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## Influence of Search Algorithms on Aerodynamic Design Optimisation of Aircraft Wings

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### Abstract

The Method of search algorithms or optimisation algorithms is one of the most important parameters which will strongly influence the fidelity of the solution during an aerodynamic shape optimisation problem. Nowadays various optimisation methods such as Genetic Algorithm (GA), Simulated Annealing (SA), Particle Swarm Optimisation (PSO) etc., are more widely employed to solve the aerodynamic shape optimisation problems. In addition to the optimisation method, the geometry parameterisation becomes an important factor to be considered during the aerodynamic shape optimisation process. Since the reduction in the number of design parameters is one of the most important requirements for the aerodynamic shape optimisation problem, it becomes important to mathematically describe the airfoil geometry with minimum number of design parameters. The objective of this work 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 optimisation algorithms. It is also demonstrated that the estimation of a suitable optimisation scheme for a given optimisation problem. An aerodynamic shape optimisation problem is formulated for NACA 0012 airfoil and solved using the methods of Particle Swarm Optimisation and Genetic Algorithm for 5.0 deg angle of attack. The results show that the particle swarm optimisation 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.

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**Keywords** - Aerodynamic Shape Optimization; Parametric Section; Particle Swarm Optimisation; Genetic Algorithm

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## 1. 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 thirty years. This becomes more complicated to deal with when the given problem is an optimisation 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 optimisation for quite some years. When the number of result(s) influencing variables are large in a given optimisation problem, the required computational time per simulation increases automatically. This will severely influence the required computational resources to solve the given design optimisation 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. Nowadays various parametrisation methods are employed: (a) Partial differential equation approach (time consuming and not suitable for multidisciplinary design optimisation), 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 optimisation) are the three basic approaches to describe the geometry of a general airfoil. Previous research works in design optimisation suggest that the parametrisation schemes highly influences the final optimum design which is obtained as a result of the optimisation [1]. In this work, 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 optimisation process. Both PSO and GA are employed to carry out the design optimisation problem. Three MATLAB codes are developed to implement PARSEC, Panel and PSO approaches. A freely available FORTRAN code is picked for the GA. The results and issues faced during the whole design process in discussed in the following sections.

## 2. PARSEC

In PARSEC parametrisation scheme, an unknown linear combination of suitable base functions is used to describe the airfoil geometry. [1] [2] This approach is considered to be more suitable for design optimisation 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 ( $\alpha_{TE}$ ), trailing edge wedge angle ( $\beta_{TE}$ ), as shown in Figure 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: [1] [2]

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

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

where  $y_u$  is the upper  $y$  coordinate,  $y_l$  is the lower  $y$  coordinate and  $a_i$ ,  $b_i$  are 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. [1]

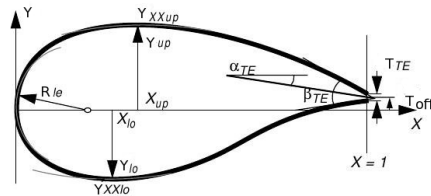


Figure 1. Control variables for PARSEC

### 3. 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 optimisation 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 work. 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: (a) the source strength is constant over each panel but has a different value for each panel (b) the vortex strength is constant and equal over each panel [3] [4]. 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,

$$\phi = \phi_{\infty} + \phi_{\delta} + \phi_v \quad (3)$$

Where,  $\phi$ , 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 depicts the notations of the panel approach.



Figure 2. 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

( $V_{ii}$ ) at the centre of each panel is estimated by imposing a flow tangency condition at each panel. The coefficient of pressure ( $C_p$ ) at each panel is calculated using the following relation.

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

#### 4. PARTICLE SWARM OPTIMISATION

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 [5] [6]. 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  $d^{\text{th}}$  dimensional value of the vector of position and velocity of  $j^{\text{th}}$  particle in the swarm, respectively, at time  $t$ . The PSO model can be expressed as

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

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

where  $x_{j,d}^*$  (PBEST) denotes the best position of  $j^{\text{th}}$  particle up to time  $t-1$  and  $x_d^\#$  (GBEST) denotes the best position of the whole swarm up to time  $t-1$ ,  $\varphi_1$  and  $\varphi_2$  are random numbers, and  $c_1$  and  $c_2$  represent 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 (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: [7] [8]

- a) Set the swarm size. Initialize the velocity and the position of each particle randomly.
- b) For each  $j$ , evaluate the fitness value of  $x_j$  and update the individual best position  $x_{j,d}^*$  if better fitness is found.
- c) 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.
- d) If the stopping criterion is satisfied, then stop.
- e) For each particle, update the position and the velocity according (6) and (5). Go to step b.

#### 5. GENETIC ALGORITHM

Genetic algorithms (GA), in contrast to gradient optimisation 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 optimisation 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 optimisation 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. [9]

## 6. Optimisation of NACA 0012 airfoil

The aerodynamic shape optimisation 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 optimisation in both the optimisation schemes. These constraints are placed in 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 optimisation process. The flow constraint is implemented by fixing the angle of attack at 5.0 deg. 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 deg 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, optimisation objectives and constraints, which are used during the optimisation process using PSO and GA, are tabulated in Table I.

Table I. Optimisation objectives and constraints

Angle of attack	5.0 deg
Flow constraint	Subsonic and incompressible
Geometric constraint 1	Max thickness must be less than 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

## 6. 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 indicated in Figure 3. The comparison of pressure distribution over the surface of the original NACA 0012 airfoil and the optimised airfoil using PSO is shown in Figure 4. It can be seen from these figures that the actual airfoil geometry is modified in such a way that the airflow is 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 given in Figure 6. The comparison between the original NACA 0012 airfoil and the optimised airfoil using both GA and PSO is indicated in Figure 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.

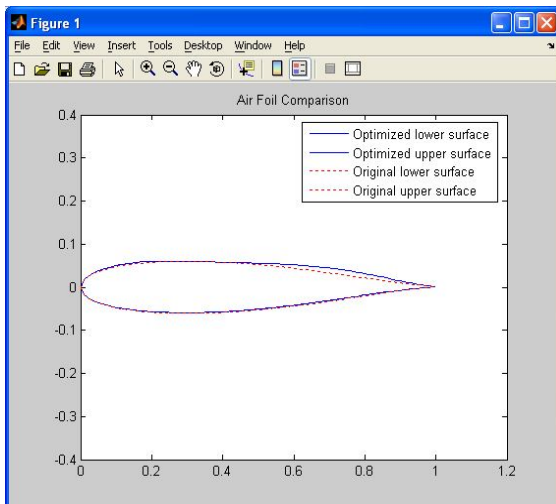


Figure 3: Comparison of Original NACA 0012 airfoil and Optimised airfoil using PSO

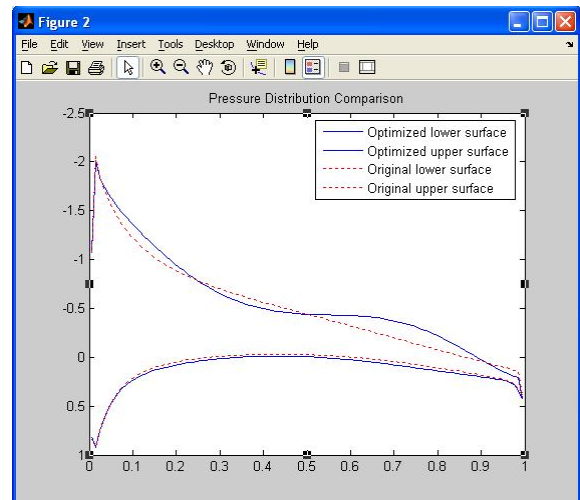


Figure 4: Comparison of pressure distribution over the surface of original NACA 0012 airfoil and Optimised airfoil using PSO

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 depicted in Figures 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 II and III respectively. It can be 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.

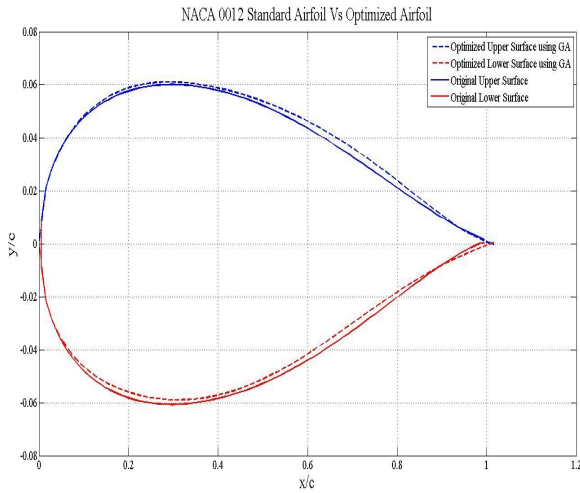


Figure 5: Comparison of Original NACA 0012 airfoil and Optimised airfoil using GA

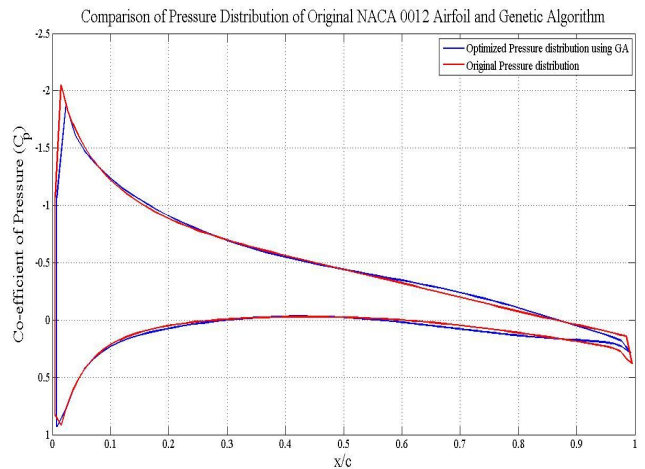


Figure 6: Comparison of pressure distribution over the surface of original NACA 0012 airfoil and Optimised airfoil using GA

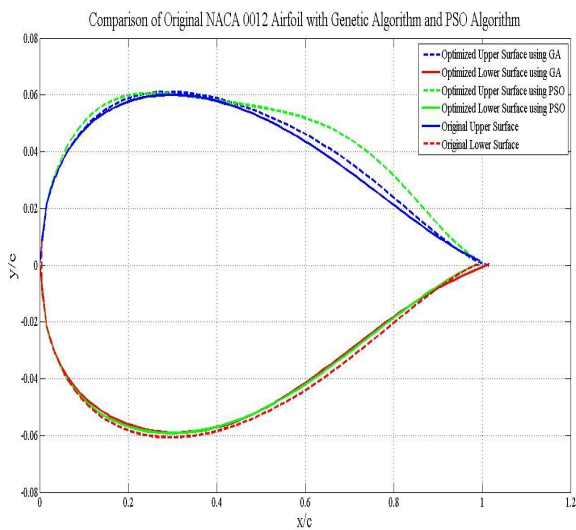


Figure 7: Comparison of Original NACA 0012 airfoil and Optimised airfoil using both GA and PSO

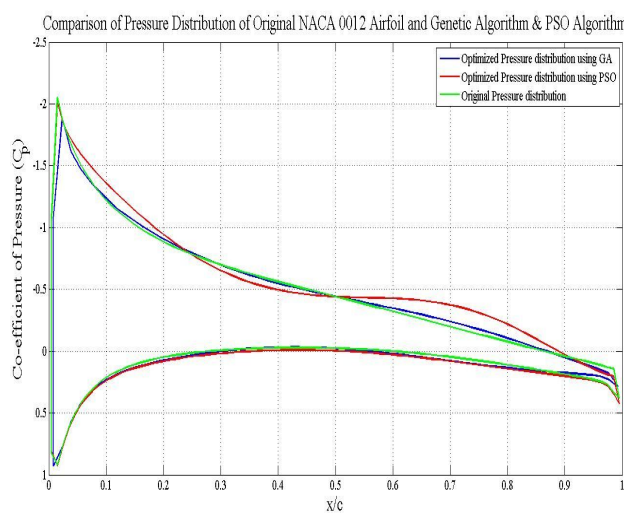


Figure 8: Comparison of pressure distribution over the surface of original NACA 0012 airfoil and Optimised airfoil using both GA and PSO

Table II. Optimised PARSEC parameters

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

Table III Original vs. Optimised Coefficient of Lift

Angle of attack	$C_{loriginal}$	$C_{lOptimised}$ Using PSO	$C_{lOptimised}$ Using GA
5.0 deg	0.55	0.6754	0.62571



## 7. Conclusions

A problem of optimising the actual NACA 0012 airfoil geometry for the above discussed flow and geometrical conditions is formulated and solved using two optimisation 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 optimisation scheme in the current formulated problem. During the optimisation 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.

## References

- [1] R. Balu and U. Selvakumar, "Optimum hierarchical Bezier parameterization of arbitrary curves and surfaces," 11<sup>th</sup> Annual CFD Symposium, Indian Institute of Science, Bangalore, India, pp. 46-48, August 2009.
- [2] Helmut Sobieczky, "Parametric airfoils and wings", Notes on Numerical Fluid Mechanics, Volume 68 Vieweg verlag, pp. 71-88, 1998.
- [3] J.L. Hess, "Panel methods in computational fluid mechanics", Annual Review of Fluid Mechanics, Vol.22, pp. 255-274, 1990.
- [4] J. Katz and A. Plotkin, "Low-speed aerodynamics from wing theory to panel methods", McGraw-Hill, Inc., New York, 1991.
- [5] J. Kennedy, R.C. Eberhart, Particle swarm optimization, in: Proceedings of IEEE International Conference on Neural Networks, Perth, Australia, vol. 4, 1995, pp. 1942–1948.
- [6] R.C. Eberhart, J. Kennedy, A new optimizer using particle swarm theory, in: Proceedings of IEEE International Symposium on Micro Machine and Human Science, Nagoya, Japan, 1995, pp. 39–43.
- [7] Ping Xu, Changsheng Jiang, "Aerodynamic Optimization Design of Airfoil Based on Particle Swarm Optimization", Aircraft Design, Vol.28, No. 5, pp. 6-9, 2008.
- [8] M. S. Khurana I, H. Winarto, and A. K. Sinha, "Airfoil optimization by swarm algorithm with mutation and artificial neural networks," in AIAA Aerospace Sciences Meeting Including The New Horizons Forum and Aerospace Exposition, 2009
- [9] Goldberg, D. E., "Genetic Algorithms in Search, Optimization and Machine Learning," Addison- Wesley, Reading, MA, 59-88, 1989.