MACHINE LEARNING-DRIVEN OPTIMIZATION OF UAV AERODYNAMICS USING CFD SIMULATIONS FOR ENHANCED PERFORMANCE

by

Qurrat-Ul-Hussnain

Emaan Noor

Supervisor:

Dr Muhammad Umer Sohail

Department of Aeronautics and Astronautics

Institute of Space Technology, Islamabad

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APPROVAL BY SUPERVISOR

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Abstract

In this thesis, the power of Machine Learning (ML) and Computational Fluid Dynamics (CFD) is combined to create an intelligent aerodynamic prediction and optimization tool for Unmanned Aerial Vehicles (UAVs). Ten NACA airfoils are compared in 2D and 3D CFD analysis at subsonic Mach numbers (0.02–0.3) and angles of attack ($-2°$–$10°$) to start the study. To guarantee precision and consistency, the aerodynamic coefficients (CL and CD) were verified.

To precisely predict lift and drag coefficients, a machine learning model was trained on a dataset of more than 28,000 CFD data using a Python-based gradient optimization framework. Rapid aerodynamic estimation for both 2D airfoils and 3D wing geometries using techniques like the Vortex Lattice Method (VLM) and turbulent models was made possible by the model's further integration into an interactive Stream lit-based interface. The resultant tool offers immediate, accurate predictions appropriate for conceptual design stages, greatly cutting down on the time and computational expense related to UAV aerodynamic design. The system is applicable to defense, commercial, and research applications because it is open-ended and has the potential to expand into multiple flight regimes beyond cruise-condition analysis.

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1. Introduction

1.1 UAVs in modern aerospace systems

In technical terms, drones are known as unmanned aerial systems (UAS) or unmanned aerial vehicles (UAVs). These are remotely or autonomously piloted aircraft that can be controlled from the ground and fly without a human pilot on board. Wireless communication beyond human trajectory frequently necessitates the use of UAVs. Military operations, mining, agriculture, and general-purpose uses like surveillance, exploration, rescue, delivery of weapons and products, mapping and surveying, entertainment, photography, etc. are just a few of the many uses for drones that have emerged recently.

A variety of Micro-electromechanical Systems (MEMS), such as sensors, cameras, controllers, and more, are installed on these UAVs. UAVs support implicit particularities like access to disaster-stricken areas, quick mobility, airborne missions, and payload features. This manuscript reviews a novel taxonomy of flying drones with their explicitly defined applications, encompassing UAVs to smart sensors.

Despite these alluring advantages, UAVs are limited in their ability to operate due to several serious issues, including limited payload carrying capacity, flight autonomy, path planning, battery endurance, and flight time. It is generally not advised to load heavy objects, like batteries. Therefore, the main objective of this study is to shed light on the potential of UAVs as well as their features and functional problems. A thorough analysis of UAV types, swarms, classifications, charging techniques, and regulations is given in this study.

1.2 Importance of Aerodynamic Efficiency for MALE UAVs

Medium Altitude Long Endurance (MALE) UAVs are built to function for extended periods of time, frequently longer than 24 hours, at altitudes between 10,000 and 30,000 feet. These UAVs are essential for environmental monitoring, disaster relief, border surveillance, and military reconnaissance. Aerodynamic efficiency is critical in such long-duration missions. Range and loiter time are directly improved by a higher lift-to-drag ratio, which allows the UAV to use less fuel or power while keeping altitude and stability. Effective aerodynamic design also lessens the structural load on the airframe and increases payload capacity. Optimizing aerodynamic performance is crucial to mission success for MALE UAVs, where endurance and operational cost are crucial factors.

An unmanned aerial vehicle (UAV) is an aircraft that can be remotely controlled or autonomously programmed for flight paths without a human pilot on board. Unmanned Aerial Systems (UAS), commonly referred to as UAVs, are equipped with cameras, sensors, communication devices, and other payloads. As the market for UAVs grows and its uses become more varied, there is an increasing need to improve flight capabilities and adaptability for challenging tasks. [1] UAVs were first created for military use, but they are now extensively employed in both military and civilian settings, helping to protect borders and for other purposes. When combined with cutting-edge sensing technologies, their exceptional ability to reach remote or dangerous locations allows for high-resolution imagery for a range of humanitarian and civilian missions [2].

UAVs are divided into two primary categories: rotary-wing UAVs and fixed-wing UAVs, which are categorized according to their design, capabilities, and intended uses. The fixed wing UAVs are renowned for their high cruising speeds while in flight, long endurance, and payload capacity [3], [4]. By affecting variables like lift-to-drag ratio, flight range, and endurance, aerodynamics is essential to maximizing the effectiveness and performance of UAVs. By guaranteeing stability, controllability, and maneuverability, effective aerodynamic considerations allow UAVs to fly for longer periods of time and cover greater ground [5, 6]. Because they produce lift, regulate the lift-to-drag ratio, and affect stall behavior, airfoils are essential to aerodynamics. The air pressure differential between an airfoil's upper and lower surfaces produces the lift force.

Aerodynamic efficiency, in particular a high lift-to-drag ratio (Cl/Cd), is crucial for MALE UAVs' long endurance and effective flight performance [7]. Performance, fuel efficiency, and mission duration can all be greatly increased by optimizing airfoil shapes (Austin, 2010).

Though accurate [8], conventional CFD-based design techniques are time-consuming and computationally costly. By learning from CFD data and accurately predicting aerodynamic coefficients, machine learning provides a quick and clever solution to this problem [9].

This project aims to integrate CFD and ML to create a fast, reliable optimization tool for MALE UAV airfoils reducing simulation time while maintaining accuracy.

1.3 Objectives of the Project

The aim of this project is to develop a machine learning-assisted aerodynamic optimization framework for MALE UAV airfoils. The specific objectives include:

1. To run 2D and 3D CFD simulations on a subset of NACA airfoils at various subsonic flow rates and angles of attack.

2. To confirm the accuracy and dependability of simulation results using different tools like XFLR5 or JAVAFOIL.

3. To produce an extensive dataset of the aerodynamic coefficients (Cl and Cd) for training machine learning models and optimization.

4. To put into practice a gradient optimization algorithm based on Python to find airfoil configurations that optimize aerodynamic efficiency.

5. To develop a machine learning model that, given airfoil shapes and flight conditions, can reliably predict Cl and Cd values.

6. To develop a predictive tool that eliminates the need to repeat CFD simulations by enabling users to enter the geometry of MALE UAV airfoils and receive estimates of aerodynamic performance.

1.4 Scope

This project uses a hybrid CFD and machine learning approach to optimize the aerodynamic performance of airfoils used in MALE UAVs. Among the main topics discussed are:

• 2D and 3D CFD simulations of specific NACA airfoils at different angles of attack (2°–10°) and low subsonic Mach numbers (0.02–0.3).

• CFD results are validated using JAVAFOIL or XFLR5.

• The creation of a gradient optimization algorithm based on Python.

• Developing a machine learning model to forecast aerodynamic coefficients (Cl and Cd).

• Development of a tool that uses user input to estimate airfoil performance.

• Adapting the framework to the unique flight conditions and design requirements of

UAVs

1.5 Limitations

Notwithstanding the project's breadth and depth, several restrictions were found:

Types of limited airfoils: Ten NACA airfoils serve as the basis for the analysis.

Streamlined flow conditions: Compressibility, gust response, and transition turbulence

were not modeled; only steady-state, incompressible flow was examined.

Data-driven prediction constraints: The size and caliber of the training dataset

determines how accurate the machine learning model can be.

Tool range: The predictive tool may not generalize well to other aircraft classes or high-

speed regimes because it is tailored for MALE UAV-related airfoils.
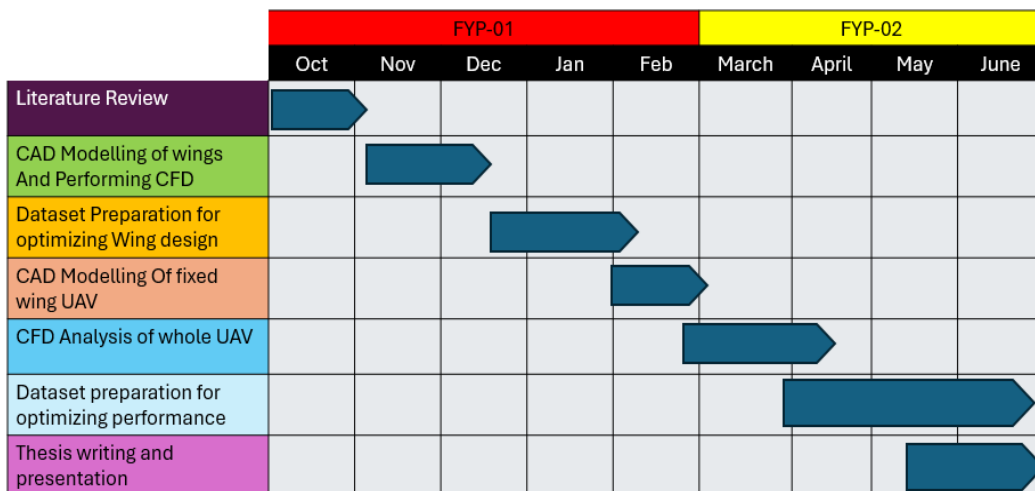
Figure 1.1 Gantt Chart

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2. Literature Review

2.1 Studies on CFD-Based UAV Optimization

Because it can accurately predict flow around complex geometries, computational fluid dynamics, or CFD, has become a standard tool in UAV design. Optimizing UAV aerodynamic performance with CFD tools such as ANSYS Fluent and XFLR5 has been the subject of numerous studies. For example, Altug and Kaymaz (2018)[9] optimized a fixed-wing UAV using CFD to improve its lift-to-drag ratio. Similarly, Zhang et al. (2020) [10] examined NACA airfoils for surveillance drones using CFD with an emphasis on enhancing stability and endurance.

These techniques, however, frequently require laborious mesh creation, solver tuning, and post-processing procedures. Hours may pass between each design iteration, particularly when simulating turbulent or unsteady flows.

These techniques, however, frequently require laborious mesh creation, solver tuning, and post-processing procedures. Hours may pass between each design iteration, particularly when simulating turbulent or unsteady flows.

2.2 Applications for Machine Learning in Aerodynamics

Particularly when trained on CFD or experimental data, machine learning (ML) has recently become a potent tool to support aerodynamic predictions. Lift and drag coefficients have been successfully estimated using models such as Gaussian Process Regression (GPR), Artificial Neural Networks (ANNs), and Support Vector Regression (SVR).

For instance, Bhargava et al. (2021) [11] used CFD-generated datasets to create a deep learning model that predicts aerodynamic coefficients. Their findings

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demonstrated that ML models can accurately and significantly reduce the computational cost of CFD results. In a different study, Liu et al. (2022) [12] predicted the pressure distribution over airfoils using convolutional neural networks (CNNs), which allowed for quick predictions without meshing.

2.3 Summary of Gaps in Current Research

- Although ML allows for quicker predictions and CFD yields high-fidelity results, a combined framework that utilizes both is still comparatively underdeveloped, particularly for applications unique to MALE UAVs. Most of the current research either investigates ML models using sparse aerodynamic datasets or only focuses on CFD-based optimization.

  A glaring gap exists in:

- Using machine learning to integrate validated CFD simulations for real-time aerodynamic prediction.

- Creating lightweight instruments that can be utilized in the early stages of UAV design, customizing optimization for MALE UAV airfoils at low subsonic speeds

3. Airfoil Selection

3.1 Airfoil Selection and Geometry Creation

To evaluate and optimize performance for MALE UAVs, **10 NACA airfoils** were selected based on literature and prior aerodynamic studies. These airfoils are commonly used in long-endurance and low-speed UAVs due to their high lift-to-drag characteristics and structural simplicity.

Table 2. 1 Naca Airfoils that are selected based on literature review

NACA 2412	Trainer UAVs, General Aviation UAVs
NACA 4412	Slow-flying UAVs, STOL UAVs
NACA 0012	High-speed UAVs, Tail Sections
NACA 2415	Endurance UAVs, Reconnaissance UAVs
NACA 4415	Agricultural UAVs, Long-Endurance UAVs
NACA 23012	Transport UAVs, MALE UAVs
NACA 2408	Strategic Long-Range UAVs
NACA 43012	Strategic Long-Range UAVs

NACA 23112	Medium Altitude UAVs
NACA 4418	Cargo UAVs, Slow-Speed UAVs

Although the present study focuses on these ten airfoils, **additional airfoils could also be considered** for future analysis. Due to time constraints, only the above-listed airfoils were evaluated in the current phase of the work.

3.2 Focus on Cruise Efficiency in Airfoil Evaluation

Since the objective of this study is to evaluate airfoil performance under operational cruise conditions, the analysis and subsequent optimization are focused on L/D Cruise values rather than L/D Max. This approach ensures that the selected airfoil will deliver optimal endurance and performance during actual missions rather than only under laboratory or ideal conditions.

Figure X presents a comparison of the maximum lift-to-drag ratio (**L/D Max**) and the cruise lift-to-drag ratio (**L/D Cruise**) for the ten selected NACA airfoils.
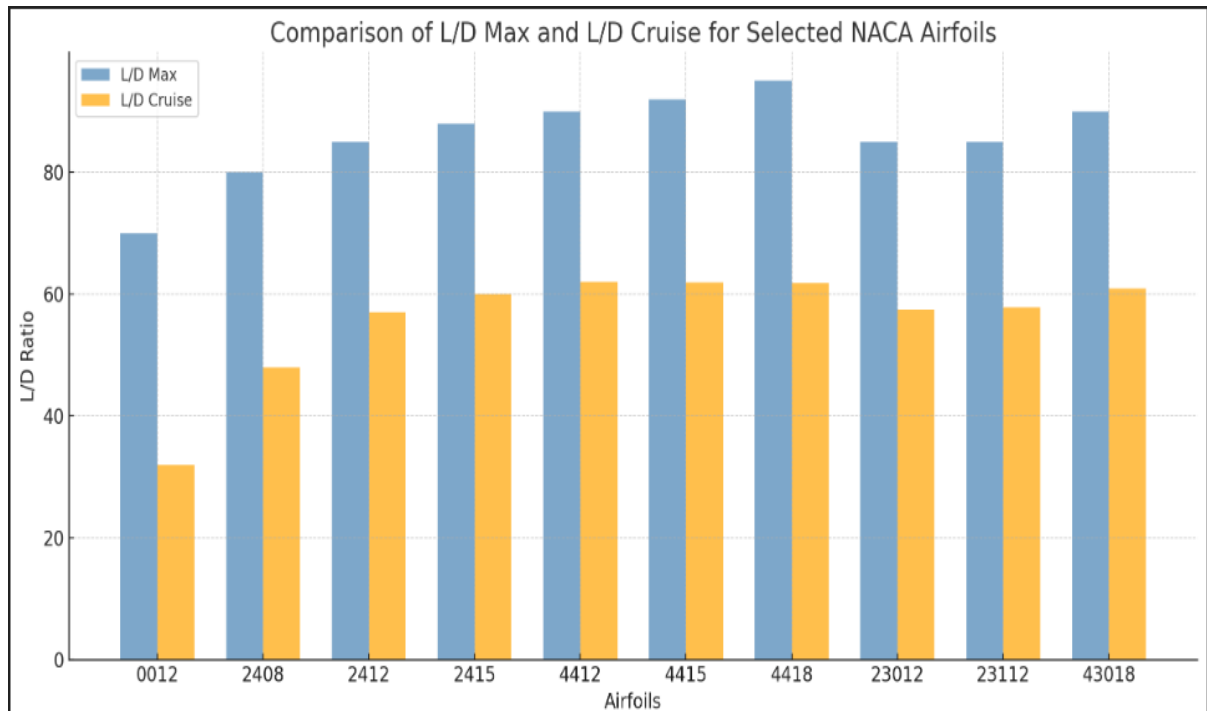
Figure 3. 1 Comparison of L/D Max and L/D Cruise for selected NACA Airfoils

Here is the **bar graph** comparing:

🔵 **L/D Max** (blue bars): the maximum aerodynamic efficiency each airfoil can achieve

🟠 L**/D Cruise** (orange bars): the realistic efficiency during typical UAV cruise

The results indicate that while all airfoils show a reduction in efficiency from L/D Max to L/D Cruise, profiles such as NACA 4415 and NACA 4412 maintain relatively high cruise efficiencies, making them strong candidates for long-endurance UAV applications. Conversely, airfoils like NACA 0012 exhibit a greater drop in cruise efficiency, suggesting suitability for higher-speed or specialized applications rather than endurance-focused missions.

4. Parameters for 2D and 3D Dataset Collection

Before proceeding to the integration of 3D analysis, it is important to outline the difference in parameters considered during 2D and 3D dataset generation for the developed tool.

4.1 2D Analysis Parameters:

In 2D analysis, the geometry under consideration is a single airfoil section. The input parameters are:

- Chord length (fixed at 1 m)

- Velocity

- Mach number

- Reynolds number

The corresponding output parameters are:

- Coefficient of Lift (CL)

- Coefficient of Drag (CD)

4.2 3D Analysis Parameters

In 3D analysis, the airfoil evolves into a complete wing, introducing additional geometric and aerodynamic parameters. The input parameters expand to:

- Wingspan

- Taper ratio

- Velocity

- Mach number

- Reynolds number

The output parameters remain the same as in the 2D case.

This distinction in parameter set highlights the increased complexity of 3D aerodynamic prediction, as geometric influences such as span and taper ratio begin to play a significant role in the overall aerodynamic performance of the wing.

4.3 CFD-Based Airfoil Analysis
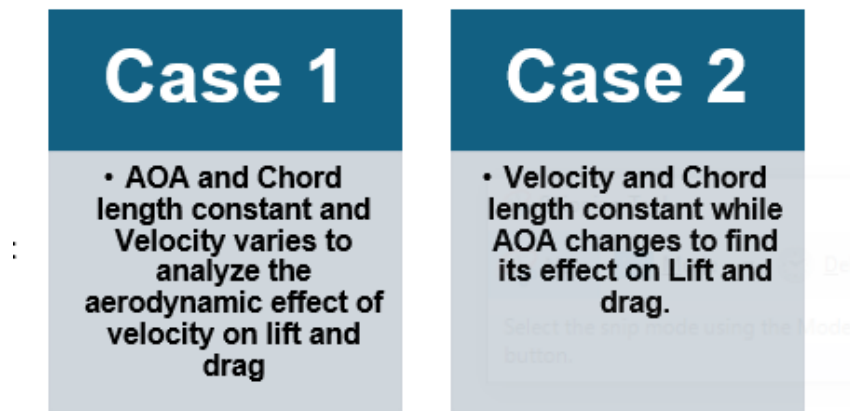
Figure 4.1 Cases for 2D Analysis of Airfoil

In Figure 4.1 2D cases were considered:

1. When the chord length was kept constant and velocity increased, the Mach number increased (AOA remained constant).

2. In another case, the AOA was increased while keeping the velocity constant. In both cases, the output obtained were CL (lift coefficient) and CD (drag coefficient).

4.4 CFD-Based Wing Analysis
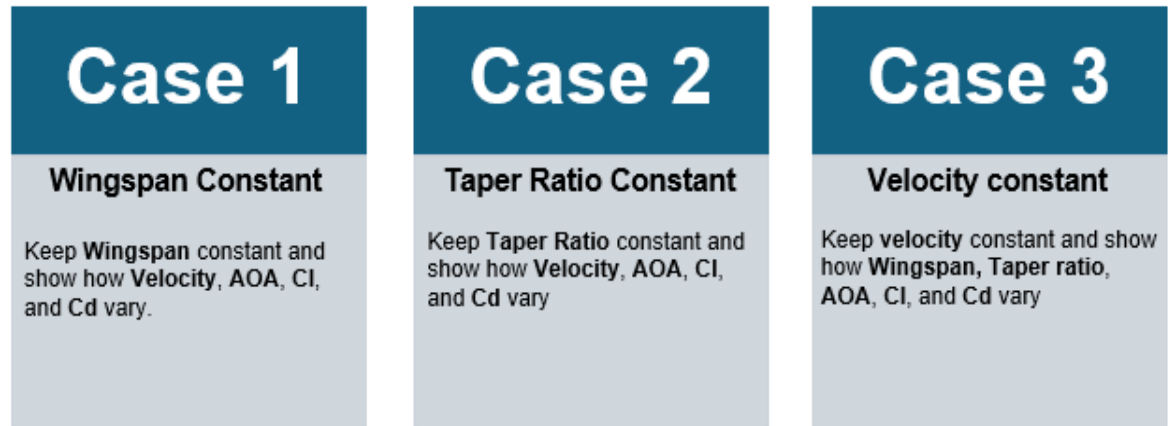
Figure 4. 2 Cases for 3D Analysis of Wings

In Figure 4.2 Three 3D parameter cases were considered:

1. When the taper ratio and wingspan were kept constant and velocity increased, the Mach number increased (AOA remained constant).

2. In another case, the AOA was increased while keeping the velocity constant. In both cases, the output obtained were CL (lift coefficient) and CD (drag coefficient).

4.5 Constraints of our project

Table 4. 1 Limitations of our simulation tool

Angle of Attack	-2 - 10 (degrees)
Velocity	17m/s-103m/s
Mach Number	0.05-0.3
Chord length	1m

Taper Ratio	1-0.4
Wingspan	2-12m
Reynolds number(3D)	$10^6 – 10^7$
Reynolds number(2D)	$11*10^6 - 70*10^6$

4.6 Reason for Limitations

The constraints on Angle of Attack ($-2°$ to $10°$), Velocity (17 m/s to 103 m/s), and Reynolds Number ($\leq 10^7$) were set to ensure that all analyses remain within the subsonic flow regime, which is representative of MALE UAV cruise conditions.

Another reason for these constraints is that the current phase of the project focuses only on cruise conditions. However, the project is open-ended and can be extended in the future to include other flight regimes beyond cruise, such as climb, descent, and maneuvering conditions.

5. Simulation Tools and their working

For the aerodynamic analysis, two tools were employed: **ANSYS Fluent** and **XFLR5**. Half of the selected airfoils were simulated in ANSYS, while the remaining half were analyzed using XFLR5. To validate the consistency of results, one airfoil was analyzed using both tools, and the outcomes were found to be in close agreement. This verification confirmed the reliability of both approaches, providing the basis for using the two tools in parallel for the simulations.

5.1 XFLR5 Approach

In the case of XFLR5, **two different analysis approaches** were applied depending on the dimensionality of the model:

5.1.1   2D Analysis:

Conducted using the Foil Analysis module in XFLR5, focusing on individual airfoil sections to determine their aerodynamic coefficients.
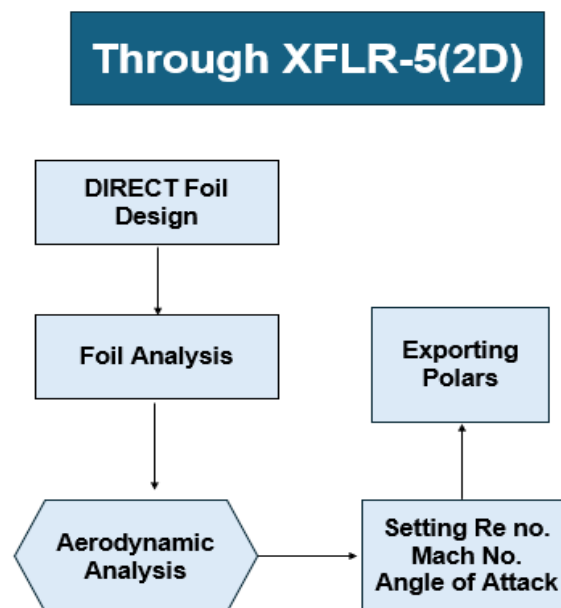
Figure 5. 1 2D Airfoil Analysis in XFLR5

5.1.2   3D Analysis:

Figure 5.2 shows Simulation conducted using the *Vortex Lattice Method (VLM)*, also known as the **Horseshoe Vortex Method**, to simulate complete wing geometries and capture three-dimensional aerodynamic effects.
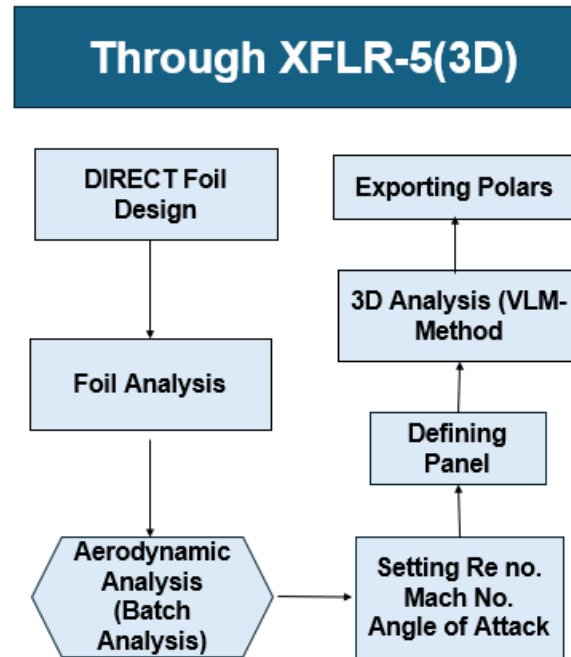
Figure 5. 2 3D Wing Analysis in XFLR5

Each profile was modeled to maintain geometric accuracy, consistent chord length, wingspan and taper ratio for comparison.

5.2   Ansys Approach

The **CFD simulation flowchart** outlines the key steps followed in the simulation process:

1. **Problem Definition**: Define the study (airfoils) and simulation conditions (Mach number, angles of attack).

2. **Geometry Creation**: Create the 2D airfoil geometry (e.g., NACA airfoils) in **SolidWorks**.

3. **Meshing**: Generate the mesh in **ANSYS Fluent**, applying structured grids and refining the boundary layer.

4. **Boundary & Initial Conditions**: Set boundary conditions (inlet, outlet, walls) and initial conditions (velocity, pressure).

5. **Solver Setup**: Select the appropriate solver and turbulence model, then configure settings for steady-state simulations.

6. **Simulation**: Run the simulations across different Mach numbers and angles of attack.

7. **Results Analysis**: Analyze the lift and drag characteristics, then validate the results.

Figure 5.3 shows the 2D Airfoil domain in ansys and this domain is followed for all airfoils.

CFD simulations were conducted to analyze the **lift** and **drag characteristics** of the selected airfoils under low subsonic conditions, which are typical of **MALE UAV** flight regimes.
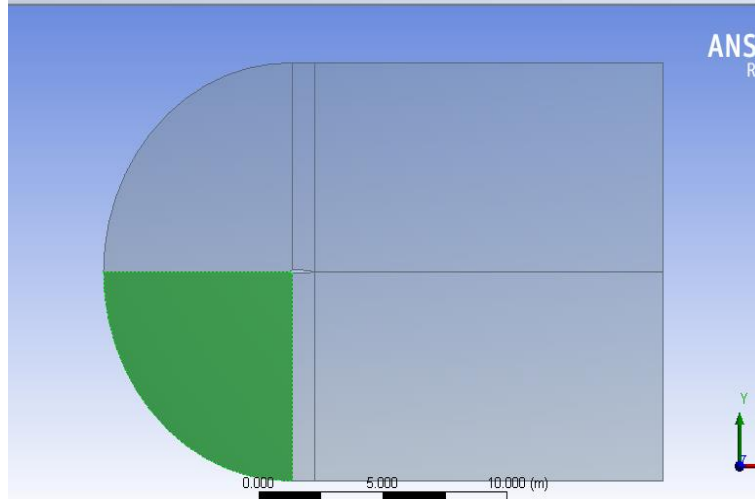
Figure 5. 3 2D Domain
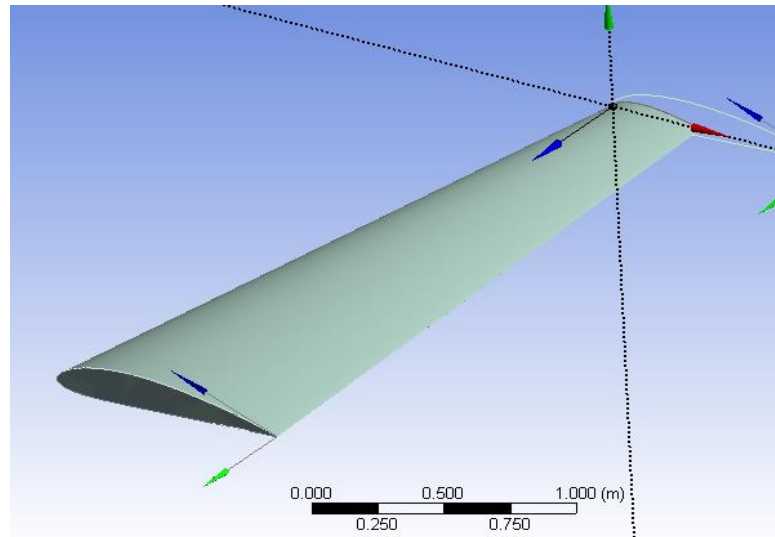
Figure 5. 4 3D Geometry in Ansys

Meshing Software: The mesh generation was performed using **ANSYS Fluent** due

to its robust capabilities in structured and unstructured meshing, as well as its

flexibility in boundary layer refinement.

5.2.1 Mesh Type:

- **O-grid** and **C-grid** structured meshes were used to improve the accuracy of the simulations.

- **Boundary layer meshing** was implemented to accurately capture the near-wall effects, ensuring that the flow behavior close to the surface was well-represented.
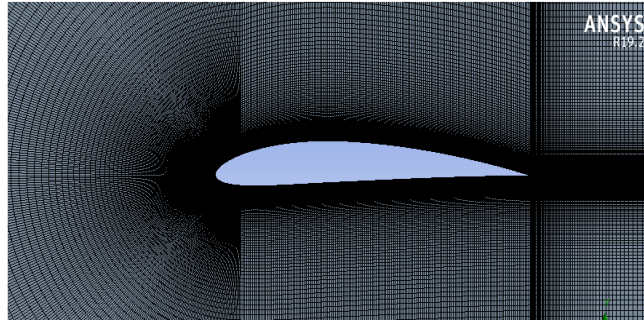
Figure 5. 5 Mesh at the boundary of the airfoil

- **Y+ < 1** was maintained in regions where boundary layer refinement was critical to capture the viscous effects effectively.

Mesh Quality	
Maximum Skewness	0.78
Max Aspect ratio	3200

Mesh Statistics	
No. of nodes	21940

Figure 5. 6 Mesh Quality
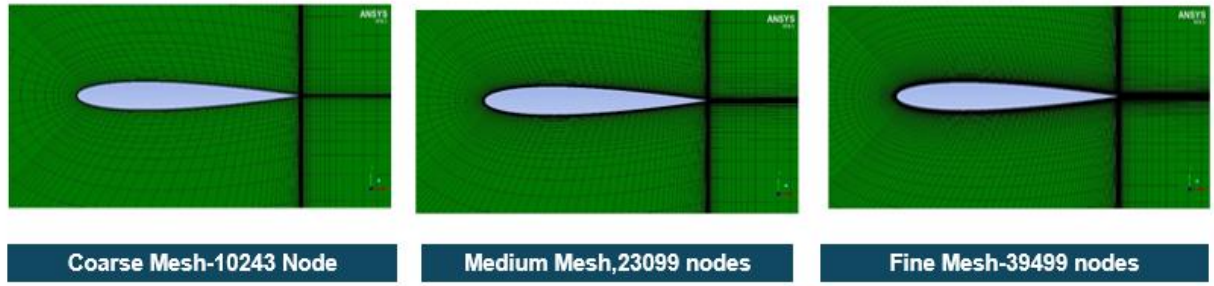
Figure 5. 7 mesh refinement

Coarse, medium, and fine meshes were tested to evaluate their effect on **CL** and **CD** values. The coarse mesh gave less accurate results, the medium mesh improved accuracy, and the fine mesh provided stable and reliable values. Therefore, the **fine mesh** was used for all final simulations.
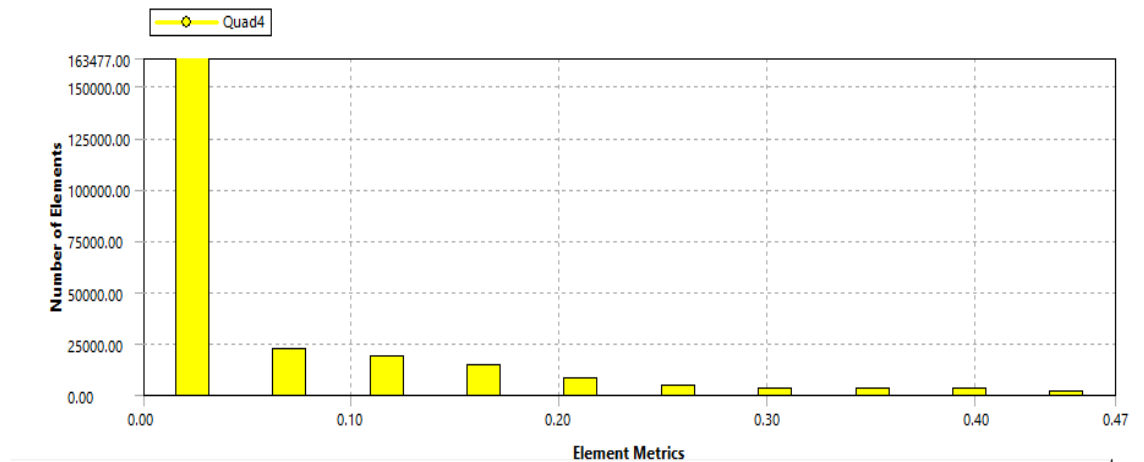
Figure 5. 8 Mesh Skewness Study

5.3 Parametric Method:

A **parametric method** was applied to systematically explore the effect of different **angles of attack (AoA)** and **Mach numbers** on the aerodynamic characteristics of

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the airfoils. This method involved varying the following parameters across multiple

simulations:

- **Mach Number Range:** 0.02 to 0.3

- **Angle of Attack (AoA):** 2° to 10°

  Each combination of these parameters was run to understand how changes in

  flight conditions influence the **lift** and **drag** performance.

|	A	C	D	E	F
1	Name	P2 - parameter-2	P3 - y velocity	P4 - cd-op	P5 - cl-op
2	Units	m s^-1	m s^-1		
11	DP 8	38.655	2.703	-0.0040228	1.5117
12	DP 9	38.538	4.05	-0.062078	2.0591
13	DP 10	38.328	5.392	-0.1403	2.5955
14	DP 11	38.161	6.7288	-0.23849	3.13
15	DP 12	41.745	0	0.058668	0.46723
16	DP 13	41.725	1.457	0.038352	1.1122
17	DP 14	41.648	2.9123	-0.0055856	1.7545
18	DP 15	41.521	4.364	-0.073064	2.391
19	DP 16	41.343	5.8104	-0.16397	3.0193
20	DP 17	41.116	7.2498	-0.27815	3.6367
21	DP 18	45.75	0	0.069194	0.5575
22	DP 19	45.722	1.59	0.04497	1.3303
23	DP 20	45.639	3.191	-0.007971	2.1062
24	DP 21	45.499	4.782	-0.089108	2.8721

Table of Design Points

Figure 5. 9 Parametric approach in Ansys

The parametric approach allowed for efficient exploration of multiple configurations,

leading to a deeper understanding of the aerodynamic behavior across different

operating conditions.

6.Validation of Results and Data Extraction

Validation was carried out for airfoils, namely NACA 4412 and NACA 0012, using experimental data and theoretical techniques to guarantee the accuracy of the simulation results obtained from ANSYS Fluent and XFLR5.

6.1 Validation Method:

For the NACA 4412 and NACA 0012 airfoils, the lift and drag coefficients (Cl and Cd) derived from the simulations were contrasted with experimental and theoretical findings. Because of their widespread application in aerodynamic research, these airfoils were chosen to provide accurate experimental data for comparison.

6.1.1   Experimental Data Comparison:

➢ The simulated Cl vs. AoA and Cd vs. AoA curves for the NACA 4412 and NACA 0012 airfoils were compared to experimental results from wind tunnel tests and literature. The Cl and Cd values from the simulations were directly compared to experimental measurements for different angles of attack (AoA).

6.1.2   NACA 4412 Validation:

Figure 6.1 and 6.2 shows NACA 4412 airfoil was validated for angles of attack ranging from 0° to 10°. The simulation results for CL and CD were compared with reference data to ensure accuracy. The trends observed in lift and drag coefficients closely matched the theoretical and experimental data, confirming the reliability of the aerodynamic analysis setup
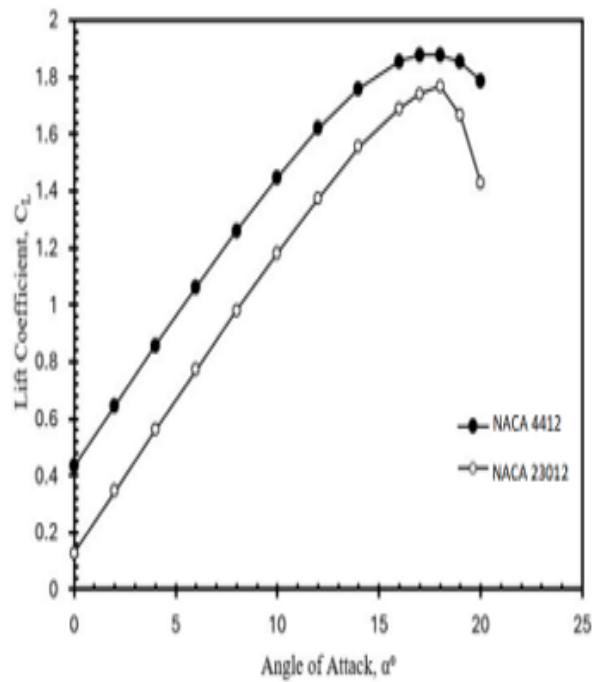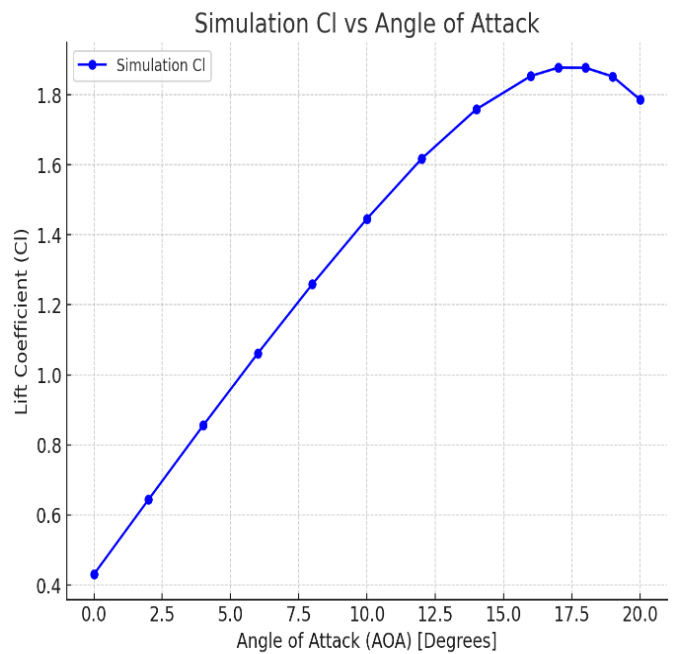
Figure 6. 2 Paper graph of naca 4412

Figure 6. 1 MATLAB Graph validated- Naca 4412
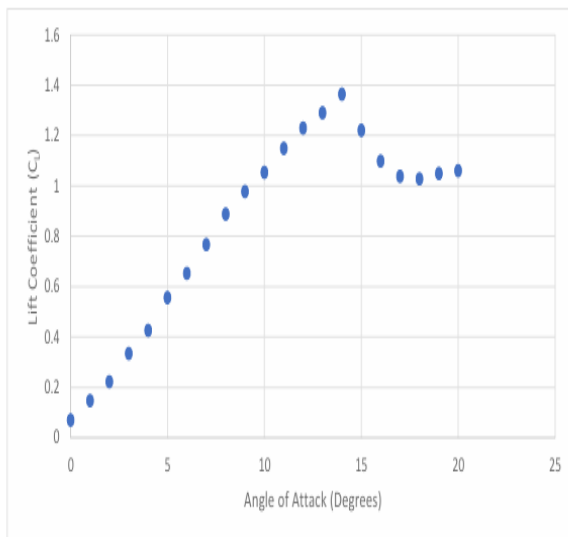
6.1.3 NACA 0012 Validation
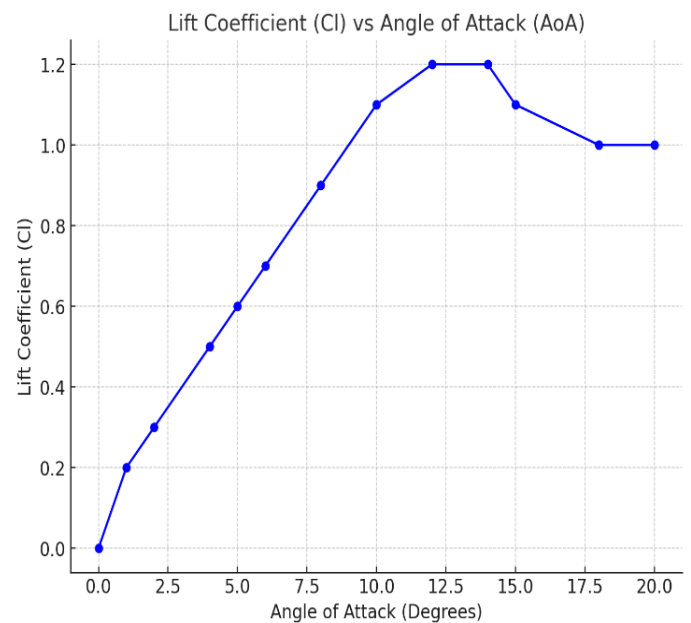

Figure 6. 3 Paper Graph of naca 0012

Figure 6. 4 MATLAB Graph of Naca 0012-Validated

Figure 6.3 and 6.4 shows NACA 0012 airfoil validations for angles of attack ranging from 0° to 10°. The simulation results for CL and CD were compared with reference data from a NASA research paper to verify accuracy. The lift and drag trends showed close agreement with the published data, confirming the validity of the aerodynamic analysis method used

6.2 Data Collection:

> Collected a large dataset of **Cl and Cd values** in an **Excel sheet**, which includes simulation results for different airfoils, **AoA**, and **Mach numbers**

6.2.1 2D Dataset

Mach	Re	alpha	CL	CD	Airfoil	velocity	max_thickness
0.05	1135000	-2	0.2443	0.0083	0	17	0.18
0.05	1135000	-1	0.3540	0.0082	0	17	0.18
0.05	1135000	0	0.4638	0.0082	0	17	0.18
0.05	1135000	1	0.5702	0.0079	0	17	0.18
0.05	1135000	2	0.6763	0.0078	0	17	0.18
0.05	1135000	3	0.7781	0.0077	0	17	0.18
0.05	1135000	4	0.8940	0.0081	0	17	0.18
0.05	1135000	5	1.0320	0.0087	0	17	0.18
0.05	1135000	6	1.1144	0.0091	0	17	0.18
0.05	1135000	7	1.1989	0.0098	0	17	0.18
0.05	1135000	8	1.2860	0.0107	0	17	0.18
0.07	1630000	-2	0.2473	0.00771	0	24	0.18
0.07	1630000	-1	0.3593	0.00765	0	24	0.18
0.07	1630000	0	0.4708	0.0076	0	24	0.18
0.07	1630000	1	0.5814	0.0075	0	24	0.18
0.07	1630000	2	0.6886	0.0073	0	24	0.18
0.07	1630000	3	0.7977	0.00714	0	24	0.18
0.07	1630000	4	0.8979	0.00723	0	24	0.18
0.07	1630000	5	1.0279	0.00781	0	24	0.18

Figure 6. 5 2D Dataset (1)

172	0.27	6290000	-1	0.1040	0.00473	9	92	0.18	
173	0.27	6290000	0	0.0000	0.0048	9	92	0.18	
174	0.27	6290000	1	0.1040	0.00473	9	92	0.18	
175	0.27	6290000	2	0.2111	0.00501	9	92	0.18	
176	0.27	6290000	3	0.3151	0.00532	9	92	0.18	
177	0.27	6290000	4	0.4199	0.00554	9	92	0.18	
178	0.27	6290000	6	0.6758	0.00673	9	92	0.18	
179	0.27	6290000	7	0.8052	0.00784	9	92	0.18	
180	0.3	6900000	-2	-0.2139	0.0051	9	103	0.18	
181	0.3	6900000	-1	-0.1059	0.0048	9	103	0.18	
182	0.3	6900000	0	0.0000	0.0048	9	103	0.18	
183	0.3	6900000	1	0.1059	0.0048	9	103	0.18	
184	0.3	6900000	2	0.2139	0.0051	9	103	0.18	
185	0.3	6900000	3	0.3207	0.0054	9	103	0.18	
186	0.3	6900000	4	0.4259	0.0055	9	103	0.18	
187	0.3	6900000	5	0.5409	0.0058	9	103	0.18	
188	0.3	6900000	6	0.6621	0.0068	9	103	0.18	
189	0.3	6900000	7	0.8128	0.0078	9	103	0.18	
190	0.3	6900000	8	0.8920	0.0084	9	103	0.18	
191									

Figure 6. 6 2D Dataset (2)

6.2.2 3D Dataset

	Wingspan	MAC	Taper Ratio	Velocity	AOA	Cl	Cd	Airfoil	Reynolds Num	Mach Num
2	2	1.25	1	17	-2	0.051856	0.005281	0	1,454,000	0.30
3	2	1.25	1	17	-1	0.090413	0.006052	0	1,454,000	0.05
4	2	1.25	1	17	0	0.128897	0.007431	0	1,454,000	0.05
5	2	1.25	1	17	1	0.167267	0.009345	0	1,454,000	0.05
6	2	1.25	1	17	2	0.205481	0.01191	0	1,454,000	0.05
7	2	1.25	1	17	3	0.2435	0.0152	0	1,454,000	0.05
8	2	1.25	1	17	4	0.281284	0.019294	0	1,454,000	0.05
9	2	1.25	1	17	5	0.318792	0.02413	0	1,454,000	0.05
10	2	1.25	1	17	6	0.355987	0.029511	0	1,454,000	0.05
11	2	1.25	1	17	7	0.39283	0.035381	0	1,454,000	0.05
12	2	1.25	1	17	8	0.064402	0.00665	0	1,454,000	0.05
13	4	1.25	1	17	-2	0.12263	0.007496	0	1,454,000	0.05
14	4	1.25	1	17	-1	0.180773	0.008988	0	1,454,000	0.05
15	4	1.25	1	17	0	0.238778	0.011163	0	1,454,000	0.05
16	4	1.25	1	17	1	0.296595	0.014037	0	1,454,000	0.05
17	4	1.25	1	17	2	0.354172	0.017651	0	1,454,000	0.05
18	4	1.25	1	17	3	0.411459	0.021949	0	1,454,000	0.05
19	4	1.25	1	17	4	0.468406	0.026923	0	1,454,000	0.05
20	4	1.25	1	17	5	0.524964	0.032556	0	1,454,000	0.05
21	4	1.25	1	17	6	0.581084	0.038821	0	1,454,000	0.05
22	4	1.25	1	17	7	0.071647	0.006541	0	1,454,000	0.05
23	4	1.25	1	17	8	0.140958	0.007259	0	1,454,000	0.05
24	6	1.25	1	17	-2	0.210182	0.008596	0	1,454,000	0.05
25	6	1.25	1	17	-1	0.279265	0.010641	0	1,454,000	0.05
26	6	1.25	1	17	0	0.348154	0.013413	0	1,454,000	0.05
27	6	1.25	1	17	1	0.416796	0.016894	0	1,454,000	0.05
28	6	1.25	1	17	2	0.485138	0.021063	0	1,454,000	0.05
29	6	1.25	1	17	3	0.553128	0.025908	0	1,454,000	0.05

Figure 6. 7 3D Dataset (1)

28054	8	1.35	0.4	103	0	0	0.004976	9	9,888,000	0.30
28055	8	1.35	0.4	103	1	0.075452	0.00516	9	9,888,000	0.30
28056	8	1.35	0.4	103	2	0.150849	0.006137	9	9,888,000	0.30
28057	8	1.35	0.4	103	3	0.226135	0.007854	9	9,888,000	0.30
28058	8	1.35	0.4	103	4	0.301257	0.010181	9	9,888,000	0.30
28059	8	1.35	0.4	103	5	0.376158	0.013056	9	9,888,000	0.30
28060	8	1.35	0.4	103	6	0.450784	0.016507	9	9,888,000	0.30
28061	8	1.35	0.4	103	7	0.525083	0.020576	9	9,888,000	0.30
28062	8	1.35	0.4	103	8	0.599001	0.025419	9	9,888,000	0.30
28063	10	1.35	0.4	103	-2	-0.16186	0.006067	9	9,888,000	0.30
28064	10	1.35	0.4	103	-1	-0.08096	0.005127	9	9,888,000	0.30
28065	10	1.35	0.4	103	0	0	0.004976	9	9,888,000	0.30
28066	10	1.35	0.4	103	1	0.080958	0.005127	9	9,888,000	0.30
28067	10	1.35	0.4	103	2	0.161861	0.006067	9	9,888,000	0.30
28068	10	1.35	0.4	103	3	0.242655	0.007678	9	9,888,000	0.30
28069	10	1.35	0.4	103	4	0.323286	0.009844	9	9,888,000	0.30
28070	10	1.35	0.4	103	5	0.403701	0.012503	9	9,888,000	0.30
28071	10	1.35	0.4	103	6	0.483845	0.015704	9	9,888,000	0.30
28072	10	1.35	0.4	103	7	0.563667	0.019579	9	9,888,000	0.30
28073	10	1.35	0.4	103	8	0.643112	0.024149	9	9,888,000	0.30
28074	12	1.35	0.4	103	-2	-0.16988	0.005994	9	9,888,000	0.30
28075	12	1.35	0.4	103	-1	-0.08497	0.005098	9	9,888,000	0.30
28076	12	1.35	0.4	103	0	0	0.004976	9	9,888,000	0.30
28077	12	1.35	0.4	103	1	0.084965	0.005098	9	9,888,000	0.30
28078	12	1.35	0.4	103	2	0.169878	0.005994	9	9,888,000	0.30
28079	12	1.35	0.4	103	3	0.254684	0.007502	9	9,888,000	0.30
28080	12	1.35	0.4	103	4	0.33933	0.009507	9	9,888,000	0.30
28081	12	1.35	0.4	103	5	0.423764	0.011963	9	9,888,000	0.30
28082	12	1.35	0.4	103	6	0.507934	0.014925	9	9,888,000	0.30

Figure 6. 8 3D Dataset (2)

6.3 Data Conversion:

Converted the **Excel sheet data** into a format suitable for further analysis and use in

machine learning algorithms for optimization.

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7.Predicting Machine Learning Model

For predicting the aerodynamic performance of MALE UAV airfoils, **multiple regression** is the ideal model. Since **Cl** and **Cd** values are continuous, not categorical, regression is well-suited for capturing the gradual variation in airfoil performance. It allows us to model the relationship between input parameters (e.g., AoA, Mach number) and the aerodynamic coefficients. This approach helps develop a **machine learning-based aerodynamic prediction tool**, which can predict **Cl** and **Cd** for different airfoils, enabling optimization for better UAV performance.
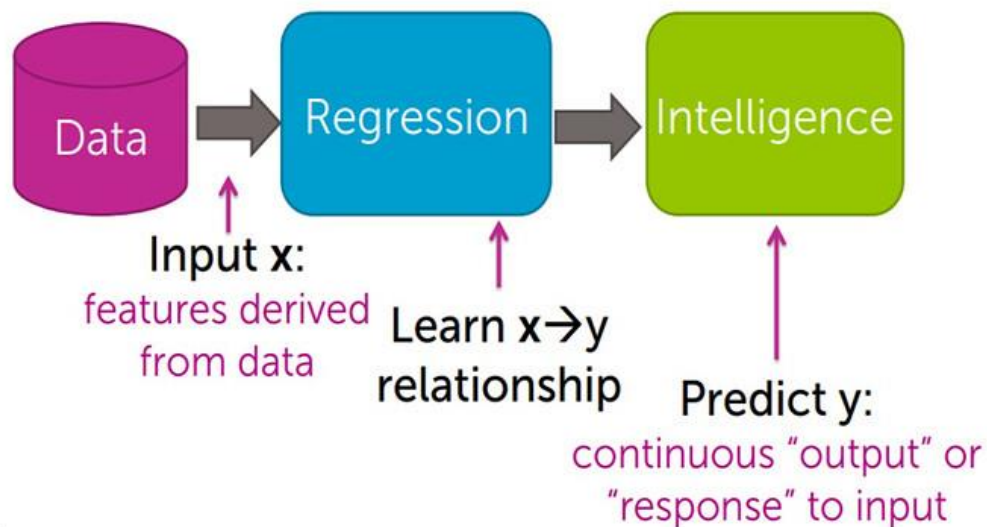
Figure 7. 1 Regression overview

Table 7. 1 Diff b/w Classification and Regression

Aspects	Classification	Regression
Definition	Predicts **categorical** labels (e.g., "stall" or "no stall").	Predicts **continuous** numerical values (e.g., Cl, Cd).
Output Type	Discrete classes (e.g., 0 or 1, Yes or No).	Continuos values (e.g., Lift Coefficient, Drag Coefficient)
Use Case	Used for spam detection, image recognition, etc.	Aerodynamics, Weather Forecasting
Best For FYP	❌	✅

7.1 Multiple Regression

➢ We are predicting aerodynamic performance **(Cl, Cd values)**, which are **continuous** rather than categorical.

➢ Airfoil performance varies **gradually**, requiring a model that captures trends, not just classes.

Regression allows us to develop an **ML-based aerodynamic prediction tool** for MALE UAV airfoils.
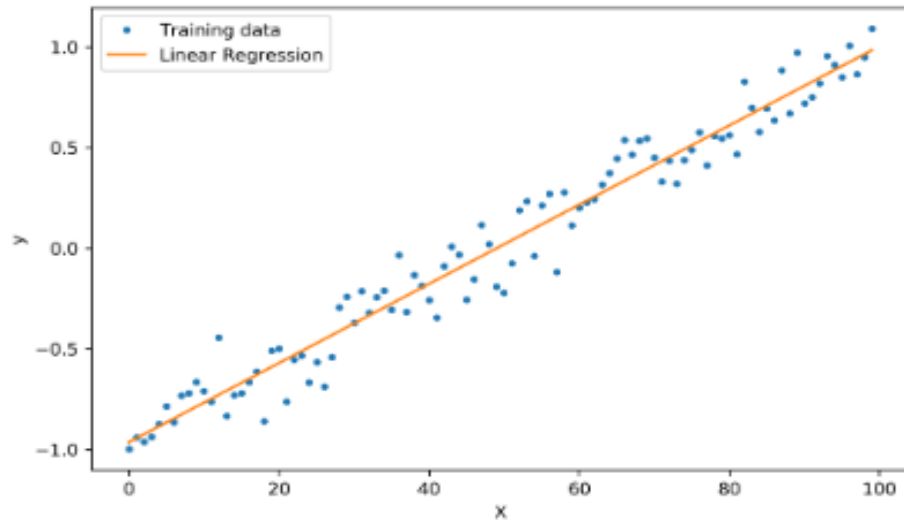
Figure 7. 2 Multiple regression generated graph

The following occurs in a multiple regression linear graph, which is typically a scatter plot with a line:

The actual observed values from your dataset, or what you actually measured, are represented by dots (points) as shown in figure 7.2

Line of regression → This displays the values that your regression model predicted.

Table 7. 2 Types of Optimizers

Features	Particle Swarm Optimizer	Genetic Algorithm	Gradient Based Optimizer
Types	Stochastic (Random Based)	Stochastic (Evolutionary Based	Deterministic

Convergence speed	Slower (requires multiple iterations of swarm movement)	Slower (requires mutation, crossover, selection)	**Faster** (uses derivatives to move toward optimal solution)
Computational Cost	**Higher**	Higher	Lower
Accuracy	Moderate	Moderate	High
Best For	Multi-modal, complex landscapes	Problems with unknown/noisy gradients	**Smooth, continuous functions** with clear gradients

7.2 Gradient-Based Optimization
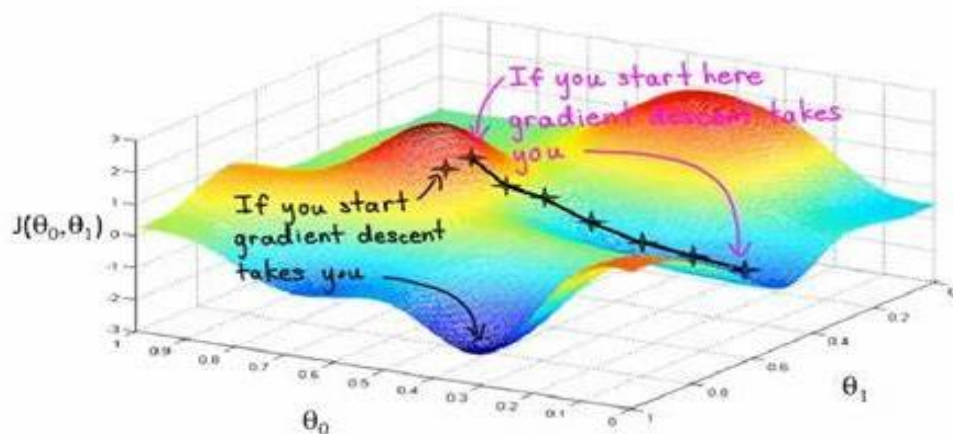
Figure 7. 3 Gradient Based Optimizer

Figure 7.3 shows that gradient based optimizer:

❖ **Faster convergence** (few iterations needed)

❖ **More precise** (reaches the exact local/global optimum)

❖ **Computationally efficient** (fewer function evaluations)

❖ **L/D and Range equations are differentiable** (making gradients useful)
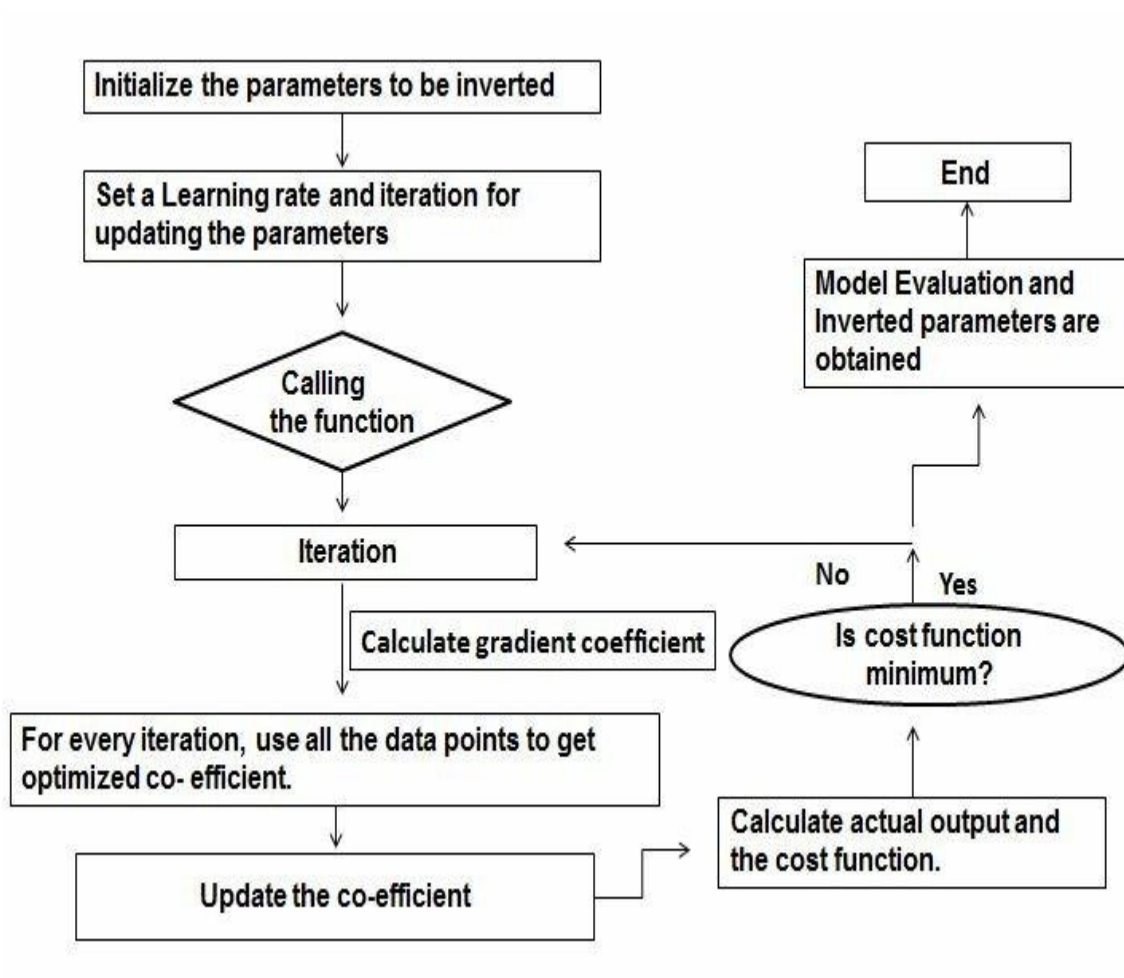
Figure 7. 4 Generic flowchart of gradient based optimizer

8. Performance optimizer for UAVs

A pinch to develop a performance optimizer for UAVs was to optimize the performance parameters of UAVs including Range, Endurance and aerodynamic efficiency.

There are a lot of techniques of optimization, but gradient based optimizer was used due to its faster convergence speed because it uses derivatives in code to move towards optimal solution, it has lower computational cost and is best for smooth continuous functions with clear gradients.

Any optimizer includes three parts:

8.1 Objective Function:

- Maximizing L/D ratio (aerodynamic efficiency)

$$\frac{L}{D} = \frac{Cl}{Cd}$$

8.1.1   Optimizing Range of UAVs

Using Range eq from Anderson book of Performance:

$$R = \eta_p/c * (\frac{L}{D}) g . \ln(\frac{Wi}{Wf})$$

8.1.2   Drag Model (Raymer's approach):

CD=CDo+KCl^2

8.1 3 Optimizing endurance of UAVs

Using Endurance eq from Anderson book of Performance:

$$R = \eta_p/c * (\frac{Cl^{\frac{3}{2}}}{Cd}) . \sqrt{\frac{2}{W}}$$

8.2 Design Variables:

- Taper ratio

- Aspect Ratio

8.2.1 Constraints:

- The limit: 5<AR<20

- Coefficient of Lift (0.3 – 1.5)
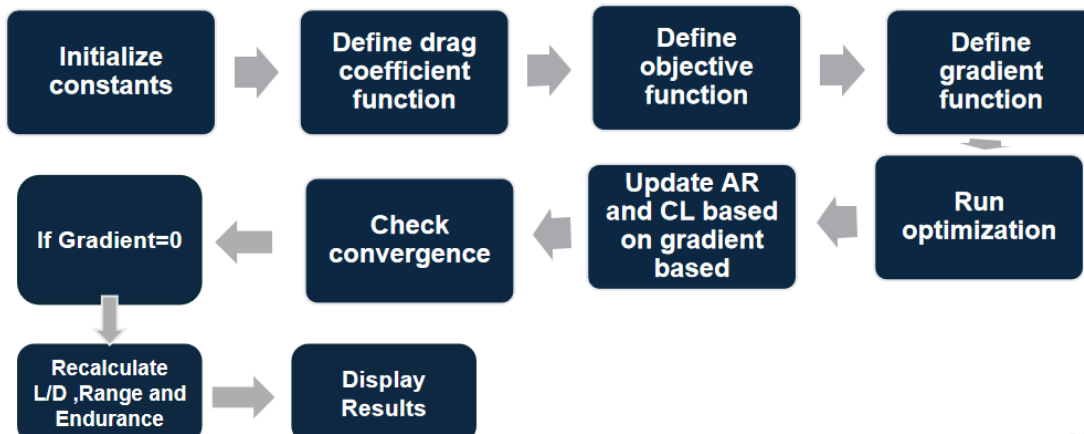
Figure 8. 1 Flowchart of working of Performance optimizer

8.3 Output of Code:
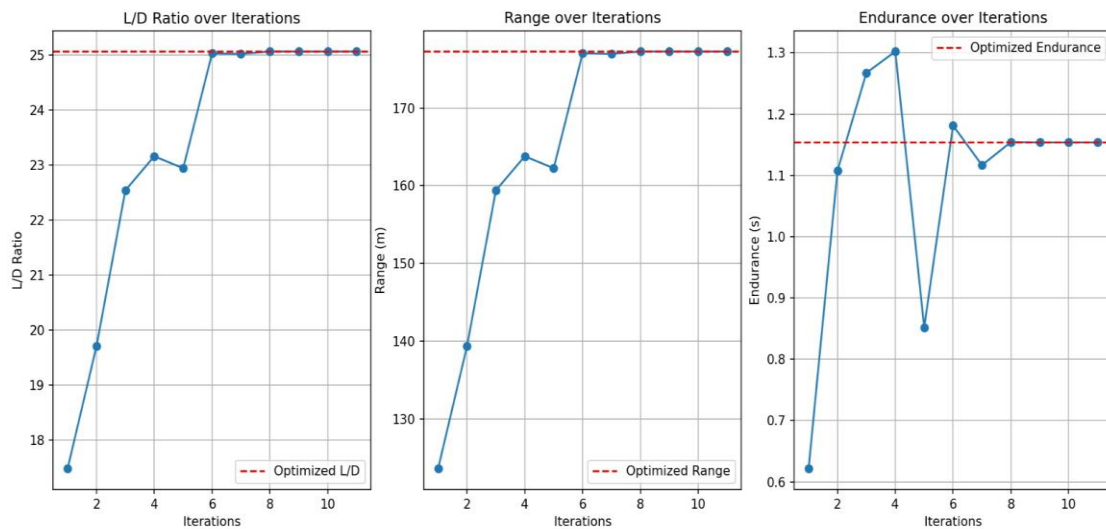
Figure 8. 2 Optimized L/D Range and Endurance

8.4 Conclusion:

This graph confirms that the gradient-based optimization successfully found the optimal

aerodynamic design for maximizing L/D, range and endurance.

The optimization process is efficient, reaching near-optimal values within 10 iterations.

The optimizer avoids overfitting or instability, as the values remain stable in later

iterations.

9. Machine learning model training

For 2D dataset, it was trained using different Regression models because according to our dataset it acquires continuous values and also inputs and outputs both were given in the dataset .So under supervised based learning ,different regression models were applied to it in order to determine the best accuracy .This dataset was of 1200 datapoints including Mach ,Re ,Angle of attack ,Airfoil ,Velocity and max thickness (according to selected airfoil) as input features and CL ,CD as output features .

9.1 Regression Algorithms applied:

9.1.1 Random forest:

Random Forest is an ensemble learning method used for both classification and regression tasks. It creates a forest (collection) of decision trees and makes predictions by averaging the predictions of the individual trees (for regression)


```
📈 Random forest - CL
R2 Score: 0.7518745992320806
MSE: 0.03855837626735834

📈 Random forest - CD
R2 Score: 0.8031754560789336
MSE: 4.879576143561076e-07
```
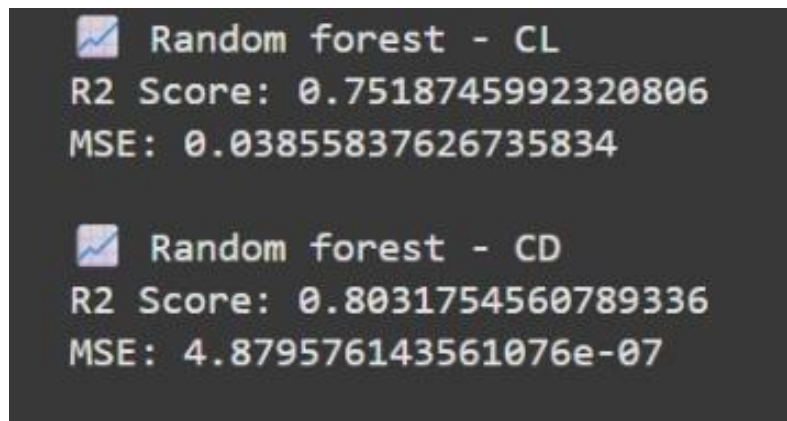
Figure 9. 1 Random Forest for 2D Dataset

9.1.2 Multiple linear regression:

MLR is a statistical technique used to model the relationship between a dependent variable (Y) and multiple independent variables (X1, X2, ... Xn). It assumes a linear relationship between the inputs and output.
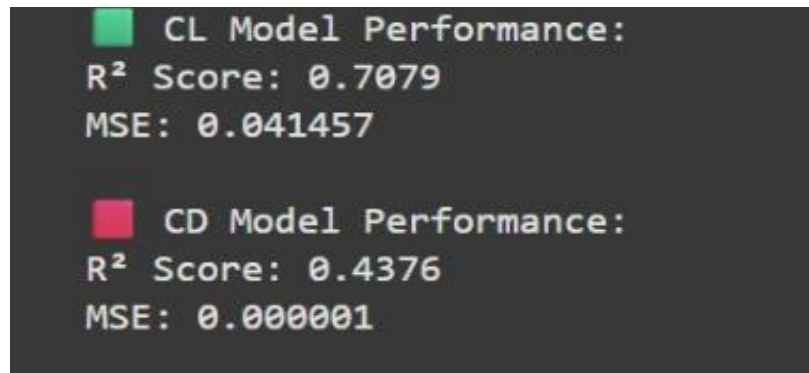
Figure 9. 2 Multiple regression for 2DDataset

9.1.3 XG – boost Regressor

XG Boost is an implementation of gradient boosting that is particularly efficient for complex relationships. It builds an ensemble of decision trees, where each tree tries to correct the errors of the previous tree.
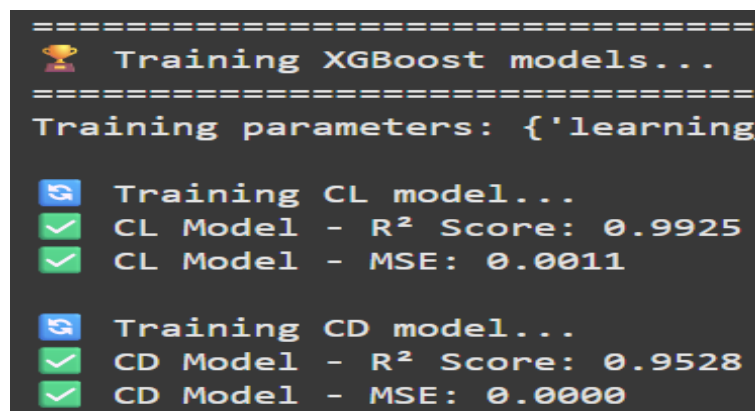
Figure 9. 3 XG-Boost regressor for 2D Dataset

9.1.4 Support Vector Regressor:

Use when your data is non-linear and you have high-dimensional or complex data. SVR works well in these situations but can be slow for large datasets.

Figure 9. 4 Support vector regressor for 2D Dataset

9.2 For 3D Dataset:

For 3D dataset, it was of 28000 datapoints including wingspan, Mean Aerodynamic chord, taper ratio, velocity, angle of attack, wings, Re no. ,Mach no. as input features and CL, CD as output features. The regression models which were applied to this dataset were only that which can handle large datasets easily.

9.2.1 Random forest:

Random Forest Regression is an ensemble method that builds multiple decision trees and averages their predictions to provide a more accurate and stable result for continuous values.

Figure 9. 5 Random Forest for 3D Dataset

9.2.2 Gradient boost:

Gradient Boosting Regression is a technique that builds decision trees sequentially, each correcting the errors of the previous one, to predict continuous values.
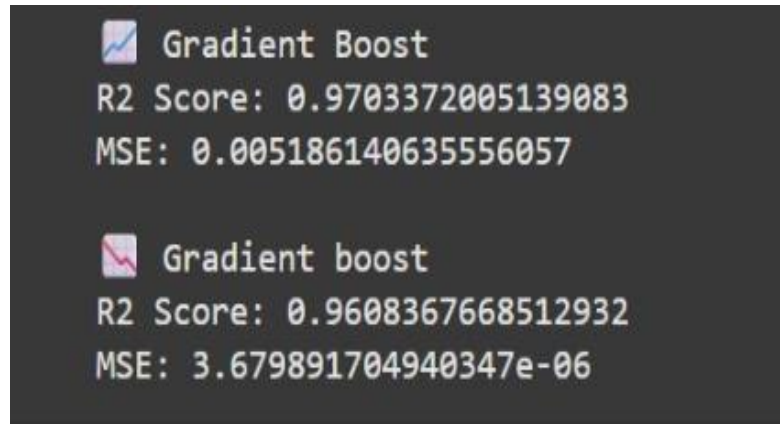
Figure 9. 6 Gradient boost for 3D Dataset

9.3 Conclusion:

As observed from above data, our airfoils dataset generated from cfd software was best trained by applying Xg -boost Regressor with 99% accuracy (R2 score) value for CL trained and 95% accuracy (R2 score) value for CD.

On the other hand, our wing dataset was best trained by applying random forest with 97% accuracy (R2 score) value for CL and 98% accuracy (R2 score) value for CD.

2D Regression Model Performance

Model	R^2 Score (CL)	R^2 Score (CD)
Multiple Linear Reg.	0.7079	0.4376
Random Forest	0.7524	0.801
SVR Regression	0.6960	0.6462
XG boost regressor	0.9925	0.9528

3D Regression Model Performance

Model	R^2 Score (CL)	R^2 Score (CD)
Gradient Boost	0.9703	0.9608
Random Forest	0.9710	0.9792

Figure 9. 7 A comparison of different models with their R^2

So, for 2D -XG Boost Regressor:
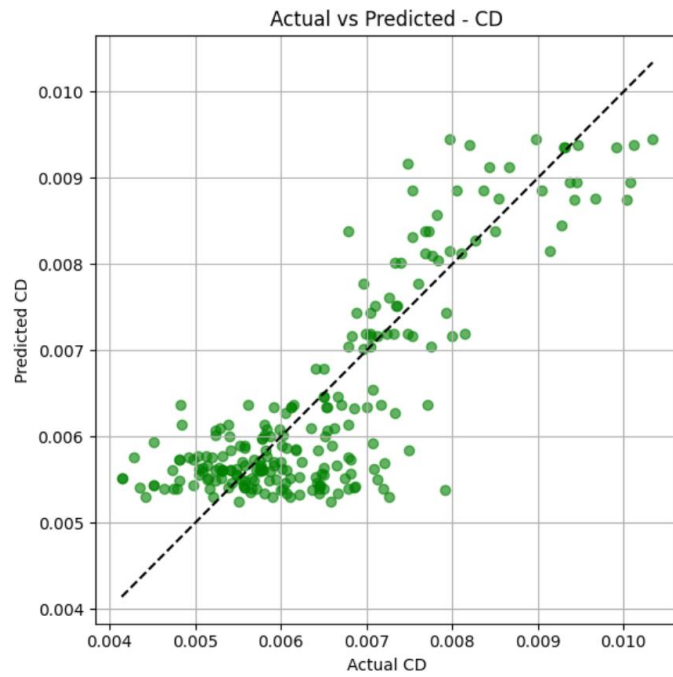
Figure 9. 8 XG Boost Regression Graph for 2D-CD
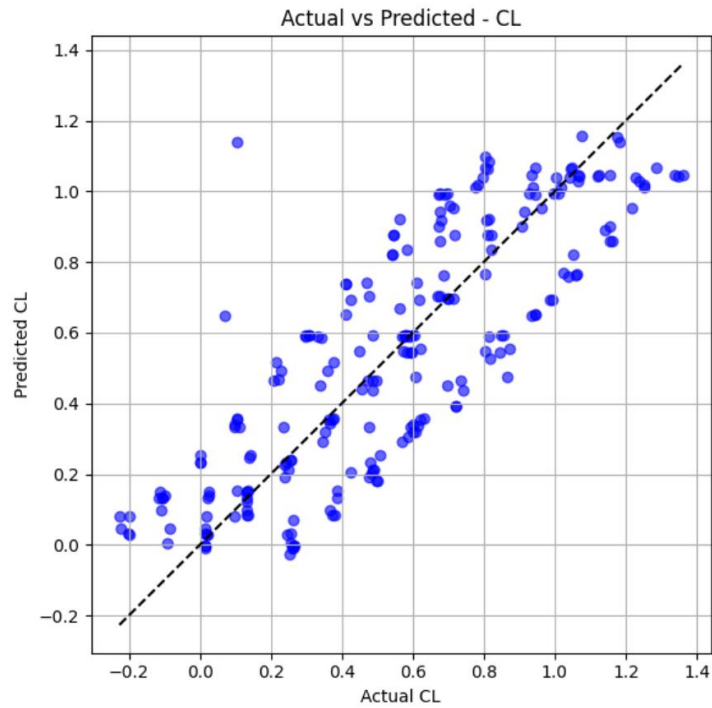
Figure 9. 9 XG-Boost regression for 2D-Cl

For 3D Random Forest regressor
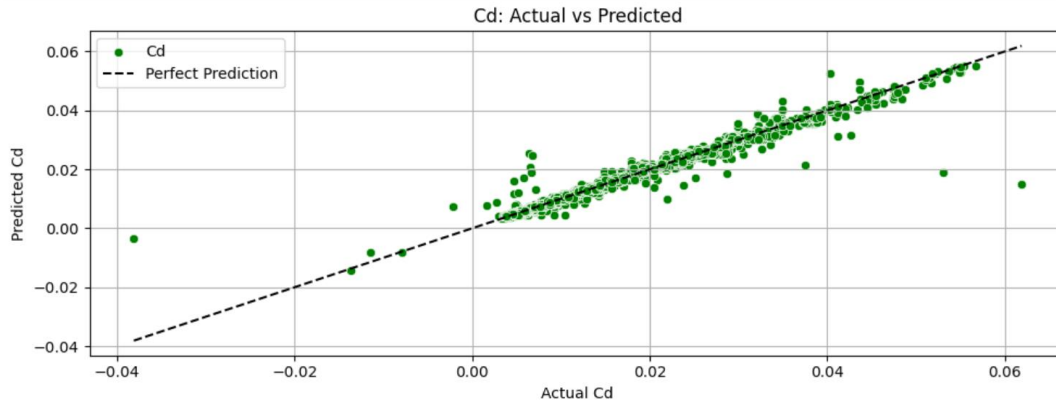
Figure 9. 10 Random Forest for 3D -CD
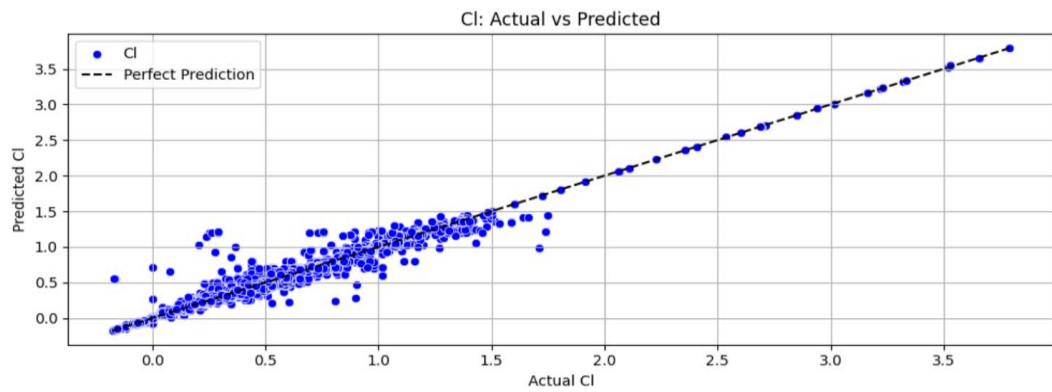
Figure 9. 11 Random Forest 3D Dataset-CL

10. User Interface Development

The user interface was designed to provide an interactive, web-based platform for

aerodynamic analysis. Its development involved the following components:

10.1 Development Environment

- Language: Python

- IDE: Visual Studio Code (VS Code)

10.2 Frontend

- Tool: Stream lit library

- Purpose: Provides an interactive web interface for user input and output display.

- Functions:

  - ➢ Accepts aerodynamic parameters from the user.

  - ➢ Displays results and visualizations (CL, CD, graphs).

10.3 Backend

- Tool: Python scripts with scikit-learn integration.

- Purpose: Implements the machine learning models for aerodynamic coefficient prediction.

- Functions:

  - ➢ Processes input data from the frontend.

  - ➢ Runs the ML prediction engine.

  - ➢ Sends results back to the interface for display.

10.4 System Architecture

- Data Flow:

  User → Stream lit Frontend → Python + scikit-learn Backend → ML Model → Output Visualization

- This structure ensures seamless communication between the machine learning model and the user interface, enabling efficient data input, computation, and visualization.

Following images show us the display of our developed Tool:
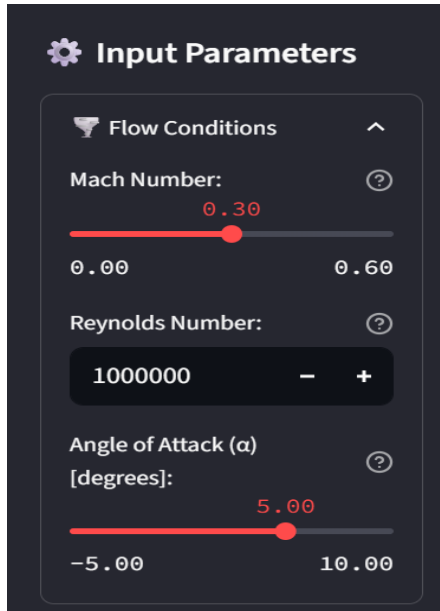
Figure 10. 2 Input parameters in 2D Interface
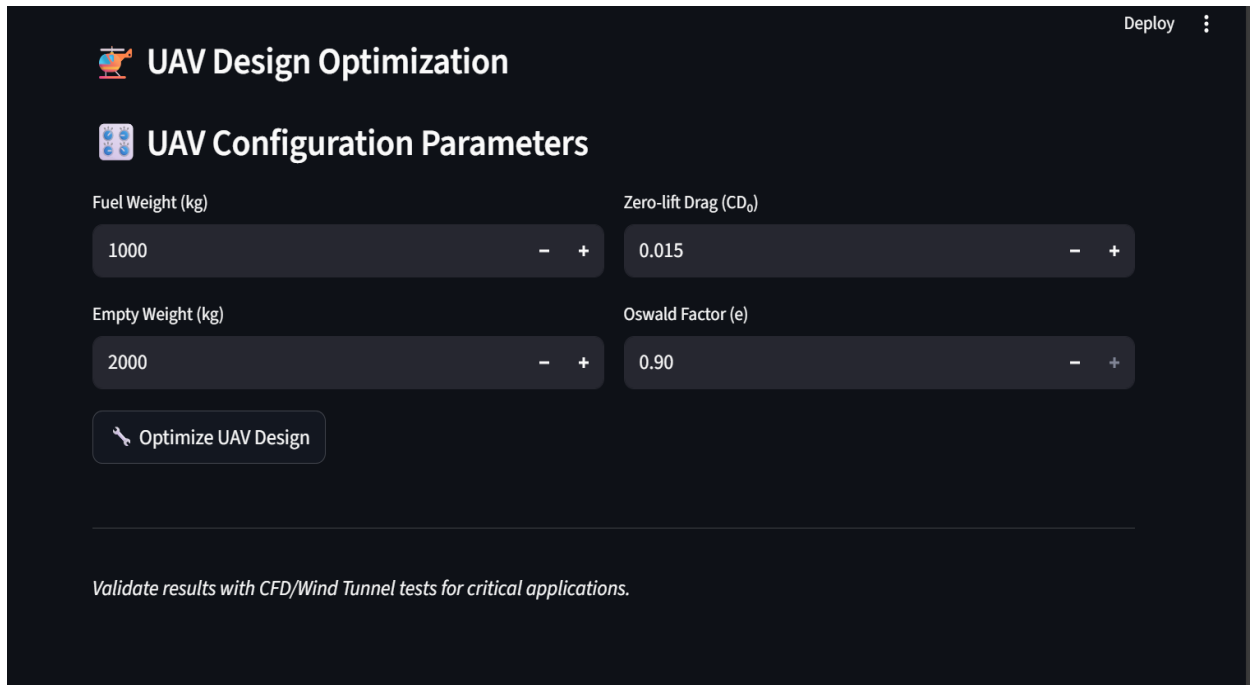
Figure 10. 1 Options of Airfoil in interface

Figure 10. 3 2D Aero Analysis interface with predicted CL and CD

10.5 UAV OPTIMIZER SUITE:

Figure 10. 4 Optimizer interface

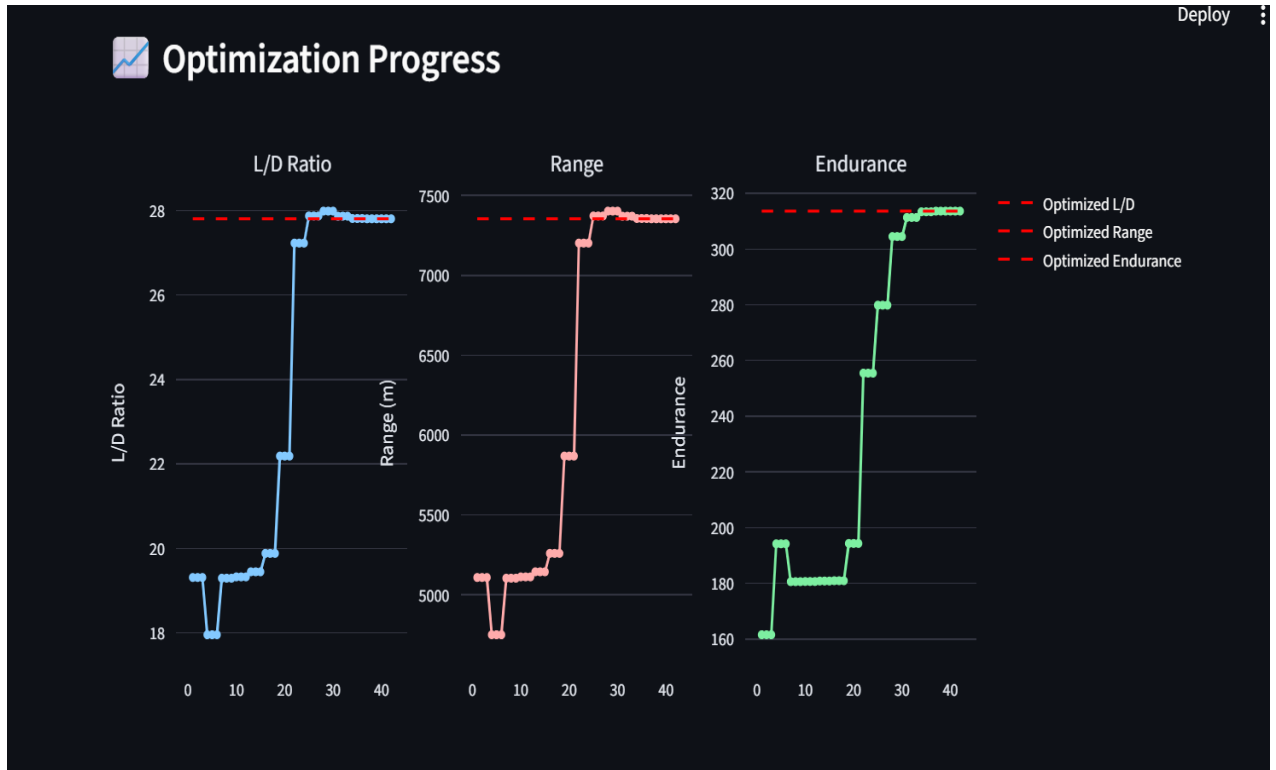Figure 10. 5 Optimized performance parameters

Figure 10. 6 Optimized results in form of graphs

Figure 10.6 shows the input of our optimizer. Our interface receives user inputs like the UAV's gross weight, fuel mass, and CD_0 (zero-lift drag coefficient). The code currently sets the CD_0 value to 0.02 by default, but users can change it if necessary.

The optimizer runs for a predetermined number of iterations after the inputs are supplied, producing graphs that display the outcomes. Using the inputs provided, it maximizes important performance metrics like range, endurance, and lift-to-drag ratio (L/D).

10.6 3D Aerodynamic Prediction Tool:

Figure 10. 8 3D Input parameters

Figure 10. 7 3D interface parameters (flow)
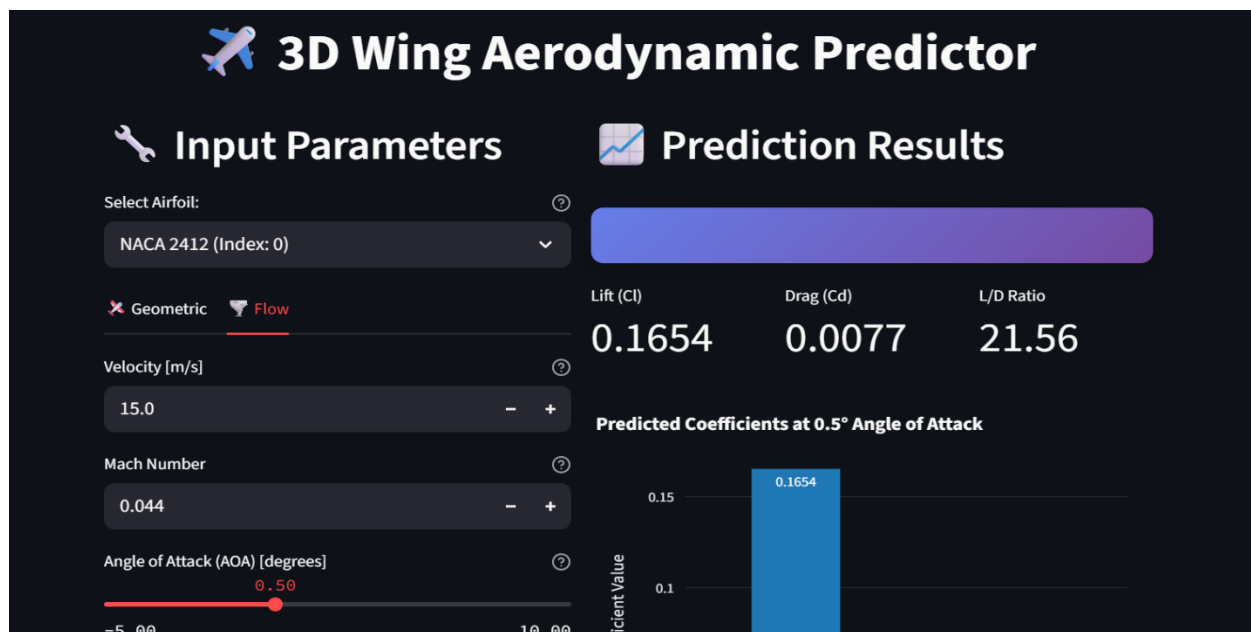
Figure 10. 9 Results display-3D Cl and Cd prediction

Input Summary

Parameter	Value
Airfoil	NACA 2412
Wingspan	10.00 m
MAC	0.100 m
Taper Ratio	0.50
Velocity	15.0 m/s
AOA	0.5°
Reynolds No.	1,000,000
Mach No.	0.044

Figure 10. 10 Input summery in Interface

Taper ratio, wingspan, angle of attack (AOA), velocity, and airfoil selection for root and tip are among the inputs needed by the 3D interface as shown in figure 10.7 and 10.8. The system analyzes aerodynamics based on these parameters and outputs the Reynolds number, CL (lift coefficient), and CD (drag coefficient) as shown in figure 10.9.These findings aid in assessing the 3D wing configuration's aerodynamic performance.

11. Future Goals and Industrial Relevance

The developed ML-based aerodynamic prediction tool holds strong potential for industrial adoption and further development. Its future applications and relevance to the UAV industry include:

11.1 Rapid UAV Design Prototyping

The tool can significantly reduce the time and cost required for UAV design iterations by quickly predicting lift and drag values. This capability enables aerospace companies to bring new drone models to market faster, minimizing dependence on lengthy CFD simulations during early design stages.

11.2 Integration into UAV Design Software

The model can be embedded into existing aerospace design platforms, such as XFLR5 or ANSYS add-ons, to provide intelligent suggestions and real-time performance predictions. This integration would allow designers to receive instant aerodynamic insights without the need for complete CFD workflows.

11.3 Customized UAV Performance Optimization

Industries such as defense, agriculture, and delivery services can leverage the tool to fine-tune UAV wings for specific mission profiles—whether the objective is extended range, enhanced endurance, or improved payload capacity—resulting in higher operational efficiency and improved mission success rates.

12.Sustainable Development Goals:

Figure 1 Sustainable Development Goals:

12.1 Goal 9:

Fostering Innovation: The use of machine learning and CFD simulations

represents a significant technological advancement in UAV design and operation,

promoting innovation in aerospace technology and autonomous systems.

12.2 Goal 12

Responsible Consumption. UAVs optimized for efficiency can replace larger, more

energy-consuming vehicles

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