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Sensors optimization strategies for an efficient shape sensing using the inverse Finite Element Method: a comparative study

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Abstract. The inverse Finite Element Method is attracting significant attention as a crucial tool for the Structural Health Monitoring framework. This method allows for the monitoring of the displacements field of a structure from discrete strain sensors. Its accuracy, and consequently its applicability to real structures, strongly depends on the strain sensors configuration. In this work three optimization algorithms, the Genetic Algorythm (GA), the Particle Swarm Optimization (PSO) and the Whale Optimization Algorithm (WOA), are explored to assess their effectiveness as a fast and robust tool for the optimization of the strain sensors for the iFEM. The study proves that the GA is preferable when the considered configuration requires the exploration of a broad search space, whereas the PSO and WOA are preferable when a fast optimization of a reduced set of possible sensors is required.

INTRODUCTION

The inverse Finite Element Method (iFEM) is a shape sensing algorithm that allows to reconstruct the displacement field of a structure from discrete strain measurements. It is based on the discretization of the structural domain with Finite Elements and on the minimization of a functional that expresses the error between the measured strains and the ones analytically expressed in terms of the discretized displacement field [1, 2]. The accuracy, and consequently the success of this method as an efficient Structural Health Monitoring (SHM) tool, strongly depends of the strain sensors configuration installed on the monitored structure. For this reason, previous works have focused their attention on the optimization of the sensors configuration. Among the several optimization algorithm, the existing literature only explored the Genetic Algorithm [2] and the Particle Swarm Optimization (PSO) [3]. The GA is an optimization algorithm inspired by the evolution of the species mechanism [4]. The PSO is a bio-inspired algorithm and it is based on the movement and intelligence of swarms [5]. The previously cited works only considered one algorithm at time and lack a comparison of the efficiency and robustness between at least two optimization algorithms. In this work, for the first time, the performances of the GA and the PSO are compared on the sensors optimization for the reconstruction of the displacement field of a composite stiffened wing-shaped plate. The analysis is performed numerically and experimentally. Moreover, a third optimization algorithm is also included in the comparison, the Whale Optimization Algorithm (WOA). This recently developed algorithm, inspired by the social behavior of the humpback whales, has never been associated with iFEM's sensors optimizations, but has been adopted for other applications related to the structural analysis framework [6].

NUMERICAL STUDY

This study is focused on comparing the performances of the three optimizing algorithms of interest, the GA, the PSO and the WOA, on the optimization of the strain sensors configuration for the shape sensing of a composite wing-shaped panel. The panel is presented in Fig. 1, where the geometry and the inverse mesh, used for the application of the iFEM, are shown. The panel is 4 mm thick as a result of a symmetric composite layup of eight layers. The panel is stiffened by three T-shaped stringers. The layup stacking sequence of the panel and of the web of the stringers is [45/0/0/45/0/0/0/45]s. The T-section stringers are manufactured by bending the layers of the web at a 90° angle to obtain the two caps. Therefore, the stacking sequence of each cap is derived by folding one half of the web's stacking sequence. Each layer is made of a TWILL T-300 carbon-fibre fabric prepreg ($E_{11} = E_{22} = 59.7\ GPa$; $\nu_{12} = 0.09$; $G_{12} = G_{23} = G_{13} = 3.8$; $Thickness = 0.25\ mm$). The panel is simply supported on the two sections located at 41 mm from the two tips of the two half-wings and it is loaded by a concentrated transverse load on the mid section of the wing panel (See Fig.1). This load configuration provokes a deformation that combines bending and torsion. A more detailed description of the structure and of the loading condition can be found in [2]. The inverse model of the specimen, also shown in Fig. 1, is constituted by 672 four-node quadrilateral inverse shell elements (iQS4) [7] and 144 two-node 0th-order Timoshenko inverse beam elements [8]. The quad elements are used to model the panel

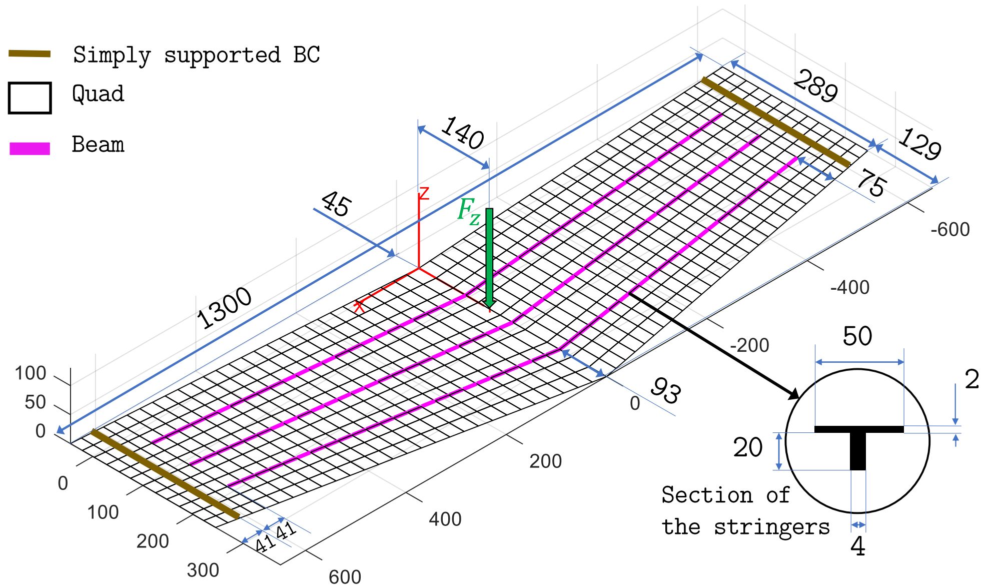

FIGURE 1. Composite stiffened panel - the geometry and the inverse mesh of the analysed structure are shown. All dimensions are expressed in mm.

and the stringers' caps, whereas the beam elements are associated to the stringers' webs. A more refined FE model of the structures, constituted of only shell elements, is also adopted to generate the strain inputs and the reference displacements required to perform the optimization of the sensors.

The comparison of the optimization strategies is performed considering two scenarios with different characteristics. The first scenario considers a very broad search space, with multiple possible combinations of sensors, resulting in a very difficult challenge for the optimizers. In this case, the optimizers should select the best configuration of 20 strain rosettes among 672 possible locations. Each eligible location is represented by the centroid of each inverse iQS4 element. The second scenario considers a reduced subset of the search space and it is inspired by the use of fibre optic sensors combined with strain rosettes. In this case, the optimizers should find the best configuration that considers 8 fibres running along the wing span and 6 strain rosettes located close to the root of the wing (an exemple of the fibres and rosette locations is shown in Fig. 3). The search space is highly reduced. In fact, the optimizer has to select 8 out of 15 possible fibres' locations and 6 out of 24 possible rosettes' locations. The objective of the optimizations is to minimize the root mean square percentage error in the reconstruction of the transverse displacements. The error is computed as:

$$\%Erms_w = 100 \times \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(\frac{w_i - w_i^{ref}}{w_{max}^{ref}}\right)^2} \tag{1}$$

where, N is the number of nodes of the inverse mesh, w_i are the reconstructed transverse displacements, w_i^{ref} are the reference displacements computed with the refined FE model and w_{max}^{ref} is the maximum value of the reference displacements.

The three optimization algorithms are based on an iterative process that requires the evaluation of the objective function multiple times. The number of the iterations depends on multiple parameters, specific to the selected optimization algorithm, i.e. number of individuals (GA), swarm size (PSO), number of search agents (WOA). The computation of the $\%Erms_w$ implies the solution of the iFEM problem, that, especially for complex structures, can result in a computationally demanding process. Therefore, the objective of this work is to compare the performances of the GA, the PSO and the WOA in terms of the selected optimal value of the objective function and of the number of required computations to reach those optima. Since stochasticity characterizes the process of these optimization algorithms, a statistical approach is used for this evaluation. Multiple optimizations are performed for each optimization algorithm. From these analysis the value of the optimal solutions and of the number of iFEM's runs to reach that solution are

TABLE 1. Numerical results - 20 rosettes optimization.

	GA	PSO	WOA
Mean $\%Erms_w$	19.83	27.25	29.04
Mean iFEM iterations	582040	124080	589560

TABLE 2. Numerical results - 8 fibres and 6 rosettes optimization.

	GA	PSO	WOA
Mean $\%Erms_w$	0.26	0.22	0.18
Mean iFEM iterations	3980	3162	3456

collected. For each algorithm, the avarage values of the multiple optimizations' results are extracted and used as a term for the comparison.

For the first scenario, relative to the optimization of 20 strain rosettes, ten runs per algorithm are performed. The mean values of the best $\%Erms_w$ and of the number of required iterations over the ten runs are reported in Table 1. For this kind of problem, where the variables search space is significantly broad, the results show that the GA is able to averagely reach the best minimization of the objective function, $\%Erms_w = 19.83$, performing a consistent number of iterations, 582040. On the other hand, the PSO quickly converges to a higher minimum with few iterations. The WOA shows the less promising results for the two considered parameters. The second scenario, relative to the optimization of 8 fibres and 6 rosettes, leads to different considerations. Also in this case, ten runs are considered and the mean value of these runs are extracted and reported in Table 2. The PSO and the WOA seem to show an advantage in the analysis of this scenario, that presents a much smaller variables search space. In fact, these two algorithms are able to find a better sensor configurations with a strongly reduced number of iterations with respect to the GA.

EXPERIMENTAL APPLICATION

The experimental application is aimed at consolidating some of the conclusions derived from the numerical study. The same structure numerically simulated in the previous section has been realized and the same loading configuration also applied to the real structure. The testing configuration is presented in Fig. 2. The panel is instrumented with a set of 7 fibre optic strain sensors and 8 strain rosettes, as shown in Fig. 3. This configuration has been optimized using a GA in [2]. Moreover, the panel is also instrumented with six LVDTs that measure the transverse displacements in six randomly distributed locations over the surface of the panel (see Fig. 2). The scope of this activity is to try to reduce the number of strain sensors from the original configuration through an optimization procedure. Considering that the search space, represented by the installed sensors is considerably small, the results of the numerical study suggested the use of the PSO and WOA for this activity. The optimization aims to select 3 out of the 7 installed fibres and 3 out of the 8 installed rosettes. Also for this optimization, the numerical values of strains and displacements, derived from the refined model, are considered and the objective is the minimization of the $\%Erms_w$. Both the PSO and the WOA selected the same reduced configuration of sensors over multiple runs. This configuration is illustrated in Fig. 3. In Table 3 the mean and the maximum percentage error in the reconstruction of the six measured displacements are reported for the experimental reconstructions using the full and the reduced set of sensors. The errors show that the reconstructions using the reduced set, obtained trough the PSO and WOA optimizations, are as accurate as the ones obtained using the full set, with a mean error of 4.84% and a maximum error of 8.68%. Therefore, this experimental activity proves the effectiveness of the PSO and the WOA as efficient and robust tools for the sensors optimization, when a reduced search space is considered.

TABLE 3. Experimental results.

	Full set (7 fibres - 8 rosettes)	Reduced set (3 fibres - 3 rosettes)
Mean $\%Err_w$	5.51	4.84
Max $\%Err_w$	9.33	8.68

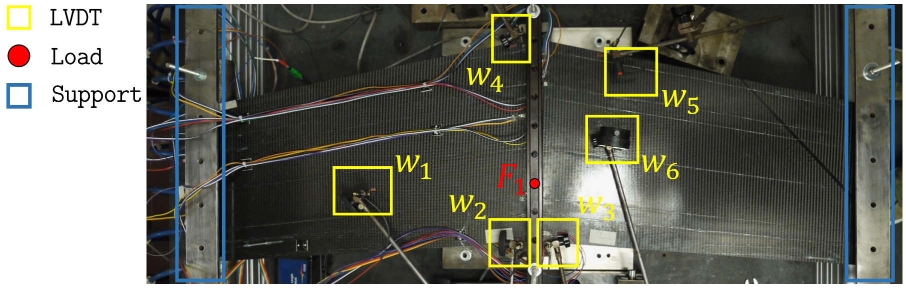

FIGURE 2. Experimental test configuration.

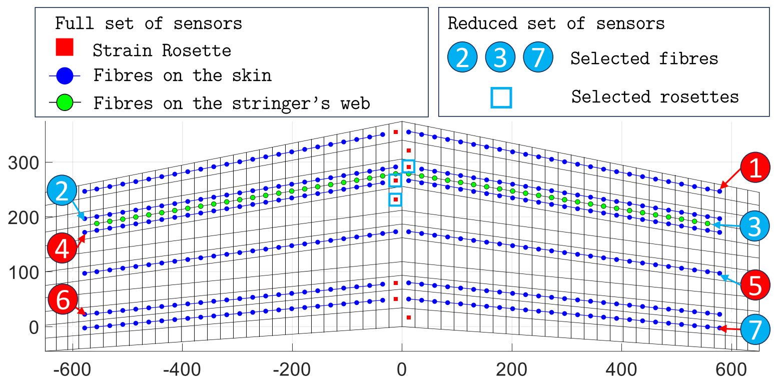

FIGURE 3. Experimental sensors configuration - The full set of strain sensors and the reduced one obtained trough the optimization are presented.

CONCLUSION

In this work, three different optimization algorithms, the GA, the PSO and the WOA, are tested on the optimization of the strain sensor configuration for the reconstruction of the displacement field trough the inverse Finite Element Method. The comparison is performed numerically and experimentally on the analysis of a composite stiffened panel subject to a deformation that combines bending and torsion. The results of the investigation show that the the GA is preferable when the search space of the optimization is characterized by a large number of possible solutions. On the other hand, when the solution space is smaller, the GA and the PSO guarantee a faster convergence toward a more accurate sensors configuration.

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