IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

OPTIMIZATION OF FIXED WING AERODYNAMIC SHAPE OF UNMANNED AERIAL VEHICLE THROUGH GENETIC ALGORITHM AND PYFLUENT SIMULATION

[1] Bahadursha A V L Sainadh, [2] Santosh Gandhi Doddipatla, [3] Bharath Tatavarthi, [4]Veerababu Kilarapu

[1] Assistant Professor, [2,3,4] UG Student

[1,2,3,4] Department of Mechanical Engineering,

[1,2,3,4] Godavari Institute of Engineering and Technology, Rajamundry-533296, Andhra Pradesh, India

Abstract: The increasing significance of remote control has spurred the development of Unmanned Aerial Vehicle (UAV) capable of flight, ranging from small insect sized drones to large conventional airplanes. These UAVs find diverse applications in agriculture, surveillance, environmental monitoring, search and rescue, aerial photography, infrastructure inspection and scientific research. This study aims to optimize the aerodynamic shape of a fixed wing UAV by enhancing lift-to-drag ratio at 0-degree angle of attack (AOA) using a completely automated workflow. Our research, including Genetic Algorithm (GA), mimics the evolutionary process of natural selection to discover optimal solutions within complex problem space and PyFluent, a robust Computational Fluid Dynamics (CFD) tool. The work is structured into three stages: Initial stage, Optimization stage and Simulation stage. The optimal airfoil configuration achieves a lift-to-drag ratio of 24.8 at 0-degree AOA, particularly at a velocity of 40 m/s.

Index Terms **- UAV, lift-to-drag ratio, 0-degree AOA, Genetic Algorithm (GA), PyFluent**

I. INTRODUCTION

Unmanned Aerial vehicle (UAV) is an aircraft without human pilot on board and can be controlled remotely or autonomously programmed for specific flight paths. UAVs, also known as Unmanned Aerial Systems (UAS), encompass cameras, sensors, communication equipment and other payload devices. The UAV market expands and applications diversify, there is a growing demand to enhance flight capabilities and adaptability for complex tasks[1]. Initially UAVs are developed for military purposes, now widely used in both military and civilian contexts, contributing to border protection and various applications. Their unique capability to access remote or hazardous areas, coupled with advanced sensing technologies, enables high-resolution imagery for various civilian and humanitarian missions[2].The classification of UAVs based on design, capability and intended purposes, with two main categories, they are Rotary-wing UAVs and Fixed wing UAVs. The Fixed wing UAVs are known for their extended endurance, payload capabilities, and ability to achieve high cruising speeds during flight [3], [4]. Aerodynamics plays a crucial role in optimizing the performance and efficiency of UAVs by influencing factors such as lift-to-drag ratio, flight range, and endurance. Efficient aerodynamic considerations enable UAVs to achieve longer flight times and cover larger areas by ensuring stability, controllability, and maneuverability [5], [6]. Airfoils are pivotal in aerodynamics, as they generate lift, control lift-to-drag ratio, and influence stall behavior. The lift force is generated by the difference in air pressure between the upper and lower surfaces of an airfoil.

In recent studies, (Laghari et al) stated lift-to-drag ratio is a critical factor influencing the aerodynamic efficiency of UAV wings [1]. (Rashid et al) Revealed that adjusting the angle-of-attack significantly impacts lift and drag forces [7]. (Chakraborty et al. n.d.) Compared the Boeing 737 and NACA 2412 airfoils, indicating the latter's superior lift-to-drag ratio under typical operating conditions [8]. (Khalid) Studied the NACA 0012 airfoil, emphasizing the impact of flow separation on the lift coefficient at various angle of attack [9]. (Adawy et al.) emphasized the importance of a phased approach in UAV design optimization[10]. (Kontogiannis et al.) suggested enhancing aerodynamics through increased wingspan and aspect ratio to improve UAV aerodynamics[11]. (Gowda) Highlighted the NACA 2412 airfoil's advantage in a UAV mission profile with a broader range of angle of attack[12]. (Chumbre et al) conducted a comprehensive study on various airfoil sections, focusing on the coefficients of lift and drag, concluded that an increase in the angle of attack results in proportional increase in lift force[13]. (Panagiotou et al) This analysis aimed to identify the factors influencing aerodynamic performance, especially in the low-speed subsonic regime the study includes a detailed examination of the drag contributions from various components of the UAV[14]. (Ramanan et al.) aimed to enhance UAV operations in defense areas through improved airfoil design using genetic algorithm[15]. (Gibert Martinez et al.) demonstrated that optimizing UAV wing shape not only improve flight performance but also reduced material requirements, contributing to overall efficiency[16]. (QIAO et al.) Explored through CFD, the aerodynamic attributes influencing flight performance, including lift-to-drag ratio and static stability, are scrutinized for formation UAVs[17]. (Murariu et al) discussed the use of genetic algorithm in designing a UAV prototype for optimal payload and flight time[18]. (Kohar et al) showcased the effectiveness of genetic algorithm in optimizing fixed-wing UAV aerodynamics[19].

This research aims to enhance the aerodynamic performance of fixed-wing UAVs. Utilizing the NACA 2412 as a reference, the study parameterizes wing shapes and employes a genetic algorithm to iteratively optimize them based on lift-to-drag ratio, which serves as fitness value. Notably, the fitness values are evaluated using PyFluent, representing a departure from conventional methods and highlighting the novelty of our approach. This innovative methodology eliminates manual intervention, streamlining the process of discovering optimal aerodynamic configurations, Ultimately, our seeks to advance efficiency and mission capabilities in the field of UAV technology.

II. METHODOLOGY

The methodology employed is delineated through a Figure II-1, which encompass three distinct stages: Initial stage, Optimization stage and simulation stage. The Initial stage constitutes the foundational groundwork of the study. The optimization stage employs Genetic algorithm, to systematically refine the design parameters. This iterative process aims to optimize the performance metrics associated with the chosen airfoil, enhancing its efficiency by increasing lift-to-drag ratio. The Simulation stage involves crucial part, which is evaluation of fitness value which is used for genetic algorithm rather than using conventional approach. Here PyFluent plays a pivotal role in both simulation process and calculation of fitness value achieved by construction of 3d geometry of wing through CadQuery then perform tasks like Meshing, Solver setup and Post-processing of Simulation results.

2.1 Initial Stage

The wing serves as the primary aerodynamic surface for lift generation in UAVs with fixed-wing configurations embodying a specific subtype defined by their static and non-moving structures, distinguishing them from other types of UAV designs Fixed-wing UAVs have rapidly emerged as the dominant platform due to their enhanced stability, efficiency, and extended range. Notably, they boast significantly longer flight endurance compared to rotary-wing or multirotor UAVs[20]. Fixed-wing UAVs encompass various types, including Medium-Altitude Long-Endurance (MALE) UAV, High-Altitude Long-Endurance (HALE) UAV, Tactical UAV, small UAV, Mini UAV and Micro UAV. Each type offers unique capabilities suited to diverse mission requirements and operational environments.

2.1.1 Abbreviations

- y_c: Camber line equation
- y_t: Thickness line equation
- m: Maximum camber
- p: Location of maximum camber
- t: Maximum thickness
- c: Chord length
- L: Lift force
- u: Random number
- η_c: Distribution index for crossover
- P_1 and P_2: Parent solutions
- O_1 and O_2: Offspring solutions
- δ: Mutation factor
- r: random number in mutation
- η_m: Distribution index for mutation

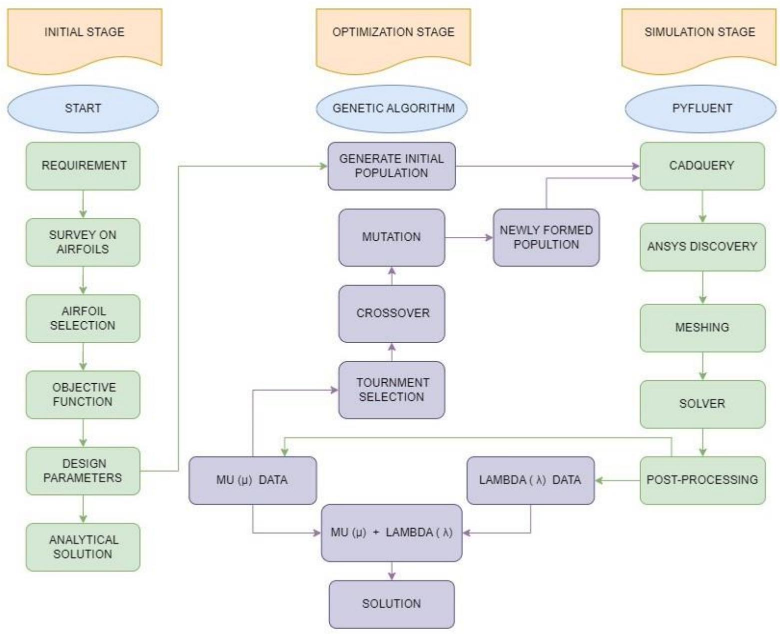

Figure II-1. Methodology Flowchart

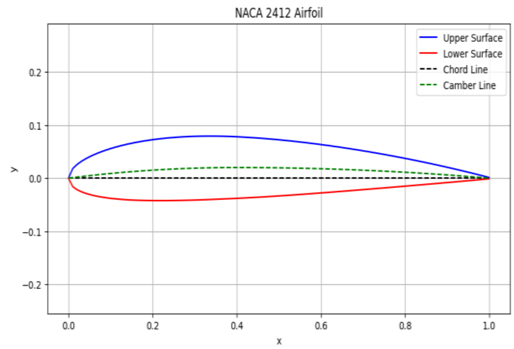

Figure II-2. Naca 2412 airfoil

- D: Drag force
- ρ: Air density
- V: Free stream velocity
- S: Wing planform area
- C_L: Coefficient of lift
- C_D: Coefficient of drag
- β: Crossover rate
- ub: Upper bound of variable
- lb: Lower bound of variable
- x_u: Upper surface x-coordinates
- y_u: Upper surface y-coordinates
- x_l: Lower surface x-coordinates
- y_l: Lower surface y-coordinates
- θ: Angle of the slope of camber line

2.1.2 Reference Airfoil

The National Advisory Committee for Aeronautics (NACA) airfoil designation system uses a series of digits to represent key parameters of the airfoil, such as its camber, thickness, location of maximum thickness and location of maximum camber. After a thorough literature review, the NACA 2412 airfoil Shown in Figure II-2 (with maximum camber of 2% at 40% chord length, and maximum thickness of 12% chord length) was selected as the reference due to its widespread use, moderate characteristics suitable for various applications, ease of manufacturing, and well-documented stall behavior. In this study, the NACA four-digit equation was employed to calculate the coordinates of airfoil's upper and lower surfaces. To compute the mean camber line coordinates, the equation for y_c are utilized by substituting the values of m and p. This process is performed for each x coordinate, delineated from $x = 0$ to $x = c$. The thickness distribution above and below the mean line is then determined using the equation incorporating the given t value. Finally, the airfoil's upper and lower surface coordinates (x_u, y_u and x_l, y_l) are calculated using provided relationships:

$$y_c = \begin{cases} \frac{m}{p^2}(2px - x^2) & from\ x = 0\ to\ x = p \\ \frac{m}{(1-p)^2}[(1-2p) + 2px - x^2] & from\ x = p\ to\ x = c \end{cases} \quad \text{(II.1)}$$

$$\pm y_t = \frac{t}{0.2}\left(0.2969\sqrt{x} - 0.1260x - 0.3516x^2 + 0.284x^3 - 0.1015x^4\right) \quad \text{(II.2)}$$

$$x_u = x - y_t \sin\theta$$
$$y_u = y_c + y_t \cos\theta$$
$$x_l = x - y_t \sin\theta$$
$$y_l = y_c - y_t \cos\theta \qquad \text{where } \theta = \tan^{-1}\left(\frac{dy_c}{dx}\right)$$

2.1.3 Objective Function

In this study, the lift-to-drag(L/D) ratio not only pivotal for assessing fixed-wing UAVs aerodynamic performance but also serves as the fitness value for the optimization process. It represents the efficiency of the lift generation relative to drag and plays a central role in guiding the iterative refinement conducted by the Genetic Algorithm (GA). Through parameterizing UAV wing shapes and leveraging PyFluent simulations to compute lift (C_L) and drag (C_D) coefficients, the methodology aims to maximize the L/D ratio as the primary objective function. The L/D ratio calculated as the ratio of the lift coefficient to the drag coefficient.

$$\frac{L}{D} = \frac{\frac{1}{2}(\rho V^2 S C_L)}{\frac{1}{2}(\rho V^2 S C_D)} = \frac{C_L}{C_D} \qquad \text{(II.3)}$$

2.1.4 Design Parameters

The study focuses on investigating several key design parameters that significantly impact the aerodynamic performance of UAVs. These parameters include maximum camber, position of maximum camber, maximum thickness, wing span, root chord, and tip chord. Through systematic variation and optimization within specified ranges, the aim is to enhance the lift-to-drag ratio. Table II-1 provides an overview of the key design parameters essential for NACA four-digit airfoil and Wing, with desirable ranges.

Table II-1. Design Parameter Ranges

Parameter	Range (mm)
Maximum Camber (m)	0.01 to 0.09
Position of Maximum Camber (p)	0.1 to 0.5
Maximum Thickness (t)	0.08 to 0.20
Wing Span (b)	500 to 2000
Root Chord (C_R)	100 to 1000
Tip Chord (C_T)	50 to 500

Table II-2. Input Parameters

Input Parameters	Value
Iterations	60
Population size	10
Crossover Rate	0.8
Crossover Distribution	25
Mutation Rate	0.3
Mutation Distribution	15
Velocity, V m/s	40
Angle of Attack, θ^0	0
Number of Solver Iterations, n	500
Turbulence Model	K- ω SST

2.2 Optimization Stage

2.2.1 Genetic Algorithm

In the Optimization stage, a genetic algorithm is employed to iteratively refine and enhance the aerodynamic shapes of the fixed-wing UAV. Python emerges as the most suitable language for automation and simulation tasks due to its versatility and extensive library ecosystem. Additionally, python's compatibility with PyFluent enables the generation of large-scale design evaluations and performance analysis with minimal manual intervention. Visual Studio enhances our workflow by providing robust tools for code editing, debugging, and project management, ensuring efficient collaboration and code maintenance. Genetic Algorithm, inspired by natural selection principles to optimize complex problems. Real-Coded Genetic Algorithm (RCGA) are preferred for their ability to handle real-valued parameters effectively. A novel approach integrates Fitness Value evaluation using PyFluent, deviating traditional fitness value evaluation using Fitness Function (Equation).

Table II-2, consists of set of input parameters for genetic algorithm optimization process, begins by generating a population of potential wing designs, incorporating parameters like airfoil characteristics, wing span, root chord, tip chord. Random sampling within predefined parameter ranges ensures the feasibility and validity of designs, with each individual representing a unique combination of six design parameters. These parameters are used to create 3D wing models, and PyFluent analysis evaluates their fitness based on the L/D ratio. The roulette wheel selection method is employed to select parent populations for subsequent genetic operations. Selection probabilities for each individual is proportional to individual fitness. This method ensures higher fitness individuals have a greater chance of being selected as parents for next generation. Crossover, a fundamental genetic operator, combines genetic material from parent solutions to generate offspring with potentially improved characteristics. In our study, Simulated Binary Crossover (SBX) is employed in real-coded GA. SBX mimics mating in biological systems, inheriting traits from both parents to explore diverse solution spaces. The SBX process begins with the selection of two parent solutions from current population. A random number 'u' is generated to compute the scaling factor 'β', which determines degree of crossover between the parents. Depending on the value of 'u', 'β' are calculated to either promote exploration or exploitation within the search space. Fine-tuning parameters like the scaling factor and distributive index enables SBX operator to suit the specific requirements of optimization task.

$$\beta = \begin{cases} (2u)^{\frac{1}{(\eta_c+1)}} & \text{if } u \leq 0.5 \\ \left(\frac{1}{2(1-u)}\right)^{\frac{1}{(\eta_c+1)}} & else \end{cases} \tag{II.4}$$

- Generate Offspring $O_1 = 0.5[(1+\beta)P_1 + (1-\beta)P_2]$
  $O_2 = 0.5[(1+\beta)P_1 + (1-\beta)P_2]$

Mutation in evolutionary algorithms, such as genetic algorithm, is a genetic operator crucial for introducing diversity into the population space. It plays a vital role in maintaining genetic diversity, preventing premature convergence, and facilitating the exploration of potential beneficial solutions. In this study, Polynomial mutation is utilized as the mutation operator. Unlike uniform mutation, which randomly alters genes within specified ranges, polynomial mutation induces smoother transitions between solutions. The procedure of polynomial mutation involves initializing mutation parameters. The mutation probability determines the likelihood of mutation for each gene, while η_m controls the intensity of mutation, influence extent of changes applied to the genes.

$$\delta = \begin{cases} (2r)^{\frac{1}{(\eta_m+1)-1}} & if\ r < 0.5 \\ 1-[2(1-r)]^{\frac{1}{(\eta_m+1)}} & if\ r \geq 0.5 \end{cases} \tag{II.5}$$

- Generate Offspring

$$O = O + (ub - lb)\delta$$

In the genetic algorithm's optimization process, the initial populations known as Mu(μ) data and corresponding fitness values merge with a new set of offspring population emerges through mutation forming Lambda(λ) data. This μ + λ strategy combines diverse genetic material from the original population and mutated individual. The combined dataset becomes the foundation for the next iteration of genetic algorithm in loop of roulette wheel selection, crossover and mutation.

2.3 Simulation Stage

2.3.1 CadQuery

In the context of the genetic algorithm (GA) based optimization process, the transformation of randomly generated individual design parameters into 3D wing geometries is facilitated by the powerful capabilities of the CadQuery library serves as Python-based parametric 3D CAD modelling tool, offering seamless integration within the GA framework. Due to the symmetric nature of the wing design and the computational constraints associated with the student version of the software, only one half of the wing was modeled and analyzed in this study. The aerodynamic simulation was conducted within a rectangular domain, representing the airflow around the wing design. This domain was chosen for its simplicity and computational efficiency.

The finalized design was exported as a STEP file. The STEP file was imported into Ansys Discovery script file for efficient processing. Named selections were assigned within Discovery, like inlet, outlet, wall, symmetry, wing, leading edge and trailing edge. Export the geometry after named selections as Discovery file type.

2.3.2 PyFluent

PyFluent facilitates Pythonic interaction with Ansys Fluent allowing seamless integration of fluent within the python ecosystem. It facilitates launching Fluent, using Fluent's Text User Interface (TUI) commands for meshing and solver operations, and accessing Fluent's built-in postprocessing capabilities [22]. The library is comprised of several components, including PyFluent Core, which Provides core functionalities for interacting with Ansys Fluent, PyFluent Parametric for accessing Fluent's parametric workflows, and PyFluent Visualization, which offers postprocessing and visualization capabilities using PyVista and Matplotlib. To use PyFluent, a licensed copy of Ansys Fluent must be installed locally, with support for Fluent versions 2022 R2 and later.

2.3.2.1 Meshing

Fluent Meshing integrated into PyFluent, is excellent at making high-quality CFD meshes. With its sophisticated built-in intelligence and automation, it streamlines mesh generation processes, notably reducing total meshing time while augmenting overall efficiency. The meshing procedure commences with the initialization of watertight geometry. It handles surface mesh details well by adjusting minimum and maximum mesh size and growth rates. The utilization of both global and local sizing controls, along with mesh refinement strategies, ensures optimal mesh quality while effectively managing computational resources. Skewness, a pivotal metric monitored to preserve mesh integrity, adhering to recommended thresholds (skewness< 0.7) for superior mesh quality. Moreover, orthogonal quality(with recommended thresholds > 0.1) ensures mesh integrity and stability in simulations. The workflow is applicable for student licenses, which have a limitation of meshes containing either 1,048,576 cells or unmeshed faces.

2.3.2.2 Solver

Table II-2, summarizes the Solver setup input Parameters [23], the study employed steady-state simulations based on pressure, offering insights into the system's long-term behavior and its response to consistent pressure conditions. The units were standardized to millimeters to ensure dimensional consistence, followed by the enable of the energy equation to account for thermal effects. The selection of the k-omega SST turbulence model provides robust predictions of turbulent flow behavior. Material properties such as density and viscosity were specified to define the fluid medium's behavior accurately. Boundary conditions, including velocity magnitude and components at inlet, no-shear boundary condition on solid surface like wing, and pressure outlet, were meticulously defined to accurately represent the physical scenario. Reference values for length and area were computed from inlet to ensure consistent scaling of results across simulations. Report Definitions for lift, drag and moment calculations were set up to monitor key aerodynamic parameters during the simulation, while lift-drag plots were generated for visualization. Residuals were monitored to ensure solution convergence. The solver was initialized using a hybrid initialization and run calculations based on no of iterations. The case and data files were created to store simulation setup information and solution data, respectively facilitating post-processing.

2.3.2.3 Post-Processing

In the post-process phase, critical aerodynamic parameters such as lift coefficient (C_L) and drag coefficient (C_D) are extracted from the simulation results to evaluate the fitness value (C_L/C_D) of the wing design. Additionally, velocity and pressure distributions across the wing surface are analyzed to understand the flow characteristics and aerodynamic loading. Flow patterns and separation phenomena are investigated to uncover potential area of flow separation and recirculation.

2.4 Genetic Algorithm and PyFluent Integration

During the initial iteration of the Genetic Algorithm (GA), the population comprises multiple individuals, each defined by six design parameters representing different wing configurations. These individuals undergo fitness evaluation within PyFluent, where the fitness values are obtained from post-processing results. The resulting fitness values are then appended to the "mu" dataset, representing the current state of the population. The GA proceeds to generate offsprings through operations such as selection, crossover and mutation and these offspring undergo a similar fitness evaluation process. The fitness values of the offspring are added to the "lambda" dataset. In subsequent iterations, the combined "mu + lambda" population is used as inputs for the GA operations, allowing for further exploration of design space. This iterative cycle continues until the desired number of iterations are reached, leading to the identification of optimal wing configurations for the given design objectives, such as maximizing Lift-to-Drag ratio. Due to constraints imposed by Ansys student version, the computational workload was managed efficiently. The initial iteration consumed approximately 2 hours of runtime. Subsequently, from second iteration onwards, PyFluent active only once per iteration, required 1 hour of runtime. Over the course of 60 iterations, the total runtime amounted to 53 hours, highlighting the iterative and time-intensive nature of the optimization process.

III. RESULTS AND DISCUSSIONS

The optimization process revealed significant insights into the aerodynamic performance of the wing design. The iterative progression of the genetic algorithm (GA) is depicted in Figure III-1, Showing a steady increase in the lift-to-drag (L/D) ratio with each iteration. The final iteration yielded an optimized wing design with parameters of m=0.09, p=0.5, t=0.11, wing span of 1660 mm, root chord of 340 mm, tip chord of 200 mm with an impressive L/D ratio of 24.84. The NACA designation for the optimized airfoil is NACA 9511, an improvement over the reference airfoil of NACA 2412 at 0-degree angle-of-attack. The visualization of the optimized wing, planform and side views, including airfoil profile, are provided in Figure III-2 and Figure III-3. The pressure contour around the optimized wing is presented in Figure III-4, providing insights into the flow behavior and further validating the aerodynamic performance of the optimized design. These contours reveal regions of high and low pressure. The optimization process was conducted with limited computational resources, highlighting the efficiency of the methodology utilized in this study.

In Figure III-5, the lift-to-drag (L/D) plot depicts the efficiency of the NACA 9511 airfoil across various angles of attack, showcasing optimal L/D ratio typically observed around 0 to 2 degrees. This indicates a favorable balance between lift generation and drag production, crucial for achieving efficient aerodynamic performance. Concurrently, in Figure III-6, the individual lift, drag, and moment curves provide additional insights into the airfoil's behavior. The lift curve demonstrates a typical nonlinear trend, with lift coefficients increasing with increasing angle of attack, peaking around 10 to 20 degrees before slightly declining. Conversely, the drag curve exhibits a gradual increase in drag coefficient with increasing angle of attack, reflecting the increased aerodynamic resistance encountered as the airfoil's angle of attack is elevated. Additionally, the moment curve reveals variations in pitching moments experienced by the airfoil, highlighting the complex interactions between aerodynamic forces and the airfoil's structure.

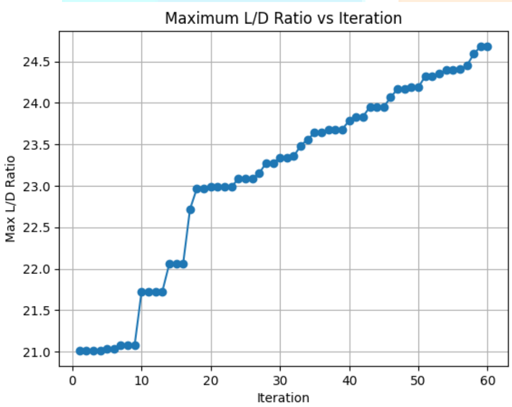

Figure III-1. GA Iterations

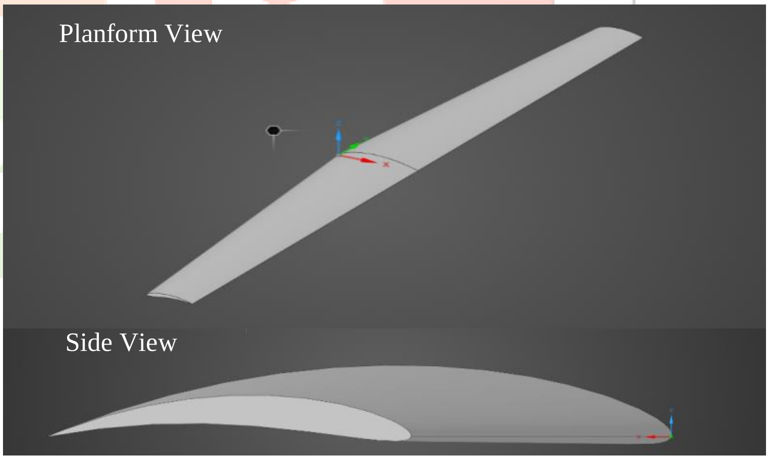

Figure III-2. Optimized Wing Views

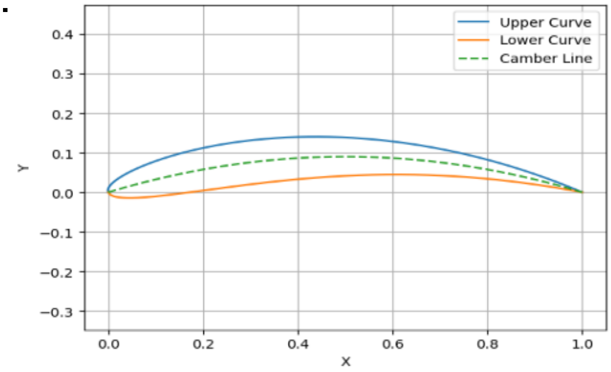

Figure III-3. Naca 9511 airfoil

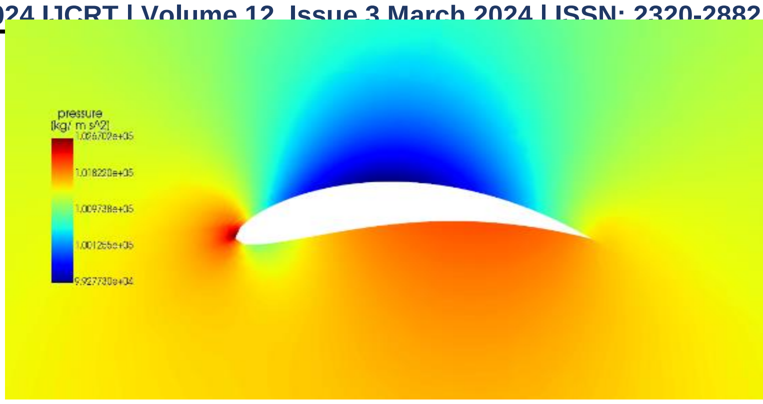

Figure III-4. Pressure Contour

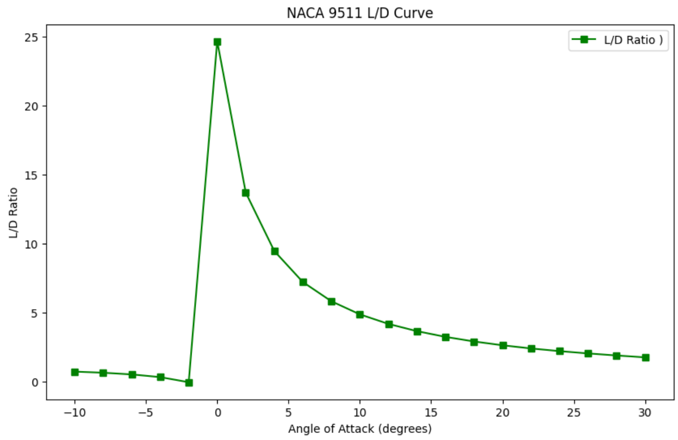

Figure III-5. Naca 9511 L/D plot

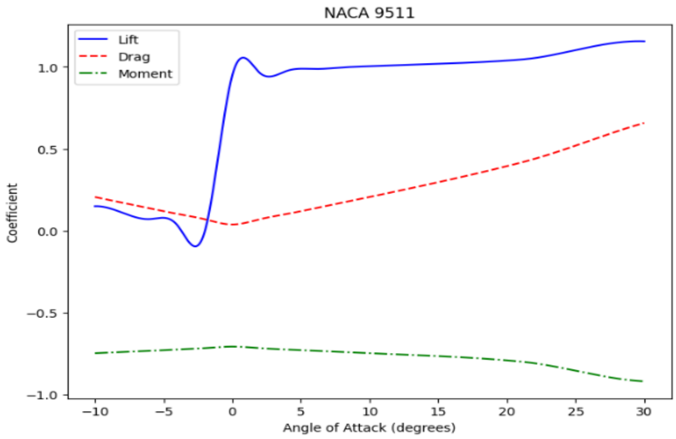

Figure III-6. Lift, Drag, and Moment plot

IV. CONCLUSION

In summary, this study successfully optimized the aerodynamic performance of a fixed wing UAV through a comprehensive automated workflow. Leveraging the Genetic Algorithm (GA) methodology and PyFluent, a Computational Fluid Dynamics (CFD) tool, at a 0-degree angle of attack and a velocity of 40 m/s, a remarkable lift-to-drag (L/D) ratio improvement was achieved, surpassing the performance of the reference NACA 2412 airfoil. Visual analyses confirmed the aerodynamic enhancements, while comparative assessments underscored the efficiency of optimization process. The study demonstrated the potential of automated workflows in advancing UAV design. This research contributes valuable insights to the field, laying the groundwork for future innovations in fixed-wing UAV aerodynamic optimization. In addition to the remarkable achievements highlighted in this study, future research could explore the implementation of multi-thread processing techniques to address computational constraints encountered during the optimization process. By leveraging parallel computing capabilities, such as multi-core processors can significantly enhance the efficiency and scalability of aerodynamic simulations.

V. REFERENCES

[1] A. A. Laghari, A. K. Jumani, R. A. Laghari, and H. Nawaz, "Unmanned aerial vehicles: A review," *Cognitive Robotics*, vol. 3. KeAi Communications Co., pp. 8–22, Jan. 01, 2023. doi: 10.1016/j.cogr.2022.12.004.

[2] I. Dronova, C. Kislik, Z. Dinh, and M. Kelly, "A review of unoccupied aerial vehicle use in wetland applications: Emerging opportunities in approach, technology, and data," *Drones*, vol. 5, no. 2. MDPI AG, Jun. 01, 2021. doi: 10.3390/drones5020045.

[3] S. G. Gupta, M. M. Ghonge, and P. M. Jawandhiya, "Review of Unmanned Aircraft System (UAS)," 2013. [Online]. Available: www.ijarcet.org

[4] A. Koreanschi *et al.*, "Optimization and design of an aircraft's morphing wing-tip demonstrator for drag reduction at low speeds, Part II - Experimental validation using Infra-Red transition measurement

from Wind Tunnel tests," *Chinese Journal of Aeronautics*, vol. 30, no. 1, pp. 164–174, Feb. 2017, doi: 10.1016/j.cja.2016.12.018.

[5] Mardanpour, Pezhman, Mehrabi, and Armin, "C3-FIU05 4. Title and Subtitle 5. Report Date Principal and Considerations for Design of Small Unmanned Aerial Vehicles for Inspection and Survey," 2019. [Online]. Available: https://orcid.org/0000-0002-1423-0304

[6] I. Mir, A. Maqsood, and S. Akhtar, "Dynamic Modeling & Stability Analysis of a Generic UAV in Glide Phase," *MATEC Web of Conferences*, vol. 114, p. 01007, Jan. 2017, doi: 10.1051/matecconf/201711401007.

[7] F. L. Rashid, H. S. Abd, and E. Q. Hussein, "Numerical study of the air flow over modified NACA 2412 airfoil using CFD," in *AIP Conference Proceedings*, American Institute of Physics Inc., Dec. 2022. doi: 10.1063/5.0092303.

[8] S. Chakraborty, S. Bhattacharjee, S. Karmakar, S. Sadhukhan, M. A. Mukherjee, and R. Kumar, "A Comparative Study of Boeing 737 and NACA 2412 Airfoils using CFD." [Online]. Available: www.ijert.org

[9] M. H. Khalid, "CFD Analysis of NACA 0012 Aerofoil to Investigate the Effect of Increasing Angle of Attack on Coefficient of Lift and Coefficient of Drag," *Journal of Studies in Science and Engineering*, vol. 2, no. 1, pp. 74–86, Mar. 2022, doi: 10.53898/josse2022216.

[10] M. El Adawy *et al.*, "Design and fabrication of a fixed-wing Unmanned Aerial Vehicle (UAV)," *Ain Shams Engineering Journal*, vol. 14, no. 9, Sep. 2023, doi: 10.1016/j.asej.2022.102094.

[11] S. G. Kontogiannis and J. A. Ekaterinaris, "Design, performance evaluation and optimization of a UAV," *Aerosp Sci Technol*, vol. 29, no. 1, pp. 339–350, Aug. 2013, doi: 10.1016/J.AST.2013.04.005.

[12] A. S. Gowda, "Comparison of Aerodynamic Performance of NACA 4412 and 2412 using Computational Approach," *International Journal of Engineering Trends and Technology*, vol. 67, 2019, [Online]. Available: http://www.ijettjournal.org

[13] V. Chumbre, T. Rushikesh, S. Umatar, and S. M. Kerur, "CFD analysis of aerofoil sections," *International Research Journal of Engineering and Technology*, vol. 5, no. 7, pp. 349–353, 2018.

[14] P. Panagiotou and K. Yakinthos, "Aerodynamic efficiency and performance enhancement of fixed-wing UAVs," *Aerosp Sci Technol*, vol. 99, Apr. 2020, doi: 10.1016/j.ast.2019.105575.

[15] G. Ramanan, P. Radha Krishnan, and H. M. Ranjan, "An aerodynamic performance study and analysis of SD7037 fixed wing UAV airfoil," in *Materials Today: Proceedings*, Elsevier Ltd, 2021, pp. 2547–2552. doi: 10.1016/j.matpr.2021.05.051.

[16] I. Gibert Martínez, F. Afonso, S. Rodrigues, F. Lau, and R. Loja, "A Sequential Approach for Aerodynamic Shape Optimization with Topology Optimization of Airfoils † A Sequential Approach for Aerodynamic Shape Optimization with Topology Optimization of," *Airfoils. Math. Comput. Appl*, 2021, doi: 10.3390/mca.

[17] N. QIAO, T. MA, X. WANG, J. WANG, J. FU, and P. XUE, "An approach for formation design and flight performance prediction based on aerodynamic formation unit: Energy-saving considerations," *Chinese Journal of Aeronautics*, 2024, doi: https://doi.org/10.1016/j.cja.2024.01.002.

[18] G. Murariu, R. A. Mahu, A. G. Murariu, M. D. Dragu, L. P. Georgescu, and B. G. Carp, "Using Ansys for design and numerical study of a specific fixed wing UAV," *Materiale Plastice*, vol. 55, pp. 652–657, Dec. 2018, doi: 10.37358/mp.18.4.5095.

[19] N. Kohar, S. Ali Ansari, N. Yadav, and V. R. Tech Rangarajan Sagunthala, "STUDY OF FLUID FLOW AND AERODYNAMIC FORCES ON NACA 4412 AIRFOIL USING COMPUTATIONAL FLUID DYNAMICS," 2022. [Online]. Available: https://www.researchgate.net/publication/362126883

[20] M. Heaphy, M. S. Watt, J. P. Dash, and G. D. Pearse, "UAVs for data collection-plugging the gap," 2017. [Online]. Available: www.parrot.com

[21] "GitHub - ansys_pyfluent_ Pythonic interface to Ansys Fluent".

[22] P. Saha and H. Singh Kaberwal, "Numerical Analysis of Aerodynamic Performance Characteristics of NACA 2312 and NACA 2412," 2020. [Online]. Available: www.ijisrt.com420