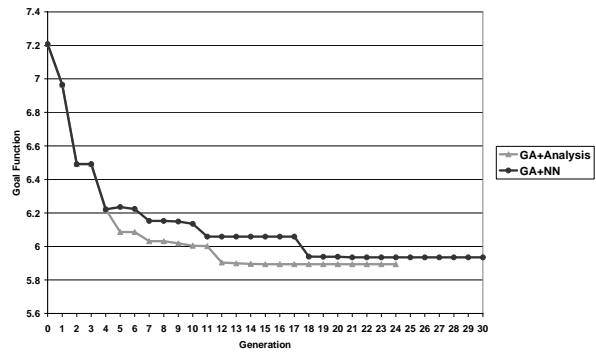


Fig. 10 Comparison between RBFNN and Analysis in solving example (1)

The optimum solutions obtained using RBFNN are listed in Table IV which shows that at least the optimum θ and M match those anticipated.

TABLE IV
PARAMETERS OF OPTIMISED LAMINATES FOR EXAMPLE (1)

Layer no.	Angle (degree)	Thickness(cm)	Material
1(9)	90	0.28	Generic IM6
2(8)	90	0.10	Generic IM6
3(7)	90	0.08	Generic IM6
4(6)	90	0.08	Generic IM6
5	90	0.08	Generic IM6
Optimum solutions			
$N_y = 3481960 \text{ kg/m}$		Weight=11.2 kg/m^3	Cost = 8.09 U

B. Example (2)

This example is a laminated plate with 12 layers, six of which are symmetrical as shown in Table V. The plate is under distributed N_x and M_x loading where $N_x = 2 M_x$.

Also there is a temperature change of $+15^\circ C$ for all the layers. The training of the network was completed similar to Example (1). The optimum solutions were obtained then by setting the trained RBFNN as the analyzer. For the means of comparison, the same individuals in all generations were also analyzed the developed analysis program. Figure (11) shows the comparisons made.

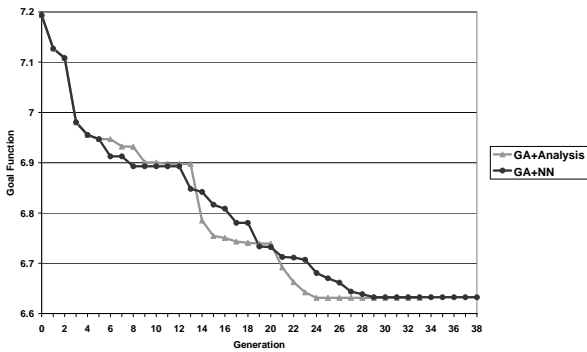


Fig. 11 comparison between RBF and Analysis in solving Example (2)

Table (V) shows the parameters of optimized laminated plate.

TABLE V
PARAMETERS OF OPTIMISED LAMINATES FOR EXAMPLE (2)

Layer no.	Angle (deg)	Thickness (m)	Material
1 (12)	0	0.0022	Generic IM6
2 (11)	0	0.003	Generic IM6
3 (10)	0	0.0006	Generic Kevlar
4 (9)	0	0.0006	Generic Kevlar
5 (8)	0	0.0006	Generic Kevlar
6 (7)	0	0.0008	Generic Kevlar
Optimum solutions			
$N_x = 16175 \text{ kg/m}$		$M_x = 8087 \text{ kg.m/m}$	$N_y^T = 7180 \text{ kg/m}$
Weight = 16.6 kg/m^3		Cost = 9.95U	

C. Example (3)

This example is a laminated plate with 7 layers, three of which are symmetrical as shown in Table VI. Thus, the plate is symmetrical about its mid layer. It is under the effect of a 10% moisture change. Different to previous examples, here, increase of failure load is not of concern; however, the

objective is to minimize the loads due to moisture, while minimizing weight and cost. Here, similar to example 2, the plate boundary conditions are such that, by changing the moisture percentage, only forces N_x^M , N_y^M and N_{xy}^M will be exerted to it. Therefore, the objective function will be needed to change and therefore modified to the following form:

$$\varphi = (1 + \frac{W}{W_{max}})^2 + (1 + \frac{C}{C_{max}})^2 + \frac{(1 + \frac{N_x^M}{N_{x_{max}}^M})^2 + (1 + \frac{N_y^M}{N_{y_{max}}^M})^2 + (1 + \frac{N_{xy}^M}{N_{xy_{max}}^M})^2}{3} \quad (19)$$

Maximum loads on denominators of Eq. (19) are not failure loads, but the maximum moisture loads in a 7-layered plate. Table VI Lists values for these loads. The loading constraint in this example has been set to 0.2. Thus, the moisture loads are constrained not to alleviate 20% of the maximum moisture load. These coefficients and percentages may differ depending on the application and other administrative purposes. Since the angle of orientation of the laminates could be ± 45 , the maximum load may also include positive or negative values. Therefore, the absolute value of the force will be accounted for while computing the objective function.

Since the failure load is not needed in this example, for optimization process only genetic algorithm and the analysis of moisture loads were employed.

Having run the problem, using a population size of 75, as indicated in Figure 12, a convergence for the objective function has occurred after 23 generations. Note that, in the process of optimization, if the moisture load reaches or exceeds the failure load, it will be deleted prior to genetic operations.

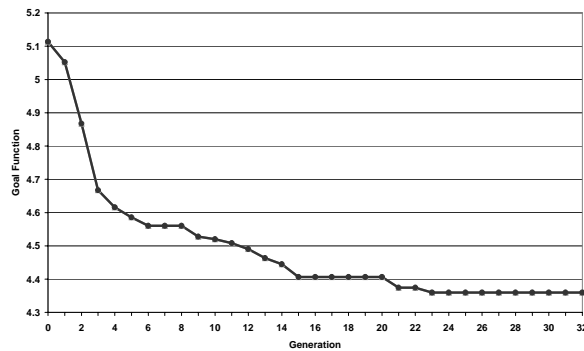


Fig. 12 A convergence history of the multi-objective variations with generations for Example (3).

Table VI indicates the optimum values obtained for the weight and cost of Example 3. This example may again be regarded as a benchmark example, since there was no source of reference available in the literature.

TABLE VI
PARAMETERS OF OPTIMIZED LAMINATES FOR EXAMPLE (3)

Layer no.	Angle (deg)	Thickness (cm)	Material
1 (7)	30	0.08	T300/976
2 (6)	30	0.08	T300/976
3 (5)	90	0.08	T300/976
4	30	0.08	Generic Kevlar
Optimum solutions			
$N_x^M = 195306$ kg/m	$N_y^M = 198608$ kg/m	$N_{xy}^M = -64646$ kg/m	
Weight = 5.5937 kg/m ³		Cost = 5.3735 U	

VIII. CONCLUSIONS

With regard to the thermal and moisture effects on the analysis of composite laminates, the analysis program developed well matched that in the literature.

Also, the new Genetic Algorithm introduced here to handle real variables and to deal with multi-objective functions, resulted on a fast and global convergence of the optimum solution, as for such examples on composite laminates, in particular for example 1, it is rather simple to anticipate the solution. It was also shown that by emphasizing more on the role of mating pool, one can reduce selection contribution in the genetic operations.

Involving RBF Neural Networks as to predict and cover for the analysis, it concluded in closely satisfied comparisons for both examples attempted. This investigation closely validates the clear power of neural network techniques in solving laminated composite plates.

Therefore, regarding a reasonable accuracy of the results performed using RBFN networks; it is possible to produce software that could promptly expose the optimum without a need to analyze the structure. This is particularly effective where a very quick response to the problem is vital.

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