AERODYNAMIC SHAPRE OPTIMIZATION OF TYPICAL AIRFOIL USING GENETIC ALGORITHM

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***Abstract:** Nowadays high performance aircraft designers are interested in high-fidelity design using Computational Fluid Dynamics (CFD).A PARametric SECtion method for airfoil shape optimization using genetic algorithm and it is usually used as a preliminary step to wing optimization. It is reasonable to expect that good aerodynamic performance of an airfoil will be reflected in good properties of a wing having this airfoil as a cross section. In this paper, Shapes of airfoils were defined by modified PARSEC method with 12 parameters, which is the design condition of NACA 2411 airfoil and also this airfoil is a well known airfoil used in aerospace applications. A FORTRAN program has been developed to implement PARSEC, surface panel theory and genetic algorithm. This program has been tested for a standard NACA 2411 airfoil and optimized to improve its co-efficient of lift for 5.0 deg angle of attack.*

***Keywords:** PARSEC, Panel, Genetic Algorithms.*

1. INTRODUCTION

Numerical methods for optimizing aerodynamic performance have been widely studied for many years. Most engineering problems are multi-objective in nature. Design objectives are often conflicting and may have tradeoffs among them. For instance, the design of airfoil parameters considered as lift, drag, stall angle, etc., to be optimized. Although the current computational fluid dynamics (CFD) codes are capable of solving these values for a given shape, in most cases, the trade off relation between each shape is estimated by the researcher.

The gradient methods [2] have been utilized to produce optimal aerodynamic performance in a wide variety of different forms. The reliability and success of gradient methods generally requires a smooth design space and the existence of only a single global extremum. In contrast to gradient methods, genetic algorithms (GA) [3] 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 iteration (or "evolution" using GA terminology) the decision variables or "genes" are manipulated using various operators (selection, crossover or mutation) to create new design populations, i.e., new sets of genes. Each design is evaluated using an objective like "biological fitness function" to determine survivability.

Because GA optimization requires no gradients, it does not need sensitivity derivatives. It theoretically works well in non-smooth design spaces containing several or perhaps many local extrema. A disadvantage of the GA approach is expense, In general, the computational effort required for a GA algorithm exceeds that required by a gradient-based optimization method by an order of magnitude or more.

2. PARSEC

Most of the aerodynamic parameters can be well-fitted using polynomial functions. The PARSEC method [5] defines the shape of an airfoil by eleven parameters. By these eleven parameters, the airfoil shape is given by the following equation, upper and lower independently.

$$Z_{PARSEC} = \sum_{n=1}^{6} a_n(p)\, X^{n-1/2} \tag{1.0}$$

Where, the coefficients a_n is determined by the given geometrical parameters shown in Fig.1.

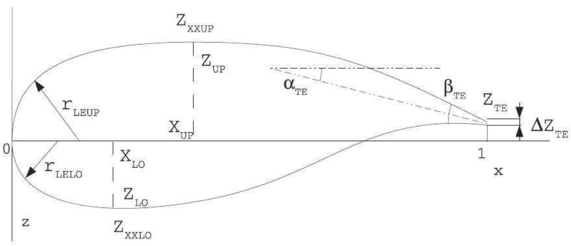

Figure 1: Demonstration on Modified PARSEC

Since the PARSEC method was specially designed to airfoils. We noticed that this method to be modified to increase its robustness for our purpose. The center of the leading edge radius is always on the x-axis for the original PARSEC method. For our optimization, the leading edge radius was defined by two parameters (r_{LEUP} & r_{LELO}) instead of one parameter (r_{LE}).

The PARSEC method is used to generate the wide range of airfoil shapes and no baseline shape is needed. The impact of individual design parameters on the aerodynamic properties of the airfoil can be predicted more easily. The main drawback of this method is not suitable for turbine blade designs when compared to other parameterization methods and not applicable to wide class of problems as spline curves.

3. PANEL THEORY

Panel methods are numerical models based on simplifying assumptions about the physics and properties of the flow of air over an aircraft. The viscosity of air in the flow field is neglected, and the net effect of viscosity on a wing is summarized by requiring that the flow leaves the sharp trailing edge of the wing smoothly [1].

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The compressibility of air is neglected, and the curl of the velocity field is assumed to be zero (no vorticity in the flow field). Under these assumptions, the vector velocity describing the flow field can be represented as the gradient of a scalar velocity potential, $Q = \nabla\phi$ and the resulting flow is referred to as potential flow. A statement of conservation of mass in the flow field leads to Laplace's equation as the governing equation for the velocity potential, $\nabla^2\phi = 0$ the potential flow over an airfoil can be calculated to a very high degree of precision. The two-dimensional flow around an aerofoil is selected for illustrative purposes. The basic concept of panel method is shown in Fig.2.

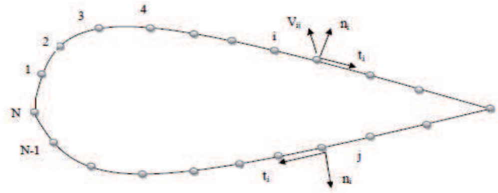

Figure 2: Discretization of airfoil contour into straight line segments

The first step is to number all the end points or *nodes* of the panels from 1 to *N* as indicated in Fig. 2. The individual panels are assigned the same number as the node located to the left when facing in the outward direction from the panel. The mid-points of each panel are chosen as *collocation* points. It will emerge below that the boundary condition of zero flow perpendicular to the surface is applied at these points. Also define for each panel the unit normal and tangential vectors, n_i and t_i respectively. Consider panels *i* and j in Fig.2. The sources distributed over panel j induce a velocity, which is denoted by the vector V_{ij}, at the collocation point of panel *i.* The components of V_{ij} perpendicular and tangential to the surface at the collocation point ***i*** are given by the scalar (or dot) products V_{ij} .n_i and V_{ij} .t_i respectively. Both of these quantities are proportional to the strength of the sources on panel ***j.*** Both of these quantities are proportional to the strength of the sources on panel ***j.*** Finally the Bernoulli equation can then be used to calculate the pressure acting at collocation point ***i,*** in particular the coefficient of pressure is given by Equation (2.0)**.**

$$C_{p,i} = 1 - \frac{V_{ti}}{U} \tag{2.0}$$

4. GENETIC ALGORITHM

Genetic Algorithms (GA) are stochastic optimization algorithms based on the mechanics of natural selection and natural genetics. They combine survival of the fittest among string structures with a structured yet randomized information exchange to form a search algorithm with some of the innovative flair of human search. 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. The basic genetic algorithm comprises four important steps [3] are initialization, evaluation, exploitation (or selection), and exploration.

The first step is the creation of the initial population of chromosomes either randomly or by perturbing an input chromosome. How the initialization is done is not critical as long as the initial population spans a wide range of variable settings (i.e., has a diverse population). Thus, if explicit knowledge about the system is being optimized is available that information can be included in the initial population.

In the second step, the chromosomes are evaluated and their fitness functions are computed. The goal of the fitness function is to numerically encode the performance of the chromosome. For this problem of optimization, the choice of fitness function is the most critical step.

The third step is the exploitation or natural selection step. In this step, the chromosomes with the largest fitness scores are placed one or more times into a mating subset in a semi-random fashion. Chromosomes with low fitness scores are removed from the population. There are several methods for performing exploitation. In the binary tournament mating selection method, each chromosome in the population completes for a position in the mating subset. Two chromosomes are drawn at random from the population, the chromosome with the highest fitness score is placed in the mating subset. Both chromosomes are returned to the population and another tournament begins. This procedure continues until the mating subset is full. A characteristic of this scheme is that the worst chromosome in the population will never be selected for inclusion in the mating subset.

The fourth step, exploration, consists of recombination and mutation operators. Two chromosomes (parents) from the mating subset are randomly selected to be mated. The probability that these chromosomes are recombined (mated) is a user-controlled option and is usually set to a high value (e.g., 0.95). If the parents are allowed to mate, a recombination operator is employed to exchange genes between the two parents to produce two children. If they are not allowed to mate, the parents are placed into the next generation unchanged. The two most common recombination operators are the one-point and two-point crossover methods. In the one-point method, a crossover point is selected along the chromosome and the genes up to that point are swapped between the two parents. In the two-point method, two crossover points are selected and the genes between the two points are swapped. The children then replace the parents in the next generation. A third recombination operator, which has recently become quite popular, is the uniform crossover method. In this method, recombination is applied to the individual genes in the chromosome. If crossover is performed, the genes between the parents are swapped and if no crossover is performed the genes are left intact. This crossover method has a higher probability of producing children that are very different than their parents, so the probability of recombination is usually set to a low value (i.e.0.1). The probability that a mutation will occur is another user-controlled option and is usually set to a low value (e.g., 0.01) so that good chromosomes are not destroyed. A mutation simply changes the value for a particular gene.

5. OPTIMIZATION OF NACA 2411 AIRFOIL

Many optimization technologies have been developed to obtain the optimal solutions for various industrial applications. Optimization is to find the best values of the design variables that minimize and/or maximize the objective functions while satisfying the constraints and bounds. The optimization problems comprise the ingredients are design variable(s), objective function(s), constraint(s), and side constraint(s). The main objective of NACA 2411 airfoil optimization process is to improve the co-efficient of lift. The flow region is subsonic & incompressible flow. The angle of attack is 5.0 deg. The maximum thickness of the airfoil must be less than 10% chord length and the trailing edge thickness & trailing edge offset of the airfoil is zero.

6. RESULTS

The geometry of the airfoil expressed by the best twelve PARSEC parameters resulting from genetic algorithm exhibits a considerable to improve in the coefficient of lift. The comparison between the standard NACA 2411 airfoil and the optimized airfoils are indicated in Fig. 3. The comparison of pressure distribution over the surface of the standard NACA 2411 airfoil and the optimized airfoils are given in Fig. 4. The comparisons of original value and optimized values have given in Table. I. The comparisons with the experimental and previous & present studies of optimized results have shown in Table. II.

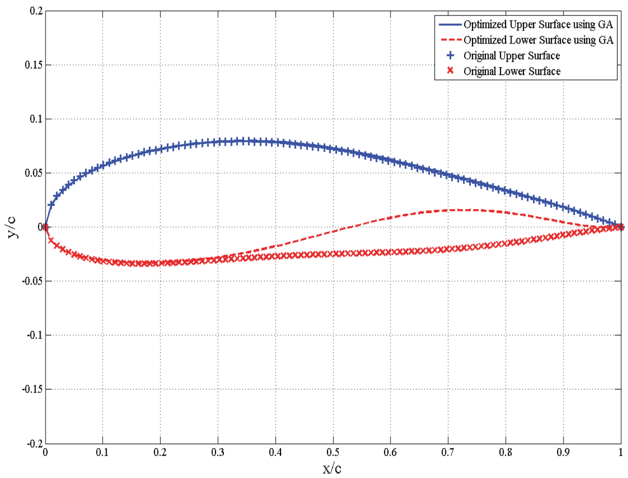

Figure 3: Comparison between the standard NACA 2411 and the optimized airfoils

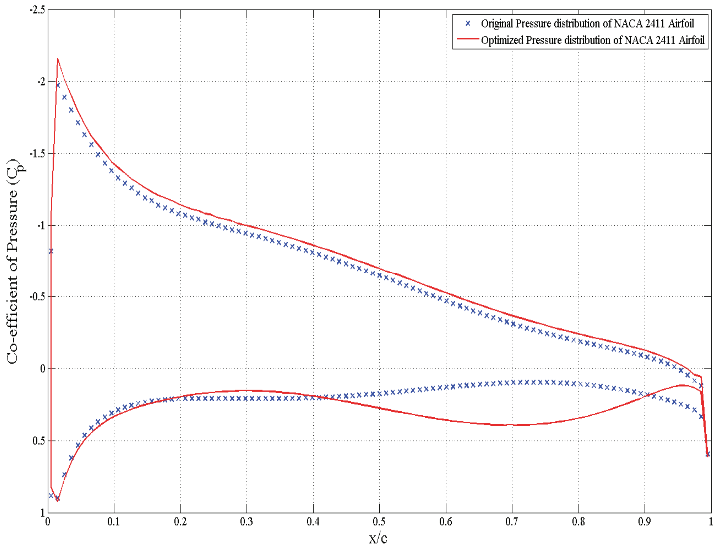

Figure 4: Comparison of pressure distribution over the surface of the standard NACA 2411 airfoil and the optimized airfoils

Table I: Optimized PARSEC Parameters

Parameter	Original Value	Optimized Value
Leading edge radius upper (r_{LEUP})	0.0216	0.020023
Leading edge radius lower (r_{LELO})	0.0080	0.00900
Position of upper crest along chord (X_{UP})	0.3445	0.349678
Upper crest point (Z_{UP})	0.07912	0.079497
Upper crest curvature (Z_{XXUP})	-0.6448	-0.640039
Position of lower crest (X_{LO})	0.16912	0.174886
Lower crest point (Z_{LO})	-0.03379	-0.033010
Lower crest curvature (Z_{XXLO})	0.6748	0.677939
Trailing edge thickness (ΔZ_{TE})	0.0000	0.0000
Trailing edge offset (Z_{TE})	0.0000	0.0000
Trailing edge direction angle (α_{TE})	-4.785	-4.799707
Trailing edge wedge angle (β_{TE})	15.082	15.088692

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Table II: Comparative study of Original and Optimized value of Previous and Present Study

AOA (deg)	C_L ORIGINAL	Present Study		Selvakumar [4]	
		$C_{LOptimized}$	Achieved	$C_{LOptimized}$	Achieved
5	0.8420	1.0168	20.76 %	0.9681	14.97 %

7. CONCLUSION

The Genetic Algorithm has been successfully applied to NACA 2411 airfoil and to improve the lift coefficient. The Lift coefficient improved from 0.8420 for the original airfoil to 1.0168 for the optimized airfoil, which is about 20.76% improvement. The results demonstrated the powerful reliability and robustness of the genetic algorithms. The PARametric SECtion method to be modified to increase the robustness and the leading edge radius has defined by two parameters (r_{LEUP} & r_{LELO}) instead of one parameter (r_{LE}). It shows very high effectiveness in controlling the aerodynamic characteristics of airfoil. Panel method gives reasonable accuracy over the prediction of co-efficient of lift for low speed, subsonic incompressible flows. 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 results demonstrate that the profile optimization method has the potential to be used for real-world airfoil shape optimization over a range of flight conditions.

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