Proceedings IRF2018: 6th International Conference Integrity-Reliability-Failure
Lisbon/Portugal 22-26 July 2018. Editors J.F. Silva Gomes and S.A. Meguid
Publ. INEGI/FEUP (2018); ISBN: 978-989-20-8313-1

PAPER REF: 7106 *(Invited Paper)*

MULTI-OBJECTIVE OPTIMIZATION AIMING THE SUSTAINABLE DESIGN OF FRP COMPOSITE STRUCTURES

Carlos Conceição António(*)
LAETA / INEGI, Faculty of Engineering, University of Porto, Porto, Portugal
(*)*Email:* cantonio@fe.up.pt

ABSTRACT

The optimal design of hybrid composite stiffened structures addressing the sizing, topology and sustainable material selection in a multi-objective optimization framework is proposed. Minimum weight (cost), minimum strain energy (stiffness) and maximum sensitivity to sustainable factors (minimum variability of energy) are the objectives of the proposed structural robust design approach. The model performs the trade-off between the performance targets against sustainability, depending on given stress, displacement and buckling constraints imposed on composite structures. The design variables are ply angles and ply thicknesses of shell laminates, the cross section dimensions of stiffeners and the variables related to material selection for sustainability and distribution on structure.

Keywords: multi-objective optimization, sustainability, hybrid composites, robustness, memetic algorithm

INTRODUCTION

The recent increases in structural material prices is further evidence that global consumption will raise both awareness and need to design for the efficient and rational use of materials. From a structural engineering point of view, the biggest influence results by focusing on optimizing the structural systems to reduce the material requirements of a project supported by sustainability concepts. FRP composites' potential benefits may potentially mitigate some environmental impacts. In particular, FRP composites are durable and sustainable due to their long lifetime without noteworthy maintenance and low environmental impact.

Lightweight structures using FRP composite materials augment the competitive advantages for both users and suppliers in markets where operational costs and higher efficiency are the first considerations. The market where lightweight engineering plays the most prominent role is the transportation industry. In the past, are recognized a number of features in material use, optimizing the ratio of structural strength and stiffness and weight, in order to improve efficiency (increase payload and safety). In sustainability, there is the concept of three "R's": reduce, reuse and recycle. However, "reduce" is extremely important, even more so than "reuse" or "recycle". By minimizing material, fuel consumption decreases notably - regardless as the power source. Therefore, lightweight design is the easiest way to minimize fuel consumption and CO2 emissions.

PROPOSED APPROACH

An approach for decreasing costs in lightweight structures using FRP composite materials is to adopt a hybrid construction where expensive and high-stiffness materials performs together with inexpensive and low-stiffness material. The optimization problem of topology associated with material distribution and stacking sequence design of hybrid composites is very complex when sizing variables, as ply angle and layer thickness are simultaneously considered. Furthermore, since the balance between weight/sustainable cost and stiffness is important in hybrid laminates construction the use of multi-objective design procedures are necessary. The optimal design of hybrid composite stiffened structures addresses the sizing, topology and sustainable material selection in a multi-objective optimization framework. Minimum weight, minimum strain energy and maximum sensitivity to sustainable factors are the objectives of the proposed structural robust design approach. The model performs the trade-off between the performance targets against sustainability, depending on given stress, displacement and buckling constraints imposed on composite structures. The design variables are ply angles and ply thicknesses of shell laminates, the cross section dimensions of stiffeners and the variables related to material selection for sustainability and distribution on structure.

Multi-objective Memetic Algorithm (MOMA) searching Pareto-optimal front is proposed. MOMA applies multiple learning procedures exploring the synergy of different cultural transmission rules. The approach uses the following concepts: multiple populations, species conservation, migration, self-adaptive, local search, controlled mutation, age control and features-based allele's statistics. These aspects are associated with some kind of problem knowledge and learning classified as Lamarckian or Baldwinian (Moscato 1989, Krasnogor and Smith, 2005). The memetic learning procedures aim to improve the exploitation and exploration capacities of MOMA. It is implemented the selfish gene theory using a fusion of concepts. The age structure (Conceição António, 2013, 2014) performs together with feature-based allele's statistics analysis used in the learning procedure implemented inside a virtual population (VP). The age structured VP plays important role in evolutionary process based on two rules: the first one is to store the ranked solutions aiming to obtain the Pareto front and the second one is to evolve as a virtual population of alleles. The relationship between continuous statistical parameters of alleles and their dominance is established. The selection of the most promising alleles for genes emulates the cultural and genetic evolution. A detailed analysis of solutions/individuals at the Pareto-optimal front reveals that they belong to different species. From this, it concludes that MOMA is successful in preserving the population diversity. Furthermore, MOMA is able to indicate alternative optimal designs based on different species what might be very important for the designers in multi-objective design sustainable optimization of stiffened composite structures.

PROBLEM FORMULATION

The structural analysis of hybrid composites uses the formulation defined previously with the Marguerre shell element and a Timoshenko beam element (Conceição António, 2006). The structural system with non-linear behaviour is in equilibrium if the internal forces are equal to the external applied loads. Since in the numerical process of solution it is not possible to reach an exact equilibrium situation the goal is to obtain a close state near equilibrium and within a small error. A measure of the error at this equilibrium state based on the Total Lagrangian formulation is the vector of *non-balanced forces* defined as

$$\boldsymbol{\Psi}({}^{t}\mathbf{d},\ {}^{t}\lambda) = \mathbf{R}\big({}^{t}\mathbf{d}\big) - {}^{t}\lambda\bar{\mathbf{F}} \tag{1}$$

where **R** is the vector of equivalent nodal forces associated with the actual stress field on the structure, $\bar{\mathbf{F}}$ is the equivalent nodal forces due to the external applied forces, ${}^{t}\lambda$ is a scale factor related to the load level t and ${}^{t}\mathbf{d}$ is the corresponding displacement vector. The equilibrium path is traced using the arc-length method enabling the identification of the load factors λ_b associated with buckling and λ_{FPF} related to first ply failure (Conceição António, 2006). Huber-Mises law checks the first ply failure. The same procedure enables to obtain the corresponding critical displacements.

An unified approach (Conceição António, 2006) for buckling and first ply failure is used to check the integrity of hybrid composite structures through the concept of *critical load factor c* defined as

$$\lambda_{crit}(\mathbf{x},\boldsymbol{\pi}) = MIN[\,\lambda_b(\mathbf{x},\boldsymbol{\pi}),\ \lambda_{FPF}(\mathbf{x},\boldsymbol{\pi})\,] \tag{2}$$

From the equilibrium path, the critical displacement d_{crit} can be associated with buckling d_b, or related to first ply failure d_{FPF},

$$d_{crit}(\mathbf{x},\boldsymbol{\pi}) = MAX[\,d_b(\mathbf{x},\boldsymbol{\pi}),\ d_{FPF}(\mathbf{x},\boldsymbol{\pi})\,] \tag{3}$$

The design variables $\mathbf{x}$ and $\boldsymbol{\pi}$ are associated with the sizing and material distribution, respectively. The constraints are imposed on the critical load factor λ_{crit}, and on the critical displacement d_{crit}, both of which are associated with buckling and first ply failure.

The multi-objective optimization problem of plates and shells built with hybrid composite structures reinforced with stiffeners under static loading is,

$$\text{Minimize}\ \ G(\mathbf{x},\boldsymbol{\pi}) = [W(\mathbf{x},\boldsymbol{\pi}),\ T_k(\mathbf{x},\boldsymbol{\pi})\,]\quad,\quad k = 1,2 \tag{4}$$

subject to

$$g_1(\mathbf{x},\boldsymbol{\pi}) = 1 - \frac{\lambda_{crit}(\mathbf{x},\boldsymbol{\pi})}{\overline{\lambda}_a} \leq 0 \tag{5}$$

$$g_2(\mathbf{x},\boldsymbol{\pi}) = \frac{d_{crit}(\mathbf{x},\boldsymbol{\pi})}{\overline{d}_a} - 1 \leq 0 \tag{6}$$

with $\overline{\lambda}_a$ and $\overline{d}_a$ the allowable values for critical load factor and critical displacement, and the size constraints:

$$x_j^l \leq x_j \leq x_j^u \quad,\quad j = 1,\dots,\overline{N}_x \tag{7}$$

satisfying the equilibrium equation set:

$$\boldsymbol{\Psi}(\,{}^{t}\mathbf{d},\ {}^{t}\lambda,\mathbf{x},\boldsymbol{\pi}) = \mathbf{R}\left(\,{}^{t}\mathbf{d},\mathbf{x},\boldsymbol{\pi}\right) - \ {}^{t}\lambda\overline{\mathbf{F}} = \mathbf{0} \tag{8}$$

and the additional arc-length method equation:

$$\boldsymbol{\Phi}(\,{}^{t}\mathbf{d},\ {}^{t}\lambda,\mathbf{x},\boldsymbol{\pi}) = \mathbf{0} \tag{9}$$

In equilibrium Equation (8), $\mathbf{R}\left(\,{}^{t}\mathbf{d},\mathbf{x},\boldsymbol{\pi}\right)$ denotes the internal forces in the structural system reflecting the dependence relatively to design variables. The composite structure with nonlinear geometric behaviour reaches the equilibrium after an iterative and incremental loading process based on the arc-length method in Equation (9) for a load level t. In the objective function given by (4) the term $W(\mathbf{x},\boldsymbol{\pi})$ is the total weight of the laminated structure, and it is defined as

$$W(\mathbf{x},\boldsymbol{\pi}) = \sum_{j=1}^{Nlam} \sum_{i=1}^{np(j)} \mu_{ij}(\boldsymbol{\pi}) V_{ij}(\mathbf{x}) \tag{10}$$

where $\mu_{ij}(\boldsymbol{\pi})$ is the specific weight of the composite system and $V_{ij}(\mathbf{x})$ is the volume both of them defined for the *i-th* ply of the *j-th* laminate. In Equation (10), *Nlam* is the number of laminates used to build the hybrid composite structure and $np(j)$ is the number of plies of the *j-th* laminate. The term $T_k(\mathbf{x},\boldsymbol{\pi})$ in Equation (4) is associate with the sustainability of the composite structure. This second objective function depends on the studied case as follows:

1st case study: In this case the second objective to minimized is the mean value of the strain energy corresponding to the deformed configuration of the structure valuated in close form as

$$T_1(\mathbf{x},\boldsymbol{\pi}) = U(\mathbf{x},\boldsymbol{\pi}) = \frac{1}{2}\ {}^{t}\lambda\, \bar{\mathbf{F}} \bullet\ {}^{t}\mathbf{d} \tag{11}$$

for the structural equilibrium defined in (8) and (9).

2nd case study: The standard deviation of the strain energy on the deformed configuration of the structural system is the second case studied. The mean value and the variance of the energy is obtained respectively as

$$E(U) \equiv U^0 \tag{12}$$

$$var(U) \equiv E((U-U^0)^2) = \sum_{i=1}^{n} S_i^2 var(x_i) + 2\sum_{i\neq j=1}^{n} S_i\, S_j\ cov(x_i,x_j) \tag{13}$$

being U^0 the calculated value for the energy for the *nominal values* $\mathbf{x^0} = (x_1^0,\dots,x_n^0\,)$. The matrix form of the equation (13) is

$$var(U) = \mathbf{S}\,\mathbf{C}_x\,\mathbf{S}^T \tag{14}$$

where the superscript "T" denotes the transposition, $\mathbf{C}_x$ is the covariance matrix for parameters $(x_1,\dots,\ x_n)$ with components defined as

$$(\mathbf{C}_x)_{ij} = \begin{cases} cov(x_i,x_j) = \rho_{ij}\,\sigma_i\,\sigma_j\ ,\ i\neq j\ ,\ \rho_{ij} = correlation\ coefficient \\ var(x_i) = \sigma^2 \quad ,\quad i=j \end{cases} \tag{15}$$

and the column vector $\mathbf{S} = (S_1,\dots,\ S_n)$ has components $S_i = (\partial U/\partial x_i)_{\mathbf{x}^0}$.

If the design variables $(x_1,\dots,\ x_n)$ are uncorrelated then equation (13) is

$$var(U) = \sum_{i=1}^{n} S_i^2 var(x_i) = \sum_{i=1}^{n} S_i^2\ \sigma_i^2 \tag{16}$$

and the second objective function in this case is written as

$$T_2(\mathbf{x},\boldsymbol{\pi}) = \{var[U(\mathbf{x},\boldsymbol{\pi})]\}^{1/2} \tag{17}$$

In this paper, a robust design optimization approach supported by multiple-objective Memetic Algorithm (MOMA) is proposed. Multi-objective Memetic Algorithm (MOMA) searching Pareto-optimal front is proposed. MOMA applies multiple learning procedures exploring the synergy of different cultural transmission rules. The approach is based on multiple populations, species conservation, migration, self-adaptive, local search, controlled mutation, age control and features-based allele's statistics. These aspects are associated with some kind of problem knowledge and learning classified as Lamarckian or Baldwinian (Krasnogor and Smith, 2006). The memetic learning procedures aim to improve the exploitation and exploration capacities of MOMA.

At isolation stage of each MOMA sub-population POP1 POP2 and POP3 different segments of chromosomes are active as is shown in Figure 1. The activation procedures correspond to a decomposition of the original multi-objective optimization problem formulated from Equation (4) to Equation (9). The sorting of individuals at those sub-populations are based on local non-constrained-dominance. The problem of stacking sequence design of composite structures known for having many local optima, and so, dominated solutions are expected. The memetic properties and the local and global dominance concepts of the multi-objective genetic algorithm are applied together with feature-based allele's statistics analysis used in the learning procedure. This performs considering an age and dominance-based structured virtual population (VP). The VP plays important role in evolutionary process based on two rules: the first one is to store the ranked solutions aiming to obtain the Pareto front and the second one is to evolve as a virtual population of alleles.

The proposed approach involves a continuous model of generation of individuals adopted for age and dominance-structured virtual population VP. This enlarged population performs in parallel with the hierarchical topology of sub-populations of MOMA. Two parameters identify each individual belonging to population VP: individual age and his rank position according the concepts of global dominance. The individual age increases one unit after each generation. Any individual removed from MOMA sub-populations either by elitist strategy or by finishing of isolation stage of evolution and not selected for migration, will survive in the population with age and dominance-structured VP. Furthermore, its individual age will continue increasing until removed definitively due to lethal age. The population VP ranked according to non-dominance concepts enables to trace the corresponding global Pareto front.

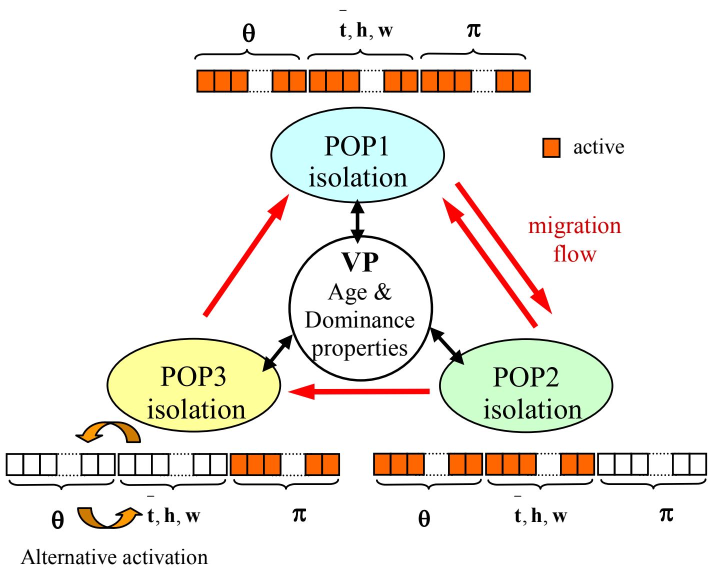

Fig. 1 - Multiobjective Memetic Algorithm (MOMA) flow diagram

The following crossover operators are used in the MOMA: *Elitist Hybrid Crossover with genetic improvement* (EHCgi) (Conceição António, 2006 and 2009); *Elitist parameterized Uniform Crossover* (EpUC) (Conceição António, 2006 and 2009), *Age-Dominance* *parameterized Uniform Crossover* (ADpUC) (Conceição António, 2013) and the new operator denoted by *Age-Dominance parameterised Selfish Gene* (ADpSG) crossover.

Continuous statistical parameters of alleles in VP and its relationship with dominance is established. Then, selecting the most promising alleles for each offspring gene, it is emulating the cultural and genetic evolution. Figure 2 shows the linkage of age structure and dominance for the ADpSG proposed crossover.

In this work, the evolution at each sub-population of MOMA performs based on the selection of two or three crossover schemes as follows:

POP1: EpUC or (ADpUC and ADpSG)

POP2: EpUC or EHCgi (local optimizer)

POP3: EpUC or (ADpUC and ADpSG)

The probability selection of the appropriate crossover operator comes from the success rate (Conceição António, 2009) during the evolutionary process. The ADpUC and ADpSG are applied together to build the offspring group.

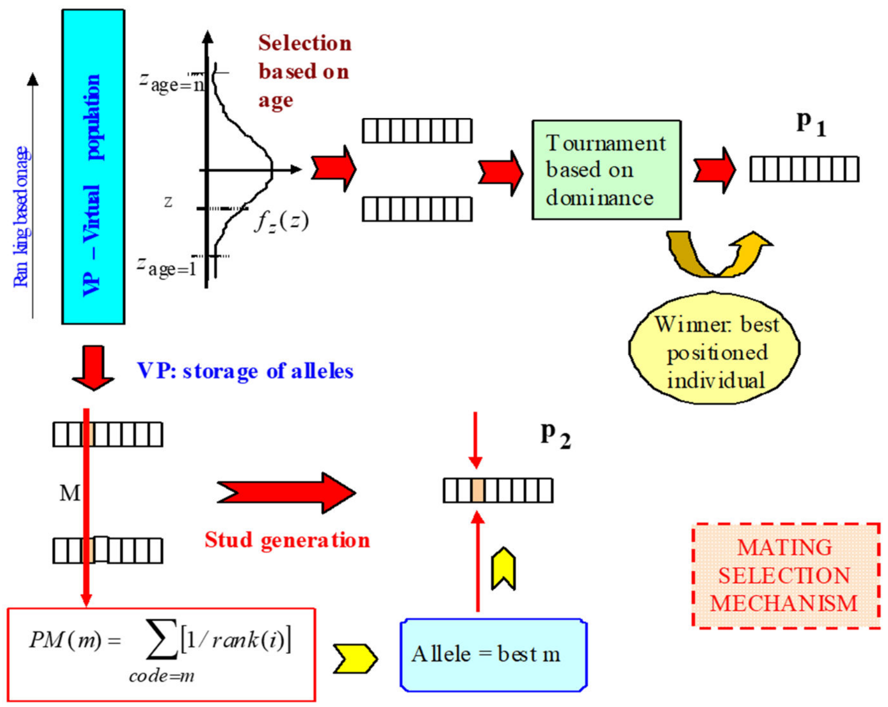

Fig. 2 - The mating selection mechanism of the *Age-Dominance parameterised Selfish Gene* (ADpSG)

Other Lamarckian learning procedures such as the *Controlled Mutation* (Conceição António, 2006 and 2009). The incorporation of data related to the behavior of the state variables of the structural system is the main objective of the Controlled Mutation for the Selfish Gene Theory application. The Controlled Mutation operator performs in two steps:

First step: The establishment of a relationship between the stress field on the composite structure and the genes of the chromosome directly associated with the structural behavior.

Second step: To change the gene composition by controlled mutation aiming to improve the fitness of the selected individual and inserting it back in the population.

The Controlled Mutation performs in an alternative way with the *Implicit Mutation* (Conceição António, 2006).

RESULTS

Let us consider a spherical composite shell structure reinforced with beam stiffeners, as shown in Figure 3. The shell is hinged at its perimeter and subjected to a reference load, $F_{max} = 10\,kN$, applied at central point of the structure. Three shell laminates (1 to 3) compose the structure reinforced with three beam laminates (4 to 6), as defined in Figure 3. The laminates are symmetric with six layers. The j-th shell laminate is defined by i-th ply angle $\theta_{i,j}$ and by i-th ply thickness $\bar{t}_{i,j}$ design variables. For the j-th beam laminate, the design variables of the cross-sections are the width w_j and the height h_j. Figure 1 defines these design variables active during the isolation stage of each sub-population. The numbering of plies follows from upper ply to lower ply. The stiffeners connected below the shell elements and the fibres aligned with their longitudinal axis. Figure 3 shows the stiffeners built with beam laminates plotted by bold lines.

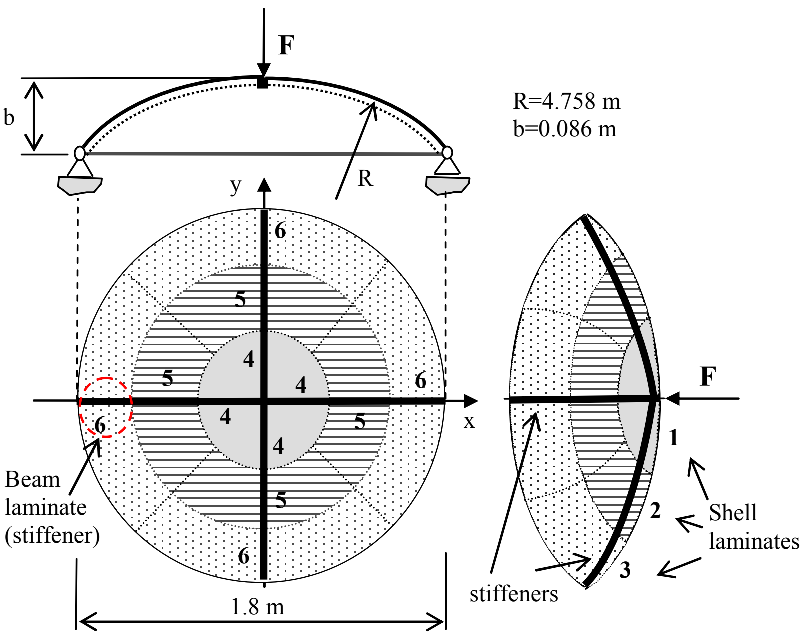

Fig. 3 - Spherical shell composite structure with stiffeners and laminate definition

It can be selected one material among the four composite systems presented in Table 1 for ply laminates: one carbon/epoxy composite, two glass/epoxy composites and one Kevlar/epoxy composite (Tsai, 1987). The Kevlar/epoxy is a possible material choice only for the inner ply of the symmetric laminates. The remaining materials are free selection and the hybrid composite laminate construction uses at least two materials. Then there are 33 possible combinations of these four materials for the stacking sequence π_j considering the defined rules and six plies in the symmetric *j-th* composite shell laminate construction.

Table 1 - Mechanical properties of the materials used in the composite laminate

Material		E_1 [GPa]	E_2 [GPa]	G_{12} [GPa]	ν
Type	Code				
CFRP: T300/N5208	1	181.00	10.3	7.17	0.28
GFRP: Scotchply 1002	2	38.60	8.27	4.14	0.26
GFRP: E-glass/epoxy	3	43.00	8.90	4.50	0.27
KFRP: Kevlar 49/epoxy	4	76.00	5.50	2.30	0.34
		X [MPa]	Y [MPa]	S [MPa]	ρ [kg/m3]
CFRP: T300/N5208	1	1500	40	68	1600
GFRP: Scotchply 1002	2	1062	31	72	1800
GFRP: E-glass/epoxy	3	1280	49	69	2000
KFRP: Kevlar 49/epoxy	4	1400	12	34	1460

The material of the six plies of the beam laminates is the material number 2 from Table 1 and does not change during the optimization process. The allowable value for critical displacement in buckling or FPF failure modes is, $\bar{d}_a = 9.0 \times 10^{-2}$m. The lower bound for the critical load factor defined in Equation (4) is, $\bar{\lambda}_a = 0.2$. The size constraints on the design variables are:

$$
\begin{gathered}
-90° \leq \theta_{i,j} \leq 90° \\
1.0 \times 10^{-3}\text{m} \leq \bar{t}_{i,j} \leq 4.0 \times 10^{-3}\text{m} \\
2.0 \times 10^{-2}\text{m} \leq h_j \leq 4.0 \times 10^{-2}\text{m} \\
5.0 \times 10^{-3}\text{m} \leq w_j \leq 2.0 \times 10^{-2}\text{m}
\end{gathered}
\tag{18}
$$

The uncertainty in design variables $(\bar{\mathbf{t}}, \boldsymbol{\theta}, \mathbf{h}, \mathbf{w})$ considered for robustness analysis is formulated from equation (12) to equation (17). The random design variables used in uncertainty and sensitivity analysis is the vector $\mathbf{X} = (\bar{\mathbf{t}}, \boldsymbol{\theta}, \mathbf{h}, \mathbf{w})$ being:

- the ply thickness of shell laminates group $\bar{\mathbf{t}}$;
- the ply angle of shell laminates group $\boldsymbol{\theta}$;
- the height and width beam laminates group (**h**, **w**).

The standard deviations $\sigma(\theta_i) = 5°$ are prescribed for all random design variables belonging to the ply angle group, $\boldsymbol{\theta}$. The standard deviation, $\sigma_{\mu_i} = 0.05\bar{\mu}_i$, is considered for each design variable μ_i, belonging to the remaining groups $\bar{\mathbf{t}}$ and (**h**, **w**). In this case, $\bar{\mu}_i$ is the mean value of the design variable taken from the values of RDO at each generationof the evolutionary process.

Table 2 presents the genetic parameters of MOMA. Ten individuals belonging to different species (Conceição António, 2006, 2009, 2013 and 2014) participate in each migration flow between the three MOMA sub-populations. The number of digits in code format refers to the binary coding of the first two segments and the last number refers to the integer code used in third segment of the chromosome associated with laminate identification and laminates distribution on the composite structure as shown in Figure 3.

Table 2 - Genetic Algorithm parameter definitions

Subpopulation	POP1	POP2	POP3
Population size	27	27	27
Elite group size	11	11	11
Mutation group size	5	5	5
Nr. digits/binary or integer code	4/4/4	4/4/4	4/4/4
Generations/isolation time	8	8	8

In the age and dominance-structured population VIP, the *lethal age* is equal to 35 generations. In the self-adaptive crossover procedure, the parameters are according to author previous research (Conceição António, 2009). After the lethal age, only non-dominated (rank 1) solutions survive inside VIP population. An epoch is a complete cycle of isolation stages of POP1, POP2 and POP3.

Figures 4 and 5 show the Pareto fronts (rank 1) for both studied cases after thirty epochs: (1) weight vs strain energy objectives; and (2) weight vs standard deviation of strain energy objectives. The global dominance measured in age and dominance-structured population VP enables to trace the associated Pareto fronts. It can be observed the performance of the proposed approach to search for Pareto front' solutions considering the multi-objective optimization problem.

Table 3 and Table 4 show the two Pareto-optimal non-dominated solutions (rank 1) for the two bi-objective optimization studied cases marked on Figure 4 and Figure 5. The solutions come from the convergence at the 30th epoch of age and dominance-structured population VP.

The strain energy is associated with the stiffness properties of the structure. When the minimized objectives are the weight and the strain energy (1st case study), it is observed a fair variability of strain energy measured by its CV as shown in Figure 4. The nominal values of strain energy follow the same behaviour of Pareto front if the objectives are the weight minimization and the standard deviation of strain energy minimization (2nd case study) as presented in Figure 5.

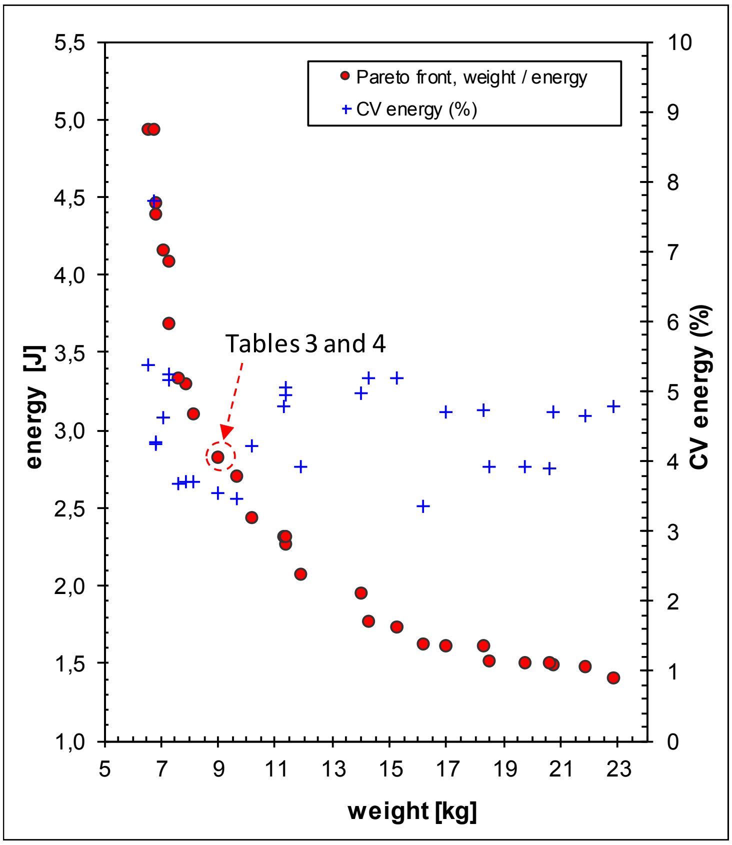

Fig. 4 - Optimal Pareto front corresponding to bi-objective optimization weight vs strain energy (1st case study); variability of energy (CV energy %) for each solution on Pareto front

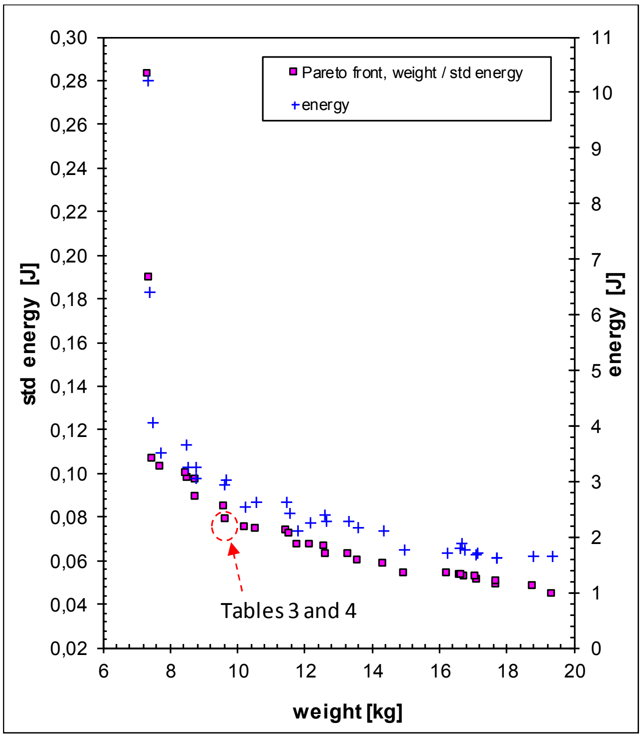

Fig. 5 - Optimal Pareto front corresponding to bi-objective optimization weight vs standard deviation of strain energy (2nd case study); strain energy for each solution on Pareto front

Table 3: Decoding results of the Pareto-optimal front solutions for the first two segments of chromosome ($\bar{t}_{i,j}$, h_j, w_j [mm] and $\theta_{i,j}$ [degrees])

Laminate		Design variables	Pareto optimal solutions	
Shell	Beam		Weight vs Energy	Weight vs Std Energy
1		$\bar{t}_{1,1} / \theta_{1,1}$	2.00/ 18	1.00 / 30
1		$\bar{t}_{2,1} / \theta_{2,1}$	1.00/ 78	2.20 / 6
1		$\bar{t}_{3,1} / \theta_{3,1}$	3.20/ 54	2.00 /-66
2		$\bar{t}_{1,2} / \theta_{1,2}$	1.00/ 54	1.00 / 42
2		$\bar{t}_{2,2} / \theta_{2,2}$	1.00/ 6	2.60 /-78
2		$\bar{t}_{3,2} / \theta_{3,2}$	1.00/ 66	1.00 / -30
3		$\bar{t}_{1,3} / \theta_{1,3}$	2.40/ -18	1 40 / 66
3		$\bar{t}_{2,3} / \theta_{2,3}$	1.00/ -78	1.00 /-54
3		$\bar{t}_{3,3} / \theta_{3,3}$	1.00/ -30	1.40 / -6
	4	h_1 / w_1	40.0 / 10.0	40.0 / 17.0
	5	h_2 / w_2	26.7/ 7.0	20.0 / 6.0
	6	h_3 / w_3	28.0/ 6.0	33.3 / 5.0
Objectives:		Weight [kg]	9.001	9.664
		Energy [J]	2.823	(3.0283)
		Std Energy	(9.9795E-02)	7.8504E-02

Table 3 and Table 4 show the details of two design solutions belonging optimal Pareto fronts both of them marked in Figure 4 and Figure 5. In particular, Table 4 presents the description of the third segment of the chromosome for the two referred Pareto-optimal front solutions (rank 1) of Table 3 associated with optimal material distribution on spherical composite structure. These correspond to optimal stacking sequence at laminate level and optimal laminate distribution on structure level. According geometric definition of the RDO problem in Figure 3 the composite structure have three shell laminates. The stacking sequence of each symmetric shell laminate done in closed brackets uses the composite system numbering defined in Table 1. The optimal laminate distribution on the structure takes different laminates for the minimization of weight vs Std energy. However, when the minimized objectives are the weight vs strain energy (1^{st} case study), the optimal solution takes the same laminates.

Table 4: Decoding results of the Pareto-optimal front solutions corresponding to the third segment of each chromosome (ply material properties defined in Table 1)

Pareto-optimal solutions	Optimal stacking sequence at laminate level & optimal laminates distribution on structure π_1 ; π_2 ; π_3
Weight vs Energy ^{t}	$[1/1/4]_S$; $[1/1/4]_S$; $[1/1/4]_S$
Weight vs Std Energy	$[1/3/4]_S$; $[1/1/2]_S$; $[1/1/4]_S$

CONCLUSIONS

This paper presents an approach for RDO of composite structures that simultaneously consider minimum weight versus minimum strain energy or minimum strain energy variability. The goal is to obtain the sustainable design for hybrid composite structures. A Multi-objective Memetic Algorithm (MOMA) was developed and applied to the optimization of hybrid composite shell structures with stiffeners. The memetic learning procedures aims to improve the exploitation and exploration capacities of MOMA. The robustness-based design optimization performs comparing two constrained bi-objective optimization problems: (1) weight vs strain energy minimizations; and (2) weight vs standard deviation of strain energy minimizations. From the trade-off of both bi-objective optimization problems, depending on given stress, displacement and buckling constraints imposed on composite structures, the global Pareto-optimal fronts are built. Results show that MOMA is promising in multi-objective optimization of FRP composite hybrid structures.

ACKNOWLEDGMENTS

The authors gratefully acknowledge the funding by Fundação para a Ciência e Tecnologia (FCT), Portugal, through the funding of the “Associated Laboratory of Energy, Transports and Aeronautics (LAETA)”.

REFERENCES

[1] Conceição António C.A., A hierarchical genetic algorithm with age structure for multimodal optimal design of hybrid composites, Structural and Multidisciplinary Optimization, 2006, 31, pp. 280-294.

[2] Conceição António C. Self-adaptation procedures in genetic algorithms applied to the optimal design of composite structures. International Journal of Mechanics and Materials in Design, 2009, 5, pp. 289-302.

[3] Conceição António CA. Local and global Pareto dominance applied to optimal design and material selection of composite structures. Struct and Multid Optimiz, 2013, 48, pp. 73-94.

[4] Conceição António C. A memetic algorithm based on multiple learning procedures for global optimal design of composite structure, Memetic Computing, 2014, 6, pp. 113-131.

[5] Krasnogor N, Smith J. A tutorial for competent memetic algorithms: Model, taxonomy and design issues. IEEE Transactions on Evolutionary Computation, 2005, 9(5), pp. 474-488.

[6] Moscato P. On evolution, search, optimization, genetic algorithms and martial arts: towards memetic algorithms. Caltech Concurrent Computation Program, C3P Report, 826, California Institute of Technology, Pasadena, CA, 1989.

[7] Tsai SW. Composites Design. Think Composites, Dayton, USA, 1987.