OPTIMIZATION OF NiTi BASED SMART COMPOSITES FOR SHAPE CONTROL

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1. Introduction

The aim of this work consists in developing a simple numerical method which is able to design NiTi based laminated composites for shape control. These composites can be constructed by using traditional unidirectional plies and NiTi based ones (passive and active plies in the following). The active plies can be obtained by embedding previously trained NiTi wires, *i.e.* with TWSME (Two-Way Shape Memory Effect) capabilities, into the matrix. The activation of thermally induced phase transformation in NiTi wires allows to change the shape of the smart composite, depending on several design parameters, such as number, orientation, thickness and volume fraction of each passive and active ply.

The proposed method combines finite element (FE) analysis and genetic algorithms (GA) to choose the optimal design of smart composites for shape control, in terms of the aforementioned parameters, starting from a pre-defined target shape. The optimisation process updates the properties of the NiTi plies and the laminate stacking sequences in the FE model, until the numerical displacements fit the pre-defined ones, which correspond to the target shape. The effectiveness of the procedure was tested by means of a series of numerical simulations carried out on a clamped cantilever laminate.

2. The optimising process

A real-coded adaptive range genetic algorithm was developed on a personal computer in MatLab® environment (distributed by MathWorks Inc). It uses the general-purpose numerical code MSC-NASTRAN to carry out the static analysis. A schematic representation of the algorithm is shown in figure 1. The process starts with the generation of a random initial population of potential solutions. Each individuals of the population is represented by the stacking sequences of active and/or passive plies with various fiber volume fractions. Each design is randomly made by choosing the number of plies, the ply orientation angles and the component volume fractions inside a set of values given by the user.

For each design of the population, in the NASTRAN pre-processor stage, the MSC/NASTRAN input file, which is originally created by the MSC/PATRAN translator, is adjusted, by modifying PCOMP bulk data entries, to take into account the imposed layout of plies

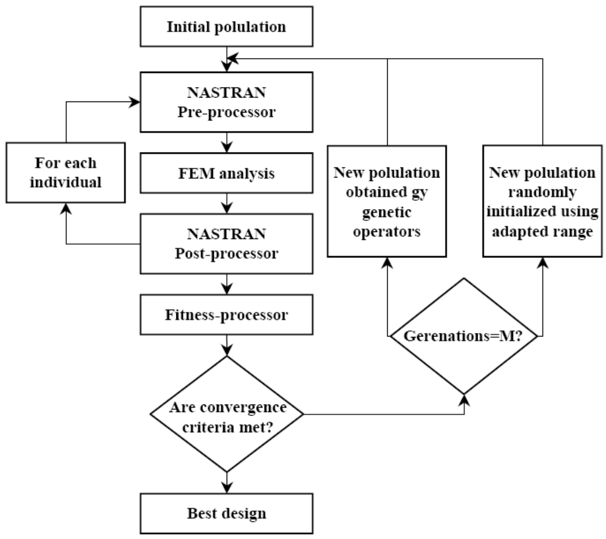

Figure 1: GA implementation

$[\theta_1, \dots, \theta_i, \dots, \theta_N]$ and their effective elastic properties $(E_1, E_2, \nu_{12}, G_{12})_i$. These latter are calculated for each ply starting from assigned fiber volume fraction and constituent material properties using the micromechanics equations given by the elementary and improved mechanics of materials approach [1]. The activation of thermally induced phase transformation in previously trained NiTi wires, *i.e.* with TWSME capabilities, induces a strain ε_{tw0} (with amplitude depending on the alloys used and on the thermo-mechanical training, see Fig. 2 [2]) which in its turn gives arise to strain ε_1 and ε_2 of the ply. These strains can be simulated on the finite element model as thermally induced strains equal to $\alpha_1\Delta t$ and $\alpha_2\Delta t$ respectively, where α_1 and α_2 are the longitudinal and the transverse fictious coefficients of thermal expansion and Δt is the variation of temperature, corresponding to the thermally induced phase transformation (see Fig. 2).

For a fixed value of Δt, α_1 and α_2 can be obtained by the following rule of mixtures:

$$\alpha_1 = \frac{E_f \alpha_0 V_f + E_m \alpha_m V_m}{E_f V_f + E_m V_m} \quad (1)$$

$$\alpha_2 = [(1+\nu_m)\alpha_m V_m + (1+\nu_f)\alpha_0 V_f] - \alpha_1 \nu_{12} \quad (2)$$

$$\alpha_0 = \begin{cases} \alpha_f & passive\,plies \\ \varepsilon_{tw0}/\Delta t & active\ plies \end{cases} \quad (3)$$

where the subscript *m* indicates the matrix while *f* represents the fiber in the passive plies and the NiTi wires in the active ones; α is the coefficient of thermal expansion; V is the volume fraction; *E* is the Young's modulus. For the sake of simplicity in the following test cases the coefficients of thermal expansion of matrix and fiber (α_m and α_f) are set to zero, because they can be neglected with respect to the quantity $\varepsilon_{tw0}/\Delta t$; this means that the passive plies are strained passively from the active ones.

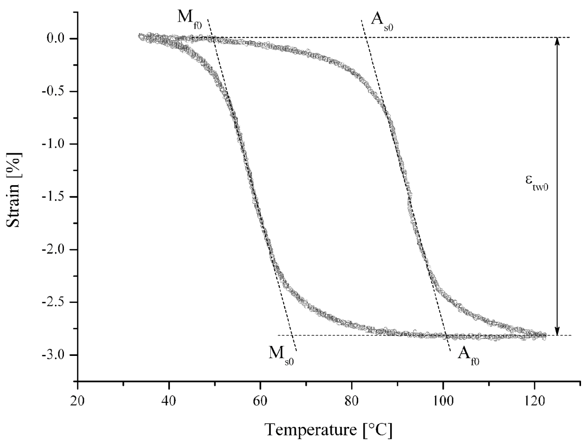

Figure 2: Thermally induced phase transformation in NiTi wires.

In the post-processing stage the error function (fitness) is evaluated for each design. The fitness processor begins to operate after the processing of the whole population arranging the fitness values of the population in decreasing order and checking the convergence criteria. If the convergence criteria are not reached, the most suitable solutions are selected and are processed by means of the genetic operators to create the new population. The process is repeated for a fixed number of analyses until there is no further improvement in the best solution.

To explore the search space more efficiently, the algorithm described above was provided with an adaptive range procedure [3] by which the entire population is regenerated every a number M of generations. The goal of the optimisation is to minimize the following objective function:

$$\varphi = \sum_{j=1}^{n}\sum_{k=1}^{3}\left[\left|u_k - \overline{u_k}\right|\right]_j , \qquad (4)$$

where u_k and $\overline{u_k}$ represent the calculated and the pre-assigned (target) components of the displacement along the axis k of a coordinate system. j is the generic point on the surface of the plate and n is the number of sampling points considered. A proportional selection scheme was adopted for the reproduction of the child generation and two procedures (arithmetical and replacing types) used to carry out the crossover operation. In order to speed up the evolution and to improve the convergence performance of the GA a mutation and elitism selection have also been introduced.

Tab. 1 Genetic algorithm parameters

Population number	120	M	35
Crossover probability	80%	$\omega_\mu=\omega_\sigma$	0.5

The values of the parameters involved (population size, probability of mutation and crossover, M, ω_m and ω_σ, i.e. the relaxation factors on the average and on the standard deviation that provide robustness during the range adaptation, and the overlapping κ) are reported in table 1. Such values were selected on the basis of systematic trials carried out by a series of numerical simulations.

3. Applications

A cantilever laminate was chosen as test case. The behaviour of the three different stacking reported in Tab. 2 (in which the apexes *a* and *p* indicate the active and the passive plies, respectively) were considered. The laminate were 300x50 mm^2 and all its plies had the same thickness t = 2 mm. ε_{tw0} and Δt were assumed equal to 0.5 % and 100 °C, respectively.

Tab.2 Test case lay-ups

	Stacking
a)	$[0^a, 90^p]$
b)	$[-45^a, 0^p, -45^a]$
c)	$[45^a, 0^p, -45^a]$

Each laminate was first modelled and meshed and then numerically processed for the calculation of the displacement at each node of the mesh. Successively, the whole surface displacement field was assumed as target shape and the inverse identification process was carried out. In each case the stacking of plies have been correctly identified. The effectiveness of the proposed procedure was also verified on other case studies not reported here for the sake of brevity. In any cases the algorithm reached the minimum after few generation with a negligible fitness, showing that the procedure is effective.

Conclusion

The results obtained are encouraging. However, this first implementation requires additional refinement to increase the efficiency and reduce computational times. Moreover, it is worth noting that even if, the proposed procedure shows a good effectiveness in the cases faced in this paper, many other efforts have to be devoted to understand its limitation and as well as the effective range of application.

References

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