Latin American Journal of
Solids and Structures
www.lajss.org

Optimization of laminated composite plates and shells using genetic algorithms, neural networks and finite elements

Abstract

Structural optimization using computational tools has become a major research field in recent years. Methods commonly used in structural analysis and optimization may demand considerable computational cost, depending on the problem complexity. Therefore, many techniques have been evaluated in order to diminish such impact. Among these various techniques, Artificial Neural Networks (ANN) may be considered as one of the main alternatives, when combined with classic analysis and optimization methods, to reduce the computational effort without affecting the final solution quality. Use of laminated composite structures has been continuously growing in the last decades due to the excellent mechanical properties and low weight characterizing these materials. Taken into account the increasing scientific effort in the different topics of this area, the aim of the present work is the formulation and implementation of a computational code to optimize manufactured complex laminated structures with a relatively low computational cost by combining the Finite Element Method (FEM) for structural analysis, Genetic Algorithms (GA) for structural optimization and ANN to approximate the finite element solutions. The modules for linear and geometrically non-linear static finite element analysis and for optimize laminated composite plates and shells, using GA, were previously implemented. Here, the finite element module is extended to analyze dynamic responses to solve optimization problems based in frequencies and modal criteria, and a perceptron ANN module is added to approximate finite element analyses. Several examples are presented to show the effectiveness of ANN to approximate solutions obtained using the FEM and to reduce significatively the computational cost.

Keywords

laminated composite plates and shells, artificial neural networks, optimization, genetic algorithms, finite element

Sergio D. Cardozo*, Herbert. M. Gomes and Armando. M. Awruch

Graduate Program in Mechanical Engineering, Federal University of Rio Grande do Sul, Rua Sarmento Leite, 425, 90050-170 Porto Alegre, RS – Brazil

Received 17 Mar 2011;
In revised form 30 Sep 2011

* Author email: sergiocardozo@gmail.com

1 INTRODUCTION

The structural optimization is not a new field. Galileo in his text "*Discorsi e Dimostrazioni Matematiche intorno a due Nuove Scienze*" (1638) studied the problem which consists of finding the shape of a beam where every transversal section has the same stress distribution.

In composite materials structures, some experiences has shown that Genetic Algorithms (GA) perform better than traditional gradient based techniques due to the discrete nature of the design variables.

A problem that arises when GAs are used is the high computational cost demanded by this method. For this reason some techniques to reduce this cost have been tested. One of them, consists of replacing the complete Finite Element Analysis (FEA) by some approximation technique. The Artificial Neural Network (ANN) have been shown to be a good alternative to avoid the large number of FEA involved in a GA.

In this work these two techniques are combined to make the process faster and cheaper in terms of computational cost.

This work is based on [2], from which some GA parameters, objective functions and results are taken in order to compare the effectiveness of substituting a complete FEA by ANN.

2 STRUCTURAL OPTIMIZATION

The structural optimization can be understand as a process to search the configuration which gives the best performance, within some criteria and subjected to certain design constraints.

To model the structural optimization as a mathematical optimization problem, the following concepts are used:

- Design variables: they are the characteristics that can be modified by the mathematical optimization algorithm to obtain the best structural performance.

- Design constrains: are the restrictions applied to the structure, such as a limit to avoid material failure, maximum or minimum value of design variables and others that depend on the problem being analyzed.

- Objective function: it is a mathematical expression in which the design variables and constrains are involved. This function represents a number which has to be maximized or minimized during the optimization process.

2.1 Structural analysis

The analysis of the composite structures is carried out using the FEM. The element used is a triangular flat plate bending element with 18 degree of freedom called DKT (*Discrete Kirchhoff Triangle*) combined with the CST (*Constant Strain Triangle*) to take into account membrane effects. This element was developed by [3] for isotropic materials and it was extended by [1] for laminated composite materials.

For the modal analysis the mass matrix is obtained using the formulation given by [8].

To solve geometrically non linear problems, the generalized displacement control method (GDCM) described by [12] is used.

The Tsai-Wu failure criterion is employed for failure prediction in a ply see [4].

2.2 Genetic algorithms for composite materials

Genetic Algorithm (GA) is a computational search tool based on concepts of natural selection and survival of the fittest individual. One aspect of fundamental importance in GAs is the way the solutions are tracked. Instead of using derivatives or gradients, as in deterministic optimization algorithms, GAs work with the objective function based on simple values of individuals. This feature makes the method suitable for problems involving discontinuous functions, and/or non-defined derivatives like in integer programming. Moreover, unlike deterministic optimization methods, which perform the search focusing on a single solution at a time, the GAs work with a population of individuals in each generation. Thus, as several search points are maintained, the convergence or stagnation to local minima, if the starting point is poorly chosen, is prevented. All these aspects result in more chances of finding the optimal solution, even on problems having hard search spaces with multiple local minimum [5].

The design of the optimal sequence of layers in laminated composite materials is a problem of global minimum. Due to the stochastic characteristics of GAs, they are more suitable to optimize than deterministic methods of optimization, which often converge to solutions representing a local minimum. Moreover, in commercial designs, fiber orientation angles and the amount and thickness of layers are discrete variables, a fact which confirms the suitability of GAs for these kinds of problems.

More details related to the use of the method for optimization of composite structures can be found in [2], [9] and [10].

The GA approach adopted here was proposed by [11] and extended by [1]. The classical GA is modified to manage composite materials structures. Two genes are used, one for materials and another for the orientation of reinforcement fibers on each ply. The genetic operations used here are crossover, mutation and gene swap. The selection scheme adopted is the Multiple Elitist 1 proposed by [11]. In this scheme some of the best individuals from the parents and sons generations are used in the son generation to maintain and to improve the evolution. N_e is defined as the number of individuals of each generation. The criterion to stop the GA is defined by two parameters. The first one is the number that limits the number of generations (N_{LG}), which is used to limit the total number of generations in the GA. The second one, is the number of generation with the same optimum design (N_{SD}), which indicates that the convergence rate has been zero for a defined number of generations.

3 ARTIFICIAL NEURAL NETWORKS

Artificial neural networks are mathematical models imitating the human brain. Based on the experience, the ANN can learn complex relationships between inputs and outputs data. The use of ANN to predict structural responses has been growing in recent years. To continue this research line here, neural networks will be applied to learn the structural response of laminated composite structures. The neural network model used here is briefly described below. More details may be found in [6].

3.1 Multilayer perceptrons

A general Multilayer Perceptron Network (MPN) architecture consists on a layered network fully connected, i.e., all neurons belonging to a layer are, each one, connected to the previous and the next layer. Such architecture representation is indicated by the number of input vector followed by the number of neurons on each layer and the output vector (e.g. 1:12:1 indicates an Artificial Neural Network with one input vector, followed by one hidden layer with 12 neurons and an output layer with one neuron).

The ANN Architecture depends on the complexity of the system being modeled. For a more complex system, a larger number of hidden units are needed. In the training process of neural networks, for an input pattern X_{pi} (where index p means "pattern" and index i means an input neuron), the weight (w_{pi}) adjustments will take place in the links of the neural network in order to get a desired output O_{pk} close to the function which are being fitted Y_{po} (o means an output neuron). For each input-output pattern, the square of the error and the average system error should be minimized. They may be written, respectively, as $E_p = \frac{1}{2}\sum_k (Y_p k - O_p k)^2$ and $E = \frac{1}{2}\sum_p E_p$, where k is the number of neurons in the output layer, and p is the number of training patterns. Employing any algorithm to minimize the error function, the weights can be evaluated and an approximated fit may be obtained. The standard back-propagation algorithm is used to adjust the different weights as well as the derivatives of O_{pk} with respect to the input data which will be fitted. After this first adjustment takes place, the network will pick up another pair of X_{pi} and Y_{po}, and will again adjust weights for this new pair. In a similar way, the process will go on until all the input-output pairs are considered. After some training epochs, the network will have a single set of stabilized weights satisfying all the input-output pairs with an average system error lower than a tolerance (10^{-3}). More details regarding the use of the MPN can be found in [7] and [6].

3.2 Artificial neural networks and genetic algorithms

To combine the ANN and GA, the scheme shown in Fig. 1 is adopted. To generate the training set for the ANN in each case, three GA are executed with two generations having large populations each one. This approach is used to make a randomly distributed generation in the first one and some elitist generation in the second one. Three executions of the GA make the generations disperse and they are enough to guarantee that almost every zone of the design space is covered.

So, when the ANNs are trained with the training set generated by the previously described process, every structural response is taken from the ANN. In the case of parameters that can be directly calculated from the genetic codification, such as cost, and weight, for example, they are calculated directly.

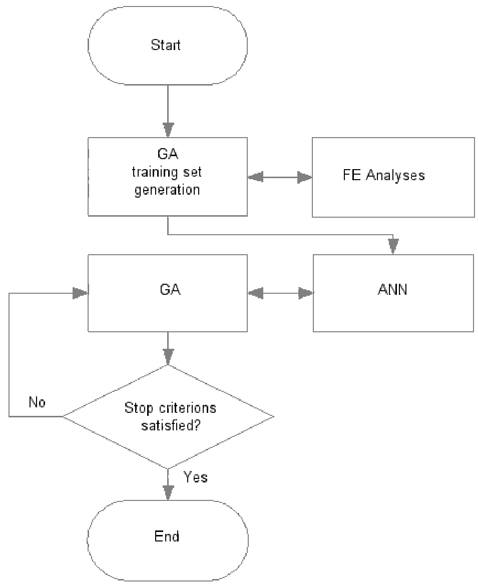

Figure 1 Flowchart of GA-ANN.

4 NUMERICAL EXAMPLES AND DISCUSSION

To evaluate the quality of the optimization scheme and the time that can be saved using ANN, three examples are shown. In each one, the GA and the training time as well as the error of the ANN (with respect to the Finite Element Method (FEM) solution) are presented, together with a comparison of GA-FEM with respect to processing time and quality of results are also presented. All examples have been executed in a 2.4 Ghz Quad Core 2 computer with 4 Gb of RAM.

4.1 Cost and weight minimization of an in-plane loaded composite laminated plate

In this problem the number of plies, the material of each ply and the orientation of reinforcement fibers are the design variables. The right combination of these variables can determine the cheapest and lightest structure. The constraints of the problem are the material failure (λ_f) derived from the Tsai-Wu criterion [4], and the structural elastic stability (λ_b). Both must be greater or equal to 1.0. The cost is proportional to the material consumption in the laminated structure, and each material has its own cost per unit weight denoted by C. The plate model with boundary and load conditions is shown in Fig. 2. The finite element mesh has 3000 elements. The objective function is defined by Eq. 1 , where Wt^* and C^* are the normalized weight and cost respectively; this normalization is shown in Eq. 2 and ϕ is the weighting factor of both objectives; in this example the weighting factor is 0.5.

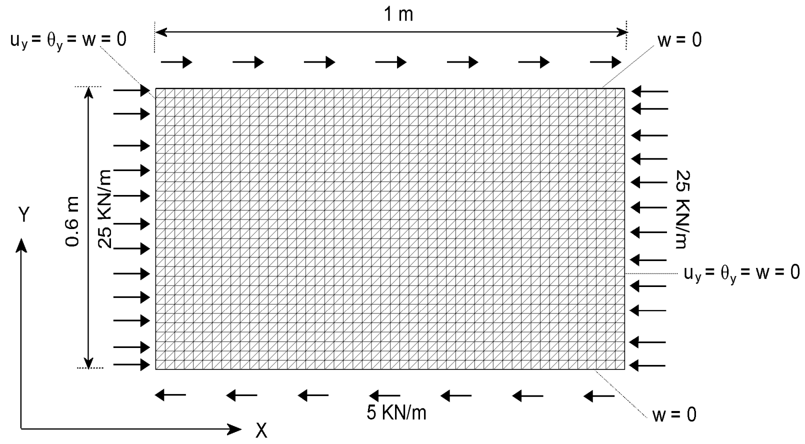

Figure 2 Composite laminated plate with its boundary and load conditions.

$$\begin{cases} OBJ = 10 - \sqrt{\left[\phi\left(Wt^*\right)^2\right]^2 + \left[\left(1-\phi\right)\left(C^*\right)^2\right]^2} + 10^{-6}\lambda^* & , \; if \;\; \lambda^* \geq 1 \\ OBJ = \left(\lambda^*\right)^2 \left\{10 - \sqrt{\left[\phi\left(Wt^*\right)^2\right]^2 + \left[\left(1-\phi\right)\left(C^*\right)^2\right]^2}\right\} & , \; if \;\; \lambda^* < 1 \end{cases} \tag{1}$$

$$C^* = \frac{C - C_{min}}{C_{max} - C_{min}} + 1 \qquad Wt^* = \frac{W - W_{min}}{W_{max} - W_{min}} + 1 \qquad \lambda^* = minimum(\lambda_f, \lambda_b) \tag{2}$$

The elastic constants, strength parameters, specific weight, ply thickness and the parameter of cost per unit weight for the Kevlar-epoxy and Graphite-epoxy are shown in Table 1. The elastic constants are the Young's modulus in the fiber direction (E_1) and transverse to the fiber direction (E_2), the shear modulus (G_{12}) and the Poisson's ratio (ν_{12}), respectively. Strength parameters for tension and compression for longitudinal and transversal directions are given by F_{1t}, F_{1c}, F_{2t}, and F_{2c}, respectively. The remainder parameters are the shear strength (F_6), the specific weight (ρ) and the thickness (t).

The alphabet used in the GA is shown in Table 2; the code 0 is used to indicate an empty layer. The laminated plate can adopt different number of plies varying from 12 to 24 and the symmetry condition is applied. The size of the design space (SDS) is 55944.

The parameters of the GA are shown in Table 3 where P is the size of population, N_e is the elitist scheme parameter, p_{ma} and p_{mm} are the probabilities of angle and material mutation respectively, p_{gs} is the probability of gene swap, p_{pa} and p_{pd} are the probabilities of ply addition and ply deletion, respectively, N_{LG} and N_{SD} are stop criterion parameters.

The training set consists in 2347 designs and the time used to generate this training set was 112.74 hours. The neural network architecture used here is 12:18:18:1. A neural network is used to approximate (λ_f) and another one is used to approximate (λ_b). The cost and the weight are calculated directly from the genetic code of each design. The training times and

Table 1 Materials properties – Example 1.

Properties	Kevlar-epoxy	Graphite-epoxy
E_1	87.0 GPa	181.0 GPa
E_2	5.5 GPa	10.3 GPa
G_{12}	2.2 GPa	7.17 GPa
ν_{12}	0.34	0.28
t	0.18 mm	0.13 mm
ρ	13.5 KN/m^3	15.7 KN/m^3
C	1.0 uc/N	3.0 uc/N
F_{1t}	1280.0 MPa	1500.0 MPa
F_{1c}	335.0 MPa	1500.0 MPa
F_{2t}	30.0 MPa	40.0 MPa
F_{2c}	158.0 MPa	246.0 MPa
F_6	49.0 MPa	68.0 MPa

Table 2 Genetic codification alphabet and possible values – Example 1.

Angle genes		Material Genes	
code	angle	code	material
1	2 plies at 0^o	1	Kevlar-epoxy
2	2 plies at $\pm 45^o$	2	Graphite-epoxy
3	2 plies at 90^o		

Table 3 GA parameters – Example 1.

P	30	N_{SD}	100	p_{pa}	4%
N_e	4	p_{ma}	4%	p_{pd}	8%
N_{LG}	300	p_{mm}	2%	p_{gs}	80%

the error (with respect to the FEM solution) using neural networks are shown in Table 4. In this table "uc/N" means unit cost per newton and the "time" is referred to the time spent whith trained ANN (time spent in the training process was not considered)

Table 4 Neural networks training time and errors – Example 1.

NN to approximate λ_f		NN to approximate λ_b	
Time	1.81 min.	Time	1.15 min.
Error	0.05	Error	0.03

The optimal design found using GA-ANN and values of the parameters are shown in Table 5.

Performing a FE analysis, using the design obtained from the GA-ANN optimization, the real differences between parameters λ_f and λ_b are shown in Table 6.

Table 5 Results using GA-ANN – Example 1.

Results	
Laminate	$\left[\pm 45^{ge}, 90_2^{ge}, 0_6^{ke}\right]_S$
λ_f	31.13
λ_b	1.03
W	27.34 N
C	46.93 uc/N
Fitness	9.790
GA Generations	171
Time	0.08 min.

Table 6 Differences between ANN and FEM – Example 1.

	λ_f	λ_b	**Fitness**
ANN	16.76	1.39	9.790
MEF	14.63	1.46	9.789
Error	-14.56%	5.07%	-0.01%

To verify the optimization quality, the design obtained with GA-ANN is compared to the design found using GA-FEM. This last design and parameters values are shown in Table 7.

Table 7 Results using GA-FEM – Example 1.

Results	
Laminate	$\left[\pm 45_4^{ge}, \pm 45^{ke}, 90_4^{ke}\right]_S$
λ_f	14.07
λ_b	1.54
W	27.34 N
C	46.93 uc/N
Fitness	9.789
GA Generations	146
Time	264.73 hours.

Differences between the designs obtained with GA-FEM and GA-ANN are shown in Table 8. These results show that the design obtained with the GA-ANN is a near optimum design.

To evaluate the processing time saved using ANN, a comparison is shown in Table 9.

In fact this problem can be solved by a mesh having much less elements, but the aim of this example is to show that major gains in processing time occurs when the FE analysis is time consuming. In this case the difference in processing time is 57.37%.

Table 8 Differences between optimum designs – Example 1.

	Laminate	λ_f	λ_b	Fitness
GA-ANN	$\left[\pm 45^{ge}, 90_2^{ge}, 0_6^{ke}\right]_S$	16.76	1.39	9.789
GA-FEM	$\left[\pm 45_4^{ge}, \pm 45^{ke}, 90_4^{ke}\right]_S$	14.07	1.54	9.789
Differences		3.80%	-5.76%	0.00%

Table 9 Processing time comparison (in hours) – Example 1.

	GA-ANN	GA-FEM
Training set generation	112.74	-
Neural networks training	0.11	-
GA execution	0.001	264.73
Total time	112.851	264.73

4.2 Stiffness maximization of a composite laminated shell with geometrically nonlinear behavior

This optimization problem aims to maximize the stiffness of a composite shallow shell under pressure load. Figure 3 shows the shell with its boundary and load conditions. The mesh has 800 elements. The nonlinear analysis is made using the GDCM method [12], with a load increment parameter $\lambda_i = 0.05$. The fitness function is defined in Eq. 3, where NC_{crit} is the critical load level(when curve load - displacement reaches its first limit point), U_{max} is the maximum displacement, which is taken at the end of incremental load process or when material failure is observed, NC_{max} is the maximum load level without material failure and V_{nlc} is a penalization for designs having more than 4 plies with same fiber orientation.

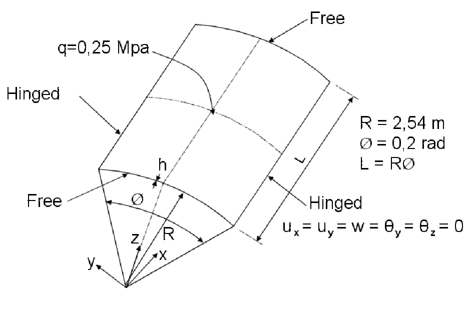

Figure 3 Composite laminated shell whit boundary and load conditions.

$$FITNESS = \left(\frac{(NC_{crit}) \cdot (NC_{max}^2)}{(U_{max}) \cdot (V_{nlc} + 1)} \right) \tag{3}$$

In the example glass-epoxy is used and the material properties are shown in Table 10.

Table 10 Properties of Glass-epoxy – Example 2.

Properties	Values	Properties	Values
E_1	39.0 GPa	F_{1t}	1080.0 MPa
E_2	8.6 GPa	F_{1c}	620.0 MPa
G_{12}	3.8 GPa	F_{2t}	39.0 MPa
ν_{12}	0.28	F_{2c}	128.0 MPa
ρ	20.6 KN/m^3	F_6	89.0 MPa

The genetic alphabet shown in Table 11 is used. In this example only the orientation of reinforcement fibers are the design variables, while the material, thickness and number of layers are fixed. The laminated has 28 plies (with thickness $t = 0.45mm$ for each ply), the symmetry condition is imposed, each gene control 2 plies and the chromosome has 7 genes to control the laminate. Due to the long codification, for the crossover is used a double break point. The size of the design space (SDS) is 2187.

Table 11 Genetic codification alphabet – Example 2.

Genes of the angles	
code	angle
1	2 plies a 0^o
2	2 plies a $\pm 45^o$
3	2 plies a 90^o

The GA parameters used here are $P = 18$, $N_e = 3$, $p_{ma} = 5\%$, $p_{mm}0\%$, $p_{gs} = 80\%$, $p_{pa} = 0\%$, $p_{pd} = 0\%$, $N_{LG} = 108$, $N_{SD} = 36$ with the same meaning as in the previous example.

In this example, three neural networks are used to approximate each one of the parameters involved in the objective function (NC_{max}, NC_{crit} and U_{max}); each ANN for the trained parameters, errors and processing time are show in Table 12. The architecture adopted is 7:15:15:1. The training set has 226 designs and the time spent to generate this training set was 117.31 minutes.

Table 12 Neural Networks training time and errors – Example 2.

NN to approximate (NC_{max})		NN to approximate (NC_{crit})		NN to approximate (U_{max})	
Time	5 sec.	Time	11 sec.	Time	7 sec.
Error	0.001	Error	0.001	Error	0.001

The design obtained using GA-ANN and its parameter values are shown in Table 13.

Table 13 Results using GA-ANN – Example 2.

Results	
Laminate	$[90_4, \pm 45, (90_2, 0_2)_2]_S$
(NC_{max})	0.989
(NC_{crit})	0.637
(U_{max})	$26.6 \times 10^{-3} m$
Fitness	23.42
GA Generations	47
Time	0.01 min.

To evaluate the quality of the approximation using neural networks, the parameter values are compared to the parameter values for the same design using FEM without ANN. These differences are shown in Table 14.

Table 14 Differences between ANN and FEM – Example 2.

	(NC_{max})	(NC_{crit})	(U_{max})	**Fitness**
ANN	0.989	0.637	$26.6 \times 10^{-3} m$	23.42
FEM	1.000	0.495	$27.4 \times 10^{-3} m$	18.03
Error	1.10%	-28.62%	3.18%	-29.94%

Result and processing time used in the optimization process using GA-FEM is show in Table 15.

Table 15 Results using GA-FEM – Example 2.

Results	
Laminate	$[(90_4, \pm 45)_2, 90_2]_S$
(NC_{max})	1.000
(NC_{crit})	0.560
(U_{max})	$27.2 \times 10^{-3} m$
Fitness	20.60
GA Generations	40
Time	239.72 min.

To verify the quality of the optimization process using GA-ANN, parameter values for both designs, obtained with ANN and FEM, are compared in Table 16. A graphical comparison of both designs is shown in Fig. 4, where NC_{crit} and U_{max} are indicated.

Processing time comparison, using GA-ANN and GA-FEM, is shown in Table 17.

In this example the time saved using GA-ANN is 50.79%; to evaluate the optimization quality, the whole design space analysis was used, and in this space the design obtained by the GA-ANN is the 9th. among the near optimum designs (this set includes the optimum design).

Table 16 Differences of optimum designs obtained by GA-ANN and GA-FEM – Example 2.

	GA-ANN	GA-FEM	Differences
Laminate	$[90_4, \pm 45, (90_2, 0_2)_2]_S$	$[(90_4, \pm 45)_2, 90_2]_S$	
(NC_{max})	1.000	1.000	0.00%
(NC_{crit})	0.495	0.560	-13.03%
(U_{max})	$27.4 \times 10^{-3} m$	$27.2 \times 10^{-3} m$	1.08%
Fitness	18.03	20.60	-14.26%

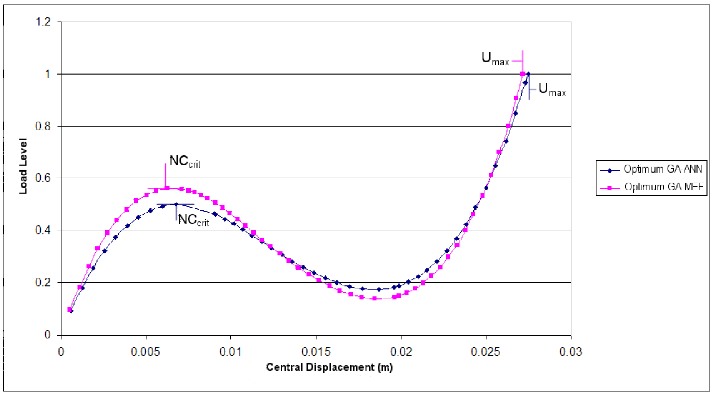

Figure 4 Curve load level – central displacement.

Table 17 Time comparison (in minutes) – Example 2.

	GA-ANN	GA-MEF
Training set generation	117.31	-
Neural Network training	0.65	-
GA execution	0.01	239.72
Total time	117.97	239.72

4.3 Natural frequency maximization of a laminated plate

The objective of this optimization is to maximize the first natural frequency of vibration (ω) of a simply supported composite laminated plate. No constraints are imposed to the problem. To obtain ω the eingenvalues problem is solved. The GA modifies only the reinforcement fibers orientation in each ply. The material and number of plies are fixed. The number of plies is fixed in 8, with thickness equal to 2 mm each one. Then the total height is 16 mm. Figure 5 shows the plate, boundary conditions and the mesh (with 256 elements). Graphite-epoxy is used to build this plate, and the material properties are given in Table 18.

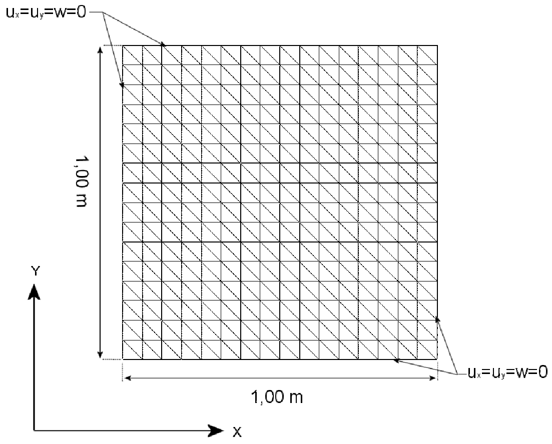

Figure 5 Composite laminated plate with its boundary conditions and the FE mesh.

Table 18 Properties of Graphite-epoxy.

Properties	Values	Properties	Values
E_1	181 GPa	F_{1t}	1500.0 MPa
E_2	10.3 GPa	F_{1c}	1500.0 MPa
G_{12}	7.17 GPa	F_{2t}	40.0 MPa
ν_{12}	0.28	F_{2c}	246.0 MPa
ρ	15.7 KN/m^3	F_6	68.0 MPa

The genetic alphabet used in this example is shown in Table 19. The chromosome length is 8. Double break point is used in the crossover operation. The size of the design space (SDS) is 6561.

Table 19 Genetic codification alphabet – Example 3.

Angle genes	
code	angle
1	1 ply a 0^o
2	1 ply a 45^o
3	1 ply a 90^o

The GA parameters used here are $P = 30$, $N_e = 3$, $p_{ma} = 5\%$, $p_{mm}0\%$, $p_{gs} = 80\%$, $p_{pa} = 0\%$, $p_{pd} = 0\%$, $N_{LG} = 200$, $N_{SD} = 100$, with the same meaning as in the first example.

The neural network architecture used in this example is 8:17:17:1. The training time and error are shown in Table 20. The training set has 420 designs and the time to generate the training set was 26.75 minutes.

Table 20 Neural Network training time and error for Example 3.

Neural network to approximate ω	
Time	1.25 min.
Error	0.01

Table 21 Result using GA-ANN – Example 3.

Result	
Laminate	$[90, 45, 0_3, 90, 45_2]_S$
ω	6.24 rad/s.
Generations	182
Time	0.03 min.

The design obtained here, as well as ω, are shown in Table 21

The difference of ω, obtained using ANN and FEM, is shown in Table 22.

Table 22 Difference between ANN and FEM – Example 3.

	ω
ANN	6.24
FEM	6.27
Error	0.48%

Making a GA-FEM optimization, the same design is found. A comparison of the processing time required for each method is shown in Table 23.

Table 23 Processing time comparison (in minutes) – Example 3.

	GA-ANN	GA-FEM
Training set generation	26.75	-
Neural networks training	1.25	-
GA execution	0.03	68.44
Total time	28.03	68.44

In this example the processing time saved is 59%. The optimization quality using ANN is high. This occurs because the function that has to be replaced by the neural network is very simple.

5 FINAL REMARKS

Some important remarks can be outlined from the examples, such as following:

- An important amount of processing time can be saved using GA-ANN instead of GA-

FEM. This is particularly true when Finite Elements Analyses are applied for structures requiring refined meshes and for cases where the structure has a nonlinear behavior.

- The optimum design is very little affected if well trained ANNs are used substituting complete Finite Element Analyses, or, in other words, accuracy of ANNs can be improved with a longer and more elitist training set and increasing the number of GA application to generate samples of the training set.
- In cases where the cost function is simple, final design using GA-ANN will be very similar to that obtained using GA-FEM.

In future works other kind of ANNs, such as ANN with Radial Basis, (substituting Multilayer Perceptrons) will be tested. These tools (GAs and ANNs) may be employed also in Reliability Based Optimization Problems.

References

[1] Felipe Schaedler Almeida. Laminated composite material structures optimization with genetic algorithms. Master's thesis, PPGEC/UFRGS, Porto Alegre, Rio Grande do Sul, Brazil, 2006. [in Portuguese].

[2] F.S. Almeida and A.M. Awruch. Design optimization of composite laminated structures using genetic algorithms and finite element analysis. *Composite Structures*, 88(3):443 – 454, 2009.

[3] Klaus-Jrgen Bathe and Lee-Wing Ho. A simple and effective element for analysis of general shell structures. *Computers & Structures*, 13(5-6):673 – 681, 1981.

[4] Isaac M. Daniel and Ori Ishai. *Engineering Mechanics of Composite Materials*. Oxford Press, 1994.

[5] David E. Goldberg. *Genetic Algorithms in Search, Optimization, and Machine Learning*. Addison-Wesley Professional, January 1989.

[6] Herbert Martins Gomes and Armando Miguel Awruch. Comparison of response surface and neural network with other methods for structural reliability analysis. *Structural Safety*, 26(1):49 – 67, 2004.

[7] Simon Haykin. *Neural Networks: A Comprehensive Foundation (2nd Edition)*. Prentice Hall, July 1998.

[8] Z. Luo and S. G. Hutton. Formulation of a three-node traveling triangular plate element subjected to gyroscopic and in-plane forces. *Computers & Structures*, 80(26):1935 – 1944, 2002.

[9] A. Muc and W. Gurba. Genetic algorithms and finite element analysis in optimization of composite structures. *Composite Structures*, 54(2-3):275 – 281, 2001.

[10] G. Narayana Naik, S. Gopalakrishnan, and Ranjan Ganguli. Design optimization of composites using genetic algorithms and failure mechanism based failure criterion. *Composite Structures*, 83(4):354 – 367, 2008.

[11] Grant A. E. Soremekun. Genetic algorithms for composite laminate design and optimization. Master's thesis, Department of Mechanical Engineering, Virginia Polytechnic Institute, Blacksburgh, Virginia, February 5 1997.

[12] Yeong-Bin Yang and Ming-Shan Shieh. Solution method for nonlinear problems with multiple critical points. *AIAA Journal*, 28:2110–2116, 1990.