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Influence of Search Algorithms on Aerodynamic Design Optimization of Aircraft Wings

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Abstract: The method of search algorithms or optimization algorithms is one of the most important parameters which will strongly influence the fidelity of the solution during an aerodynamic shape optimization problem. Now a days various optimization methods such as Genetic Algorithm (GA) and Simulated Annealing (SA), Particle Swarm Optimization (PSO), etc. are more widely employed to solve the aerodynamic shape optimization problems. In addition to the optimization method, the geometry parameterization becomes an important factor to be considered during the aerodynamic shape optimization process. Since, the reduction in the number of design parameters is one of the most important requirements for the aerodynamic shape optimization problem, it becomes important to mathematically describe the airfoil geometry with minimum number of design parameters. The objective of this study is to introduce the knowledge of describing general airfoil geometry using twelve parameters by representing its shape as a polynomial function and coupling this approach with flow solution and optimization algorithms. It is also demonstrated that the estimation of a suitable optimization scheme for a given optimization problem. An aerodynamic shape optimization problem is formulated for NACA 0012 airfoil and solved using the methods of Particle Swarm Optimization and Genetic Algorithm for 5.0 deg angle of attack. The results show that the particle swarm optimization scheme is more effective in finding the optimum solution among the various possible solutions. It is also found that the PSO shows more exploitation characteristics as compared to the GA which is considered to be more effective explorer.

Key words: Aerodynamic shape optimization, parametric section, particle swarm optimization, genetic algorithm, geometry, design

INTRODUCTION

The computational resources and time required to solve a given problem have always been a problem for engineers for a long time though a sufficient amount of growth is achieved in the computational power in the last 30 years. This becomes more complicated to deal with when the given problem is an optimization problem which requires huge amount of computational simulations. These kind of problems have been one of the important problems to be addressed in the context of design optimization for quite some years. When the number of result (s) influencing variables are large in a given optimization problem, the required computational time per simulation increases automatically. This will severely influence the required computational resources to solve the given design optimization problem. Due to this reason, a need arises to describe a general geometry with minimum number of design variables. This leads to a search activity of finding some of the best parametrisation methods. Now a days various parametrisation methods are employed: partial differential equation approach (time consuming and not suitable for multidisciplinary design optimization), discrete points approach (number of design variables becomes large) and polynomial approach (number of design parameters depends on the degree of the polynomial chosen and suitable for multidisciplinary design optimization) are the three basic approaches to describe the geometry of a general airfoil. Previous research works in design optimization suggest that the parametrisation schemes highly influences the final optimum design which is obtained as a result of the optimization (Balu and Selvakumar, 2009). In this research, the Parametric Section (PARSEC) parametrisation scheme is employed. The Panel Method is used to compute the flow field around the airfoil geometry during the design optimization process. Both PSO and GA are employed to carry out the design optimization problem. Three MATLAB codes are developed to implement PARSEC, Panel and PSO

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approaches. A freely available FORTRAN code is piced for the GA. The results and issues faced during the whole design process in discussed in the following sections.

PARSEC

In PARSEC parametrisation scheme an unknown linear combination of suitable base functions is used to describe the airfoil geometry (Balu and Selvakumar, 2009; Sobieczky, 1998). This approach is considered to be more suitable for design optimization problems since, the geometric constraints on the airfoil shape can be described by some simple linear constraints. Twelve design variables are chosen to have direct control over the shape of the airfoil. The twelve design variables are upper leading edge radius (R_{leu}), lower leading edge radius (R_{lel}), upper crest point (Y_{up}), lower crest point (Y_{lo}), position of upper crest (X_{up}), position of lower crest (X_{lo}), upper crest curvature (YXX_{up}), lower crest curvature (YXX_{lo}), trailing edge offset (T_{off}), trailing edge thickness (T_{TE}), trailing edge direction angle (α_{TE}), trailing edge wedge angle (β_{TE}) as shown in Fig. 1. The leading edge radius parameters provide more control at the leading edge of the airfoil geometry. The mathematical relations for the PARSEC approach are given as follows (Balu and Selvakumar, 2009; Sobieczky, 1998):

$$y_u = \sum_{i=1}^{6} a_i x^{i-(1/2)} \tag{1}$$

$$y_l = \sum_{i=1}^{6} b_i x^{i-(1/2)} \tag{2}$$

Where:

- y_u = The upper y coordinate
- y_l = The lower y coordinate
- a_i, b_i = The unknown coefficients to be solved from the specified values of the twelve design variables

The above polynomial equations are solved using a set of geometrical conditions (Balu and Selvakumar, 2009).

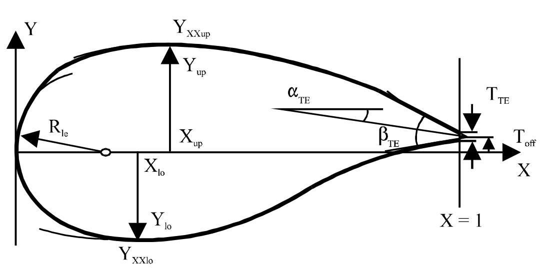

Fig. 1: Control variables for PARSEC

PANEL TECHNIQUE

Panel Method is used to solve the potential equations without being computationally expensive. It provides more reasonably accurate results. These two properties make the panel method to be more suitable for design optimization problems where the number of simulations is incredibly large.

Since, the current problem deals with the incompressible subsonic flow region, this approach is employed in this research. The solution procedure for panel technique consists of discretising the surface of the airfoil into straight line segments or panels and assuming the following conditions.

The source strength is constant over each panel but has a different value for each panel the vortex strength is constant and equal over each panel (Hess, 1990; Katz and Plotkin, 1991).

The compressibility and the viscosity of air in the flow field are neglected. But it is required to satisfy the condition that the net viscosity of the flow should be such that the flow leaving the trailing edge is smooth. The curl of the velocity field is assumed to be zero. Hence,

$$\phi = \phi_\infty + \phi_d + \phi_\upsilon \tag{3}$$

where, ϕ which is expressed as a summation of the free stream potential, source potential and vortex potential is the total potential function. Except the free stream potential, the other potentials have potentially locally varying strengths. Figure 2 shows the notations of the panel approach.

As the number of panel increases, the accuracy of the solution increases. Indeed, the computational time will increase as the number of panel increases. N+1 node points define N panels. The tangential velocity (Vti) at the centre of each panel is estimated by imposing a flow tangency condition at each panel. The Coefficient of pressure (Cp) at each panel is calculated using the following relation:

$$C_p(x_i, y_i) = 1 - [V_{ti}^2 / V_\infty^2] \tag{4}$$

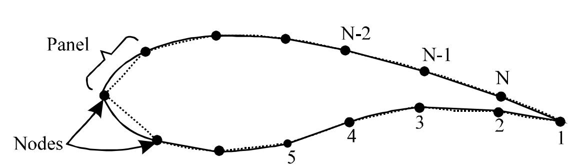

Fig. 2: Panel approach

PARTICLE SWARM OPTIMIZATION

PSO is a population-based algorithm for searching global optimum. It ties to artificial life like fish schooling or bird flocking and has some common features of evolutionary computation such as fitness evaluation. The original idea of PSO is to simulate a simplified social behaviour (Kennedy and Eberhart, 1995; Eberhart and Kennedy, 1995).

Similar to the crossover operation of the GA, in PSO the particles are adjusted toward the best individual experience (PBEST) and the best social experience (GBEST). However, PSO is unlike a GA in that each potential solution, particle is flying through hyperspace with a velocity. Moreover, the particles and the swarm have memory in the population of the GA memory does not exist.

Let $x_{j,d}$ (t) and $v_{j,d}$ (t) denote the dth dimensional value of the vector of position and velocity of jth particle in the swarm, respectively at time t. The PSO model can be expressed as:

$$v_{j,d}(t) = v_{j,d}(t-1) + c_1.\varphi_1.(x^*_{j,d} - x_{j,d}(t-1)) + c_2.\varphi_2.(x^\#_d - x_{j,d}(t-1)) \quad (5)$$

$$x_{j,d}(t) = x_{j,d}(t-1) + v_{j,d}(t) \quad (6)$$

Where:

$x^*_{j,d}$ (PBEST)	=	The best position of jth particle up to time t-1
$x^\#_d$ (GBEST)	=	The best position of the whole swarm up to time t-1
φ_1 and φ_2	=	Random numbers
c_1 and c_2	=	The individuality and sociality coefficients, respectively

The population size is first determined and the velocity and position of each particle are initialized. Each particle moves according to Eq. 5 and 6 and the fitness is then calculated. Meanwhile, the best positions of each swarm and particles are recorded. Finally as the stopping criterion is satisfied, the best position of the swarm is the final solution. The main steps of PSO are given as follows (Ping and Jiang, 2008; Khurana *et al*., 2009):

- Set the swarm size. Initialize the velocity and the position of each particle randomly
- For each j, evaluate the fitness value of x_j and update the individual best position $x^*_{j,d}$ if better fitness is found
- Find the new best position of the whole swarm update the swarm best position $x^\#$ if the fitness of the new best position is better than that of the previous swarm
- If the stopping criterion is satisfied then stop
- For each particle, update the position and the velocity according to Eq. 6 and 5

GENETIC ALGORITHM

Genetic Algorithms (GA), in contrast to gradient optimization approaches offer an alternative approach with several attractive features. The basic idea associated with the GA is to search for optimal solutions using an analogy to the theory of evolution. During solution advance (or evolution using GA terminology) each chromosome is ranked according to its fitness vector-one fitness value for each objective. The higher-ranking chromosomes are selected to continue to the next generation while the probability of the selection of lower-ranking chromosomes is less. In every generation, a new set of artificial creatures (strings) is created using bits and pieces of the fittest of the old an occasional new part is tried for good measure. While randomized, genetic algorithms are no simple random walk. They efficiently exploit historical information to speculate on new search points with expected improved performance. The newly selected chromosomes in the next generation are manipulated using various operators (combination, crossover or mutation) to create the final set of chromosomes for the new generation. These chromosomes are then evaluated for fitness and the process continues-iterating from generation to generation-until a suitable level of convergence is obtained or until a specified number of generations has been completed. GA optimization requires no gradients; it does not need the sensitivity of derivatives. It theoretically works well in non-smooth design spaces containing several or perhaps many local extrema. It is also an attractive method for multi-objective design optimization applications offering the ability to compute the so called pareto optimal sets instead of the limited single design point traditionally provided by other methods. The basic genetic algorithm comprises four important steps. They are initialisation, selection, cross over and mutation (Goldberg, 1989).

OPTIMIZATION OF NACA 0012 AIRFOIL

The aerodynamic shape optimization process is carried out with an intention of increasing the vertical aerodynamic force subject to aerodynamic and structural constraints. The structural constraints are implemented by fixing the values of trailing edge thickness and trailing edge offset parameters during the optimization in both the optimization schemes. These constraints are placed in

Table 1: Optimization objectives and constraints

Factors	Characteristics
Angle of attack	5.0°
Flow constraint	Subsonic and incompressible
Geometric constraint 1	Max thickness must be <10% chord length
Geometric constraint 2	$T_{TE} = 0.0$ and $T_{off} = 0.0$
Aerodynamic constraint	Lift not less than original one
Objective	Maximize coefficient of lift

order to avoid the optimiser to get converged at inefficient locations and to avoid getting unrealistic aerodynamic shapes. Since, the panel method is only applicable for low speed flows, a flow constraint is placed to keep the assumptions valid throughout the whole optimization process. The flow constraint is implemented by fixing the angle of attack at 5.0°. For each design parameter a lower and upper bound values are defined. Each generation produced by the PSO and genetic algorithms have the best set of twelve PARSEC parameters. The corresponding airfoil profile is generated using PARSEC parametrisation. Then, the panel method is used to compute the flow around the airfoil at 5.0° angle of attack. From the pressure distribution, the lift coefficient is calculated using the trapezoidal rule. This new coefficient of lift is compared to the original one. The PSO and genetic algorithms in the end will lead to the best set of PARSEC parameters which will maximise the objective function within the search space. The design conditions, optimization objectives and constraints which are used during the optimization process using PSO and GA are shown in Table 1.

RESULTS AND ANALYSIS

The initial PARSEC parameters have been given approximately by specifying its lower and upper bound values. There is no need for specifying this accurately. The geometry of the airfoil is expressed by the best twelve PARSEC parameters resulting from the PSO algorithm which exhibits a considerable increase in the coefficient of lift as compared to the best solution found by the genetic algorithm. There is a history for the PSO to be good for problems involving highly non-linear functions where the function has large number of peaks and valleys. It is again witnessed from the obtained results that the PSO has not got stuck with the local optima or extrema. The comparison between the original NACA 0012 airfoil geometry and the optimised airfoil geometry using PSO is shown in Fig. 3. The comparison of pressure distribution over the surface of the original NACA 0012 airfoil and the optimised airfoil using PSO is shown in Fig. 4. It can be seen from these figures that the actual airfoil geometry is modified in such a way that the airflow is

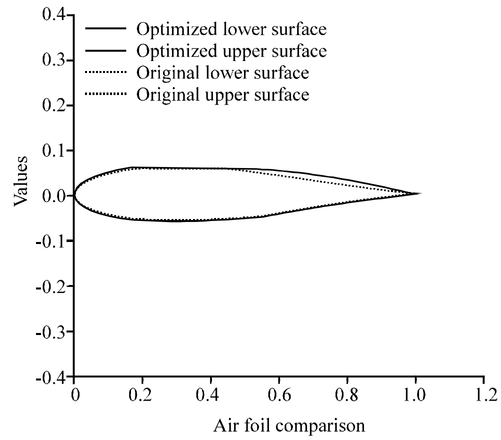

Fig. 3: Comparison of original NACA 0012 airfoil and optimized airfoil using PSO

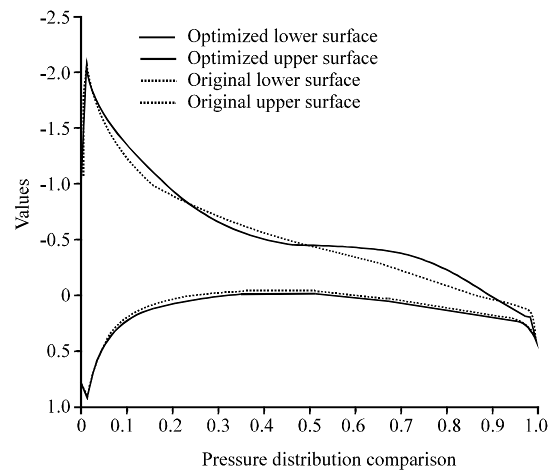

Fig. 4: Comparison of pressure distribution over the surface of original NACA 0012 airfoil and optimized airfoil using PSO

highly accelerated in the upper surface of the optimised airfoil as compared to the actual airfoil. From this it can be clearly understood that the increase in the lift coefficient is caused by the pressure variation in the upper surface of the optimised airfoil. Figure 5 shows the comparison between the original NACA 0012 airfoil geometry and the optimised airfoil geometry found by GA.

The comparison of pressure distribution over the surface of the original NACA 0012 airfoil and the optimised airfoil found by GA is shown in Fig. 6. The comparison between the original NACA 0012 airfoil and the optimised airfoil using both GA and PSO is shown in Fig. 6. It can be seen from this figure that the flow is slightly accelerated at the upper leading edge of the optimised airfoil which leads to an increased coefficient of lift in the optimised airfoil found by GA.

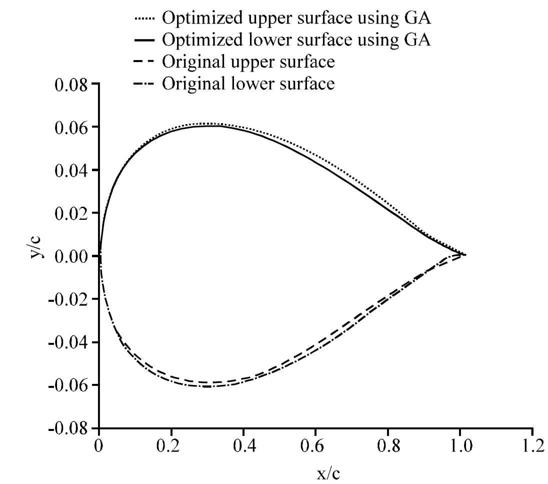

Fig. 5: Comparison of original NACA 0012 airfoil and optimized airfoil using GA

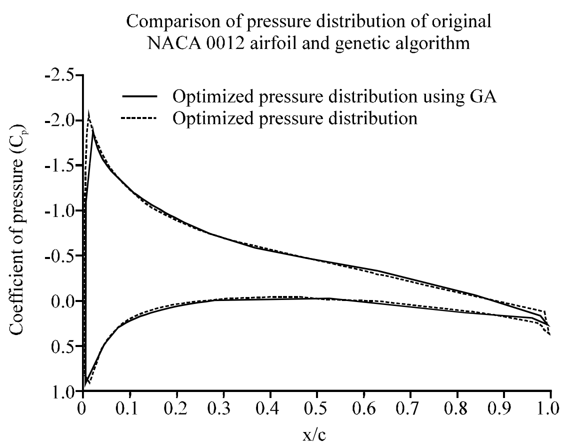

Fig. 6: Comparison of pressure distribution over the surface of original NACA 0012 airfoil and optimized airfoil using GA

The comparison of geometry and their corresponding pressure distribution between the actual NACA 0012 airfoil geometry and the optimum designs which are found by both PSO and GA are shown in Fig. 7 and 8, respectively. It can be clearly seen that the variation of the geometry found by the GA is quite less as compared to the PSO though the same design space is given to them to be explored. It can also be noticed that the geometry found by PSO has more negative pressure at the upper surface which is one of most important requirements for an efficient aerodynamic design. The optimised values of PARSEC parameters which are found by both GA and PSO and their corresponding coefficient of lift values are tabulated and compared with the actual values in Table 2 and 3, respectively. It can be

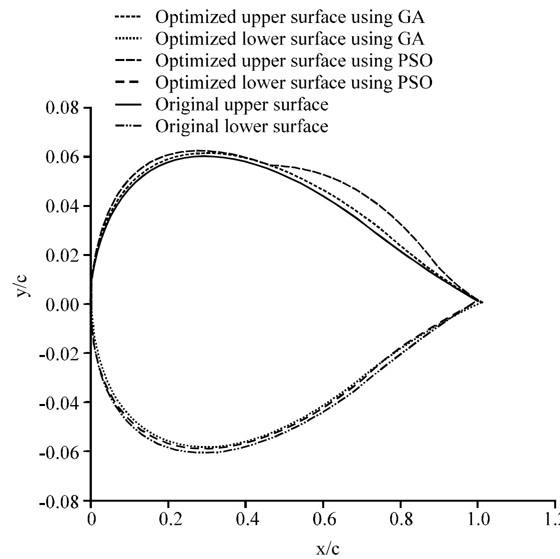

Fig. 7: Comparison of original NACA 0012 airfoil and optimized airfoil using both GA and PSO

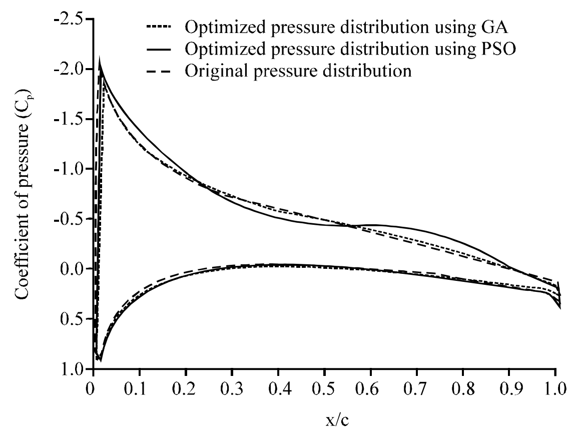

Fig. 8: Comparison of pressure distribution over the surface of original NACA 0012 airfoil and optimized airfoil using both GA and PSO

Table 2: Optimized PARSEC parameters

Parameters	Value original	Value optimised using PSO	Value optimised using GA
Upper leading edge radius (R_{leu})	0.0155	0.015637	0.014503
Lower leading edge radius (R_{leL})	0.0155	0.016199	0.016000
Position of upper crest (X_{up})	0.296632	0.25258	0.290010
Upper crest point (Y_{up})	0.060015	0.060603	0.061000
Upper crest curvature (YXX_{up})	-0.4515	-0.45333	-0.448023
Position of lower crest (X_{lo})	0.296632	0.29812	0.310000
Lower crest point (Y_{lo})	-0.06055	-0.05908	-0.059008
Lower crest curvature (YXX_{lo})	0.45309	0.44157	0.459990
Trailing edge thickness (T_{TE})	0	0	0
Trailing edge offset (T_{off})	0.001260	0.0011017	0.001299
Trailing edge direction angle (α_{TE})	0	0	0
Trailing edge wedge angle (β_{TE})	7.36	7.3931	7.248462

Table 3: Original vs. Optimized coefficient of lift

Angle of attack	$Cl_{original}$	$Cl_{optimised}$ using PSO	$Cl_{optimised}$ using GA
5.0 deg	0.55	0.6754	0.62571

clearly seen that airfoil geometry which is found by PSO has more coefficient of lift as compared the airfoil geometry which is found by GA.

CONCLUSION

A problem of optimising the actual NACA 0012 airfoil geometry for the above discussed flow and geometrical conditions is formulated and solved using two optimization schemes, Particle Swarm and Genetic Algorithm. The optimised airfoil geometries have an improved coefficient of lift of 0.6754 (PSO) and 0.6257 (GA) as compared to the actual NACA0012 airfoil geometry which has 0.55 at 5.0 deg angle of attack. The PARSEC parametrisation scheme is used to express the shape of the airfoil. The result shows that the PARSEC parameters show proper control over the aerodynamic performance of the airfoil by effectively controlling the aerodynamic shape of the airfoil.

The PARSEC approach eases the way of understanding the impact of individual geometrical parameters on the aerodynamic properties of the airfoil. It is once again witnessed that the panel method gives reasonably accurate results without being computationally expensive. It is concluded from the results that the PSO algorithm is so effective in finding the best solution among many possible solutions within a search space as compared to the GA optimization scheme in the current formulated problem. During the optimization process plenty of airfoil data is obtained. It can be effectively used for the airfoil design by making use of these data for constructing mathematical models. The constructed mathematical models can be suitably applied to new design studies of innovative configurations.

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