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Optimization by Particle Swarm Algorithms of an UAV performed by Hot Wire Cutting Techniques

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Abstract

This paper describes an original application of unconventional optimization techniques by Particle Swarm Algorithms. An Unmanned Aerial Vehicle performed by Hot Wire Cutting is designed for a typical civil mission defining geometry and aerodynamics with a Particle Swarm Algorithm. The tailless configuration of the vehicle requires an accurate design to gain the satisfaction of all the requirements and to obtain a low cost solution. Only an unconventional technique can be applied because of the high non linearity of the problem and the high number of parameters to be defined. A first preliminary series of tests have been carried out to define the best values for inertia and acceleration coefficients of the Particle Swarm algorithm; in the following the algorithm results have been compared with those obtained by other two techniques like Genetic Algorithms and Monte Carlo Simulations. The result of this study shows how the Rapid Prototyping techniques can be applied to the performing of small lots of UAV: the required optimal design is gained applying the Particle Swarm Algorithm. The conclusion of this work confirms the suitability of non conventional optimization methods to non linear problems: Genetic Algorithms and Particle Swarm optimization provide similar results in term of fitness maximization, while Monte Carlo algorithm presents a lower efficiency. The Particle Swarm and Monte Carlo algorithms are simple to implement within a software code with respect to the Genetic Algorithms which are quite difficult to code.

1 Introduction

1.1 State of the art

Unmanned Aerial Vehicles (UAV) are aircrafts without a pilot on-board. UAVs are systems composed by an air vehicle and by a Ground Control Station (GCS). The flight can be performed by a remote pilot, who commands the aircraft trajectory using a camera and a joystick or in automatic mode, so that the aircraft follows a series of waypoints. In this latter case the operator watches a monitor in which a map of the terrain to fly over is visualized; the flight path is imposed by moving on the map a series of waypoint and the operator check the UAV activity as a back-up of the internal logic. The UAV brain is an on-board autopilot in which the flight management system (FMS) algorithm in implemented. The FMS provide dialogue with the GCS and the interface with airframe actuators. In civil field, the UAV are now mainly used by government's agencies in D3 (Dull, Dangerous and Dirty) missions. The interest in such vehicles is also increasing since the future of the commercial air transport seems to be unmanned: UAV can be so used to gain experience in unmanned flight and in autonomous operations. Two of the main factors limiting the wide spreading of UAV in civil missions are flight rules and costs. Civil protection, territory monitoring, scientific data collection, naufraghi search in sea, police and firefighter operations, volcanoes activity studies, pipelines integrity check, floods and landslides alert are applications in which UAVs can be suitable. One of the way to reduce the cost of UAV system manufacturing and operation is the reduction of the aerial platform cost. The GCS can be in fact standardized to reach "economy scale" production, but the vehicle must be designed "on the mission": flight profile, autonomy, ceiling, speed and payload drive the dimensions and the features of the air vehicle. Thus, a standardization of the vehicles dimensions and configuration is impossible; a too large aircraft implies high fuel consumption, and a too small aircraft doesn't alloy to carry the payload or accomplish the mission. At the University of Bologna a family of UAVs has been developed since 2000, with increasing dimensions and following costs. One of the research herein deployed aims to reduce the manufacturing costs of the UAV vehicles. The main idea is to apply new techniques like rapid prototyping to reduce "time to market" and production' costs, also in case of small lots. The hot wire (HW) technique permits to cut a polystyrene block as to obtain ruled surfaces. The HW cutting machine is equipped with a series of electric motors which allow the wire to translate in space, following an imposed trajectory; the ends of the wire move in two lateral planes of a frame. The precision and ease of use of the HW machines has been increased at Bologna University developing a managing software tailored for such type of machines [1]. As a previous study showed [2], the structure of a UAV of medium size (up to 4-5 meters of wingspan) can be obtained with parts realized with HW technique. Parts belonging to ruled surfaces, like tapered or straight wing, can be in fact obtained by HWC. A tailless configuration [3], with a double sweep wing requires only parts bounded by ruled surfaces. This configuration has been considered also by other Universities and Research Centres; in South Africa studies of optimization has been carried out on the Sekwa UAV [4]. The main problems of such configuration are:

stability and efficiency. The UAV aerodynamic configuration, and the whole structure must be accurately designed. Differently from aircrafts with tail (in which the angle of attack of the horizontal plane can be modified without efforts), tailless configuration requires a good design. The tailless stability is in fact achieved with sweep and with wing tip profile twist. But the wing twist can't be changed once the wing has been manufactured: a not satisfactory design imply the waste of the prototype. The efficiency of the tailless configuration is low, so that the aerodynamic profiles of the wing, the twist, the taper, the wing surface and the weight must be chose within an optimal compromise. By this way, the UAV airframe permits mission requirements' accomplishment, with the maximum efficiency and minimum weight. The parameters to define are more than ten, so that a conventional design doesn't guarantee best results. Only of the possible way to overcame these problems is to apply unconventional optimization techniques [5] like Genetic Algorithms (GA), Particle Swarm Algorithms (PSO), or Monte Carlo Techniques (MCT). Genetic algorithms has been developed by authors like Goldberg [6] and Koza [7]: the main idea is to apply the rules of the natural selection to mathematical problems. The use of mutations, crossover of genes, and elitarism over generations allows a quick solution [8]. The problem of local minimum values is well solved since the algorithm explores all the dimensional space of the possible solutions. GA has been widely used in aeronautical design by many authors, also for aircraft design and optimization [9]. As an example, Marta [10] describes results obtained in an aircraft design optimization by varying GA settings. A similar UAV configuration has been optimized in a study from South Africa [Broughton 2008]: results show how the geometry and the wing airfoils can be designed and optimized with GA to reduce the drag of the vehicle. Studies [11] have been also carried out to optimize wing using GA and a Fuzzy logic controller to evaluate solutions: by this way multiple design criteria can be tested. Particle Swarm Optimization is described in the seminal paper of Kennedy and Eberhart [12]: also in this case the optimization strategy idea derives from nature. It is implemented the logic of a swarm of birds or fish in which each individual explores a zone and communicate to the other the position in which the food has been found. A territory is so explored depending on the best position found by the single individual and by the whole swarm; by this way, in few iterations the fitness (food detection for birds or fish) is maximized. The PSO algorithm [13] has been widely used in several industrial applications as bibliography [14] shows, and many toolbox are available on the net; one of the most popular has been developed for Mathworks' Matlab® and GNU Octave by [15]. The latter unconventional technique considered in this work is MCT: it is based on a simple algorithm in which a random set of parameters is evaluated and an optimal solution is found after a large number of simulations. The unconventional optimization techniques [16] have been widely applied in aeronautics [17] since they are suitable in cases in which: a large number of factors affects the results, no solution of the problem in a "close" form is possible, it is difficult a prevision of the final result. The optimization of a UAV in tailless configuration obtained with HWC respects all of these conditions.

1.2 In this work

This work describes the application of PSO to a complex optimization problem: the multidisciplinary optimization of a UAV obtained by HWC technique. The results obtained have been compared with other optimization techniques like Monte Carlo and Genetic Algorithm.
Aim of the paper is to show how well unconventional optimization techniques are suitable to solve such a problem. The attention will be focused in particular on: fitness maximization, convergence, time required, repeatability of the results, and computational complexity required by algorithm.
In the second paragraph UAV main features are presented; in the third paragraph the attention is focused on how the RP techniques can be applied to UAV manufacturing. The fourth paragraph describes the PSO theory and its implementation to the case study proposed. In the fifth chapter the optimization algorithm is described: the fitness definition, the parameters to optimize list, and the code layout are described. The sixth paragraph shows a comparison of the results obtained with PSO and other optimization techniques like GA and MCT. The final paragraph presents conclusions and future developments related to this work.

2 Unmanned Aerial Vehicle Design Critical Issues

The design of UAVs is critical since many aspects should be considered at the same time. Aim of the project is the satisfaction of the requirements, which are expressed in terms of: mission profile (speeds, heights, cruise distance, loiter time, landing/takeoff type), flight safety, costs, operational requirements, man/machine interface. The aircraft design can be so considered as the definition of a compromise.
Aerodynamics, structures, materials, propulsive system, stability and control, operational and manufacturing cost, ease of production, maintainability and end-cycle dismissing should be considered. The maximization of one of these issues can affect another one; there is in fact a high correlation between these design aspects. For instance, the use of high performance materials can reduce weight but typically buying cost are increased, ease of manufacturing is reduced and maintainability cost can raise up. The maximization of the aerodynamics performances can be obtained by a high aspect ratio and by thin airfoils; but this affects the structure. The wing spars must be oversized since the moment and the shear on the wing are higher. Moreover, the design of an industrial product should be faced considering the whole life-cycle: solutions leading to a low cost of manufacturing can imply high operative costs so that the initial gain is overcome by the following drawbacks. Studies to apply the tailless configuration have been carried out also for large passengers transport aircraft, but the problems related to the cabin height and the internal space revealed the lack of economic exploitation for this configuration. Also the payload require some considerations: civil UAVs usually carry instruments like cameras, batteries, radio devices, Radar, magnetometers or similar devices. Moreover, flight computers, radio link with the GCS, motor, batteries and servoactuators are necessary for the flight operations. For a medium size UAV, like the model considered in this study the payload consist of: a small camera in the nose for external view transmission to the GCS, a better quality camera pointing the terrain for the monitoring of the interest zone (e.g. a forest fire, a leak

from an oil pipe, a ship in trouble), a pack of batteries need to supply the on board electric devices. The avionic consists of an autopilot (MEMS accelerometers, magnetometers, gyroscopes and an electric board) of small dimensions and small mass (less than 100 grams). The miniaturization of devices is so advanced that the payload and avionic weight for a small UAV can be less than 500 grams. The propulsive system of the UAV is based upon a fan (of 69 mm of external diameter) moved by an electric brushless motor (with a peak power of 600 Watt), which can assures a maximum thrust of 10-12 Newtons. The throttle setting of the motor decrease as the required thrust by the UAV decrease; a lower electric motor consumption allows an higher autonomy (or a smallest pack of battery and an increased payload with the same weight).

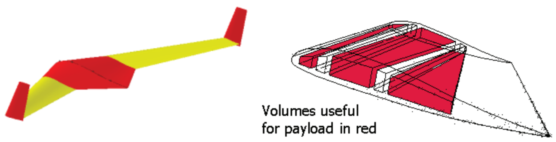

Fig. 1 UAV configuration and wing payload compartment.

Figure 1 shows in the left a UAV tailless configuration; in the right side the volumes of the internal part of a semi-wing useful to load the payload are in red. The payload compartement can be obtained in the thick of the airfoil, in the central part of the wing.

3 Application of Hot Wire Cutting to UAV Performing

The HWC technique has been applied to obtain in a small amount of time the skeleton of UAVs in foam material. The design loop starts from a 3D design of the aircraft, like explained in Figure 2 (rendering in the left; wireframe in the right).

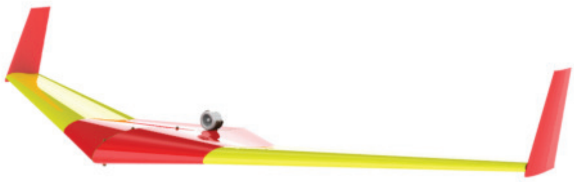

Fig. 2 Tailless 3D modeling

In a rough way, this tailless configuration can be considered as the sum of four elements: two external wings (right and left), and two internal wings (right and left). [see Figure 3].

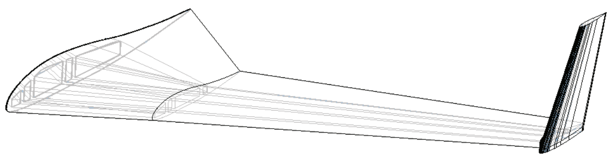

Fig. 3 Left wing – internal and external part

All of these four parts can be obtained interpolating two bi-dimensional airfoils. Moreover, the path of the wire can be designed so that also the compartment for the payload bay (in the internal wing), or the track for spars (in the external wings) can be obtained, as Figure 4 shows for the internal wing, and Figure 5 for the external wing.

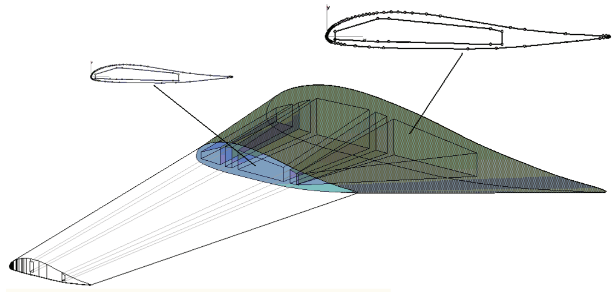

Fig. 4 Internal wing airfoils to be interpolated with the HWC machine.

Figure 4 shows also the features of the internal wing compartment: the payload bay is obtained within the airfoil. Three zones are available (see also Fig. 1): ahead the main spar, between main and rear spar, and after the rear spar.

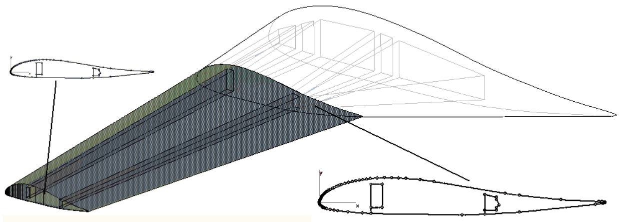

Fig. 5 External wing airfoils to interpolate with the HWC machine.

The cut of the 3D foam shape of the internal and external wings requires: the 2D drawing of the two airfoils, their relative position and twist, and the span of the wing. The HWC machine needs also the dimensions of the block, and its distance from the X-Y plane of the machine. As figure 6 shows, in fact, the machine is made by a frame in which the ends of a wire can move on two parallel planes represented by the axis X1 and Y1, and X2, Y2 in Figure 6: each axis is moved by a stepper motor. The moving of the motors is piloted by a driver board which converts the input of a PC software in steps of rotation to be run by the motors. For a better description of the machine features and software see reference [1].

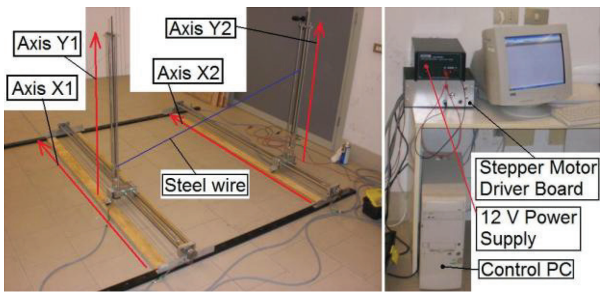

Fig. 6 HWC machine during wing cut

A simulation of cut (Fig. 7) within the cutting software can be useful to evaluate the correctness of the data provided by the operator and for a preview of the final result.

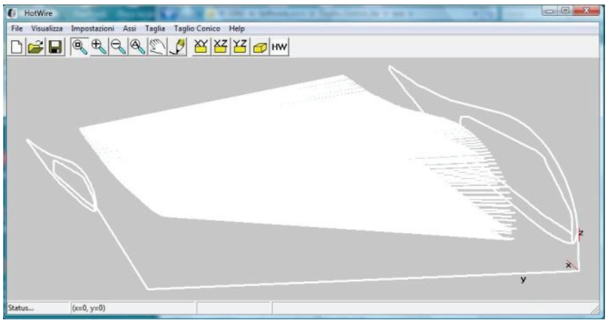

Fig. 7 Simulation of the wire cut

The polystyrene block is finally cut to obtain the external and internal wing as reported in Figure 8. The cutting operations takes few minutes and the precision is good.

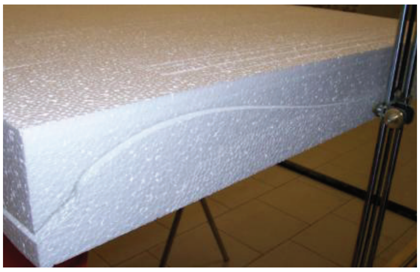

Fig. 8 HWC machine during wing cut [2]

All of the four parts of the wing are performed in such way and finally assembled to check the final structure, as can be seen in Figure 9.

Fig. 9 The wing of the UAV performed by HWC

Finally the components in polystyrene are covered with composite materials (glass fiber and epoxy resin); spars in composite or wood are glued in the wings, the payload bay is equipped with sensors, the airframe is added by controls and electric motors. As previously stated the geometry of the wing can't be modified after the manufacturing of the wing sections. This is the main reason for which an optimization is necessary: if the design is in fact wrong, the aircraft stability can't be modified and the airframe has to be disposed.

4 Optimization algorithms

This chapter briefly introduces the algorithm used to optimize the UAV.

4.1 Particle Swarm

Kennedy can be considered the father of the PSO: further studies have been deployed to improve the original formulation. One of the most common PSO algorithm [15] consists of two steps: particle speed update, and particle position update. The position of a particle represent a solution to the problem in the n-dimensional space of the parameters; the speed indicates the direction in the n-space toward a new position to explore.

The velocity can be obtained by the following formula:

$$v_i(k+1) = \phi(k)\cdot v_i(k) + \alpha_1\left[\gamma_{1i}(p_i - x_i(k))\right] + \alpha_2\left[\gamma_{2i}(G - x_i(k))\right] \quad (1)$$

Where symbols stand for:
i : index of the single particle
k : algorithm step
Φ(k): inertia function
v_i : velocity of the i[th] particle
$\alpha_{1,2}$: acceleration constants
p: personal best, best position found by the i[th] particle
G: best position found by the whole swarm
(it is the best position within the personal bests)
$\gamma_{1,2}$: it is a random number in the interval [0÷1]

In a similar manner, the position can be obtained using the following formula:

$$x_i(k+1) = x_i(k) + v_i(k+1) \quad (2)$$

Where:
x_i : position of the i[th] particle
$v_i(k+1)$: updated velocity of the i[th] particle

The step of iterations can be fixed by the user before the simulation; a convergence condition to break the algorithm can be also introduced when no improvement in solution is achieved for a defined number of consecutive iterations.

4.2 Genetic Algorithms

Genetic Algorithm simulates the natural evolution of individuals, as introduced by C. Darwin. A solution of a problem is coded in a chromosome, composed by the sum of a number of genes equal to the parameters to optimize. A population is randomly generated (within a certain interval defined by the user) and the fitness of each individual is evaluated. Each chromosome is coded in a binary number and the fitness is evaluated. The best individual is copied as it is in the new generation (if elitarism is set), while the other individuals of this new generation are obtained by the combination of the best chromosomes of the previous generation. Two techniques are introduced to solve the problem of the local peaks: the mutations and the crossover. The first term indicates a random change of a gene, while the second describe the cross change of genes between two chromosomes.

4.3 Monte Carlo

The MCT is a technique inspired to the Casino roulette game. It consists in the whole simulation of the cases that can arise in a problem in which some parameters may vary. It is widely used in problems in which a model is unknown or in games and strategy. One of the typical application is a chess game between a human and a machine: the machine simulates all of the future moving of the human until the chess mate. The best move is the move which guarantee the highest number of mate ending for the machine. This method is effective but a large number of simulations is necessary especially in cases in which the fitness depends on a large number of parameters, whose value is continuous.

5 Optimisation framework

5.1 Fitness

One of the most critical issue in optimization is the definition of the fitness. In this work this function will consider two aspects: the satisfaction of requirements, and the maximum economy of the final product. The most important mission requirements [18] are the flight speed, the payload needs, and the stability (an aircraft unstable is difficult to fly and pilot). Moreover, the payload bay should be large enough to carry the subsystems need by the UAV: autopilot, radio, actuators, battery, camera or other sensors. The cost can be split in two main items: the manufacturing cost, and the operative cost. The weight can be considered an indicator of the manufacturing cost: raw materials quantity and manpower can be roughly dependent on the dimensions of the airframe. On the other side, the flight efficiency can be considered responsible for operational costs: the power required for flight is in fact minimized when the efficiency is maximised. A fitness formulation which consider all of these aspects is:

$$Fitness = E * SM\_ind * VOL\_ind * SPEED\_ind / WEIGHT \quad (3)$$

Where:
E: flight efficiency
SM_ind: stability margin coefficient
VOL_ind: internal volume coefficient
SPEED_ind: correct speed coefficient
WEIGHT: final weight of the aircraft

E can be computed as the coefficient of lift divided by the coefficient of drag of the airplane;

SM_ind is defined as:

$$SM\_ind = \begin{cases} 1, \ if \ 4\% < SM < 8\% \\ 0.1, \ otherwise \end{cases} \quad (4)$$

Where SM in the static margin of the aircraft: it is considered good for a tailless aircraft between 0.04 and 0.08.

VOL_ind is defined as:

$$VOL\_ind = \begin{cases} 1, \ if \ payload\_volume > 0.015m^3 \ \& \max\_thickness > 145mm \\ 0.1, \ otherwise \end{cases} \quad (5)$$

In this case study 0.015 m^3 is the volume of the payload increased by a quantity to keep into account the geometry of the items; 145 mm is the minimum height which allow to carry the most voluminous element in the bay (a frame in polystyrene of 10 millimetres should be considered so that a net height of 120 mm is obtained in the central part of the wing).
In a similar manner to the SM_ind, also the VOL_ind can be considered a penalty functions which express the lack of satisfaction of the requirements: in this case, the volume of the payload bay or the thickness of the wing are too small to fit the payload and systems.

SPEED_ind express the satisfaction of the speed requirement. In the case study we propose:

$$SPEED\_ind = \begin{cases} 1, \ if \ 0.95 * Tspeed < calculated\_cruise\_speed < 1.05 * Tspeed \\ 0.1, \ otherwise \end{cases} \quad (6)$$

Tspeed is the flight speed defined in the mission requirements (12 m/s of cruise speed).
WEIGHT is the final weight of the aircraft: it is the sum of (2) the contribution of payload, electric motor, batteries, actuators, and airframe. All of these weight are fixed by the requirements, except the airframe which depends on the aircraft shape and on the designer choices.

The formulation of the fitness can be considered as the efficiency divided by the weight of the aircraft, multiplied by a series of coefficients. By this way, the fitness value increases when the efficiency is better and the weight is low. The other terms in the formula (SM_ind, SPEED_ind, VOL_ind) can be considered as penalty coefficients which pull down the fitness when a requirements is not satisfied. The penalty terms are multiplied (and not added) so that the fitness reduces with a high ratio when two or more requirements are not in the correct range. The fitness is proportional to efficiency and weight, while the penalty coefficients can assume the value of 0.1: this formulation assures first of all the satisfaction of the requirements, and in the second place the optimization of efficiency and weight. In fact, the fitness is low and the solution is rejected when it presents a good efficiency to weight ratio, but at least one of the requirements is not satisfied.

5.2 Parameters to optimize

The parameters to define for the design of the UAV airframe are listed in the following Table 1. They include: airfoils type, geometric shape and layout, flight design angle of attack.

#	Parameter Name	Parameter Symbol (see also Fig.10 XXXX)	Min Value	Max Value
1	Wing Span [m]	b	2.5	4.0
2	Chord at tip [m]	e	0.2	0.3
3	Chord at root	c	0.8	1.2
4	Chord at intermediate section	d	0.4	0.6
5	Span from the root to the intermediate section	f	0.35	0.55
6	Sweep at 25% Wing Cord [Deg]	SW	20	40
7	Airfoil twist at intermediate section [Deg]	Int_twist	0	2
8	Airfoil twist at tip [Deg]	Tip_twist	0	4
9	Airfoil Type at root (first figure A), intermediate section (second figure N) and tip (third figure B)	ANB	111	999
10	Angle of attack [Deg]	Alfa	0	8

Tab. 1 Parameters to optimize.

The geometric parameters meaning is shown in Figure 10. The aircraft stability can be achieved using twist, sweep and “Reflex” Airfoil. Nine airfoil have been considered as suitable for the design of such an aircraft (depending on experience and bibliography), as Table 2 lists.

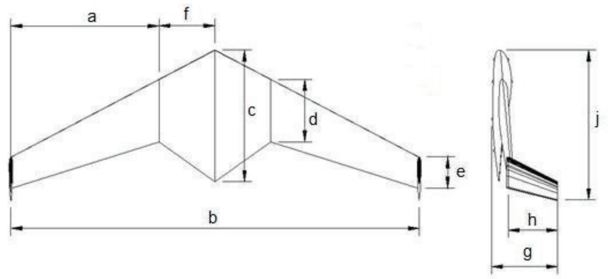

Fig. 10 Plan view of the UAV

The airfoil to use at tip, at root, and in the intermediate (junction between internal and external wing) sections are expressed by a number of three figures: the first corresponds to the type of airfoil used in the root, the last in the tip, and the second in the intermediate section. A useful simplification is obtained in such a way; instead of three different parameter the airfoil choice is represented by a unique number. The following table shows the correspondence between number and airfoil type.

Airfoil Name	Airfoil Thickness	Figure in ANB parameter
Cj25209	9.5	6
E186	12.7	7
Fauvel	14	9
Horten Standard	13	1
Martin Hepperle 45	9.85	8
Martin Hepperle 46	11.4	2
Martin Hepperle 49	10.5	3
Martin Hepperle 78	11.4	4
NACA 0012	12	5
NACA 0015	15	0

Tab. 2 Correspondence figures – airfoil in the parameter ANB.

The coefficient need for the definition of SM_ind and E are calculated using the lifting line theory, in the formulation proposed by Anderson [19]: it is an aerodynamic theory which consider a wing as a bidimensional surface. The wing is divided in a series of patches, as Figure 12 shows.

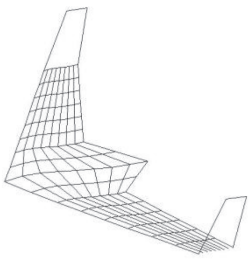

Fig. 11 Wing patches for aerodynamic computations

A series of vortex are placed in the quarter of chord of each patch, and a speed is calculated at the center. A condition of tangency of the speed in proximity of the wing surface allows to compute the lift of each panel. The other fitness terms are simply calculated by the geometrical parameter; the airframe weight is found by multiplying the volume and the surface by the polystyrene density and the fiber weight per square meter.

6 Results and Comparison with other optimisation algorithms

Two analysis have been deployed: a series of PSO optimization varying settings, and a following comparison between PSO, MCT and GA.

6.1 PSO optimization

The first test was performed to show how inertia and accelerations affect the optimization with PSA. Literature [Birge] suggest to fix accelerations around the value 2, while a good value for inertia can be considered 1.4 in case of constant inertia, or a decreasing value (as a function of k) from 0.9 to 0.4 in case of variable inertia. [Chi et al.] suggest a value of 0.8-1 for accelerations.

# Run	Particle Swarm Optimizer	Best Fitness	Time elapsed [s]	Iterations up to convergence
1	Inertia Φ=1.4 Acceleration α1=2 Acceleration α2=2	0.192	336	19
2	Φ =1.2 ; α1=2 ; α2=2	0.208	355	20
3	Φ =1 ; α1=2 ; α2=2	0.2546	323	16
4	Φ =0.9 ; α1=2 ; α2=2 run1	0.2109	337	17
5	Φ =0.9 ; α1=2 ; α2=2 run2	0.218	1308	52
6	Φ =0.9 ; α1=2 ; α2=2 run3	0.235	595	30
7	Φ =0.8 ; α1=2 ; α2=2 run1	0.199	191	13
8	Φ =0.8 ; α1=2 ; α2=2 run2	0.218	2403	88
9	Φ =0.8 ; α1=2 ; α2=2 run3	0.221	654	35
10	Φ =0.7 ; α1=2 ; α2=2	0.241	1081	74
11	Φ =0.6 ; α1=2 ; α2=2	0.2425	2156	150
12	Φ =1 ; α1=1.8 ; α2=2.2	0.207	492	24
13	Φ =1 ; α1=2.2 ; α2=1.8	0.2298	552	23
14	Φ =0.8 ; α1=1.8 ;α2=2.2	0.223	587	29
15	Φ =0.8 ; α1=2.2 ; α2=1.8	0.222	391	18

Tab. 3 Parameters to optimize.

The inertia was chosen as a constant (in the interval [0.4-1.4]) value in these test to show the best one. Acceleration were set equal to 2 in all the test, except in the last 4 runs, in which the value was a little varied.

#	Parameter Name	Value from Particle Swarm Optimization
1	Wing Span [m]	3.83
2	Chord at tip [m]	0.24
3	Chord at root [m]	0.82
4	Chord at intermediate section [m]	0.41
5	Span from the root to the intermediate section [m]	0.53
6	Sweep at 25% Wing Cord	0.527 (30.2°)
7	Airfoil twist at intermediate section [rad]	0.033 (1.9°)
8	Airfoil twist at tip [rad]	0.055 (3.15°)
9	Airfoil Type at root (first figure), intermediate section (second figure) and tip (third figure)	661
10	Angle of attack	0.093 (5.3°)
	FITNESS	0.2546

Tab. 4 Parameters of best run.

Table 3 lists the results obtained in the test in terms of best fitness, time elapsed during simulation, and finally the number of run to convergence: the simulation ends when no improvement in fitness are achieved in 10 consecutive iterations. The results of Table 4 shows the best optimization result (Fitness value=0.2546) in the case Φ=0.9 α1=2 α2=2. The design parameters obtained in the best run (#3) are listed in the following Table 2. The Figure 12 shows also the distribution of swarm during optimization during a run (Chord at root in X, Wing Span in Y), and the fitness evolution in the time.

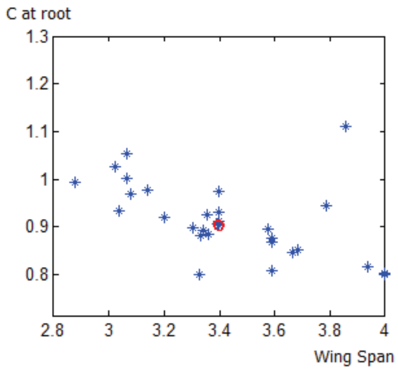

Fig. 12 Swarm distribution (wing span in X and Chord at root in Y)

The following Figure 13 shows the trend of the Fitness during an optimization with PSO.

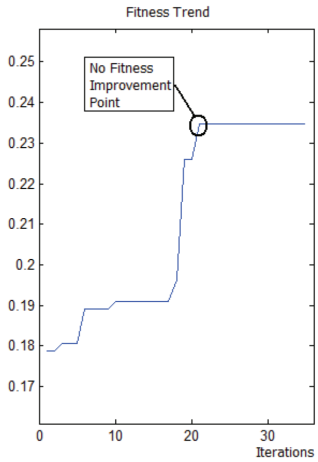

Fig. 13 Fitness Trend during optimization.

6.2 Comparison

A comparison with other optimization techniques has been carried out to prove the efficiency of the PSO: results obtained with Genetic Algorithm and Monte Carlo are herein listed. The comparison between PSO and GA has been carried out with an equal number of swarm individuals and population, and with the same number for PSO iteration to convergence and GA generations. The GA main settings have been set to standard values: elitarism, on; Mutation probability, 0.8; crossover probability, 0.04. The Monte Carlo technique has been applied in a number of test equal to swarm individuals times the number of iteration for convergence. Thus, the computation time is equal for both PSO, both GA and both MonteCarlo: the most computationally consuming activity is in fact is the fitness evaluation which occurs the same number of times.

Best Fitness Number of iterations	Particle Swarm Optimization Φ =0.9 α1=2 ; α2=2	Genetic Algorithm	Monte Carlo Optimization	Best method
10 iterations 30 particles	0.186	0.194	0.195	MCT
15 iterations 30 particles	0.231	0.193	0.025	PSO
20 iterations 30 particles	0.201	0.221	0.1889	GA
25 iterations 30 particles	0.220	0.204	0.195	PSO
30 iterations 30 particles	0.215	0.2234	0.2002	GA
35 iterations 30 particles	0.242	0.2379	0.167	PSO

Tab. 5 Results of Optimization with a constant number of iteration.

The above Table 5 shows that for small numbers of iteration the MCT provides the best results: GA and PSO algorithm in fact requires a number of iterations to work. For small iterations the MCt explore best the space. After the value of iterations of 15 the GA and PSO functions better than MC (see also Figure 14).

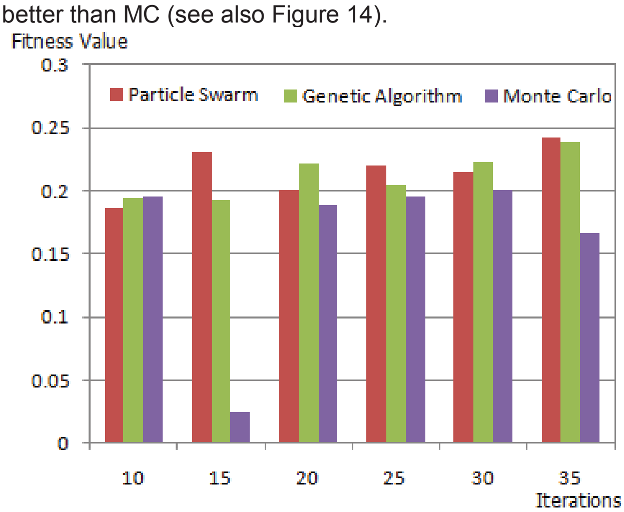

Fig. 14 Algorithm efficiency vs. number of iterations

The efficiency of GA and PSO seems to be similar. It should be noted that the PSO algorithm is more simple than the GA one.

7 Conclusions

This paper presents an application of Particle Swarm Algorithm to a complex optimization problem: the design of a UAV performed by Hot Wire Cutting Techniques. Results obtained show the PSO algorithm settings useful to achieve the best fitness. The comparison between GA, MCT and PSO showed the equivalence of GA and PSO in case of a number of iteration equal or major to 15. Future developments of the paper should consider a large number of simulations, considering a mean value and a standard deviation instead of a single optimization value. A sensibility analysis can improve the settings of inertia and accelerations. A more deep study should include also a comparison with furthermore optimization techniques.

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