ISTANBUL TECHNICAL UNIVERSITY ★ GRADUATE SCHOOL

Investigation of Reynolds Number Effects on Aerodynamic Characteristics of Generic Aircraft and Estimation of Reynolds-Dependent Aerodynamic Database Using Artificial Neural Network Models

M.Sc. THESIS

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Aeronautics and Astronautics Engineering Programme

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ISTANBUL TEKNİK ÜNİVERSİTESİ ★ LİSANSÜSTÜ EĞİTİM ENSTİTÜSÜ

Genel Uçakların Aerodinamik Özelliklerinde Reynolds Sayısının Etkilerinin Araştırılması ve Yapay Sinir Ağı Modelleri Kullanılarak Reynolds'a Bağlı Aerodinamik Veri Tabanının Tahmini

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Ramazan KARAASLAN, a M.Sc. student of İTU Graduate School student ID 511201140 successfully defended the thesis entitled "Investigation of Reynolds Number Effects on Aerodynamic Characteristics of Generic Aircraft and Estimation of Reynolds-Dependent Aerodynamic Database Using Artificial Neural Network Models", which he prepared after fulfilling the requirements specified in the associated legislations, before the jury whose signatures are below.

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To my spouse and children,

FOREWORD

This thesis represents not only my academic efforts but also the supportive atmosphere provided by many people and institutions, without whom this journey would have been significantly more difficult.

First and foremost, I would like to express my deepest gratitude to my thesis advisor, Prof. Dr. İbrahim Özkol, whose guidance and support were indispensable during this research. His comprehensive knowledge and inspiring perspective have played a crucial role in my academic growth. His encouragement and insightful feedback made it possible for me to progress and ultimately complete this work.

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Lastly, but definitely not least, I want to express my heartfelt gratitude to my family, who have always been there to provide unyielding support and encouragement throughout every decision I've made. Their unwavering faith in my capabilities and aspirations provided the strength and motivation that guided me through challenging times. I look forward to standing by them and my friends in their endeavors, just as they have done for me.

This thesis is a testimony to their unwavering trust, and I dedicate it to all those who believed in me and provided the support necessary for its completion.

Once again, I am thankful for everyone who has shared this journey with me, providing their unwavering support and encouragement along the way. It is my hope that the results presented in this thesis will contribute to our understanding and knowledge in this area, and pave the way for future researchers in the field.

May 2023 Ramazan KARAASLAN

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ABBREVIATIONS

ANN : Artificial Neural Network
CFD : Computational Fluid Dynamics
AoA : Angles of attack
AoS : Sideslip angles
Beta : Sideslip angles
AI : Artificial intelligence
UAV : Unmanned aerial vehicle
FLT : First layer thickness
BLT : Boundary layer thickness
MAC : Mean Aerodynamic Chord
SoS : Speed of Sound
RANS : Reynolds-averaged Navier-Stokes
LES : Large-eddy simulation
SGS : Subgrid-scale
SST : Shear stress transport
SVM : Support Vector Machines
KNN : K-Nearest Neighbors
MSE : Mean Squared Error
MAE : Mean Absolute Error
R-squared : Coefficient of Determination
R2 : Coefficient of Determination
L-BFGS : Limited-memory Broyden-Fletcher-Goldfarb-Shann

SYMBOLS

α : Angles of attack
β : Sideslip angles
Re : Reynolds Number
$\boldsymbol{\rho}$: Density
U : Velocity
L : Reference Length
μ : Dynamic Viscosity
$\boldsymbol{C_f}$: Friction coefficient
$\boldsymbol{T_w}$: Wall shear
k : Kinetic energy
CL : Lift coefficient
CD : Drag coefficient
Cl : Roll moment coefficient
Cm : Pitch moment coefficient
Cn : Yaw moment coefficient
T : Temperature
$\boldsymbol{T_S}$: Static Temperature
$\boldsymbol{P_S}$: Static Pressure
a : Speed of Sound

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Investigation of Reynolds Number Effects on Aerodynamic Characteristics of Generic Aircraft and Estimation of Reynolds-Dependent Aerodynamic Database Using Artificial Neural Network Models

SUMMARY

This paper examines an Artificial Neural Network (ANN) model that was constructed to create a comprehensive aerodynamic database, including the effects of Reynolds number on the aerodynamic features of a generic aircraft model, with a particular emphasis on the impacts of altitude and scale. Using Computational Fluid Dynamics (CFD) simulations and an ANN model, a comprehensive aerodynamic database that accounts for the wide-ranging impacts of Reynolds number is generated.

Using a generic aircraft model, a comprehensive set of CFD calculations were performed to evaluate the effect of Reynolds number on key aerodynamic properties. The simulations included different Mach numbers (0.2 to 0.95), angles of attack (AoA) ranging from -12 to 40 degrees, sideslip angles (Beta) ranging from 0 to 20 degrees, different altitudes, and different scales. The purpose of these simulations was to investigate the effect of Reynolds number on a variety of aerodynamic parameters, including as shock location translation, flow separation point, control surface efficiency, wing stall region change, and drag exchange.

By carefully scrutinizing the CFD results, the effects of altitude and scale on the aerodynamic database were uncovered. The findings demonstrated that the Reynolds number, which was affected by both altitude and scale, significantly affected the aerodynamic behavior of the aircraft. It has been noted that the translation of shock location, flow separation point, wing stall region, and drag change are all sensitive to variations in Reynolds number. Moreover, the Reynolds number was found to influence the effectiveness of control surfaces such as flaps, ailerons, and rudder, which could have significant ramifications for the aircraft's overall performance, stability, and maneuverability.

Using a subset of CFD results, an ANN model was created in order to construct a comprehensive aerodynamic database that accounts for Reynolds number effects. The ANN model displayed encouraging results in forecasting various aerodynamic characteristics based on Reynolds number, giving a valuable tool for comprehending and enhancing the performance of an aircraft under varying flying situations. This unique method enabled the effective identification of correlations between Reynolds number and aerodynamic properties, so contributing to a deeper comprehension of aircraft performance.

This study illuminates the major influence of Reynolds number on the aerodynamic performance of a generic airplane model. Using CFD analyses and an ANN model, a comprehensive aerodynamic database accounting for the impacts of altitude, scale, and control surface efficiency was developed. This study's findings can be utilized to enhance the design and performance of aircraft, particularly in respect to the influence of Reynolds number on various aerodynamic parameters.

Future study directions could include expanding the database to encompass a broader range of flight situations, examining the impacts of Reynolds number in supersonic and hypersonic flight regimes, and improving control surfaces further for improved efficiency and performance. In addition, the creation of new ANN models for certain flight zones and the incorporation of control surface-deflected CFD findings may provide more insights into the design and optimization of control surfaces. This study contributes to the growing body of knowledge regarding the critical function of Reynolds number in determining aerodynamic performance, with possible implications in the design and development of sophisticated aircraft and the broader area of aerodynamics.

Genel Uçakların Aerodinamik Özelliklerinde Reynolds Sayısının Etkilerinin Araştırılması ve Yapay Sinir Ağı Modelleri Kullanılarak Reynolds'a Bağlı Aerodinamik Veri Tabanının Tahmini

ÖZET

Bu çalışma, Reynolds sayısının genel bir uçak modelinin aerodinamik özellikleri üzerindeki etkileri dahil olmak üzere kapsamlı bir aerodinamik veri tabanı oluşturmak için tasarlanmış bir Yapay Sinir Ağı (YSA) modelini inceler. Bu çalışma, özellikle irtifa ve ölçek etkileri üzerinde durarak, Hesaplamalı Akışkanlar Dinamiği (HAD) simülasyonları ve bir YSA modeli kullanarak, Reynolds sayısının geniş kapsamlı etkilerini hesaba katan bir aerodinamik veri tabanı oluşturur.

Genel bir uçak modeli kullanılarak, ana aerodinamik özellikler üzerinde Reynolds sayısının etkisini değerlendirmek için kapsamlı bir dizi HAD hesaplamaları gerçekleştirildi. Simülasyonlar, farklı Mach sayıları (0.2'den 0.95'e), -12'den 40 dereceye kadar saldırı açıları (AoA), 0'dan 20 dereceye kadar yan kayma açıları (Beta), farklı irtifalar ve farklı ölçekler içeriyordu. Bu simülasyonların amacı, şok konumu kayması, akış ayırma noktası, kontrol yüzeyi verimliliği, kanat stall bölgesi değişikliği ve sürüklenme değişimi gibi çeşitli aerodinamik parametreler üzerinde Reynolds sayısının etkisini araştırmaktı.

HAD sonuçlarını dikkatlice inceleyerek, aerodinamik veri tabanı üzerinde irtifa ve ölçeğin etkileri ortaya çıkarıldı. Bulguılar, hem irtifa hem de ölçek tarafından etkilenen Reynolds sayısının, uçağın aerodinamik davranışını önemli ölçüde etkilediğini gösterdi. Şok konumu kayması, akış ayırma noktası, kanat stall bölgesi ve sürüklenme değişikliğinin, Reynolds sayısındaki değişikliklere duyarlı olduğu belirlendi. Ayrıca, Reynolds sayısının, uçağın genel performansı, stabilitesi ve manevra kabiliyeti için önemli sonuçları olabilecek flaplar, aileronlar ve dümen gibi kontrol yüzeylerinin etkinliğini etkilediği bulundu.

HAD sonuçlarının bir alt kümesini kullanarak, Reynolds sayısının etkilerini hesaba katan kapsamlı bir aerodinamik veri tabanı oluşturmak için bir YSA modeli oluşturuldu. YSA modeli, Reynolds sayısına dayalı çeşitli aerodinamik özellikleri tahmin etmede teşvik edici sonuçlar gösterdi ve böylece çeşitli uçuş durumları altında bir uçağın performansını anlama ve geliştirme için değerli bir araç sağladı. Bu eşsiz yöntem, Reynolds sayısı ile aerodinamik özellikler arasındaki ilişkilerin etkili bir şekilde tanımlanmasını sağladı ve böylece uçak performansı hakkında daha derin bir anlayışa katkıda bulundu.

Bu çalışma, Reynolds sayısının genel bir uçak modelinin aerodinamik performansı üzerindeki büyük etkisini aydınlatmaktadır. HAD analizleri ve bir YSA modeli kullanarak, irtifanın, ölçeğin ve kontrol yüzeyi verimliliğinin etkilerini hesaba katan kapsamlı bir aerodinamik veri tabanı geliştirildi. Bu çalışmanın bulguları, uçakların tasarımını ve performansını geliştirmek için kullanılabilir, özellikle Reynolds sayısının çeşitli aerodinamik parametreler üzerindeki etkisi açısından.

Gelecekteki çalışma yönleri, veri tabanını daha geniş bir uçuş durumu yelpazesi kapsayacak şekilde genişletmeyi, süpersonik ve hipersonik uçuş rejimlerinde Reynolds sayısının etkilerini incelemeyi ve kontrol yüzeylerini daha yüksek verimlilik

ve performans için daha da geliştirmeyi içerebilir. Ayrıca, belirli uçuş bölgeleri için yeni YSA modellerinin oluşturulması ve kontrol yüzeyi açılı HAD bulgularının entegrasyonu, kontrol yüzeylerinin tasarımı ve optimizasyonu hakkında daha fazla bilgi sağlayabilir. Bu çalışma, aerodinamik performansı belirlemedeki kritik Reynolds sayısının işlevi hakkındaki bilgi birikimine katkıda bulunur, bu da sofistike uçakların tasarımı ve geliştirilmesi ve aerodinamik alanının genelinde olası etkilerle sonuçlanabilir.

1. Flight Dynamic

Flight dynamics is an interdisciplinary field of study that aims to understand and predict aircraft behavior during flight by considering a wide range of topics, such as aircraft stability and control, aerodynamics, propulsion, and structural dynamics. In this section, we will explore the fundamental concepts of flight dynamics and their significance in the design, operation, and safety of aircraft (Schmidt & Vallado, 2017).

The principles of flight dynamics are based on Newton's three laws of motion, which describe the behavior of objects in motion and serve as the foundation for our understanding of aircraft flight. Newton's first law, or the law of inertia, states that an object at rest will remain at rest, and an object in motion will continue at a constant velocity unless acted upon by an external force. For an aircraft in flight, these external forces include lift, weight, thrust, and drag.

The second law of motion asserts that an object's acceleration is directly proportional to the force applied to it and inversely proportional to its mass. This law enables calculations of the forces affecting an aircraft in flight, such as lift and drag forces created by the wings and thrust and weight forces generated by the engines and the aircraft's mass.

The third law of Newton states that for every action, there is an equal and opposite reaction. This law describes the behavior of an aircraft's control surfaces, such as ailerons, elevators, and rudders, which determine the attitude and flight direction of the aircraft.

Analysis of flight dynamics necessitates comprehension of the application of these laws to the flight behavior of aircraft. For the design, operation, and safety of aircraft, four main aspects of flight dynamics are essential: aerodynamics, aircraft stability and control, propulsion, and structural dynamics.

Aerodynamics examines air forces and motion and the use of these forces to generate lift and propulsion. Lift is the force that supports an aircraft in flight, produced by the wings as they move through the air. Factors such as wing shape, angle of attack, and aircraft speed all affect lift generation.

Drag is the force opposing an aircraft's motion, resulting from air resistance as it flows around and over the aircraft. Drag depends on the aircraft's shape, speed, and air properties like density and viscosity.

The engines generate thrust, the force that propels the aircraft forward. The quantity of thrust is determined by the type and output of the engine (Stevens et al., 2016).

The study of aircraft stability and control involves understanding the aircraft's response to various inputs, such as changes in attitude, speed, or flight direction. Stability refers to the aircraft's tendency to return to its initial position after being disturbed, while control pertains to the pilot's ability to influence the aircraft's attitude and flight direction (Durham & Barker, 2013).

Aircraft stability is achieved through careful design of aerodynamic properties, such as the location of the center of gravity and the dimensions and shape of the wings and tail. Control is accomplished using control surfaces like ailerons, elevators, and rudders, which the pilot manipulates to modify the aircraft's attitude and flight direction (Cook, 2013).

Lastly, propulsion is the study of engines and ancillary systems responsible for generating thrust and providing power to the aircraft. This includes the design and operation of engines, as well as fuel systems, electrical systems, and other subsystems used to power the aircraft's instruments and systems.

1.1 Aerodynamic Database

A comprehensive compilation of data pertaining to an aircraft's aerodynamics, including information on the aircraft's behavior under varying flight conditions, including airspeed, altitude, angle of attack, and other parameters. Aerodynamic databases are integral components of aircraft design, performance evaluation, and flight simulation.

The aerodynamic database contains a variety of data categories, including lift, drag, and moment coefficients, derived from wind tunnel testing and CFD simulations (Hileman et al., 2014). These data are typically displayed in tables or diagrams and serve as the basis for aerodynamic models used in aircraft design and simulation.

A primary function of an aerodynamic database is to facilitate the creation of novel aircraft. (Hefferlin et al., 2002) The database provides designers with vital information regarding the plane's efficacy in various flight scenarios. With this information, designers can construct optimally proportioned and shaped wings, fuselages, and control surfaces. Utilizing the aerodynamic database, it is possible to evaluate the aircraft's speed, range, and fuel consumption.

Flight simulation relies heavily on aerodynamic databases as well. Flight simulators are used for pilot training and evaluating an aircraft's performance in a variety of scenarios, including takeoffs, landings, and emergency procedures. Aerodynamic databases are an essential component of flight simulators, as they provide precise data simulating the aircraft's behavior under various flight conditions. Pilots can therefore hone their abilities without actually flying an aircraft, ensuring safety and cost-efficiency.

Analysis of aircraft performance is another crucial application of aerodynamic databases. Engineers can evaluate the aircraft's performance under various flight conditions and identify areas for improvement using the database. By examining the data in the aerodynamic database, for instance, engineers can determine the optimal flight path and speed for an aircraft in order to minimize fuel consumption and maximize range (Hefferlin et al., 2002).

Additionally, aerodynamic databases are utilized in the creation of new aircraft technologies. Engineers can identify areas where new technologies can improve the performance of an aircraft by analyzing the database's data. By analyzing drag coefficient data, for instance, engineers can create innovative materials that reduce drag and increase fuel efficiency.

In addition to these applications, aircraft maintenance makes use of aerodynamic databases. By analyzing the database's data, engineers are able to identify potential problems and develop maintenance strategies to resolve them. For instance, if data reveals that a particular aircraft component is susceptible to failure at a certain altitude, engineers can devise preventative maintenance procedures to inspect and repair that component.

For steady flight conditions, including simulations of clean aircraft, control surface effects, Reynolds effects, and external influences, CFD instruments are widely employed. However, wind tunnel experiments should be combined with these tools to reduce the uncertainty of aerodynamic database information. For highly unsteady flow conditions, these instruments are only used to observe wind tunnel trends, compute control surface effects, or apply Reynolds corrections (Hileman et al., 2014). CFD tools can be utilized, for instance, to observe low spin rotation rates and validate the initial status of spin wind tunnel test campaigns. Due to the limited accuracy of RANS simulations in unstable flow fields, spin prevention systems must nevertheless rely on unsteady wind tunnel testing.

Table 1.1 : Aerodynamic Database Items and Data Sources

TOOLS	REGIME	MACH	AOA	AOS	REYNOLDS [10^6]
CFD	SUB1	0.2-0.4	-10°,40°	0°,5°,10°	5,20,80
CFD	SUB2	0.4-0.6	-10°,40°	0°	5
CFD	TRANSONIC	0.6-0.9	-10°,30°	0°,5°,10°	5,80
ANN	SUB1	0.2-0.25-0.3-0.35-0.4	Full	Full	Full
ANN	SUB2	0.4-0.45-0.5-0.55-0.6	Full	Full	Full
ANN	TRANSONIC	0.6-0.7-0.8-0.9	Full	Full	Full

The overview of the aerodynamic database is provided in Table 1.1. Some of the critical features are listed below.

These features are defined in their own sections in details. All CFD analyses are done with respect to sea level conditions and they are adapted to the flight conditions with delta Reynolds effects. In similar approach, WTT results should be corrected to sea level Reynolds conditions.

1.1.1 Flight Envelope

The flight envelope is a crucial aeronautics concept that defines the secure operational limits of an aircraft. It specifies the altitude, speed, and attitude limits within which an aircraft can be operated safely without exceeding its design limitations (Boerema, 2003). Typically, the flight envelope is depicted graphically by a set of curves that indicate the maximum and minimum values for critical performance parameters such as airspeed, altitude, and load factor.

The aerodynamic design of an aircraft has a significant impact on the flight envelope. The ability of an aircraft to generate lift, counteract drag, and maintain flight stability is influenced by factors such as wing geometry, incidence angle, and other design features. In addition, factors such as the aircraft's weight, engine performance, and atmospheric conditions affect the flight envelope (Mettler & Maertens, 2011).

The flight envelope is typically divided into distinct regions corresponding to different flight regimes, such as the normal flight regime, which encompasses the majority of flight operations, and the stall regime, overspeed regime, and spin regime. Each region presents a unique set of flight conditions, necessitating the implementation of unique operating procedures and techniques.

Normal flight regime is the flight regime in which the aircraft is designed to operate under normal conditions. In this regime, the aircraft typically flies at moderate airspeeds and altitudes and within a restricted range of attack angles. The normal flight regime is characterized by predictable aircraft behavior and control inputs and stable flight conditions.

The stall regime denotes a deviation from normal flight conditions; it occurs when the angle of attack of an aircraft's wings is excessively steep, resulting in a loss of lift and control. This can occur if the aircraft's speed is too slow or its angle of attack is too steep, such as during a sharp climb or turn. In this regime, the aircraft may experience buffeting, yawing, or rolling, necessitating a distinct skill set and recovery technique.

In contrast, the overspeed regime is the polar opposite of the stall regime, as the aircraft's speed exceeds its design limits. If flight conditions are not immediately rectified, the aircraft may sustain structural damage, loss of control, or other severe consequences (Mettler & Maertens, 2011).

The spin regime is a particularly dangerous flight condition in which the aircraft spins out of control and enters a spin. This can occur if the aircraft's wings cease to generate lift, causing it to rotate about its longitudinal axis. In this regime, it may be difficult or impossible to recover the aircraft, necessitating specialized training and equipment for secure spin termination.

To ensure safe flight operations, pilots must be familiar with the flight envelope of their aircraft and understand the unique regions and conditions associated with each regime. In addition, pilots must be trained in the correct recovery techniques for stall, overspeed, and spin situations, and they must be able to implement these techniques quickly and precisely in emergency situations.

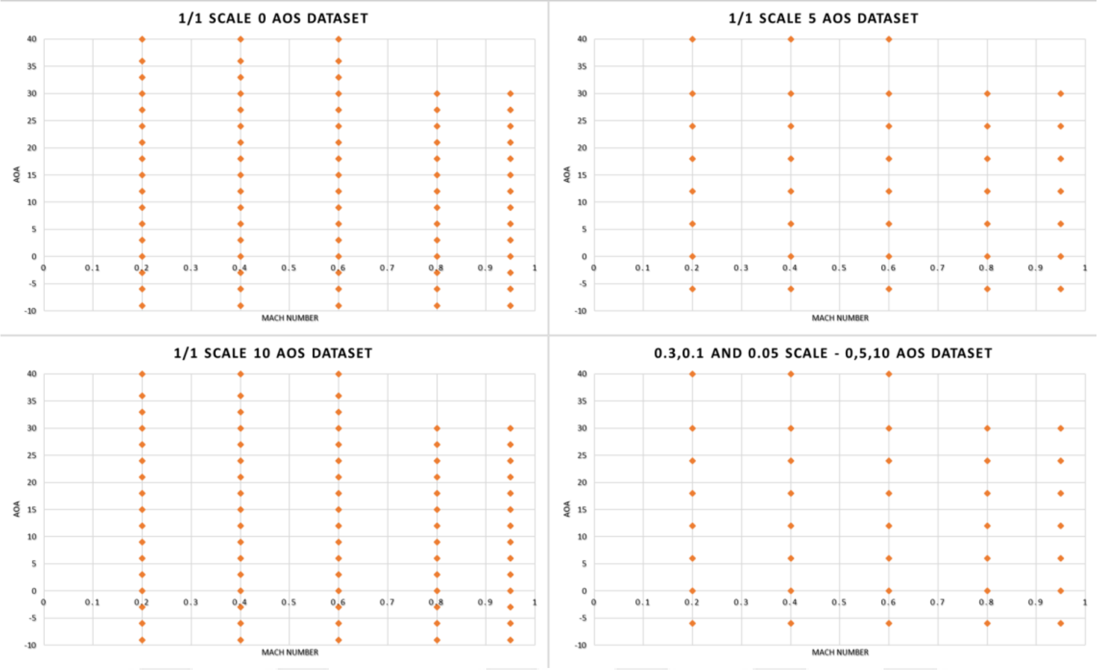

Figure 1.1 : Disturbution of the CFD Data

Figure 1.1.1 depicts the variations in AoA parameter values across all mission profiles. The figure reveals that the AoA for the inverted cases is up to -12° for the low subsonic case and up to -5° for the transonic case. In addition to the normal limits for altitude and acceleration during flight operations, parameters for the angle of side slip must also be considered.

Table 1.2 : Flight regime for aerodynamic database

REGIME	MACH	AOA	AOS	REYNOLDS [10^6]
SUB1	0.2-0.4	-10°,40°	0°,5°,10°	5,20,80
SUB2	0.4-0.6	-10°,40°	0°	5
TRANSONIC	0.6-0.9	-10°,30°	0°,5°,10°	5,80

CFD simulation activities should be driven with respect to limits provided Table 1.2. The limits are determined as higher than the expected ones.

The aerodynamic database contains a table-set for different Mach regimes, as shown in Table 1.2. Although the AoA and AoS sweep points differ from the designated breakpoints, the non-simulated or non-tested points must be interpolated. Furthermore, the data source must be incorporated into the database file as CFD. A sample aerodynamic database file is included in this document.

1.1.2 CFD

CFD is a prominent simulation technique in the field of aerospace engineering, particularly for aircraft analysis and design. It employs numerical methods, algorithms, and computer software to solve complex equations that characterize the behavior of fluids (Anderson, 1995). CFD can simulate fluid flow around a variety of aerospace vehicles, including aircraft, helicopters, and unmanned aerial vehicles, providing crucial data for the design and performance optimization of these vehicles.

The fundamental principle of CFD is discretizing the governing equations of fluid dynamics using numerical methods such as finite difference, finite volume, and finite element methods (Mader, 2011). The discretized equations are then solved iteratively using numerical algorithms, and the resultant numerical solutions allow for the visualization and analysis of fluid flow behavior in the context of aircraft aerodynamics.

CFD is utilized in aerospace engineering for the analysis and design of aircraft components like wings, engines, and control surfaces (Zingg et al., 2015). CFD simulations investigate the circulation behavior around an aircraft, including the generation of lift and drag forces, boundary layer development, and vortex formation. This data helps engineers optimize the design of aircraft components for increased efficacy and efficiency.

Aircraft engines, such as gas turbines and jet engines, are essential components in the aerospace, power generation, and transportation industries (Zingg et al., 2015). CFD also plays a crucial role in the design and analysis of aircraft engines, such as gas turbines and jet engines. Within these engines, CFD simulations investigate fluid flow behavior, including shock wave formation, turbulence, and boundary layers. This data optimizes the design of engine components, improves performance, and reduces environmental impact.

High-lift devices on aircraft, such flaps and slats, can be evaluated and constructed with CFD. These aids boost lift at low speeds, which is crucial for takeoff and landing efficiency. Using CFD simulations, engineers may better understand the flow around high-lift devices, leading to better performance during critical flight stages.

Aerodynamic performance under different flight situations, such as high angle of attack, transonic flight, and dynamic stall, are also investigated using CFD. Engineers can gain a deeper understanding of the aircraft's behavior in different flying circumstances thanks to these simulations, which is crucial for developing aircraft that can function in a wide range of conditions.

In addition to aircraft design, CFD is used to devise strategies for aircraft noise reduction. Noise produced by aircraft during launch, landing, and in-flight operations can have significant environmental and community consequences. CFD simulations aid engineers in comprehending the sources of noise generation, such as turbulent flow around landing gear and engine nacelles, allowing for the development of inventive noise mitigation techniques.

Computational Fluid Dynamics plays a crucial role in aerospace engineering, particularly in the analysis and design of aircraft and their components. CFD simulations provide crucial data on the fluid flow behavior around aircraft, allowing engineers to optimize designs for enhanced performance, efficiency, and environmental impact.

1.1.3 Wind Tunnel Test

Because it allows engineers to examine the performance of aircraft designs in a wind tunnel testing. A wind tunnel is a chamber through which air is blown or drawn at a predetermined speed, allowing for the testing of aircraft models in a range of environments. Aircraft wind tunnel testing and its many applications are discussed in this section.

With wind tunnel testing, aerodynamic performance of an aircraft may be evaluated in a controlled and repeatable environment. According to a study (Kumar et al., 2016), Aeronautical engineers can study aircraft responses under varying conditions by changing the angle of attack, velocity, and other parameters. This technique can help zero in on weak points in a design that can be fixed to boost its performance.

Additionally, wind tunnel testing is indispensable for evaluating aircraft performance in real-world conditions, such as turbulence and crosswinds. By modifying wind speed and direction within the wind tunnel, engineers can simulate various atmospheric conditions and study aircraft responses (Jaworski et al., 2017). This method can assist in identifying potential safety issues or design areas requiring refinement.

The ability to test multiple designs or variants of a single design is yet another advantage of wind tunnel testing. This comparative analysis enables engineers to evaluate the performance of various designs and, ultimately, to make well-informed judgments about which design to pursue. In addition, it can assist in the optimization of a single design by evaluating variations in wing shape, control surfaces, and other design elements.

Despite this, wind tunnel testing has limitations. The expense and time required to construct and operate a wind tunnel is one of the most significant obstacles. The apparatus is expensive and requires specialized knowledge to operate, making it out of reach for many smaller businesses and research organizations. In addition, wind tunnels can only simulate a limited range of atmospheric conditions, implying that certain performance aspects may need to be evaluated using alternative methods, such as flight testing (Jaworski et al., 2017).

Another limitation is the precision of wind tunnel testing in comparison to actual performance. Despite the fact that wind tunnels provide valuable insights into the aerodynamic performance of an aircraft design, they cannot precisely simulate actual conditions. Engineers must account for possible discrepancies between wind tunnel results and actual flight performance when interpreting test results.

1.1.4 Flight Test

Only through flight testing can the performance of an aircraft be validated and verified, making flight testing an indispensable component of aviation development, especially in the context of aircraft. The purpose of flight testing is to evaluate an aircraft's performance and identify any potential design defects (Cooley et al., 2013).

The primary objective of flight tests is to collect data on the efficacy of the aircraft and its systems under real-world conditions. Flight test results inform design enhancements, increase aircraft reliability and safety, and guarantee the aircraft's ability to accomplish its intended mission.

Flight testing typically involves multiple phases, beginning with ground evaluations to verify the aircraft's systems and components before flight. The aircraft then undergoes a series of flight tests, commencing with fundamental flight maneuvers such as takeoff, climb, and landing. As testing progresses, increasingly intricate maneuvers are performed to evaluate the aircraft's performance and handling characteristics under different flight conditions (Cooley et al., 2013).

The opportunity to evaluate the aircraft's performance in a variety of real-world conditions, including turbulence, frost, and high winds, is one of the primary benefits of flight testing. Flight testing also enables the evaluation of the aircraft's performance at varying altitudes and velocities, which is essential for determining its ability to fulfill the mission requirements (Freeman & Roggemann, 2011).

In addition to evaluating the efficacy of the aircraft, flight testing is used to evaluate its safety and dependability. During flight testing, pilots and engineers closely observe the aircraft's systems and components for signs of failure. Before the aircraft is approved for operational use, any identified issues are resolved.

Evaluation of the aircraft's avionics and instruments is an additional vital aspect of flight testing. These systems are essential for ensuring the safety and efficiency of flight operations, and flight testing provides the opportunity to validate their efficacy under real-world conditions.

Flight testing is a difficult and costly endeavor that requires a team of highly experienced pilots, engineers, and technicians to plan and execute the tests. In addition to personnel and equipment costs, there are significant costs associated with preparing an aircraft for flight testing, such as modifying its systems and components (Cooley et al., 2013).

Despite the difficulties and expenses associated with flight testing, it continues to be an essential component of aviation development. Flight testing provides a level of validation and verification unattainable through simulation or ground testing alone, and is essential for ensuring that aircraft are safe, dependable, and capable of meeting the mission requirements.

1.2 Reynolds Number Effect

Reynolds number is a dimensionless quantity used to characterize fluid behavior when traveling past an object. In aviation, Reynolds number plays a crucial role in determining an aircraft's aerodynamic characteristics.

Reynolds number represents, in essence, the ratio of inertial forces to viscous forces. It is computed by multiplying the fluid velocity by the characteristic length of the object and dividing by the fluid's kinematic viscosity. Depending on the object being analyzed, the characteristic length can vary; however, for aircraft, it is typically the chord length (Bai & Pan, 2021).

Reynolds number is particularly important in aviation because it determines whether the airflow around an object is laminar or tumultuous. Laminar flow consists of smooth, parallel layers of air traveling in the same direction, whereas turbulent flow is characterized by chaotic, swirling eddies (Alves et al., 2021).

The distinction between laminar and turbulent flow is crucial because it has a substantial effect on the aerodynamic efficacy of an aircraft. Laminar flow is generally preferred because it generates less drag and permits higher cruising velocities. However, achieving laminar flow can be difficult and is only feasible within a narrow Reynolds number range (Arora & Gupta, 2021).

At low Reynolds numbers, airflow is typically laminar around an object. Due to the dominance of viscous forces over inertial forces, airflow is seamless and uniform in direction. Nonetheless, as the Reynolds number rises, inertial forces become more pronounced, causing the flow to become unstable and eventually transform into turbulent flow (Jones et al., 2021).

This means that the Reynolds number is a crucial factor in the design of aircraft wings and other parts. Reduced efficiency and greater friction can come from an inability to achieve laminar flow at low Reynolds numbers. However, turbulence can occur if the Reynolds number is too high, leading to greater drag and poorer stability (Wang et al., 2021).

As an example of how the Reynolds number influences airplane design, consider the advent of laminar flow wings. Laminar flow across a wider surface area is what these wings are built to achieve, so they can minimize drag and increase fuel efficiency.

However, the Reynolds number, wing size, and wing shape must all be taken into account if laminar flow is to be achieved.

The Reynolds number also influences other aspects of aircraft design, including the placement and design of engine nacelles and the positioning of control surfaces. To ensure optimal and efficient aircraft performance, the Reynolds number must be meticulously considered in every circumstance (Bai & Pan, 2021).

The effects of the Reynolds number on aircraft can be classified as either direct or indirect. The direct effects are associated with a constant pressure distribution, whereas the indirect effects are associated with changes in pressure distribution caused by varying Reynolds numbers. Typically, lift and pitching moment, wave drag, drag divergence, and buffet boundary are characteristics that depend on indirect Reynolds number effects. Viscous drag, boundary layer separation, and buffet boundary are those dependent on direct Reynolds number effects.

Reynolds number has a direct effect on flow characteristics, such as the formation of the boundary layer, which influences the position and intensity of shock waves. To comprehend the mechanism of the Reynolds number effects on the aerodynamic characteristics of the supercritical wing, the boundary layer displacement thicknesses under various Reynolds numbers are numerically simulated using CFD software (Dogan & Sogut, 2021).

Reynolds number is a fundamental parameter in fluid dynamics, with particular significance in aviation. It governs the transition between laminar and turbulent flow and influences the design of a variety of aircraft components, including wings, winglets, engine nacelles, and control surfaces. Consider both the direct and indirect effects of the Reynolds number on aircraft performance, paying close attention to the equilibrium between laminar and turbulent flow. This knowledge enables designers to optimize aircraft performance, ensuring safe, efficient, and dependable flight across a broad spectrum of flight conditions.

1.2.1 Translation of Shock Location

The Reynolds number plays a crucial role in determining the position of the shock wave on an aircraft wing, which has a significant impact on the wing's overall performance. Understanding the relationship between the location of the shock wave and the Reynolds number is crucial for optimizing the design and performance of aircraft.

Reynolds number is a dimensionless quantity that represents the ratio of fluid inertial forces to viscous forces. The Reynolds number is affected by factors such as airspeed, wing chord length, and air viscosity in the context of an aircraft wing. As the Reynolds number changes, the circulation behavior around the wing alters, resulting in a shift in the location of the shock wave (McKinney, Powell, & Rae, 2019).

The location of shock waves has a direct effect on the aerodynamic efficacy of an aircraft. A shock wave is a pressure wave that forms when the airflow over the wing exceeds the speed of sound, causing an abrupt increase in pressure that can cause drag and reduce lift. If the impact wave is too far forward, the aircraft may stall. Alternatively, if the shock wave is too far behind the ship, it can increase drag and reduce fuel efficiency.

In the development of supersonic aircraft, it is possible to witness the impact of shock wave location on the Reynolds number. These aircraft encounter shock waves at substantially greater speeds than subsonic aircraft, and their design must account for the impact of shock waves on performance. As the Reynolds number increases, the location of the shock wave shifts rearward, which increases drag and slows the aircraft. A plot of the super-critical pressure distribution and a schematic view of the boundary layer is shown in figure 1.2.

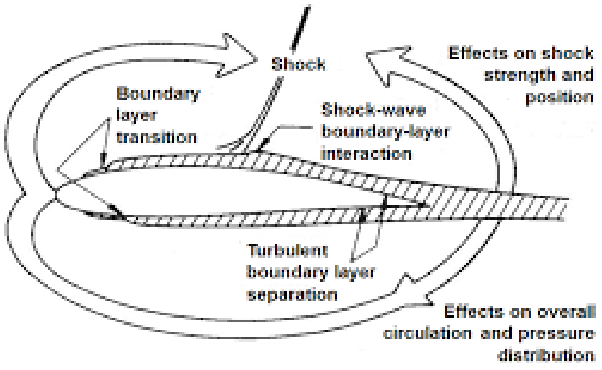

Figure 1.2 : Effects of Reynolds number and boundary-layer transition location on shock-induced separation(James A. Blackwell.,1969)

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1.2.2 Flow Separation Point

Flow separation occurs when the airflow over a body detaches from the surface, resulting in a decrease in lift and an increase in drag. The location where flow separation occurs is referred to as the separation point. Several factors, including the angle of attack, the geometry of the body, and the Reynolds number, influence the separation point. The Reynolds number, a dimensionless quantity representing the ratio of inertial forces to viscous forces in a fluid, is a crucial factor in determining the onset of flow separation (Hu et al., 2022).

The Reynolds number influences the flow separation point significantly. Flow over a body is laminar at low Reynolds numbers, and the separation point is typically located at the rear of the body. As the Reynolds number increases, however, the flow over the body changes to turbulence and the separation point advances. At higher Reynolds numbers, the boundary layer on the body's surface becomes thicker and more tumultuous, causing the flow to separate earlier.

Location of the separation point is crucial for designing efficient aircraft in aerodynamics. In aircraft design, for instance, the objective is to delay the onset of flow separation for as long as feasible in order to increase lift and decrease drag. The location of the separation point is affected by a number of design variables, including the airfoil geometry, angle of attack, and Reynolds number.

There have been numerical simulations and wind tunnel experiments conducted to investigate the effect of Reynolds number on the location of the separation point. These investigations have demonstrated that the location of the separation point is dependent on the Reynolds number (Hu et al., 2022). At higher Reynolds numbers, the separation point advances, decreasing the efficacy of the airfoil.

1.2.3 Control Surface Efficiency

Control surfaces are essential for the maneuverability and flight equilibrium of an aircraft. The efficacy of these control surfaces is determined by a number of variables, most notably the Reynolds number. Reynolds number is a dimensionless parameter that represents the flow regime of a plane's surroundings. Re is the ratio between inertial forces and viscous forces.

The Reynolds number has several effects on the effectiveness of a plane's control surface. The boundary layer that develops close to the surface is an important impact. When the Reynolds number increases, the boundary layer thins, which might result in separation occurring sooner and less efficiency. High-lift devices, like flaps and slats, that are designed to supplement the lift created by wings during takeoff and landing are particularly susceptible to this phenomenon.

How the Reynolds number influences the performance of aircraft control surfaces is a topic that has been studied extensively. One study that looked at how the Reynolds number affected flap performance was conducted by Choi and Yang (2018). The researchers examined the flow around the flap at different Reynolds values using CFD models. The peak lift coefficient and angle of stall both decreased with increasing Reynolds number. Based on these findings, it appears that as the Reynolds number increases, the effectiveness of the flap drops.

The impact of Reynolds number on aileron efficiency was studied by Zhang et al. (2017). Using a wind tunnel, scientists evaluated ailerons' aerodynamic performance at several Reynolds numbers. The peak lift coefficient and angle of stall both decreased with increasing Reynolds number. These findings point to a decline in aileron effectiveness as the Reynolds number rises.

The effect of Reynolds number on the efficiency of aircraft control surfaces extends beyond high-lift devices or surfaces generating lift. The efficiency of control surfaces producing drag, such as spoilers and air brakes, is also affected by Reynolds number. A study conducted by Choi et al. (2019) examined the influence of Reynolds number on the drag generated by a spoiler. The researchers utilized CFD simulations to analyze the flow surrounding the spoiler at various Reynolds numbers. They determined that, as the Reynolds number increased, the drag coefficient decreased, indicating that spoiler efficiency improved at higher Reynolds numbers.

1.2.4 Wing Stall Region

When the angle of attack of a wing exceeds a certain value, known as the critical angle of attack, wing stalling occurs. As the angle of attack increases, the flow over the wing becomes turbulent, and the lift generated by the wing decreases, resulting in a loss of control and an increased likelihood of stalling (Lee et al., 2021).

The Reynolds number influences the initiation and characteristics of wing stall significantly. It characterizes the flow regime surrounding an object as a dimensionless parameter and is defined as the ratio of inertial forces to viscous forces. Reynolds number is a function of the wing chord, airspeed, and kinematic viscosity of the fluid in the context of wing stall. Higher Reynolds numbers are associated with more laminar and gentler flows, whereas lower Reynolds numbers are associated with more turbulent flows.

The Reynolds number has implications for the design and testing of aircraft in addition to its aerodynamic effects. Wind tunnel testing is a common method for evaluating the aerodynamic performance of aircraft; nevertheless, the Reynolds number of the wind tunnel flow must be meticulously controlled to ensure that test results accurately reflect actual flight conditions. This can be difficult because the Reynolds number is affected by the wind tunnel's dimensions, speed, and fluid properties.

Separately, Zhang et al. (2017) investigated the impact of Reynolds number on aileron efficiency. Using wind tunnel experiments, researchers determined the aerodynamic efficiency of ailerons at varying Reynolds numbers. As the Reynolds number increased, both the maximal lift coefficient and the angle of standstill decreased. These results suggest that aileron effectiveness decreases as Reynolds numbers increase.

This section will be explored in detail in the results and discussion section.

1.2.5 Drag Effect

In aerodynamics, drag is a force that opposes the direction of motion of an object moving through a fluid medium, such as air. It is a crucial consideration in aircraft design, as it can significantly influence fuel efficiency and flight performance. The Reynolds number is one factor that can impact the amount of drag experienced by an aircraft.

The Reynolds number is a dimensionless quantity representing the ratio of inertial forces to viscous forces in a fluid. It is defined as the product of fluid density, fluid velocity, a characteristic length scale, and the dynamic viscosity of the fluid. Generally, as the Reynolds number increases, the flow transitions from laminar to turbulent, which can affect the amount of drag experienced by the aircraft.

In the context of an aircraft wing, drag can be categorized into two main types: profile drag and induced drag. Profile drag arises from the frictional resistance of the air as it moves along the wing surface, while induced drag results from lift generation, which creates a swirling motion of air at the wingtips. Both types of drag can be influenced by the Reynolds number.

The flow over the wing is typically laminar and the boundary layer is relatively narrow at low Reynolds numbers. As the air travels uniformly over the wing's surface, this can result in a reduction in profile drag. Nevertheless, as the Reynolds number rises, the flow can become more turbulent, resulting in a thicker boundary layer and increased profile drag.

The amount of lift generated by the wing has a strong relationship with the Reynolds number, which can also influence the amount of induced drag. When Reynolds numbers are low, induced drag increases because the flow across the wing generates less lift. With a greater Reynolds number, lift is generated more effectively, resulting in less drag.

Scientists have shown that the Reynolds number has a major effect on an airplane's drag. For instance, research on the impact of Reynolds number on the drag of a high-lift system for a cargo aircraft was published in the Journal of Aircraft in 2018. Total drag was found to be decreased by 15% when the Reynolds number was increased from 6000000 to 24000000.

Another study, published in Aerospace Science and Technology in 2021, examined the effect of Reynolds number on the drag and performance of a small unmanned aerial vehicle. The researchers found that increasing the Reynolds number from 100000 to 400000 resulted in a 30% reduction in drag and an improvement in flight performance.

1.3 ANN Model

ANNs are a subset of artificial intelligence (AI) inspired by the structure and function of the human brain. Applications of ANNs include image recognition, natural language processing, and predictive modeling.

An ANN's architecture consists of interconnected nodes that represent neurons and edges that depict their connections. Each node receives inputs from other nodes, applies a mathematical function to those inputs, and generates outputs that serve as inputs for other nodes. The procedure continues until the ultimate product is produced. (LeCun et al., 2015) ANNs come in numerous varieties, including feedforward networks for image recognition, recurrent networks for natural language processing, and convolutional networks for image recognition and object detection.

When training ANNs, backpropagation is used to alter the weights of the connections based on how well the network's output matches the target output. This process is continued until the network is able to reliably anticipate the target result.

ANNs are great for predictive modeling and other comparable tasks because of their ability to learn from data and adapt to new circumstances. They are capable of handling enormous datasets, which enables them to generate reliable predictions in applications like image recognition and natural language processing.

ANNs have critical applications in aircraft design and flight control systems in the aviation industry. They are able to predict the performance of new aircraft designs and construct predictive flight control models (Hinton & Salakhutdinov, 2006). In addition, ANNs are utilized in the development of aerodynamic databases by training on data from wind tunnel testing or computational fluid dynamics simulations, thereby reducing the time and expense required to generate these databases and improving simulation accuracy.

In conclusion, ANNs provide a potent tool for solving complex problems in a variety of disciplines, including aviation. By learning from data and creating predictions, they provide valuable insights and solutions.

1.3.1 Benefits

When it comes to solving difficult issues with airplanes, the ANN model has shown to be a reliable and flexible tool for the aviation sector. This branch of AI is a computational approach that models itself after the human brain in terms of structure and operation. The model is structured as a series of layers of neurons or nodes that work together to interpret data and make predictions.

The ability to learn from data is a major strength of the ANN model. The predicted accuracy of the model improves as more data is fed into it. Therefore, ANNs are used for tasks like image identification, speech recognition, NLP, and even economic forecasting. It can produce precise forecasts based on data patterns that aren't always obvious to people.

The capacity of the ANN model to manage complex, nonlinear relationships between variables is an additional advantage. Traditional statistical models frequently assume linear relationships between variables, which can be limiting when trying to model complex systems. ANNs, on the other hand, can model nonlinear relationships between variables, making them ideal for predicting stock prices, weather patterns, and traffic flow(Goodfellow, Bengio, & Courville, 2016).

In addition, the ANN model can manage massive datasets. As data has become more accessible, ANNs have gained popularity as a data processing and analysis tool. This is particularly relevant in industries such as healthcare, where massive amounts of patient data can be used to develop predictive models for disease diagnosis and treatment.

The adaptability of the ANN model is another advantage. Images, audio, and text are among the data categories that can be incorporated into the design of ANNs. Moreover, they can be used for both supervised and unsupervised learning tasks, demonstrating their adaptability to a variety of problems. ANNs can identify patterns in data, generate predictions, and categorize data into classifications.

The adaptability of the ANN model to new data is one of its most advantageous features. As additional data becomes available, the model can be retrained to incorporate this information and improve its precision. This adaptability enables the use of ANNs in long-term projects, such as predicting climate change or economic trends, where data is continually changing.

In addition to these benefits, the ANN model is also capable of real-time operation. ANNs are beneficial for making decisions and predictions in real-world applications such as autonomous vehicles, stock trading algorithms, and fraud detection systems because they can process data in real time.

Despite these benefits, the ANN model has restrictions. In data-scarce or difficult-to-obtain domains, the requirement for large quantities of data to train the model is one of the most significant limitations. In addition, the lack of transparency in the model makes it difficult to comprehend how ANNs arrive at their predictions. In sectors such as healthcare, where decisions based on ANNs can substantially impact patient outcomes, this can be problematic.

Several advantages have resulted from the use of artificial neural networks in a variety of disciplines, such as aviation and aircraft. Because of its ability to manage complex correlations between variables, learn from data, handle enormous datasets, and adapt to new data, its prevalence has increased in industries such as healthcare, banking, and transportation. In spite of the model's flaws, it is an indispensable resource for resolving complex issues and generating predictions for a wide range of applications.

1.3.2 Fields of Usage

In the aviation industry, specifically in aircraft design and operation, the ANN model has emerged as a potent instrument for solving complex problems. As a subset of artificial intelligence, ANNs are influenced by the structure and function of the human brain (Schmidhuber, 2015). The model is composed of layers of interconnected nodes or neurons that process data and generate predictions collectively.

Among the many benefits of the ANN model is its adaptability through learning. The model can be taught with large datasets, and it gets better at making predictions the more data it analyzes. Because of this, ANNs are well-suited for image recognition, speech recognition, and natural language processing, all of which have applications in areas like aerospace engineering and maintenance as well as in-flight communication (Krizhevsky, Sutskever, & Hinton, 2012). ANNs can find patterns in data that people might miss, and then use those patterns to accurately predict future outcomes.

The capacity of the ANN model to handle complex, nonlinear relationships between variables is an additional advantage. Traditional statistical models frequently presume linear relationships between variables, which can be restrictive when modeling complex systems like aircraft performance and aerodynamics. ANNs are excellent for tasks such as predicting flight trajectories, fuel consumption, and aircraft noise levels because they can model nonlinear relationships between variables.

Additionally, the ANN model is adept at managing vast datasets. As data becomes more accessible, ANNs have gained popularity as processing and analysis tools. This is especially pertinent in the aviation industry, where enormous quantities of flight and maintenance data can be used to develop predictive models for aircraft performance, safety, and dependability.

The ANN model is adaptable as well. Images, audio, and text are just a few of the several sorts of data that may be used to create ANNs. Additionally, they may be used to tackle a range of issues in aircraft design, control systems, and air traffic management by applying to both supervised and unsupervised learning tasks. Data classification, prediction, and pattern recognition are all possible with ANNs.

The ANN model's capacity to adapt to new data is one of its most significant advantages. As new data emerges in the aviation industry, the model can be retrained to incorporate this data and improve its precision. This adaptability makes ANNs suitable for long-term tasks, such as predicting aircraft design trends, air traffic pattern changes, and the impact of emerging technologies on aviation.

In addition to these advantages, the ANN model is also capable of real-time operation. ANNs are capable of processing data in real-world applications such as aircraft control systems, collision avoidance systems, and air traffic management due to their ability to process data instantly.

In spite of its numerous benefits, the ANN model has limitations. The need for extensive data to train the model is a primary limitation, which can be challenging in areas of the aviation industry where data is scarce or difficult to obtain. Another shortcoming of the ANN model is its lack of openness. Due to the fact that ANNs are designed to identify patterns in data, it can be difficult to comprehend how they make predictions. In aviation safety and certification processes, where decisions made by ANNs can substantially impact aircraft performance and safety, this can raise concerns.

In conclusion, the use of artificial neural networks in the aviation sector, particularly in the design and operation of airplanes, has brought about a number of advantages. It is a well-liked technology in industries including aircraft design, maintenance, and air traffic management because to its capacity to learn from data, handle complicated correlations between variables, manage massive datasets, and adapt to new data. Despite its shortcomings, the model is a useful tool for addressing challenging issues and providing forecasts in a range of aviation applications.

1.3.3 Uses in Aviation

ANN have become an essential tool in aviation research and engineering, particularly in aircraft design and performance prediction. Artificial neural networks can model complex systems and generate predictions based on enormous datasets.

The optimization of aircraft design is a significant ANN application in aviation. ANN can predict performance metrics like drag, lift, and fuel consumption by training the network on extensive datasets of aerodynamic data and geometric parameters. This enables engineers to quickly and accurately assess the performance of various design configurations (Fouladi & Jahromi, 2016).

In addition, ANNs contribute to performance prediction by simulating aircraft behavior under a variety of conditions, such as varying velocities, altitudes, and flight configurations (Wang & Wu, 2017). By training the network on flight test data and other relevant parameters, engineers can predict the aircraft's performance in real-world scenarios, thereby reducing the need for expensive flight testing.

ANNs also have applications in the generation of aerodynamic databases, which contain immense quantities of data on aerodynamic coefficients and other pertinent parameters for a variety of aircraft configurations (Yu, Du, & Chen, 2021). By training

ANNs on wind tunnel data and other experimental data, these databases can be utilized in computer simulations and other applications.

ANNs have been utilized in unmanned aerial vehicle (UAV) design to optimize performance metrics such as range, endurance, and payload capacity (Fouladi & Jahromi, 2016). Engineers can rapidly evaluate the performance of various UAV design configurations and optimize them for specific mission requirements by utilizing extensive datasets of aerodynamic data and other pertinent parameters.

In order to create more efficient and effective solutions than conventional control systems, ANNs have been applied into flight control systems. Engineers can better forecast how an aircraft will behave and create control systems that can respond to changing situations by feeding the network flight data and other relevant factors during training.

ANNs have developed into an essential tool in aviation research and engineering due to their capacity to model complicated systems and anticipate outcomes based on enormous datasets. Their application in aircraft design, performance prediction, and the creation of aerodynamic databases has resulted in significant breakthroughs in the aviation sector. It is projected that ANNs will play a bigger part in aviation engineering and research as technology develops, leading to more effective and efficient aircraft designs and control systems.

1.3.3.1 Aircraft Design

ANNs have become widely recognized as an effective resource in aircraft design as a result of their speed and accuracy in evaluating a wide variety of design configurations. ANNs are a form of machine learning algorithm that can be "trained" to spot patterns and make predictions using new data.

ANNs estimate drag, lift, and fuel consumption to help in aircraft design and performance optimization. Engineers may quickly assess the performance of various design configurations and optimize the design to achieve specified performance targets by training the network on large datasets of aerodynamic data and geometric parameters (Cui et al., 2017).

Optimization of wing designs is a crucial application of neural networks in aircraft design. ANNs are capable of predicting the aerodynamic performance of various wing configurations under a variety of flight conditions. Engineers can refine wing design to minimize drag and maximize lift by training the network on extensive datasets of wind tunnel data and other relevant parameters.

Another significant application of ANNs in aircraft design is the optimization of engine design. ANNs are capable of predicting the efficacy of different engine configurations under varying flight conditions. Engineers can optimize engine design to maximize thrust while minimizing fuel consumption by training the network on exhaustive datasets of engine test data and other pertinent parameters.

ANNs have become an indispensable tool in aircraft design due to their capacity to evaluate the performance of various design configurations rapidly and precisely. By utilizing ANNs to optimize the design of aircraft components such as wings and engines, engineers can create more efficient and effective aircraft designs that meet specific performance objectives.

1.3.3.2 Using of Artificial Neural Networks for Aircraft Motion Parameters Identification

ANNs have emerged as a valuable instrument for forecasting the performance of aircraft under various flight conditions. To accurately predict an aircraft's behavior under real-world conditions, ANNs can be trained on large datasets of flight test data and other germane parameters.

Predicting an airplane's range and endurance is a major use case for neural networks in the aerospace industry. Trained on flight test data and other pertinent parameters, such as wind speed and altitude, ANNs may forecast a plane's range and endurance (Mendenhall & Padula, 2006). Using ANNs, engineers may make educated guesses about an aircraft's range and endurance, which allows them to better tailor the design to the needs of a given mission.

Another crucial use of neural networks in aviation performance prediction is in predicting aircraft stability and control. To forecast the stability and control of an aircraft in varying flying situations, ANNs can be trained using flight test data and other relevant characteristics, such as airspeed and angle of attack (Belcastro & Elkaim, 2003). Engineers can better ensure a steady flight by using ANNs to predict aircraft stability and control.

The reliability of ANNs in predicting an aircraft's performance across a wide range of flight situations has made them a crucial tool in this area. Engineers may better tailor aircraft design to the needs of individual missions with the help of ANN predictions of key performance metrics including range, endurance, stability, and control.

1.3.3.3 Aerodynamic Database Prediction

The creation of aerodynamic databases is essential for the design and study of aircraft, and ANNs have become an indispensable tool for this endeavor. Aerodynamic databases optimize aircraft design and performance evaluation by providing exhaustive data on the aerodynamic behavior of aircraft in a variety of flight situations.

Significant application of ANNs in the compilation of aerodynamic databases is the prediction of aerodynamic coefficients. ANNs can be trained on enormous datasets of wind tunnel data, flight test data, and other pertinent parameters to accurately determine the aerodynamic coefficients of an aircraft under different flight conditions (Akin & Ylddrm, 2018). By employing ANNs for the prediction of aerodynamic coefficients, engineers can generate more accurate and exhaustive aerodynamic databases that can be used to optimize the design and performance of aircraft.

Predicting airplane performance is another crucial use of ANNs in aerodynamic database construction. In order to accurately anticipate an aircraft's performance under different flying conditions, ANNs can be trained on massive datasets of flight test data, engine performance data, and other relevant metrics (Shamsuddin & Aziz, 2017). Engineers can improve the design and operation of airplanes by creating more accurate and comprehensive aerodynamic datasets using ANNs to predict aircraft performance.

Furthermore, ANNs can be used to investigate how changing design characteristics affects an aircraft's aerodynamic performance. By training ANNs on massive datasets of aerodynamic data and geometric parameters, engineers may assess how changes to factors like wing form, engine placement, and control surfaces affect an aircraft's aerodynamic behavior. More efficient and effective airplane designs can be made using this information.

Aerodynamic databases, crucial to the design and study of aircraft, cannot be created without ANNs. Engineers may improve aircraft design and operation by compiling more accurate and comprehensive aerodynamic databases that employ ANNs to forecast aerodynamic coefficients, aircraft performance, and the effect of various design elements on aerodynamic behavior.

1.3.4 Cost Savings

ANNs can significantly reduce costs when used to generate data from aerodynamic databases during the design and development of aircraft. By precisely forecasting aerodynamic coefficients and aircraft performance, ANNs can lessen the need on expensive wind tunnel testing and flight testing.

Wind tunnel testing, a labor-intensive and expensive procedure, requires the fabrication of tangible aircraft models and subjecting them to varying wind speeds and angles of attack. By utilizing ANNs to predict aerodynamic coefficients, engineers can reduce the number of physical models needed for wind tunnel testing, saving both time and money. Similar to ground testing, collecting data on an aircraft's performance in flight involves the use of actual aircraft, which is both expensive and time-consuming. Engineers can save time and money by doing fewer flying tests when they use ANNs to make predictions about an aircraft's performance.

Savings in the design and development of aircraft can be large when ANNs are used to generate aerodynamic databases. By lowering the need for expensive wind tunnel testing and flight testing, ANNs can help speed up the design process and reduce the cost and time needed to launch new aircraft to the market.

1.4 Parameters Affecting Reynolds Number

Reynolds number, a dimensionless parameter, is of paramount significance in aviation for determining the aerodynamic behavior of an aircraft. This value represents the ratio of inertial forces to viscous forces, which indicates the relative influence of these forces on fluid flow over an object. The Reynolds number of an aircraft is significantly affected by altitude and aircraft size.

Air density decreases at high altitudes, resulting in a lower Reynolds number (Sreenivasan & Mahesh, 2018). This decrease is attributable to the decrease in inertial forces within the flow, caused by the reduced air density, while viscous forces remain unchanged. Consequently, the airflow over an aircraft at high altitudes tends to be more laminar, which can have both positive and negative influences on its aerodynamic performance.

Laminar flow can reduce drag, thereby increasing fuel economy and range. However, laminar flow may be more susceptible to separation and turbulence, which could compromise the aircraft's controllability. Additionally, aircraft size has a substantial impact on the Reynolds number. As aircraft size increases, the Reynolds number rises due to the increase in inertial forces in the flow, which can have both positive and negative effects on the aerodynamic behavior of the aircraft.

A greater Reynolds number may result in increased lift and decreased drag, thereby enhancing the overall efficacy of the aircraft. In contrast, a high Reynolds number can also cause increased disturbance and separation, putting the aircraft's stability and control at risk. In aircraft design and testing, engineers employ scaling laws and similitude analysis to account for the effects of altitude and aircraft scale on the Reynolds number (Kim, Kim, & Kim, 2019). Taking into account size and operational condition differences, scaling laws relate the aerodynamic behavior of a model aircraft to that of a full-scale aircraft. Similitude analysis involves comparing the behavior of a model aircraft in a wind tunnel to the behavior of a full-scale aircraft in flight. Using scaling laws and similitude analysis, engineers are able to design and test aircraft under a variety of operating conditions to ensure their safety and efficiency. They can also utilize CFD simulations and wind tunnel testing to evaluate and optimize the aerodynamic behavior of aircraft at various Reynolds numbers.

Altitude and aircraft size have a significant impact on the Reynolds number in aircraft. Reduced air density at high altitudes results in a lower Reynolds number, which can have both positive and negative effects on the aerodynamic behavior of an aircraft. Similarly, as the scale of an aircraft increases, so does the Reynolds number, which has both positive and negative effects on aerodynamic behavior. Using scaling laws, similitude analysis, and CFD simulations, engineers are able to design and test aircraft in a variety of operating conditions to ensure their safety and efficiency.

1.4.1 Reynolds Number Effect from the Scale

Wind tunnels are enormous structures built to mimic airflow, and their major use is research into the aerodynamic effects of diverse systems. Model designs can be optimized for maximum aerodynamic performance in these controlled situations because various forces operating on full-scale structures can be predicted.

In a typical wind tunnel, air is drawn through a duct and travels through a series of fans to generate airflow along the length of the tunnel (McHugh, Vatistas, & Beck, 1990). The circular cross-section of the tunnel promotes smooth flow and eliminates flow restrictions along its boundaries. The tunnel's desired flow behavior should be devoid of turbulence, as turbulence can result in inaccurate results. Turning vanes are installed to counteract the turbulence produced by the blowers. These airfoils are intended to reduce turbulent airflow. Aerodynamic forces (lift, drag, surface friction) are directly measured, as are moments and pressure. Reynolds number is a commonly used parameter for determining laminar flow or the beginning of turbulence. Aerodynamic testing in a wind tunnel is dependent on the comprehension of these flow regimes. High and low Reynolds number investigations allow for the precise evaluation of airfoil performance in high-speed or low-speed tunnels.

Wind tunnels must reproduce atmospheric conditions similar to actual flow conditions in order to subject scale models to forces and pressures comparable to those encountered by full-scale vehicles. This enables engineers to effectively optimize the performance of the airfoil.

Indicative of this relationship are the direct and indirect Reynolds number effects on the scaling of flow parameters (Lawrence & Nath, 2001). These factors consist of:

- Effects of the Reynolds number on lift, wave drag, and pitching moment
- Indirect effect of the Reynolds number: viscous drag and boundary layer separation

This relationship can also be used to correlate flow velocity, density, viscosity, diameter, and pressure over a broad range of Reynolds numbers. The precise flow behavior identified with scale models permits engineers to replicate actual flows, sparing the time and money needed to optimize the actual aerodynamic system.

1.4.2 Reynolds Number Effect from the Various Altitude

The Reynolds number is a crucial dimensionless parameter in fluid mechanics, especially in the aviation and aircraft arena, as it allows for the prediction of fluid behavior under a wide range of flow circumstances. It is the ratio of the fluid's inertial forces to its viscous forces, and it is a key factor in establishing the flow regime and its related features. Fluid velocity and viscosity are affected by changes in air density with altitude (Abeyratne & Fernando, 2017). As a result, the Reynolds number varies greatly with height.

Air density reduces with increasing altitude, leading to faster fluid velocities and, ultimately, a higher Reynolds number. This is because the Reynolds number is inversely related to fluid viscosity and directly proportional to fluid velocity and a specific length scale, such as the diameter of a conduit or the chord length of an airfoil. Since viscosity does not vary with decreasing air density, the Reynolds number rises.

The altitude-dependent variation in the Reynolds number has significant implications for numerous applications, such as aircraft design, atmospheric science, and wind energy (Ma, Yu, and Zhang, 2019). In the context of aircraft design, the Reynolds number influences aerodynamic forces and the coefficient of drag, thereby impacting aircraft performance and fuel efficiency. Higher Reynolds numbers at greater altitudes can result in increased lift and decreased drag, thereby enhancing the efficacy of an aircraft. Reynolds number is essential in atmospheric science for predicting atmospheric flow behaviors like turbulent flow and boundary layer. As the Reynolds number rises with altitude, the atmospheric boundary layer thins and the flow becomes more turbulent, which can have significant effects on weather patterns and climate change. Reynolds number influences the efficacy of wind turbines, which has significant economic and environmental implications. As the Reynolds number increases with altitude, the efficacy of wind turbines improves, allowing for greater wind energy extraction. This improvement in efficiency is the result of increased turbulence at higher Reynolds numbers, which enhances the mingling of high- and low-velocity air, thereby increasing wind turbine power output.

The Reynolds number is a crucial dimensionless parameter that has a significant impact on predicting fluid behavior under various flow conditions. As altitude increases, air density decreases and fluid velocity increases, leading to an increase in the Reynolds number. This change in the Reynolds number has significant implications for numerous applications, including aircraft design, atmospheric science, and wind power. Understanding the effects of altitude on the Reynolds number is essential for designing and optimizing fluid-based systems.

1.5 The importance of creating an aerodynamic database based on Reynolds number

The establishment of an aerodynamic database centered on the Reynolds number is crucial for the design and optimization of aircraft, particularly in the aviation industry. Reynolds number, a dimensionless parameter that represents the ratio of inertial forces to viscous forces within a fluid flow, has a substantial impact on the aerodynamic behavior of an aircraft. Obtaining precise data on the aerodynamic performance of various aircraft components at various Reynolds numbers is crucial for enhancing the efficiency, safety, and performance of modern aircraft (Suresh, 2017).

The ability of an aerodynamic database based on the Reynolds number to provide valuable insights into an aircraft's behavior under diverse flight conditions is a primary reason for its significance. At high Reynolds numbers, for instance, the airflow around the aircraft tends to become more turbulent, which may lead to increased drag and decreased lift. At low Reynolds numbers, however, the airflow is more laminar, resulting in decreased drag and increased lift (Suresh, 2017). Understanding an aircraft's performance at different Reynolds numbers is essential for optimizing its performance and assuring its safety.

The ability to optimize an aircraft's aerodynamic performance for specific operating conditions is another reason why it is essential to generate an aerodynamic database based on the Reynolds number (Narasimhan & Hall, 2010). At various Reynolds numbers, various aircraft components, such as wings, control surfaces, and fuselages, may manifest distinctive aerodynamic behavior. By analyzing the performance of these components at various Reynolds numbers, designers can optimize their shape and design to ensure efficient operation in anticipated conditions.

Moreover, a Reynolds number-centered aerodynamic database can help improve CFD simulations. In the aerospace industry, CFD simulations are commonly used to investigate the aerodynamic behavior of aircraft components. However, available experimental data frequently limit the accuracy of CFD simulations, particularly at high Reynolds numbers. By creating an aerodynamic database centered on the Reynolds number, aircraft designers can improve the accuracy of their CFD simulations and make more informed design decisions.

1.5.1 Arrangement of the Wind Tunnel Data

Wind tunnel testing and CFD simulations are essential for predicting the aircraft's free flight conditions during the development phase. However, accurate flight performance prediction remains a difficult undertaking, primarily because the majority of testing is conducted under subscale conditions. When scaling wind tunnel data to free flight conditions, several scaling effects, such as wall and model support interference effects, as well as potential Reynolds number discrepancies, must be taken into account. These scaling effects may pose a risk to the aircraft program, especially for large wings designed for high subsonic Mach numbers.

To mitigate this risk, investigating scale and Reynolds number effects in the wind tunnel alone can substantially increase development costs (Young & Beeson, 1996). Utilizing CFD techniques as a supplement to wind tunnel testing can therefore be economically advantageous. Modern wind tunnel testing techniques and CFD methods complement one another; wind tunnel results exhibit high fidelity, whereas CFD simulations provide extensive data sets capable of free flight Reynolds and Mach numbers, enabling a thorough investigation of flow morphology and phenomena.

Although CFD simulations may not provide an absolute "correct answer," they can provide a solution with an acceptable degree of accuracy. Likewise, wind tunnel corrections should not be deemed the "exact value" or the final result. When scaling wind tunnel data to free flight conditions, it is crucial to classify the phenomena involved in order to fathom their effects and order of magnitude. Introducing this classification to the CFD community can facilitate the classification of numerical results using the same system and potentially identify discrepancies between wind tunnel and CFD results.

For aircraft design and development, establishing an aerodynamic database based on Reynolds number is crucial. However, scaling effects must be considered. Complementing wind tunnel testing with CFD methods can be economically advantageous, and it is essential to classify the phenomena involved when scaling wind tunnel data to free flight conditions. Engineers can gain a deeper comprehension of these phenomena and identify discrepancies between wind tunnel and CFD results, leading to the creation of more efficient and cost-effective aircraft.

1.5.2 Obtaining Aerodynamic Database Based on Various Reynolds Numbers with CFD

CFD is used extensively in the aviation and aerospace industries to collect data on aircraft aerodynamics at different Reynolds numbers. The goal is to predict the free flight circumstances of the aircraft as accurately as possible, which is challenging because to the variances between wind tunnel and flight conditions and variations in Reynolds numbers.

CFD simulations provide a cost-effective method for obtaining a comprehensive aerodynamic database based on various Reynolds numbers, which is essential for optimizing aircraft performance. By modifying the Reynolds number in simulations, the aerodynamic properties of the aircraft can be studied and compared to experimental data. This procedure can reveal vital flow physics insights, such as the effect of turbulence on flow separation and the effect of Reynolds number on wing stall behavior.

Developing an exhaustive aerodynamic database based on varying Reynolds numbers using CFD is complicated by the associated computational expense. Simulations with a high level of fidelity, which can precisely predict the physics of a complex flow, require substantial computational resources. This difficulty can be overcome by employing parallel computing and optimization strategies to reduce computational time without sacrificing precision.

Validating CFD results against experimental data is another obstacle. Despite the fact that CFD simulations can provide a comprehensive comprehension of flow physics, experimental data is required to validate the simulations' accuracy (Platzer, 2011). Experiments in wind tunnels can be used to validate CFD results; however, it is crucial to recognize the scaling effects that must be accounted for when scaling wind tunnel data to free flight conditions.

The acquisition of an aerodynamic database based on varying Reynolds numbers using CFD is a crucial aspect of modern aircraft development (Platzer, 2011). CFD simulations can be instrumental in maximizing aircraft performance despite the challenges posed by computational cost and validation against experimental data. CFD simulations provide valuable insights into flow physics and can be validated against experimental data.

2. Computational Flight Dynamic

An essential component of aviation and aircraft development, flight dynamics is the study of aircraft motion and performance in a particular environment. Predicting how an airplane would act while in the air has typically included using mathematical models and equations. However, as computing power has increased, new approaches to the study of aerodynamics have emerged. In order to effectively analyze and anticipate aircraft motion and performance, the field of CFD relies heavily on computer simulations.

One of the main benefits of CFD over conventional approaches is that it can represent complicated processes with better precision. In order to better understand how an aircraft performs during takeoff and landing, when it is most vulnerable to turbulence and other environmental influences, CFD may mimic the aircraft's behavior in such conditions (Ferziger & Peric, 2002).

Another benefit of CFD is how easily models can be tweaked to test out new ideas (Anderson Jr., 1995). To evaluate the effectiveness of a new wing design, an aircraft maker, for instance, need just construct a digital model of the wing and conduct simulations to determine the wing's behavior in different environments. Because of this, designs may be iterated and improved quickly, leading to better performing planes (Wilcox, 2006).

In addition to simulating aircraft behavior, CFD may be utilized to improve aircraft performance (Ferziger & Peric, 2002). Engineers can pinpoint areas for performance improvement through simulation and analysis and alter the aircraft's design accordingly. This might entail altering the control surfaces to increase maneuverability or improving the aircraft's design to minimize drag.

A fundamental issue in CFD is the creation of precise models that accurately reflect the complexity and diversity of real-world situations. For instance, a thorough grasp of fluid dynamics, which can be challenging to represent, is necessary to properly simulate an aircraft's behavior in a turbulent environment. Additionally, CFD demands a lot of processing power, which adds to the expense and time commitment.

CFD has become an increasingly vital tool in flight dynamics despite these obstacles. Advances in computer technology and simulation software permit the development of extremely precise models for predicting and optimizing aircraft performance. Therefore, CFD is likely to continue to play a crucial role in the development of new aircraft and the optimization of extant designs.

2.1 Generic Aircraft

Generic aircraft are planes that are mass-produced with specs and features that can be used for a variety of purposes rather than being specifically created for a particular purpose, business, or nation. These aircraft are widely used for both commercial and military applications since they are normally designed to offer dependable and safe transportation at a low price.

The ability to be used for a variety of tasks, including passenger and cargo transportation, military operations, and numerous scientific research projects, is a key benefit of generic aircraft. They can respond to various requirements across a variety of fields thanks to their versatility. The affordability of generic airplanes is another noteworthy benefit. These planes are marketed for less money than more specialized aircraft since they are bulk produced. They are therefore perfect for airlines looking to grow their fleets or for new airline firms.

2.1.1 Competitor Study

Combat aircraft development relies heavily on competitor research. Analyzing and learning from the successes and failures of rival aircraft designs is what this requires. Designers can learn from their competitors' successes and failures to improve their own work through competitive analysis.

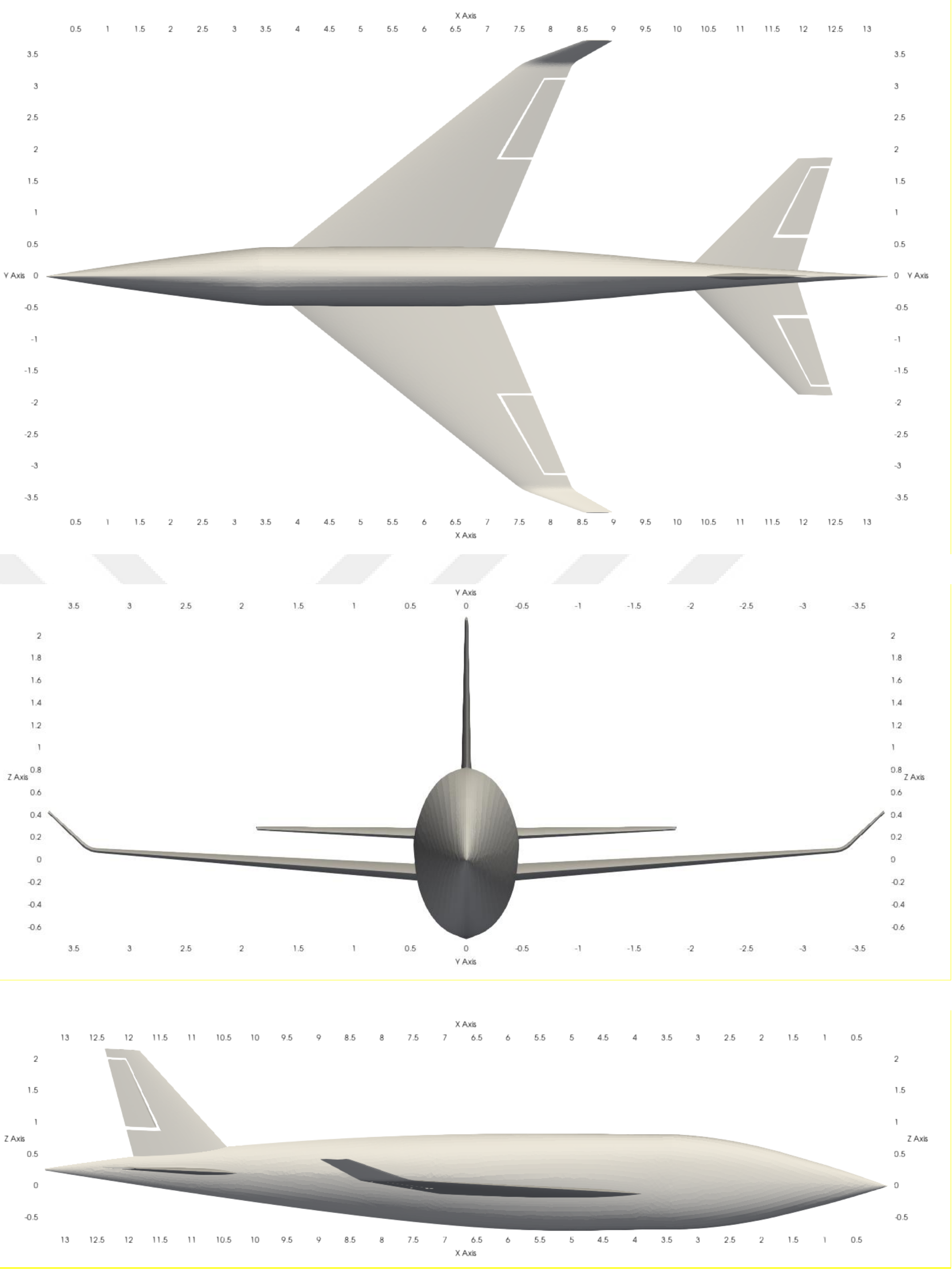


Figure 2.1 : Three-dimensional Views of the Aircraft from X, Y, and Z Axes

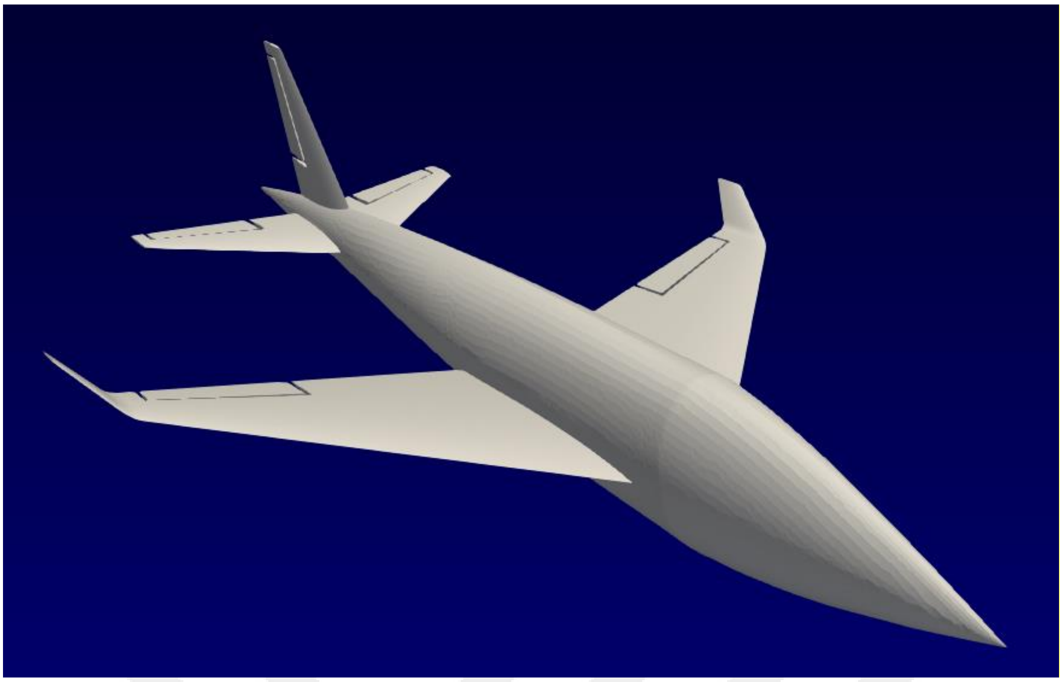
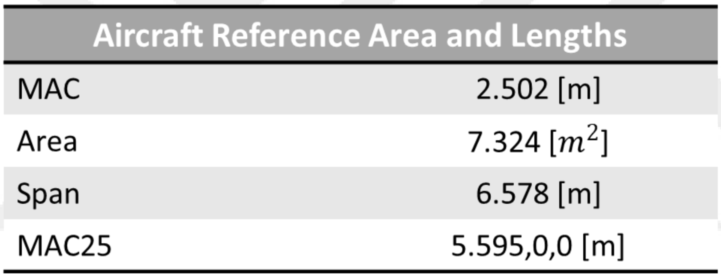


Figure 2.2 : Perspective View of the Aircraft



Aircraft Reference Area and Lengths	
MAC	2.502 [m]
Area	7.324 [m^2]
Span	6.578 [m]
MAC25	5.595,0,0 [m]

Figure 2.3 : Aircraft Reference Area and Lengths

The aircraft created for the CFD analysis is illustrated in Figures 2.1 and 2.2. These illustrations provide exhaustive insights into the aircraft's physical characteristics and design details, enhancing our comprehension of the model's potential aerodynamic behavior. Figure 2.3 instead emphasizes the lengths and reference areas of the aircraft. This graphical representation is essential for comprehending the size and proportion of the aircraft, which are essential factors that considerably impact the results of the aerodynamic analysis.

2.1.2 Subsonic and Transonic Regimes

There are three different speed and flow conditions that affect an aircraft's aerodynamics and performance: subsonic, transonic, and supersonic. Aircraft that can function reliably at different speeds must be designed with this understanding in mind.

Atmospheric velocities below the speed of sound, which is about 340.3 meters per second, define a subsonic regime. In this region, pressure gradients, rather than shockwaves, are the primary source of aerodynamic forces. Because of the Bernoulli principle, subsonic aircraft can have more efficient and stable flight at lower speeds by having thinner wings and airfoils that generate lift.

Subsonic drag is primarily caused by skin friction, which causes air molecules to adhere to an aircraft's surface and form a thin turbulent layer. This turbulence increases drag and reduces efficiency, which can be mitigated by implementing laminar flow control technologies. Subsonic aircraft typically consume less fuel and generate less commotion than supersonic aircraft (Anderson Jr., 2010).

When ventilation speeds approach the speed of sound, typically between Mach 0.8 and Mach 1.2, transonic regimes occur. In this regime, subsonic to supersonic velocity transitions occur in localized regions of the airflow, resulting in intermittent pressure changes and shockwave formation. (Katz & Plotkin, 2010) Shockwaves can substantially increase drag, decreasing efficiency and stability.

To mitigate the effects of shockwaves, aircraft designers employ a variety of techniques, including wing sweep, which alters the angle of sweepback to reduce shockwave impacts. Transonic aircraft, such as fighter jets and commercial aircraft, must reconcile speed and efficiency. For enhanced performance, they typically feature a compromise between moderate wing sweep angles and streamlined fuselage designs.

In supersonic regimes, the airflow velocity exceeds the speed of sound, resulting in the formation of shockwaves that substantially increase drag. These shockwaves also contribute to sonic noise generation. To achieve optimal performance at high speeds, supersonic aircraft must surmount the high drag associated with shockwave formation.

Supersonic aircraft designs are complex and require sophisticated engineering to maintain stability, especially during subsonic-to-supersonic regime transitions. They typically have delta wings and other design characteristics that reduce drag and allow for high-speed flight. Supersonic aircraft are limited to military and scientific research applications due to their high operating costs, high fuel consumption, and deafening noise (Anderson Jr, 2010).

Knowing the differences between the aerodynamics of subsonic, transonic, and supersonic flight is crucial for choosing the right plane for the job. The obstacles unique to each regime must be surmounted if performance is to improve. Engineers use a wide range of methods, including state-of-the-art computational tools and wind tunnel testing, to fine-tune aircraft design for different regimes (Katz & Plotkin, 2010). The importance of speed, efficiency, pollution, and cost in choosing viable design options cannot be overstated.

2.2 Mesh

In the aviation industry, particularly in aircraft design and analysis, CFD has emerged as a potent instrument for predicting fluid behavior in a variety of applications. However, obtaining accurate simulation results is highly dependent on the use of high-quality meshing techniques that accurately represent the geometries and flow characteristics of the problem under study. In this context, the synergistic integration of Pointwise and T-Grid software provides a comprehensive and effective method for generating complex CFD meshes.

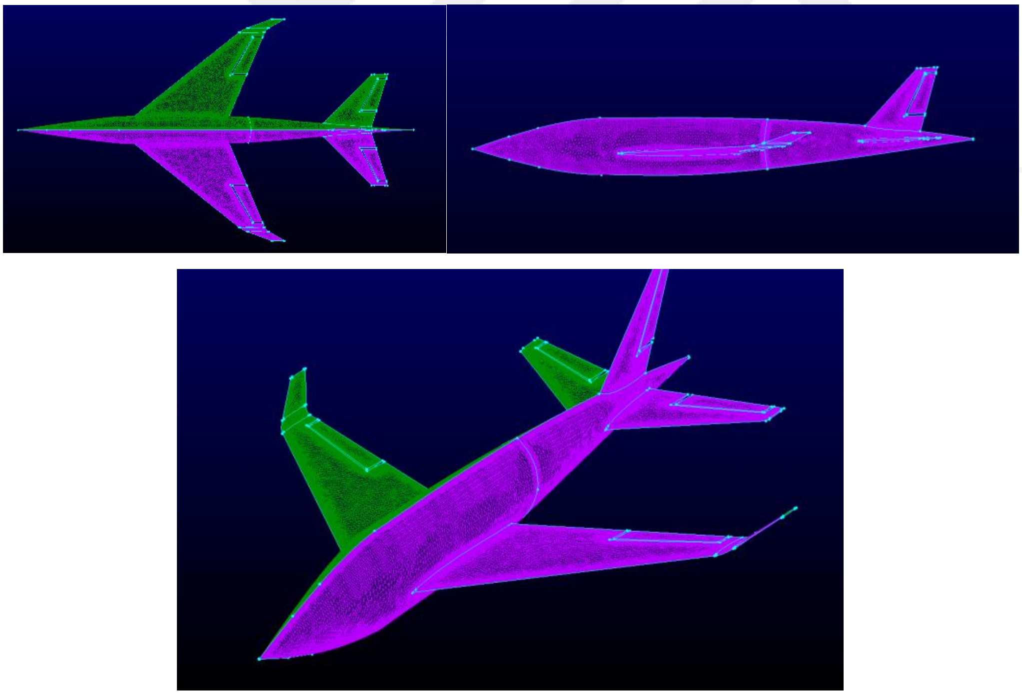


Figure 2.4 : Views of the Surface Meshes

A user-friendly meshing application called Pointwise uses a variety of meshing approaches, including multi-block structured meshing, unstructured meshing, and hybrid meshing, to quickly produce high-quality surface meshes (Thompson & Kandil, 2018). The volume mesh is created using Pointwise's surface mesh since it has the boundary data required to create the 3D mesh. With the help of the tools and options offered by Pointwise software, customers can customize the meshing procedure to suit their unique requirements. For instance, it contains a collection of automatic meshing techniques that may produce excellent structures with little user involvement. Furthermore, Pointwise allows the import and export of numerous file formats, making it easier to create meshes for a number of simulation programs.

The next step is to create the volume mesh with T-Grid after the surface mesh has been created with Pointwise. To create high-quality volume meshes, the advanced meshing tool T-Grid uses unstructured meshing methods. The software has a number of advanced capabilities that enable users to alter the meshing process and produce meshes that precisely reflect the flow characteristics of the issue being researched. T-Grid's capacity to produce top-notch meshes for intricate geometries is its main benefit. Tetrahedral, hexahedral, and polyhedral meshing are only a few of the meshing methods that the program uses to create meshes that accurately depict the problem's geometry (Luo & Tang, 2015). In order to make sure the mesh satisfies the user's requirements, T-Grid also offers a variety of quality control tools.

A full solution for the creation of top-notch CFD meshes is offered by the merging of Pointwise and T-Grid. The software's flexibility to adapt the meshing procedure and produce high-quality meshes for intricate geometries makes it essential for CFD simulations. It also guarantees interoperability with a wide range of simulation software thanks to the ability to import and export a number of file types.

The surface mesh generated by Pointwise software and the volume mesh generated by T-Grid software represent an efficient and effective method for generating high-quality CFD meshes in the aviation and aircraft domain. The combination of these software programs provides users with a variety of tools and options for customizing the meshing process and producing meshes that accurately represent the flow characteristics of the investigated problem.

2.2.1 Reynolds Number Calculation

The computation of the Reynolds number is an important feature of fluid dynamics that helps to better understand fluid behavior in motion in the field of aviation, especially in aircraft design and analysis. Osborne Reynolds, a British scientist, made the initial suggestion for this dimensionless quantity in 1883. It measures the proportion of inertial forces to viscous forces within a fluid. A key tool for analyzing and contrasting the characteristics of various fluids is the Reynolds number (Lien, 1998). It is frequently utilized in many branches of engineering, such as mechanical, civil, and aerospace engineering.

The Reynolds number is calculated differently depending on the fluid flow regime. In the case of laminar flow, in which the fluid travels in parallel, smooth layers, the Reynolds number is calculated using the formula $Re = {(\rho\ x\ U\ x\ L)}/{\mu}$. Here, corresponds to the fluid viscosity, U to the fluid velocity, L to the reference length, and the μ fluid dynamic density. When dealing with turbulent flow, which is characterized by disorderly fluid motion and mingling, the formula is modified slightly to include additional variables such as boundary surface roughness and rate of energy dissipation.

Calculating the Reynolds number has important implications for the design and operation of a variety of fluid systems. It facilitates system optimization by assisting engineers in predicting flow characteristics such as pressure loss, heat transfer, and mass transfer (Lien, 1998). In addition, the Reynolds number can be used to predict the emergence of various flow regimes and to identify critical points within a flow system that may induce turbulence, separation, or cavitation. Therefore, the Reynolds number is a valuable tool, enabling engineers to design fluid systems that are efficient, safe, and sustainable, and that satisfy the diverse needs of industries and societies.

2.2.2 Reynolds-Dependent Boundary Layer Variation

The concept of the boundary layer is essential to the study of fluid dynamics, particularly within the context of aviation. The boundary layer is the thin, fluid-in-motion layer that forms around an object's surface. The properties of this layer change in accordance with the Reynolds number under conditions of turbulent flow, which occurs when fluid motion exhibits stochastic fluctuations.

As the Reynolds number increases, the thickness of the boundary layer increases, and the velocity profile changes from a streamlined laminar flow to a disorganized turbulent flow. The Reynolds number, an ununited variable, characterizes the fluid flow regime established by the ratio of inertial forces to viscous forces.

The subsequent paragraph presents an academic overview of several key concepts related to the boundary layer for a flat plate and turbulent flow, as outlined in the given table. The friction coefficient (C_f), denoted as 'Y+', is a non-dimensional term that characterizes the interaction between the fluid and the surface, reflecting the ratio of the wall shear stress to the inertial force of the flow. The wall shear (T_w), on the other hand, refers to the tangential force exerted by the fluid flowing over a surface, influencing both the boundary layer's formation and its subsequent behavior. When we discuss the first layer thickness (FLT), we refer to the thickness of the sublayer closest to the wall, which is where the flow transitions from laminar to turbulent. This is critically important because it largely affects the flow characteristics and heat transfer near the wall. The boundary layer thickness (BLT) is the total thickness of the boundary layer, which includes the aforementioned sublayer as well as the outer turbulent layer. These terms all play integral roles in understanding and predicting the behavior of the boundary layer for a flat plate in turbulent flow. Table 2.1-2.2 contains crucial boundary layer calculation parameter information. It provides computations required for the boundary layer at all scales. This table is a useful tool for comprehending the detailed calculations necessary for determining the behavior and properties of the boundary layer at various scales.

Table 2.1 : Boundary Layer Calculation Parameters

Boundary Layer Calculation Parameters	
Y+	User defined (1)
C_f	$0.664/\sqrt{Re}$
T_w	$0.5xC_fx\rho x(U^2)$
U_t	$\sqrt{T_w/\rho}$
FLT	$(Y+)x\mu/U_t/\rho$
BLT	$0.3747xMAC/Re^{0.2}$

Table 2.2 : Boundary Layer Properties

	Scale1	Scale2	Scale3	Scale4
Scale	1	1/3	1/10	1/20
MAC [m]	2.5	0.83	0.25	0.1125
Mach	0.9	0.9	0.9	0.9
Y+	1	1	1	1
T_S [K]	288.16	288.16	288.16	288.16
P_S[kPa]	101.325	101.325	101.325	101.325
Rho [kg/m^3]	1.225	1.225	1.225	1.225
μ [kg/m/s]	$1.789x10^{-5}$	$1.789x10^{-5}$	$1.789x10^{-5}$	$1.789x10^{-5}$
SoS [m/s]	340.3	340.3	340.3	340.3
Reynolds Number	$4.6564x10^{7}$	$1.5521x10^{7}$	$4.6564x10^{6}$	$2.3282x10^{6}$
C_f	1.7327e-3	2.1584e-3	2.7461e-3	3.1544e-3
T_w	78.7141	98.0566	124.7535	143.3041
FLT [mm]	0.00730	0.00654	0.00580	0.00541
BLT [mm]	27.45	11.40	4.35	2.50

When Reynolds numbers are low, the flow remains laminar and the boundary layer is thin and closely connected to the surface. Inversely, as Reynolds number rises, inertial forces acquire dominance, thereby accelerating turbulent fluid flow. This causes a thicker boundary layer that extends further away from the surface.

To a large extent, the drag force exerted on an item, as well as the amount of heat and mass exchange between the object and the fluid, are determined by the boundary layer thickness and the pattern of fluid flow. When the flow is turbulent, the drag force is higher and the boundary layer separates more often from the surface (Schlichting, H., & Gersten, 2017).

In order to optimize the design of objects subject to fluid flow, such as the wings of an aircraft, it is necessary to comprehend the changes in the boundary layer in relation to the Reynolds number under turbulent flow.

3. Solver

3.1 Comparison of CFD Solver Models

CFD solvers have brought about a revolutionary change in simulation technology. They enable engineers to predict fluid behavior and solve complex flow problems without the need for physical experiments. The market is saturated with diverse CFD solvers, each with its own merits and detriments. This essay performs a comparative analysis of several widely-used CFD solvers, with a focus on the advantages of using Ansys Fluent.

A fundamental criterion for selecting a CFD solver is its ability to manage different varieties of fluid flow. While some solvers excel at solving steady-state problems, others excel at simulating transient conditions. Nevertheless, Ansys Fluent stands out as one of the most formidable CFD solvers available, renowned for its ability to manage complex fluid flows, including laminar, turbulent, compressible, and incompressible flows.

Accuracy is another important consideration when selecting a CFD solver. The precision of a CFD solution is of the utmost importance, as it serves as the foundation for crucial design decisions. Ansys Fluent has been subjected to stringent testing and validation against experimental data, ensuring that the model results are reliable and accurate. In addition, Ansys Fluent offers a variety of meshing methodologies, ranging from structured to unstructured grids, which contribute to improved simulation accuracy (Li, J., and T. Liu, 2019).

Numerical stability and solution convergence are significant selection criteria for CFD solvers. It is essential to recognize that some solvers may exhibit less numerical stability than others, and that the convergence rate may vary depending on the solver type. In this regard, Ansys Fluent demonstrates superior stability and converges faster than the majority of its competitors. With Fluent, iterations converge more rapidly, resulting in a more efficient solution overall.

An additional significant advantage of Ansys Fluent is its vast array of capabilities. The solver can simulate a variety of flow categories, including single-phase flow, multiphase flow, compressible flow, and reacting flow. Its user-friendly interface provides easy access to a multiplicity of features, such as parallel computation, which expedites the resolution of complex flow problems.

Ansys Fluent provides its users with exceptional support, training, and documentation, including online courses, webinars, video seminars, and community forums where they can interact with industry professionals. Ansys Fluent also provides superior customer service, with a team of seasoned engineers standing by to respond to user questions and concerns.

The selection of a CFD solver is a crucial aspect of simulations involving computational fluid dynamics. Ansys Fluent continues to be one of the top CFD solvers, outperforming competitors in terms of precision, numerical stability, convergence rate, capabilities, and customer support. Its dedication to research and development makes it an industry leader in aerospace, automotive, energy, and manufacturing, among others. For simulations of fluid dynamics, Ansys Fluent is recommended for its effectiveness and reliability.

3.2 Comparison of CFD Turbulence Models

Fluid dynamics' fundamental and pervasive phenomenon of turbulence is characterized by arbitrary and unpredictable changes in velocity, pressure, and other fluid properties. Numerous physical processes, such as fluid flow over uneven surfaces, thermal convection, and the blending of different fluid layers, can result in turbulence. Numerous natural and man-made fluxes, such as combustion, atmospheric and oceanic circulation, and most notably aerospace propulsion, exhibit this behavior.

Turbulence modeling is essential in CFD, with the aim of accurately predicting and simulating turbulent flows. Numerous turbulence models have been developed and implemented in order to solve the Navier-Stokes equations that govern fluid motion. There are two principal types of these models: Reynolds-averaged Navier-Stokes (RANS) models and large-eddy simulation (LES) models.

RANS models use Reynolds decomposition and averaging assumptions to differentiate between mean flow and fluctuating components. Using algebraic, transport, or closure equations, the Reynolds stresses that represent turbulence effects are modeled. As Spalart and Allmaras (1994) noted, RANS models have acquired significant traction in industrial applications due to their effectiveness and relatively low computational cost. However, they are incapable of precisely resolving unsteady and turbulent flow characteristics, particularly in complex geometries and turbulent regimes.

By explicitly resolving large eddies and modeling small scales, LES models attempt to comprehend a portion of the turbulent energy spectrum. To accurately depict turbulent flow dynamics, these models necessitate substantial computational resources and require fine spatial and temporal resolutions. Despite the fact that LES models effectively simulate complex turbulent flows and provide insights into the underlying physics, their precision is still limited by subgrid-scale (SGS) models that depict unresolved turbulence effects.

Among a variety of turbulence models, the k- shear stress transport (SST) model has acquired popularity by addressing the shortcomings of conventional k- models. The k-SST model is a two-equation RANS model that accounts for curvature effects and differences in the transport of turbulence kinetic energy (k) and the specific dissipation rate, as described by Wilcox (1998). This model has demonstrated accurate results for a wide range of turbulent flows, including boundary layers, disturbances, and separated flows, at comparatively lower computational costs than LES models.

In conclusion, turbulence modeling presents a formidable challenge that necessitates the careful selection of appropriate models based on flow mechanics and available computational resources. While LES models produce accurate results for intricate turbulent flows, they are computationally intensive and require grids with a high degree of resolution. In contrast, RANS models offer efficacy and are widely used in industrial applications, but their ability to resolve complex turbulent flows is limited. It has been demonstrated that the kw- SST model strikes a promising equilibrium between accuracy and efficiency for a variety of turbulent flow scenarios, making it a compelling option for practical CFD simulations.

4. CFD Results

Simulations of CFD provide crucial insights into the aerodynamic behavior of an aircraft. In this study, the CFD results span Mach numbers between 0.2 and 0.95, AoA between -12 and 40 degrees, and AoS between 0 and 20 degrees. The results indicate that the aircraft demonstrates static stability, which indicates that it returns to its initial condition after a disturbance.

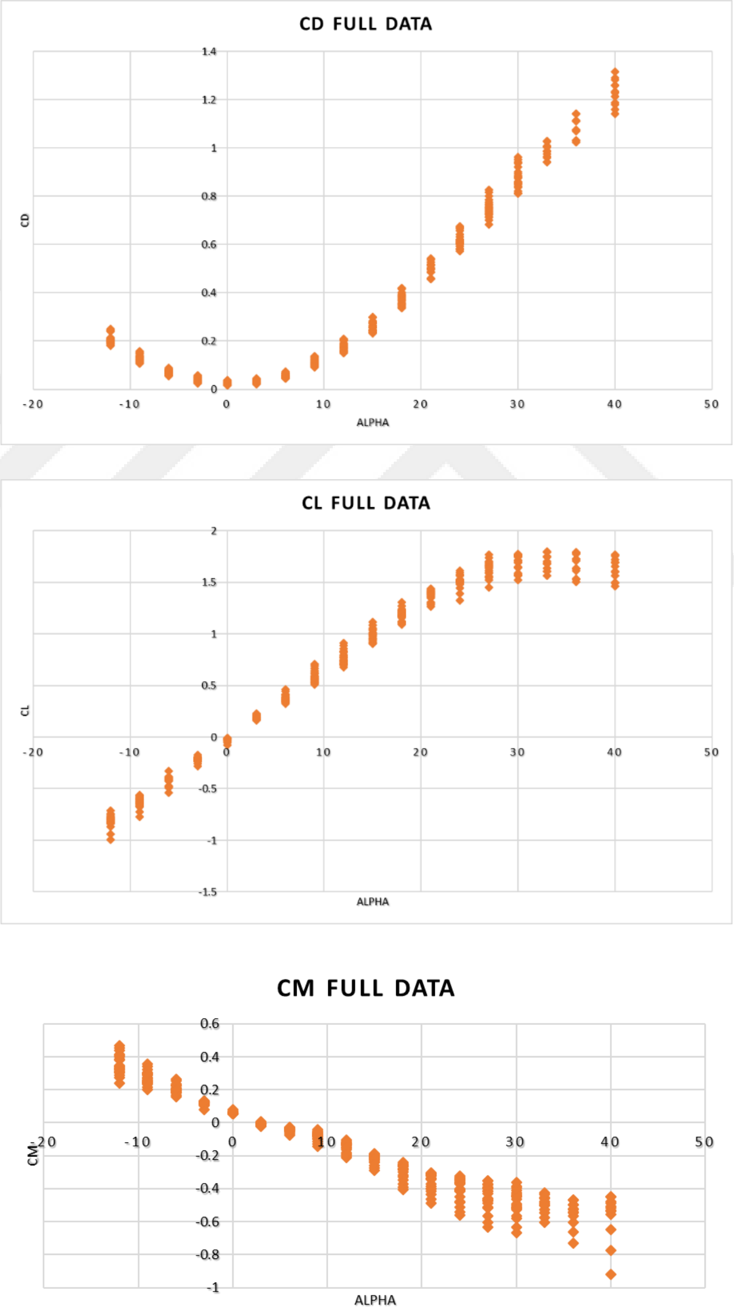


Figure 4.1 : Plots of CD, CL, and Cm from the Full CFD Dataset

As shown in Figure 4.1, exhaustive diagrams representing CL, CD, and Cm are presented, effectively illustrating the outcomes of the entire Computational Fluid Dynamics (CFD) data set. This graphical representation provides insightful information about aerodynamic coefficients and a clear and concise summary of the aerodynamic characteristics derived from the CFD dataset.

The CFD results is the fact that the aircraft stalls between 20 and 25 degrees AoA. This information is crucial, as a stall can result in a loss of lift and control, creating potentially hazardous conditions for the aircraft and its passengers. By comprehending the AoA at which an aircraft pauses, pilots can avoid this condition and maintain flight safety.

The presence of a wingtip delay in the transonic regime at an AoA of 10 to 15 degrees is another intriguing observation. A wingtip stall occurs when the outer portion of the wing stalls prior to the interior portion, resulting in a loss of lift and unstable flight. This occurrence is common in high-performance aircraft and can be mitigated through careful wing design and control.

The lift-AoA trajectory is linear up to 20 degrees AoA, indicating that the aircraft's behavior is predictable within this range. Beyond this range, the curve likely becomes non-linear as stall conditions emerge. The pitch moment, which describes the aircraft's tendency to tilt up or down, is linear between -10 and 10 degrees angle of attack. This linearity indicates that the aircraft's pitch response is predictable within this range, which is advantageous for pilots during takeoff and landing.

The CFD results reveal important details on the aircraft's stall characteristics, stability, and pitch response, all of which are essential for a successful and safe flight. Pilots and aircraft designers can improve aircraft performance and ensure safe flying by having a better understanding of these features. The results also demonstrate the importance of continuing research and development in improving our comprehension of aerodynamics and aircraft design. The effectiveness, efficiency, and safety of aircraft can be further improved with the continuous development of CFD and other technologies.

4.1 Analysis of the Subsonic Stall Region: The Reynolds Number Effect

An aircraft's aerodynamic analysis is essential for assuring its safe and efficient operation. In this analysis, the lift coefficient (CL) versus angle of attack (AoA) graph is a crucial variable. According to the CFD results, the CL-alpha graph is linear and uniform up until the halt region, where the lift coefficient experiences a precipitous drop.

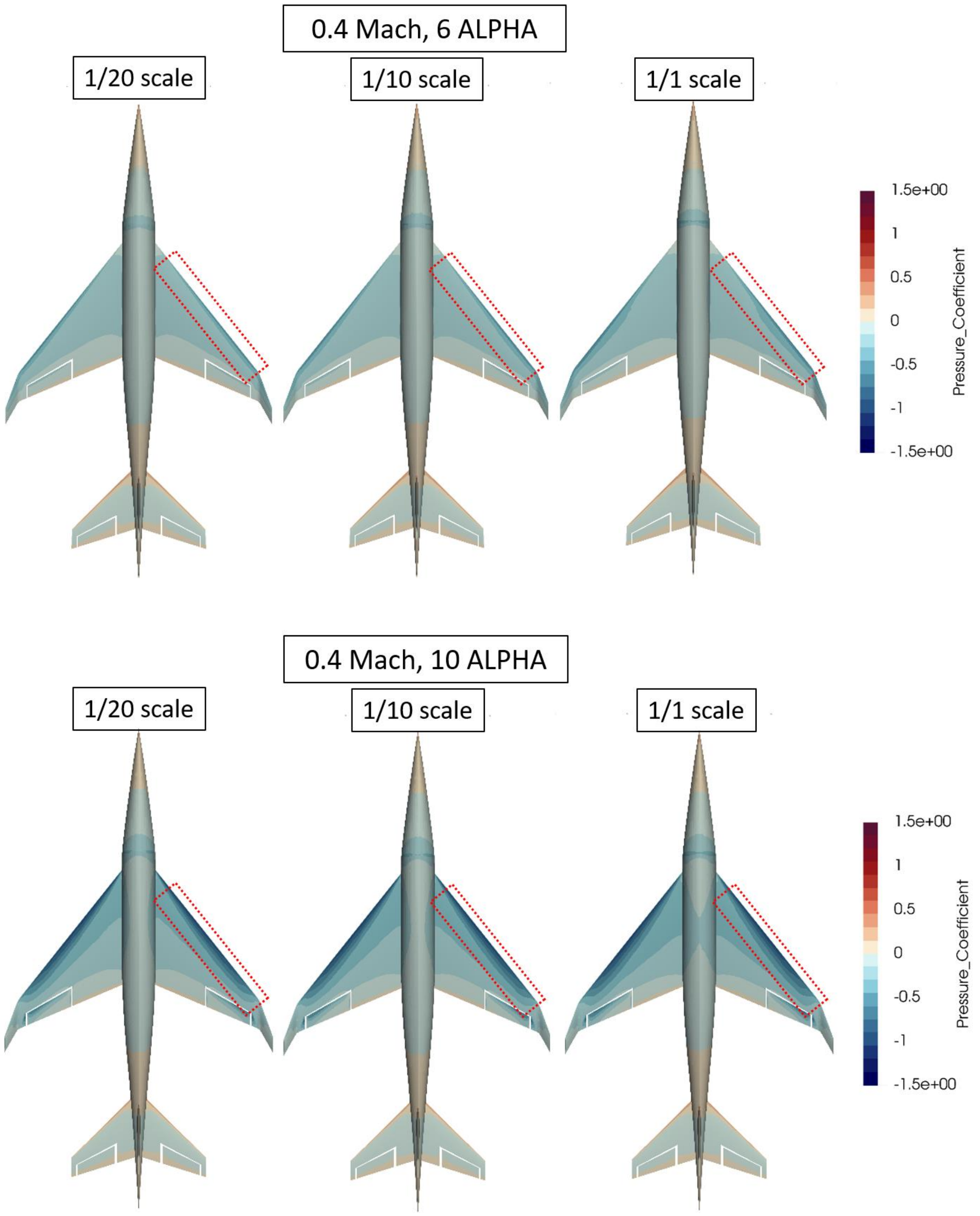


Figure 4.2 : Cp Distribution at 0.4 Mach and 6 and 10 Degrees AoA for Different Scale Number

However, the delay zone is profoundly affected by the Reynolds effect. The Reynolds effect describes how viscosity affects the flow pattern in and around an obstruction. It has been discovered that the angle of attack at which the stall occurs changes significantly as a function of the Reynolds number.

As illustrated in Figure 4.2-4.3, In low Reynolds number CFD results, the wing stalls within the range of 20-22 degrees AoA, whereas it stalls within the range of 25-27 degrees AoA in high Reynolds number CFD results. This observation suggests that aircraft experiencing a stall at higher Reynolds numbers will have a greater angle of attack.

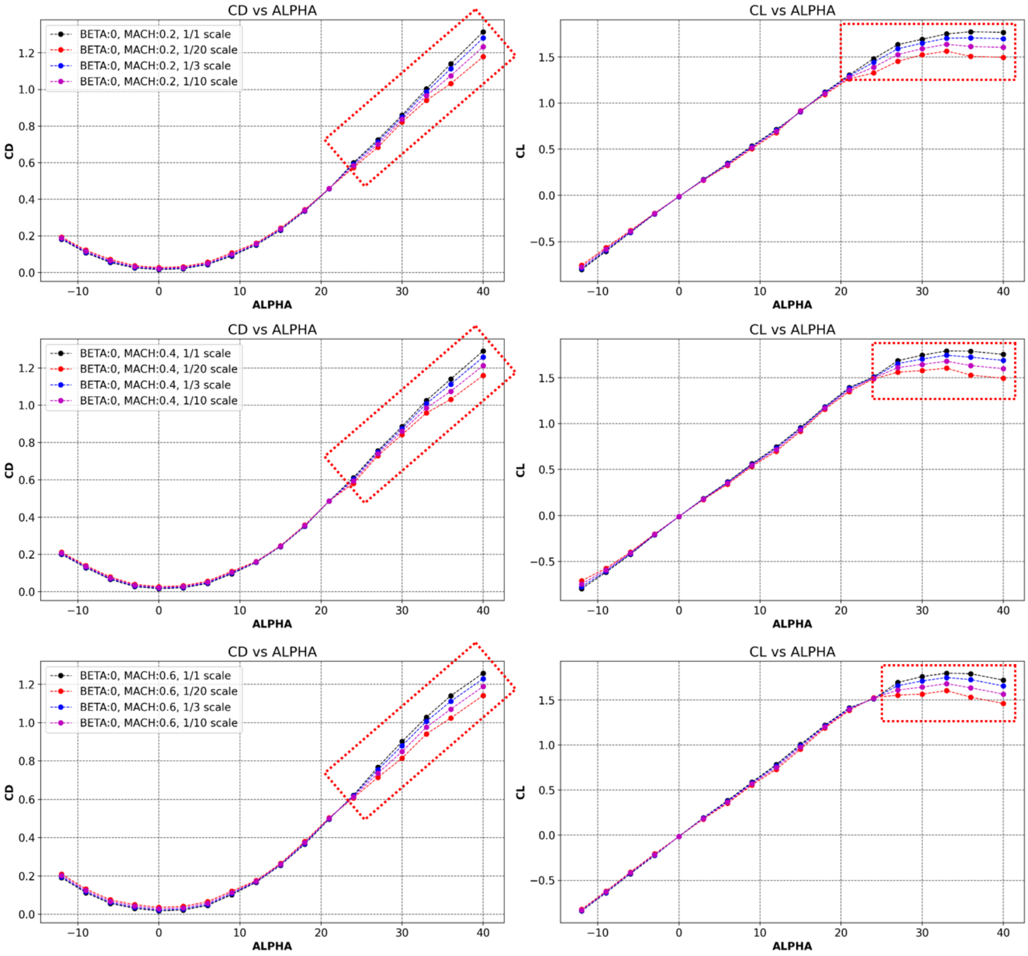


Figure 4.3 : Plots of CD and CL at 0.2,0.4 and 0.6 Mach for Different Scale Number

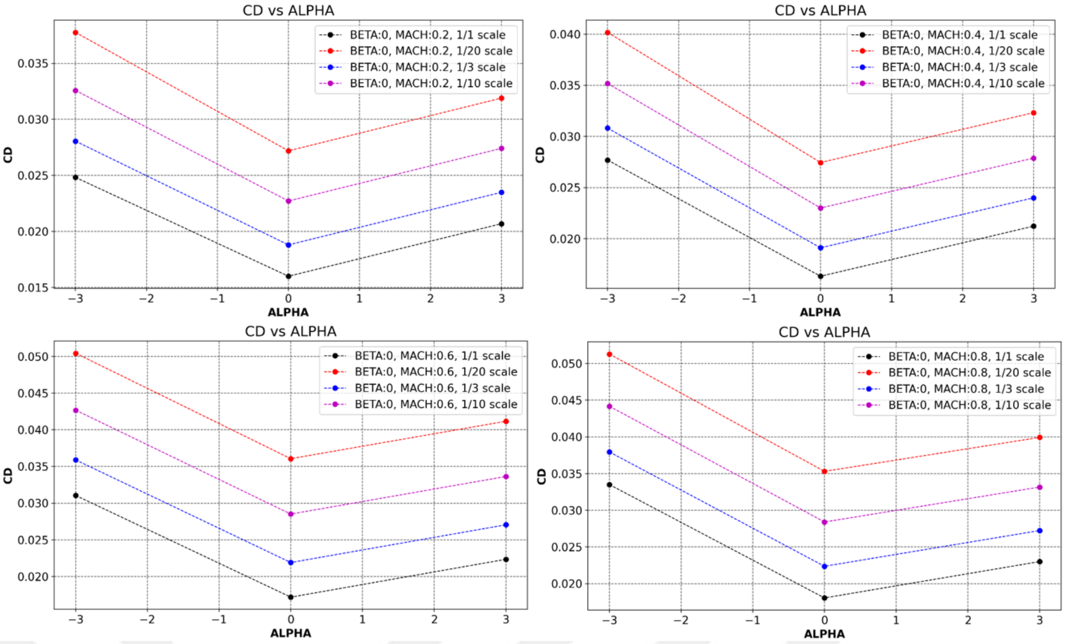


Figure 4.4 : Drag Count Investigation at 0.2,0.4 and 0.6 Mach and -3 to 3 AoA for Different Scale Number

In addition, by examining the drag count comparisons depicted in Figure 4.4, we discovered that the obtained results are consistent with existing literature. The difference in drag count between a 1/1 scale and a 1/20 scale is approximately 50 percent.

The Reynolds effect is consistent throughout all Mach regimes. This observation indicates that the Reynolds effect influences the aerodynamic behavior of an aircraft at all speeds.

The delay region also has a substantial effect on the graph of drag coefficient (CD) versus angle of attack. The loss of lift in the halt region reduces the coefficient of CD. This decrease in drag coefficient is a result of the separation of airflow from the wing, which increases the drag force acting on the aircraft.

In conclusion, CFD results indicate that the Reynolds effect plays a significant role in the halt region. This effect is consistent across all Mach regimes. Moreover, the delay region has a significant impact on the CD versus AoA graph, resulting in a decrease in CD. Understanding these effects is essential for designing secure and efficient aircraft, and ongoing research and development are necessary for advancing our knowledge of aerodynamics and aircraft design.

4.2 Investigation of the Effects on Moments

Momentum that causes the aircraft to rotate around its lateral axis is yet another crucial aerodynamic parameter. According to the CFD results, the pitch moment-AoA graph demonstrates a consistent change between -10 and 10 degrees AoA, and this trend is independent of the Reynolds number.

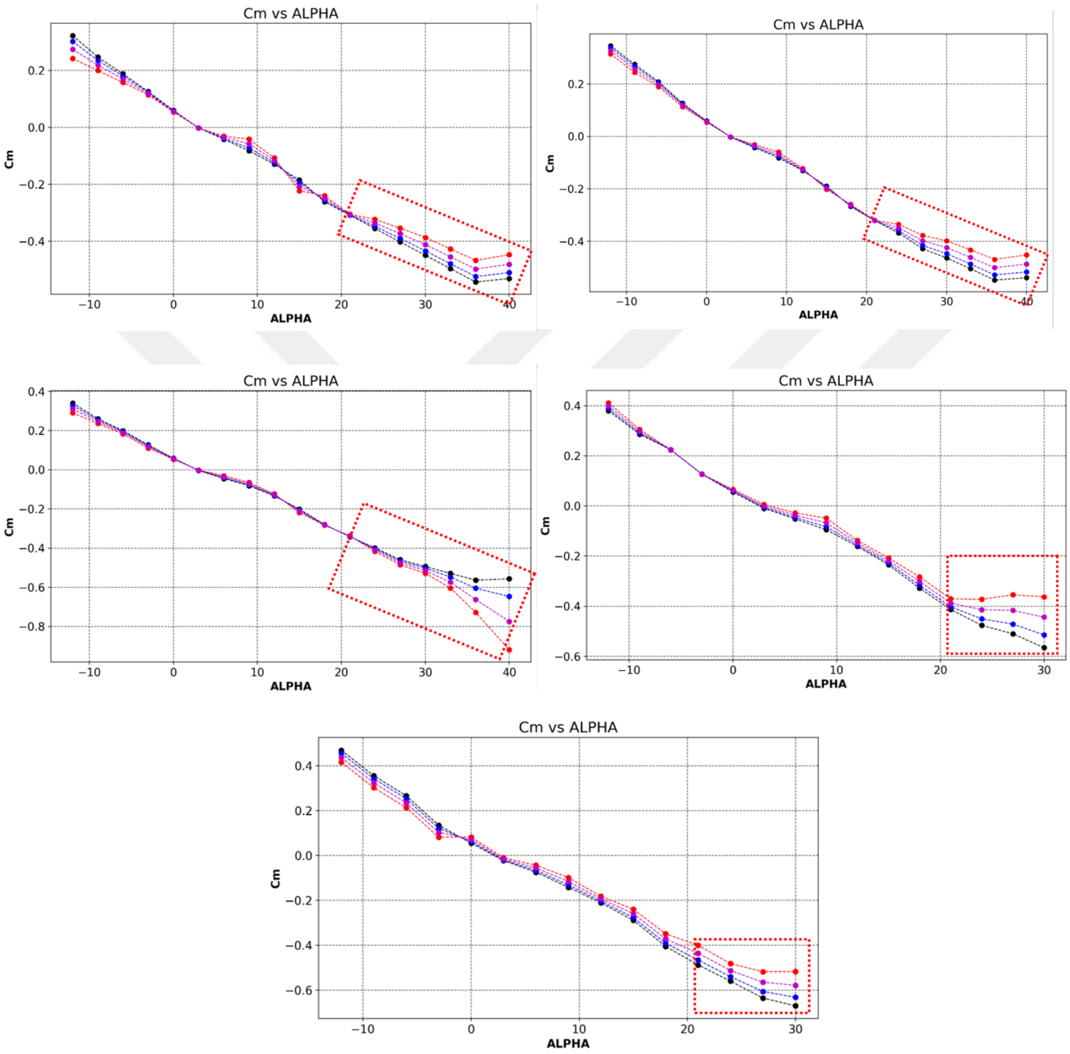


Figure 4.5 : Pitch Moment Plots for Different Scale Number

As illustrated in Figure 4.5, as the AoA increases, there are regions where linearity degrades and trend deviations are observed. In the stall region, the wing stalls at different angles of attack depending on the Reynolds number, resulting in variable pitch moments.

In addition, the 0.95 Mach regime is where the aircraft begins to lose its static stability, as revealed by the CFD results. Static stability refers to an aircraft's capacity to regain its equilibrium after being perturbed. Loss of static stability can cause unstable flight conditions, making aircraft control more difficult for pilots.

Understanding the behavior of an aircraft's pitch moment is crucial for designing secure and stable aircraft. Variations in pitch moment can affect aircraft control and equilibrium, making it challenging for pilots to maintain safe flight conditions. Consequently, it is essential to consider pitch moment behavior during aircraft design and to continuously advance our comprehension of aerodynamics in order to produce safer and more efficient aircraft.

4.3 Analysis of Shock Waves in the Transonic Region

The CFD results provide essential insights into the aerodynamic behavior of an aircraft, and visualization is an indispensable instrument for understanding and interpreting these results. Using ParaView software, the surface contour distributions of the CFD results were visualized, and flow directions on the wing were represented graphically.

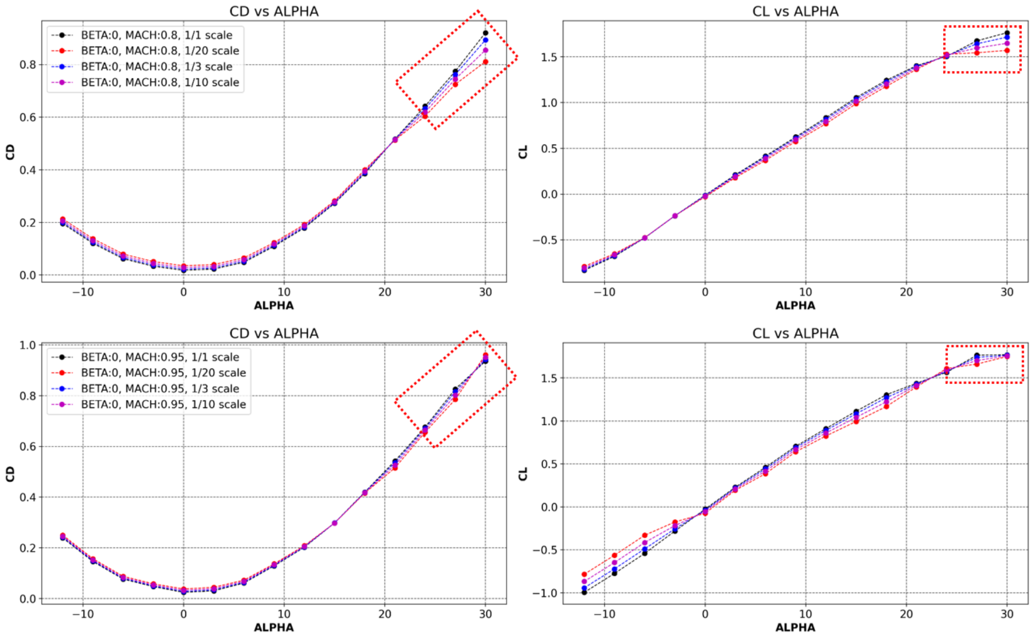


Figure 4.6 : Plots of CD and CL at Transonic Regime for Different Scale Number

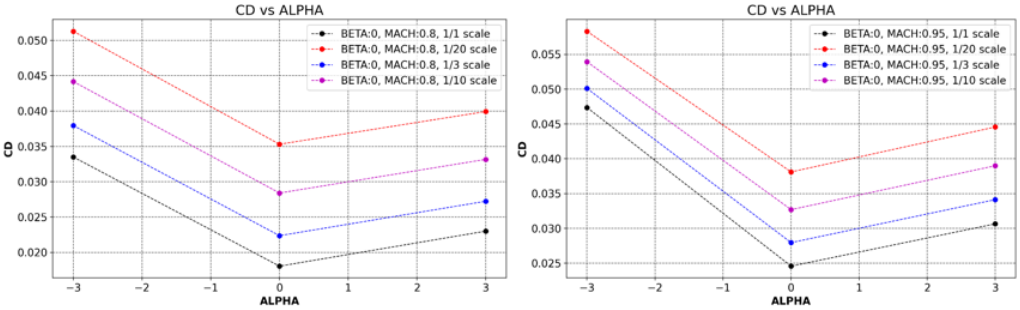


Figure 4.7 : Drag Count Investigation at Transonic Regime for Different Scale Number

Based on CFD analyses conducted in the transonic region, the delay region is investigated in Figure 4.6. By analyzing these CFD results, it was determined that the Reynolds number is a crucial parameter in this domain. In addition, by examining the drag count comparisons depicted in Figure 4.7, we discovered that the obtained results are consistent with existing literature. The difference in drag count between a 1/1 scale and a 1/20 scale is approximately 40 percent.

Regions of shock formation are crucial aspects of aircraft design and analysis in the transonic regime. The CFD results indicate that these regions of shock formation vary as the Reynolds number changes. This observation suggests that the regions of shock formation are not fixed and that changes in the Reynolds number can substantially affect the transonic aerodynamic behavior of an aircraft.

The strength and direction of the vortices that form on the aircraft are also important factors in aerodynamic analysis. These vortices have been seen to change when the Reynolds number changes, which can significantly affect an aircraft's stability and control. Designing safe and stable airplanes requires an understanding of how these vortices behave.

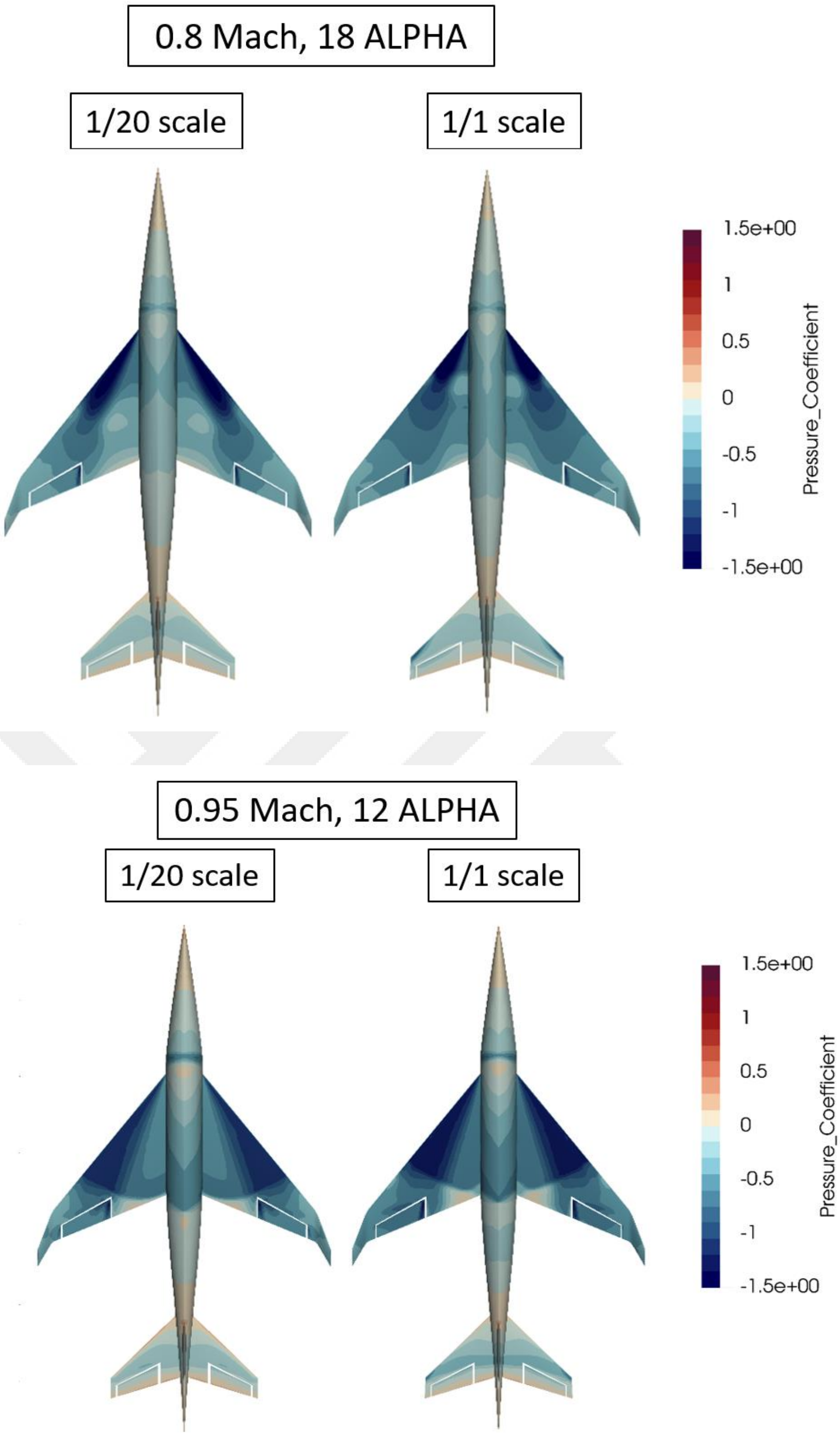


Figure 4.8 : Cp Distribution at Transonic Regime for Different Scale Number

As illustrated in Figure 4.8, a significant factor affecting an aircraft's aerodynamic performance is the wingtip stall area. As the Reynolds number changes, it has been noticed that the wingtip stall angle ranges between 10 and 15 degrees AoA. This finding suggests that variations in the Reynolds number can have a substantial impact on how an aircraft stalls, and that it is crucial to comprehend these impacts while developing safe and effective aircraft.

In conclusion, the CFD results have revealed essential insights into the aerodynamic behavior of an aircraft, and visualization is an indispensable instrument for interpreting and comprehending these results. Variations in the Reynolds number can have a significant effect on the regions of shock formation, the intensity and direction of vortices formed on the aircraft, and the region of wingtip stalling. Understanding these effects is crucial for designing aircraft that are secure and efficient, and ongoing research and development are indispensable for advancing our understanding of aerodynamics and aircraft design.

5. Models in Machine Learning

Predicting numerical outcomes, or regression, is a common use of machine learning algorithms. At the heart of these strategies is learning, through which models adjust internal parameters to lessen the gap between forecasted and observed outcomes. Linear Regression, Decision Trees, Random Forests, Support Vector Machines (SVM), and K-Nearest Neighbors (KNN) are the five popular regression models that are analyzed in this research.

Linear Regression is one of the simplest and most extensively employed statistical methods. It presupposes that there is a linear relationship between the input variables (features) and the output variable (objective). Despite its straightforwardness, it can be highly effective. However, it may grapple with complex datasets containing nonlinear relationships between variables.

Decision trees are a supervised learning technique used for classification and regression that does not rely on parameters. Since they account for nonlinear connections and the interplay of variables, they are more flexible than linear models. Among the most important decision tree hyperparameters are the minimum number of samples at a leaf node, the minimum number of samples necessary to divide an internal node, and the maximum depth of the tree.

As an ensemble learning method, Random Forests include the development of several decision trees in the course of training, with the average prediction from these trees being output. They are robust against overfitting, able to handle high-dimensional datasets, and capable of estimating the significance of features. Their hyperparameters include the maximum number of characteristics to use when partitioning a node and the maximum number of trees to use in the forest.

The objective of Support Vector Machines (SVM) for regression, also known as Support Vector Regression (SVR), is to accommodate as many instances as feasible within a set of decision boundaries while minimizing margin violations. The principal SVR hyperparameters are the kernel type (linear, polynomial, or Gaussian), the penalty parameter C, and the loss function epsilon.

K-Nearest Neighbors (KNN) is an instance-based learning technique in which the function is approximated locally and computation is deferred until function evaluation.

The KNN algorithm's hyperparameters include the number of neighbors to consider and the distance metric employed.

In machine learning, optimization of model hyperparameters is a crucial phase. It involves adjusting the hyperparameters of the model to enhance its predictive accuracy. The most common performance measures in regression problems are Mean Squared Error (MSE), Mean Absolute Error (MAE), and the Coefficient of Determination, also known as the R2 score. The MSE and MAE quantify the average squared and absolute differences between the estimated and actual values, with lesser values indicating superior performance. The R2 score, on the other hand, represents the proportion of the variance in the dependent variable that can be predicted from the independent variables, with higher values (closer to 1) indicating superior performance. Typically, the optimal hyperparameters for a model are those that minimize MSE or MAE and maximize R2.

Each regression model has its advantages and disadvantages, and their performance can vary based on the particular characteristics of the dataset. Consequently, it is generally advantageous to experiment with various models and optimize their hyperparameters to achieve the highest predictive accuracy.

6. ANN Model

ANN models are a subfield of machine learning that is inspired by the biological neural networks observed in animals. These models consist of numerous processing nodes that are interconnected and designed to conduct specific tasks. Modeled after neurons in the brain, the nodes are organized in layers that sequentially process information. A number of industries, including finance, manufacturing, healthcare, and others, have adopted ANN models in recent years, due to their growing popularity. The purpose of this paper is to provide a comprehensive overview of artificial neural network models, including their various types, architecture, applications, benefits, and drawbacks.

Types of models for artificial neural networks:

There are three fundamental categories of artificial neural network models.

Feedforward Neural Networks: Most ANN models follow this structure, with inputs passing from an initial layer through one or more hidden layers and then out to the final output layer. It has numerous applications, including pattern recognition, object identification, and speech recognition.

This form of ANN model has feedback connections between neurons, allowing previous outputs to serve as inputs. They are utilized for speech recognition, language processing, and signal processing, among other duties.

Convolutional Neural Networks: These networks are designed particularly for image and video processing tasks and have proven to be the most effective neural network type for image recognition, object detection, and facial recognition.

Models of Artificial Neural Network Architecture:

The following components constitute the architecture of an artificial neural network:

This is the initial layer of the ANN model, which is responsible for receiving input data.

Hidden Layer(s): Located between the input and output layers, hidden layers process the input layer's information.

This is the concluding layer of the ANN model, which generates the ultimate output based on the processed data.

ANN models may also include a bias neuron and recurrent connections between neurons, in addition to the previously mentioned components.

6.1 Inputs and Outputs

Inputs are the values that an ANN model uses as parameters or features to make predictions or classifications. In contrast, the output is the outcome or forecast generated by the model based on the inputs. Inputs for this particular ANN model consist of attack angle (α), sideslip angle (β), Mach number, and Reynolds number, while outputs include lift coefficient (CL), drag coefficient (CD), roll moment coefficient (Cl), pitching moment coefficient (Cm), and yaw moment coefficient (Cn).

Sideslip angle (β) is the angle between the aircraft's longitudinal axis and the relative wind vector, while angle of attack (α) is the angle between the wing and the relative airflow. How fast an airplane is compared to the speed of sound is expressed as a Mach number. To quantify the fluid dynamics around an airplane, scientists employ a metric called the Reynolds number. It gives a numerical value to the comparison of inertial and viscous forces.

The output parameters are aerodynamic coefficients describing the forces and moments exerted on the aircraft. These coefficients are crucial for determining the flight stability and maneuverability of an aircraft. CL represents the lift coefficient, CD represents the drag coefficient, Cl represents the moment of roll, Cm represents the moment of pitching, and Cn represents the moment of yaw.

PyTorch is a popular open-source machine learning library that provides a variety of tools and functionalities for building neural networks. For the development and training of this ANN model, the neural network submodule of the Scikit-Learn library was utilized.

6.2 Hidden Layers

Hidden layers in an ANN model are composed of neurons located between the input and output layers. These neurons receive input from the input layer, perform a series of mathematical operations on the input, and then transmit the information to the output layer. In order for the model to discover intricate relationships between input and output variables, hidden layers play a crucial role.

Identifying the optimal number and size of hidden layers for a particular ANN model can be a difficult undertaking. Numerous configurations of concealed layers are evaluated to determine which configuration yields the most precise results. PyTorch software was used to experiment with various combinations of hidden layers and sizes in this ANN model in order to determine the optimal configuration for the provided database.

After experimenting with four hidden layers of size 20, the optimal configuration for this ANN model was determined to be two hidden layers with sizes [7,8]. Based on the CFD results at various Reynolds numbers, this configuration was able to effectively learn and predict undesirable outcomes.

Determining the optimal hidden layer configuration is a crucial aspect of creating an effective ANN model. PyTorch software and experimentation facilitated the determination of this model's optimal configuration.

6.3 Activation Function and Training Algorithm

Each neuron's output in the hidden layer of an ANN model is determined by a mathematical function called the activation function. By introducing non-linearity via activation functions, the model may learn and represent intricate input-output interactions.

There are a variety of activation functions to choose from, including as the sigmoid, ReLU, and tanh. All possible activation methods were considered for this ANN model, but in the end, the logistic function was decided to be the best alternative. The logistic function is a sigmoid function that provides a consistent result between 0 and 1, making it a common approach to the problem of binary classification.

During training, the network's weighted connections between neurons are adjusted such that the gap between the expected and observed outputs is as small as possible. Training techniques including the Limited-memory Broyden-Fletcher-Goldfarb-

Shanno (L-BFGS) algorithm, backpropagation, and stochastic gradient descent are all at your disposal.

For this ANN model, numerous training algorithms were evaluated to determine the optimal choice. The L-BFGS algorithm demonstrated to be the most effective after extensive testing. The L-BFGS algorithm is a quasi-Newton optimization technique that approximates the Hessian matrix, which could result in quicker convergence than other optimization techniques.

Selecting the proper activation function and training algorithm is crucial to the success of an ANN model, in conclusion. The logistic activation function and L-BFGS training algorithm were selected for this model due to their ability to produce precise results with the provided dataset.

6.4 Performance Metrics

The performance metrics of an ANN model are essential for determining its predictive accuracy and efficacy. Several performance metrics, including MSE, MAE, and Coefficient of Determination (R-squared), can be used to evaluate the performance of an ANN model.

MSE is a common performance metric employed in regression analysis to quantify the average squared differences between the predicted and actual values. It is determined by averaging the squared differences between predicted and actual values. The expression for MSE is:

$$MSE = \left({}^{1}/_{n}\right) x \sum(y_i - y^i)^2$$

where y is the observed value, yi is the expected value, and n is the total number of observations.

MAE measures the average absolute discrepancies between the predicted and actual values and is another performance indicator used in regression analysis. The average absolute deviation between forecasted and observed values is used to determine this. MAE is calculated as follows:

$$MAE = \left({}^{1}/_{n}\right) x \sum\left|y_i - y^i\right|$$

R-squared is a performance metric used to measure the proportion of variability in the dependent variable that is explained by the independent variable(s). It is calculated as the ratio of the explained variance to the total variance. The formula for R-squared is:

$$R^2 = {}^{Explained\ variance}/_{\text{Total variance}}$$

where Explained variance represents the variance of the predicted values and Total variance represents the variance of the actual values.

This ANN model was optimized based on the following three performance metrics: MSE, MAE, and R-squared. Using these metrics, the accuracy and effectiveness of the optimized ANN model in predicting undesirable results based on CFD results at various Reynolds numbers were determined.

In the summary below, the performance metrics of the optimized ANN model can be examined. The MSE, MAE, and R-squared values can offer valuable insights into the performance of the ANN model, allowing for necessary adjustments and enhancements. The optimizeted parameters and performance metric outcomes for all models are comprehensively presented in Table 6.1-6.9.

The performance metrics of an ANN model are crucial for determining its predictive accuracy. Utilizing MSE, MAE, and R-squared metrics allowed for the evaluation and optimization of this ANN model's accuracy in predicting undesirable outcomes. By analyzing the performance metrics, alterations can be made to enhance the model's performance, resulting in more accurate forecasts and outcomes.

6.5 Validation and Testing

Validation and testing are essential phases in the creation of an ANN model. It is of utmost importance to ensure that the model does not overfit to the training data and can accurately predict outcomes on new, unseen data. Validation and testing of this ANN model required a distinct set of data from the CFD results that were not utilized during training.

Table 6.1 : Best Parameters for Decision Tree Model

Best Parameters for Decision Tree							
Sample Rate:1		Sample Rate:0.75		Sample Rate:0.5		Sample Rate:0.25	
Max Depth	40	Max Depth	30	Max Depth	30	Max Depth	None
Max Features	Auto	Max Features	Auto	Max Features	Auto	Max Features	Auto
Min Samples Leaf	1	Min Samples Leaf	1	Min Samples Leaf	1	Min Samples Leaf	4
Min Samples Split	2	Min Samples Split	2	Min Samples Split	2	Min Samples Split	2

Table 6.2 : Best Parameters for Random Forest Model

Best Parameters for Random Forest							
Sample Rate:1		Sample Rate:0.75		Sample Rate:0.5		Sample Rate:0.25	
Max Depth	30	Max Depth	40	Max Depth	30	Max Depth	20
Max Features	Auto	Max Features	Auto	Max Features	Auto	Max Features	Auto
Min Samples Leaf	1	Min Samples Leaf	1	Min Samples Leaf	1	Min Samples Leaf	2
Min Samples Split	2	Min Samples Split	2	Min Samples Split	2	Min Samples Split	5
n_estimators	100	n_estimators	100	n_estimators	10	n_estimators	100

Table 6.3 : Best Parameters for Support Vector Machines Model

Best Parameters for Support Vector Machines							
Sample Rate:1		Sample Rate:0.75		Sample Rate:0.5		Sample Rate:0.25	
C	10	C	1	C	100	C	0.1
epsilon	0.1	epsilon	0.1	Epsilon	0.1	epsilon	0.1
kernel	rbf	kernel	rbf	kernel	linear	kernel	linear

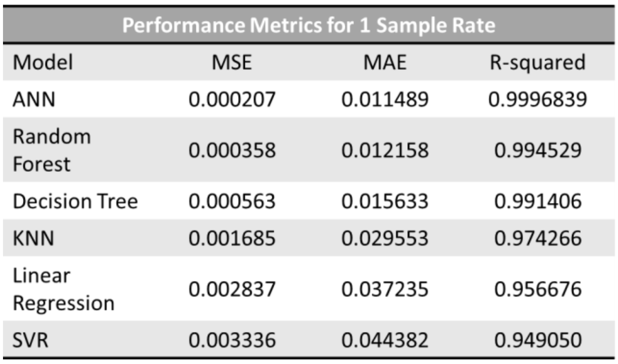
Table 6.4 : Best Parameters for KNN Model

Best Parameters for KNN							
Sample Rate:1		Sample Rate:0.75		Sample Rate:0.5		Sample Rate:0.25	
metric	Euclidean	metric	Euclidean	metric	Euclidean	metric	Manhattan
n_neighbors	5	n_neighbors	4	n_neighbors	5	n_neighbors	6
weights	distance	weights	distance	weights	distance	weights	distance

Table 6.5 : Best Parameters for ANN Model

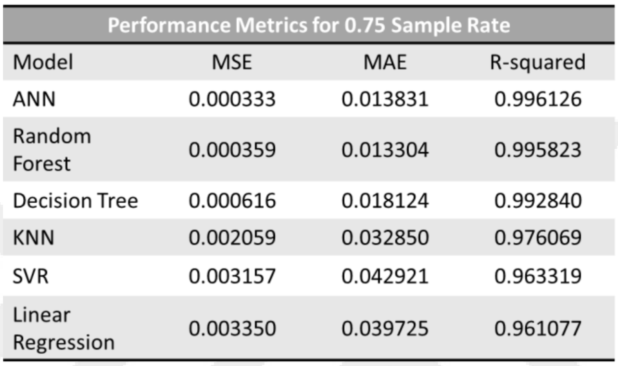
Best Parameters for ANN							
Sample Rate:1		Sample Rate:0.75		Sample Rate:0.5		Sample Rate:0.25	
Activation	ReLU	Activation	ReLU	Activation	ReLU	Activation	ReLU
Alpha	0.01	Alpha	0.01	Alpha	0.01	Alpha	0.001
Hidden layer sizes	[7,8]	Hidden layer sizes	[50,50]	Hidden layer sizes	[100,100]	Hidden layer sizes	[50,0]
Learning rate	Adaptive	Learning rate	Constant	Learning rate	Constant	Learning rate	Constant
Solver	L-BFGS	Solver	L-BFGS	Solver	L-BFGS	Solver	L-BFGS

Table 6.6 : Performance Metrics at 1 Sample Rate for All Models



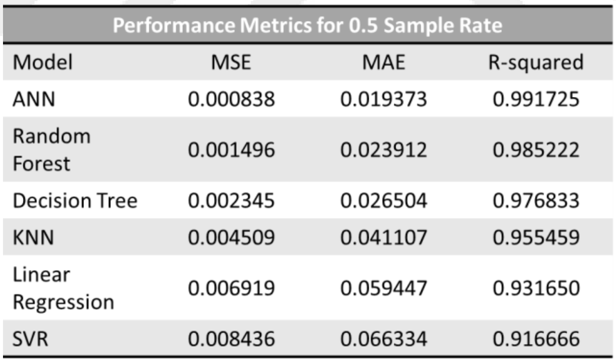
Performance Metrics for 1 Sample Rate			
Model	MSE	MAE	R-squared
ANN	0.000207	0.011489	0.9996839
Random Forest	0.000358	0.012158	0.994529
Decision Tree	0.000563	0.015633	0.991406
KNN	0.001685	0.029553	0.974266
Linear Regression	0.002837	0.037235	0.956676
SVR	0.003336	0.044382	0.949050

Table 6.7 : Performance Metrics at 0.75 Sample Rate for All Models



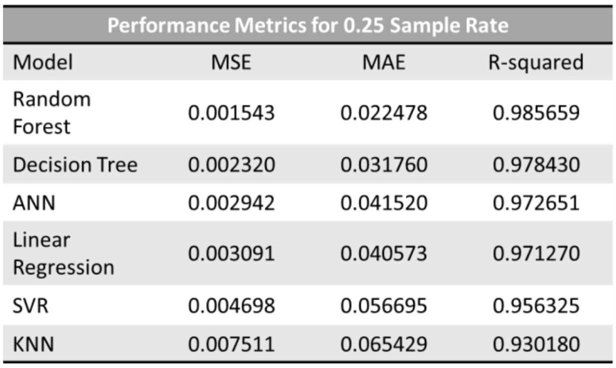
Performance Metrics for 0.75 Sample Rate			
Model	MSE	MAE	R-squared
ANN	0.000333	0.013831	0.996126
Random Forest	0.000359	0.013304	0.995823
Decision Tree	0.000616	0.018124	0.992840
KNN	0.002059	0.032850	0.976069
SVR	0.003157	0.042921	0.963319
Linear Regression	0.003350	0.039725	0.961077

Table 6.8 : Performance Metrics at 0.5 Sample Rate for All Models



Performance Metrics for 0.5 Sample Rate			
Model	MSE	MAE	R-squared
ANN	0.000838	0.019373	0.991725
Random Forest	0.001496	0.023912	0.985222
Decision Tree	0.002345	0.026504	0.976833
KNN	0.004509	0.041107	0.955459
Linear Regression	0.006919	0.059447	0.931650
SVR	0.008436	0.066334	0.916666

Table 6.9 : Performance Metrics at 0.25 Sample Rate for All Models



Performance Metrics for 0.25 Sample Rate			
Model	MSE	MAE	R-squared
Random Forest	0.001543	0.022478	0.985659
Decision Tree	0.002320	0.031760	0.978430
ANN	0.002942	0.041520	0.972651
Linear Regression	0.003091	0.040573	0.971270
SVR	0.004698	0.056695	0.956325
KNN	0.007511	0.065429	0.930180

Table 6.1-6.9 contains the refined parameters and performance metric results for all models under consideration. Examining these tables reveals that the quantity of data within the dataset has a substantial impact on the model's precision. When all models are optimized for each dataset, it has been observed that distinct optimized hyperparameters emerge. In addition, as the amount of data in the dataset increases, the ANN model tends to produce superior outcomes. On the other hand, for datasets with fewer data points, other machine learning models have been observed to produce superior results.

During the validation process, the model was trained on a subset of the available data before being evaluated on the remaining data. Several performance metrics, including the mean squared error, mean absolute error, and R-squared, were used to evaluate the model's performance.

After the model was validated, it was evaluated using CFD results that were not input into the ANN model. This entailed comparing the CFD results to the ANN model's predictions. It was observed that the ANN model performed exceptionally well, accurately and precisely predicting the desired outcomes.

Despite the fact that the ANN model demonstrated outstanding performance during testing, there is always a danger of the model being overfit to the training data. This may cause the model to perform inadequately on new, unobserved data. To mitigate this risk, it is essential to employ a rigorous validation and testing procedure, as well as regularization and cross-validation techniques.

In conclusion, the validation and testing of the ANN model demonstrated its efficacy in predicting undesirable outcomes based on aircraft CFD results at various Reynolds numbers. This study's findings are applicable to aircraft design and development, as well as the discipline of aerodynamics.

7. Limitations and Future Work

While the ANN model developed in this study has shown promising results in predicting unfavorable outcomes in aircraft CFD analysis, there are still some limitations that need to be addressed in future research. The magnitude of the aerodynamic database utilized to train the model is one of the primary limitations. Even though the current database contains 360 CFD analyses with varying Mach, alpha, beta, and Reynolds numbers, it may not be enough to depict the complex aerodynamic behavior of aircraft under diverse flight conditions. In future work, the database can be expanded to include more exhaustive and diverse CFD analyses, thereby improving the model's precision and robustness.

The existing ANN model's confinement to the subsonic flying area is another drawback. Nevertheless, supersonic flight is a crucial component of aircraft design as well, necessitating the creation of a unique ANN model to accurately represent the aerodynamic behavior in this range. As a result, more CFD analyses would be required, and the database would need to be bigger, but the forecasts for supersonic flying circumstances may be more thorough and precise.

Moreover, the present ANN model focuses on the aerodynamic behavior of the aircraft as a whole, whereas the efficacy and efficiency of control surfaces such as flaps, ailerons, and rudders can have a significant impact on the aircraft's performance. Future research could include obtaining control surface-deflected CFD results and analyzing the effectiveness of control surfaces at various Reynolds numbers. Additionally, the effect of Reynolds number on control surface hinge moment can be studied to provide design and optimization insights for control surfaces.

In conclusion, although the developed ANN model has demonstrated substantial promise in predicting undesirable outcomes in aircraft CFD analysis, there are still limitations that must be addressed in future research. By expanding the database, developing discrete models for supersonic flight, and analyzing the effectiveness of control surfaces, the model's precision and applicability can be improved.

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