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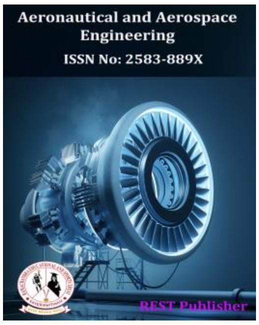

Airfoil Shape Optimization for Improved Aerodynamics

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Abstract: *This project focuses on the optimization of a custom airfoil by systematically analyzing the effects of camber percentage (2%– 6%), camber position (1– 6), and angle of attack (6°) while maintaining a fixed thickness of 12%. The primary objective is to maximize the lift- to-drag ratio (L/D) to enhance aerodynamic efficiency and stability. A parametric investigation was conducted using both unilabiate and bivariate analyses to evaluate the influence of individual and combined aerodynamic parameters on airfoil performance. To achieve this, XFOIL, a high- fidelity aerodynamic analysis tool, was integrated with MATLAB for automated batch processing, enabling efficient computation of lift coefficient (C_l), drag coefficient (C_d), and the corresponding L/D ratios. The parametric study revealed that variations in camber and its position significantly affect aerodynamic characteristics, offering critical insights for the design of optimized airfoils applicable to aircraft wings, UAVs, and wind turbine blades. In addition to parametric analysis, this study explores advanced optimization techniques, with a focus on evolutionary algorithms such as the Genetic Algorithm (GA). The GA framework was employed to systematically search for airfoil configurations that yield optimal L/D ratios by iteratively refining candidate solutions based on selection, crossover, and mutation operations. Future work will incorporate Reynolds number effects and validate the optimization results using computational fluid dynamics (CFD) simulations and experimental testing for enhanced accuracy and practical applicability.*

1. INTRODUCTION

Airfoil design is critical in aeronautical engineering, directly impacting the aerodynamic performance of aircraft wings. Traditional methods rely on trial-and-error or fixed-profile selections. This paper utilizes a Genetic Algorithm to optimize the NACA 4-digit airfoil family. The use of statistical analysis (unilabiate and bivariate) improves the interpretability of the optimization process and helps identify dominant design features.

The fundamental components of an airfoil include:
Leading Edge: The front part of the airfoil that first meets the airflow.
Trailing Edge: The rear part of the airfoil where the airflow rejoins after moving over the upper and lower surfaces.
Chord Line: An imaginary straight line connecting the leading and trailing edges.
Camber Line: A curve representing the mean line of the airfoil, determining its curvature.
Thickness Distribution: The variation of airfoil thickness from the leading to the trailing edge.

2. METHODOLOGY

2.1 Airfoil Parameterization

NACA 4-digit airfoils are defined using three parameters:
M: maximum camber (as a percentage of chord)
P: location of maximum camber (in tenths of chord)
T: maximum thickness (as a percentage of chord)

2.2 Aerodynamic Evaluation

XFOIL was used to evaluate each generated airfoil at a fixed Reynolds number and angle of attack. Output included lift and drag coefficients.

2.3 Statistical Analysis

Univar ate Analysis: Examined the effect of each parameter on Cl/Cd individually using plots and trend lines.
Bivariate Analysis: Explored interactions between parameter pairs (e.g., m vs p, p vs t) using contour plots and surface maps to reveal synergies or conflicts in design optimization.

3. LITERATURE REVIEW

Airfoil optimization has been a central theme in aerodynamic research for decades. Traditional approaches relied heavily on manual design iterations or low-fidelity empirical models. With the evolution of computational tools, optimization techniques such as Genetic Algorithms (GAs) and other evolutionary strategies have gained prominence due to their ability to handle complex, nonlinear, and multi-modal design spaces.

3.1 Airfoil Optimization Methods
Drela and Giles (1987) introduced XFOIL, a widely adopted panel method tool for low Reynolds number airfoil analysis, enabling rapid evaluation of airfoil performance. Their tool remains central to modern optimization workflows, including this study. Roth and Katz (2001) demonstrated early applications of GAs in aerodynamic shape optimization, showing that evolutionary techniques outperform gradient-based methods in complex design spaces. Similarly, Obayashi and Sasaki (1996) used GAs for multi-objective wing shape optimization, highlighting the method's flexibility.

3.2 Genetic Algorithms in Aerodynamic Design
Goldberg (1989) popularized the use of GAs for engineering problems. In airfoil optimization, GAs have been effectively used due to their robustness and global search capabilities. For example, Lian and Oyama (2003) optimized airfoil shapes under transonic flow conditions using multi- objective GAs, demonstrating superior performance over traditional single-objective designs. Recent work by Srinivas and Raghunathan (2018) combined GAs with surrogate modeling techniques to accelerate convergence, indicating the growing trend toward hybrid optimization frameworks.

3.3 Statistical Analysis in Design Exploration
While optimization provides a set of "best" solutions, understanding the role of each design variable is essential. Saltelli et al. (2008) emphasized the value of sensitivity analysis, such as univariate (one-factor-at-a- time) and bivariate (pairwise interaction) studies, in high- dimensional models. These approaches allow designers to interpret model behavior, identify dominant variables, and reduce dimensionality. In the context of airfoil optimization, Wang et al. (2014) used univariate analysis to study thickness effects on laminar separation, and Martins et al. (2017) applied bivariate plots to visualize the interplay between shape parameters and aerodynamic metrics.

4. METHODOLOGY AND DESIGN

Design Parameters and Constraints
The NACA 4-digit airfoil is defined using three shape- defining parameters:
Maximum camber (m): 4% to 6% of chord Position of maximum camber (p): 40% to 60% of chord (i.e., p = 4 to 6 in tenths)
Maximum thickness (t): 15% to 20% of chord these ranges were chosen based on preliminary tests indicating that higher thickness and camber values in this range generally yield improved lift without excessive drag in moderate Reynolds number regimes.

4.1 Airfoil Generation
Each candidate airfoil is generated in MATLAB using the selected [m, p, t] values. The NACA 4-digit formula was used to compute the airfoil surface coordinates. These coordinates are formatted as input for XFOIL, which performs aerodynamic analysis.
4.2 Aerodynamic Performance Evaluation
XFOIL is used to simulate the airfoil's performance under steady, incompressible, in viscid and viscous flow conditions at a fixed Reynolds number (e.g. Re=5×105Re = 5 \times 10^5Re=5×105) and a specific angle of attack (typically α=4∘\alpha = 4^\circα=4∘). Key outputs include: Cl (lift coefficient) Cd (drag coefficient) Cl/Cd (objective function)
Airfoils with failed convergence in XFOIL were penalized with a near-zero objective score to guide the GA away from poor geometries.

4.3 Genetic Algorithm Implementation
The Genetic Algorithm was implemented in MATLAB with the following configuration:
Population size: 50–100
Chromosome encoding: Real- valued representation of [m, p, and t]

Selection: Tournament or roulette wheel
Crossover: Single-point or arithmetic crossover
Mutation: Gaussian mutation with adaptive probability
Termination criteria: Maximum generations or convergence of fitness. Each individual represents a unique airfoil, and the fitness function is defined as the Cl/Cd value c computed from XFOIL.

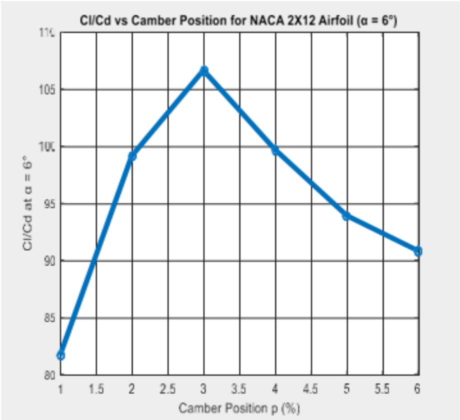


FIGURE. 2

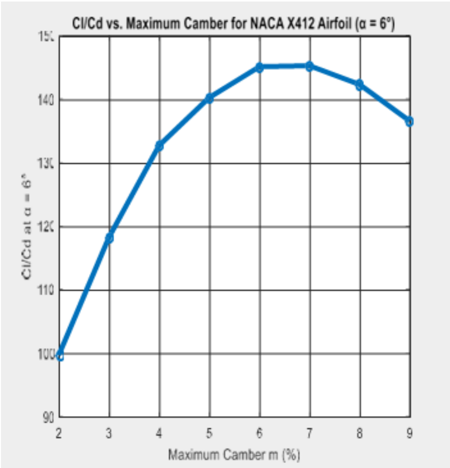


FIGURE. 3

4.4 Univar ate and Bivariate Analysis

Post-optimization, a detailed statistical analysis was conducted:
Univar ate analysis: The effect of each individual parameter (m, p, t) on Cl/Cd was examined using scatter plots and trend lines.

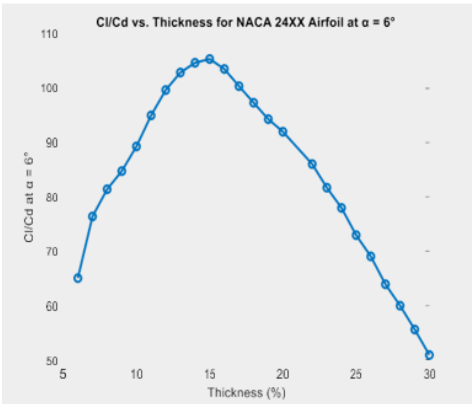
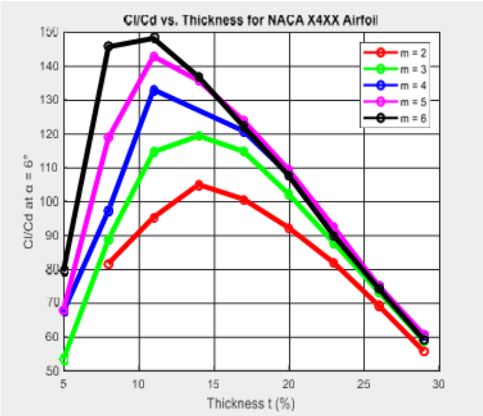


FIGURE 3.

Bivariate analysis: Pairwise interactions (e.g., m vs p, p vs t) were visualized using contour and 3D surface plots to reveal synergistic or antagonistic relationships among parameters. These analyses help explain how certain regions in the design space contribute to higher aerodynamic efficiency and guide future parametric studies.
XFOIL: Aerodynamic simulation of 2D airfoils under in viscid and viscous flow conditions. Generating Cl, Cd, and Cl/Cd values across a range of airfoil geometries



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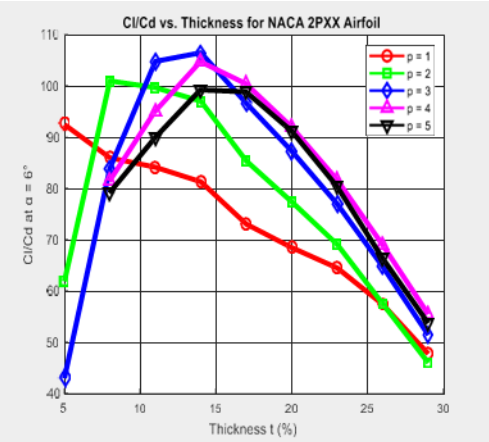

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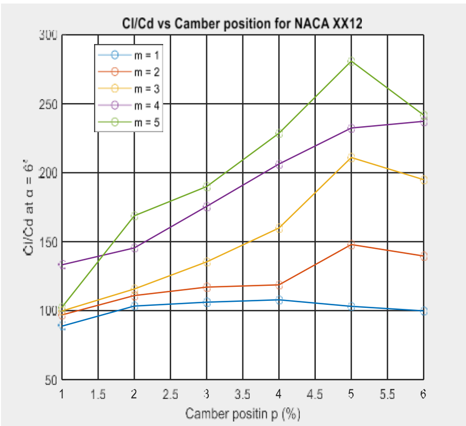

FIGURE 6.

5.4 Software and Tools

MATLAB: Algorithm implementation, air foil generation, and Data analysis, visualization, and scripting for unilabiate and bivariate analysis.

21XFOIL:Aerodynamic simulation of 2D air foils under in viscid and viscous flow conditions. Generating Cl, Cd, and Cl/Cd values across a range of air foil geometries.

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