AERODYNAMIC SHAPE OPTIMIZATION OF OMNI-DIRECTIONAL ANEMOCONE FOR MAXIMUM POWER EXTRACTION

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Certification

This is to certify that **Asna Kalsoom**, **190501023** and **Durr-e-Shahwar**, **190501064** have successfully completed the final project **Aerodynamic shape optimization of omni-directional Anemocone for maximum power extraction,** at the **Institute of Space Technology, Islamabad**, to fulfill the partial requirement of the degree **BS Mechanical Engineering.**

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Aerodynamic Shape Optimization of Omni-Directional Anemocone For Maximum Power Extraction

Sustainable Development Goals

(Please tick the relevant SDG(s) linked with FYDP)

SDG No	Description of SDG	SDG No	Description of SDG
SDG 1	No Poverty	SDG 9	Industry, Innovation, and Infrastructure ✓
SDG 2	Zero Hunger	SDG 10	Reduced Inequalities
SDG 3	Good Health and Well Being	SDG 11	Sustainable Cities and Communities
SDG 4	Quality Education	SDG 12	Responsible Consumption and Production
SDG 5	Gender Equality	SDG 13	Climate Change ✓
SDG 6	Clean Water and Sanitation	SDG 14	Life Below Water
SDG 7	Affordable and Clean Energy ✓	SDG 15	Life on Land ✓
SDG 8	Decent Work and Economic Growth	SDG 16	Peace, Justice and Strong Institutions
		SDG 17	Partnerships for the Goals

Range of Complex Problem Solving			
	Attribute	**Complex Problem**	
1	Range of conflicting requirements	Involve wide-ranging or conflicting technical, engineering and other issues.	
2	Depth of analysis required	Have no obvious solution and require abstract thinking, originality in analysis to formulate suitable models.	
3	Depth of knowledge required	Requires research-based knowledge much of which is at, or informed by, the forefront of the professional discipline and which allows a fundamentals-based, first principles analytical approach.	
4	Familiarity of issues	Involve infrequently encountered issues	
5	Extent of applicable codes	Are outside problems encompassed by standards and codes of practice for professional engineering.	
6	Extent of stakeholder involvement and level of conflicting requirements	Involve diverse groups of stakeholders with widely varying needs.	
7	Consequences	Have significant consequences in a range of contexts.	✓
8	Interdependence	Are high level problems including many component parts or sub-problems	
Range of Complex Problem Activities			
	Attribute	**Complex Activities**	
1	Range of resources	Involve the use of diverse resources (and for this purpose, resources include people, money, equipment, materials, information and technologies).	
2	Level of interaction	Require resolution of significant problems arising from interactions between wide ranging and conflicting technical, engineering or other issues.	
3	Innovation	Involve creative use of engineering principles and research-based knowledge in novel ways.	✓
4	Consequences to society and the environment	Have significant consequences in a range of contexts, characterized by difficulty of prediction and mitigation.	✓
5	Familiarity	Can extend beyond previous experiences by applying principles-based approaches.	

Abstract

Wind energy is among the most reliable sources of renewable energy. It is clean, convenient to utilize, and readily available. One innovative approach for harnessing wind energy is the use of ducted or shrouded wind turbines. These ducted wind turbines have several benefits like increased efficiency, low cut-in speed, noise reduction, and wildlife safety. Omni-Directional Anemocone (ODA) is one such shrouded wind turbine. In the past, the design of ODA has been optimized using Parametric Optimization which tends to struggle in solving non-linear or complex problems. This research aims to employ Global Optimization technique to optimize the shape of an ODA. To maximize the velocity of air at the throat and to minimize the drag coefficient on the surface of the shroud are the core objectives of the optimization. The study has utilized a Genetic Algorithm (GA) and an Artificial Neural Network (ANN) to implement the optimization process. Genetic Algorithm has been used to produce a large number of unique designs while ANN can predict the value of the desired parameters after it had been trained using numerical results obtained through Computational Fluid Dynamics (CFD). Multi-Objective optimization based on Pareto-optimal curves has been applied on these designs to obtain an optimized model. An optimized model with maximum wind velocity at throat and minimum drag coefficient on the surface of the shroud has been obtained. Validated CFD approach has been implemented on the optimized model and the results have been used to validate the developed Machine learning tool.

Keywords: Omni-Directional Anemocone, Computational Fluid Dynamics, Genetic Algorithm, Artificial Neural Networks, Multi-Objective Optimization

Undertaking

I certify that the project **Aerodynamic Shape Optimization of Omni-Directional Anemocone for Maximum Power Extraction** is our own work. The work has not, in whole or in part, been presented elsewhere for assessment. Where material has been used from other sources it has been properly acknowledged/ referred.

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List of Acronyms

ODA	Omni-Directional Anemocone
CFD	Computational Fluid Dynamics
ANN	Artificial Neural Network
NEPRA	National Electric Power Regulatory Authority
IWT	Invelox Wind Turbine
HAWT	Horizontal Axis Wind Turbine
VAWT	Vertical Axis Wind Turbine
A-GDT	Aesthetic Generative Design Technique
COE	Cost of Energy
WFLO	Wind Farm Layout Optimization
$\mathbf{M_{net}}$	Maximum net mass flow rate
$\mathbf{P_{max}}$	Maximum Wind Power
MOPSO	Multi-Objective Particle Swarm Optimization
CAD	Computer Aided Design
GA	Genetic Algorithm
RANS	Reynolds-Averaged Navier-Stokes
SIMPLE	Semi-Implicit Method for Pressure Linked Equations

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Chapter 1

1.1. Introduction

1.1.1. Background

Renewable energy is the world's fastest-growing energy source. The globe is shifting away from fossil fuels as the renewable energy transition accelerates to decrease emissions and limit global warming. Adoption of renewable energy has various advantages such as it combats climate change by lowering greenhouse gas emissions, reducing air pollution, improving energy security, creating jobs, and fueling economic growth. With growing awareness of the importance of sustainable energy practices, governments, businesses, and individuals are embracing the transition to renewables, moving us toward a future powered by clean and resilient energy systems.

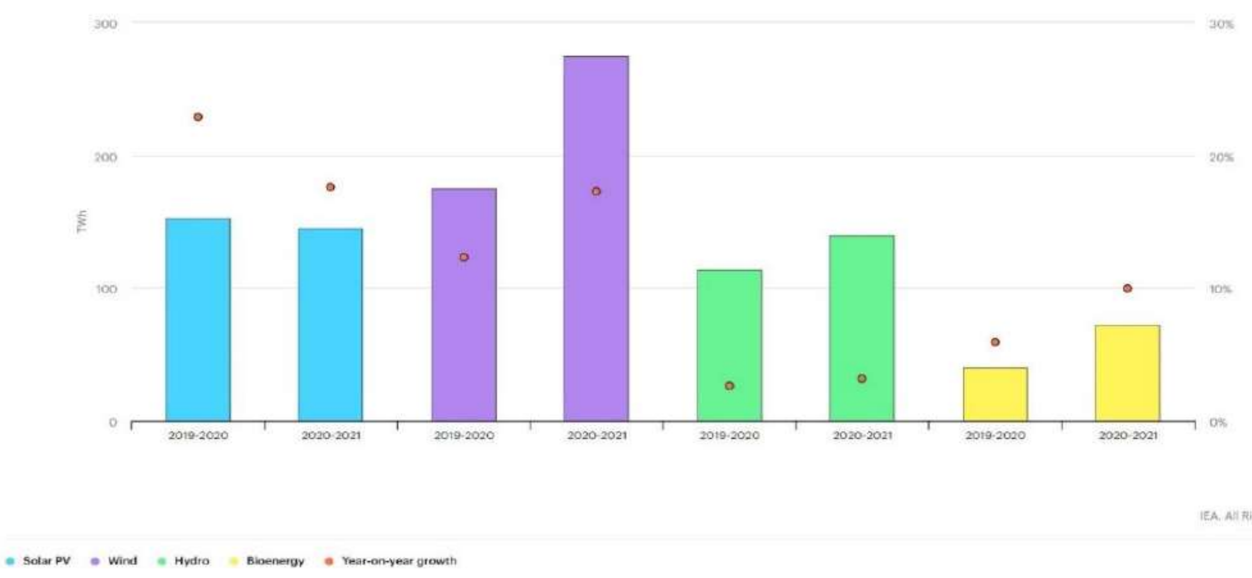

Fig. 1.1.1. Global Renewable electricity generation, 2019-2020 and 2020-2021

It is evident from the Global Energy Review 2021 that renewables made up 29 percent of global electricity generation by the end of 2020, led by wind power and solar energy as shown in Fig. 1.1. One of the most prominent sources of renewable energy is wind power and its demand has surged with recent escalation in sustainable energy generation. The wind is a nearly limitless resource that can be found in many parts of the earth. We can tap into a clean and renewable source of energy that does not destroy natural resources by harnessing the power of the wind. As nations make efforts to reduce carbon emissions and address climate change, the rise of wind energy producers has been critical in propelling this clean energy revolution. Fig. 1.2 depicts the contribution of different countries in producing electricity by utilizing wind energy with China and India representing half of the global wind output. [1]

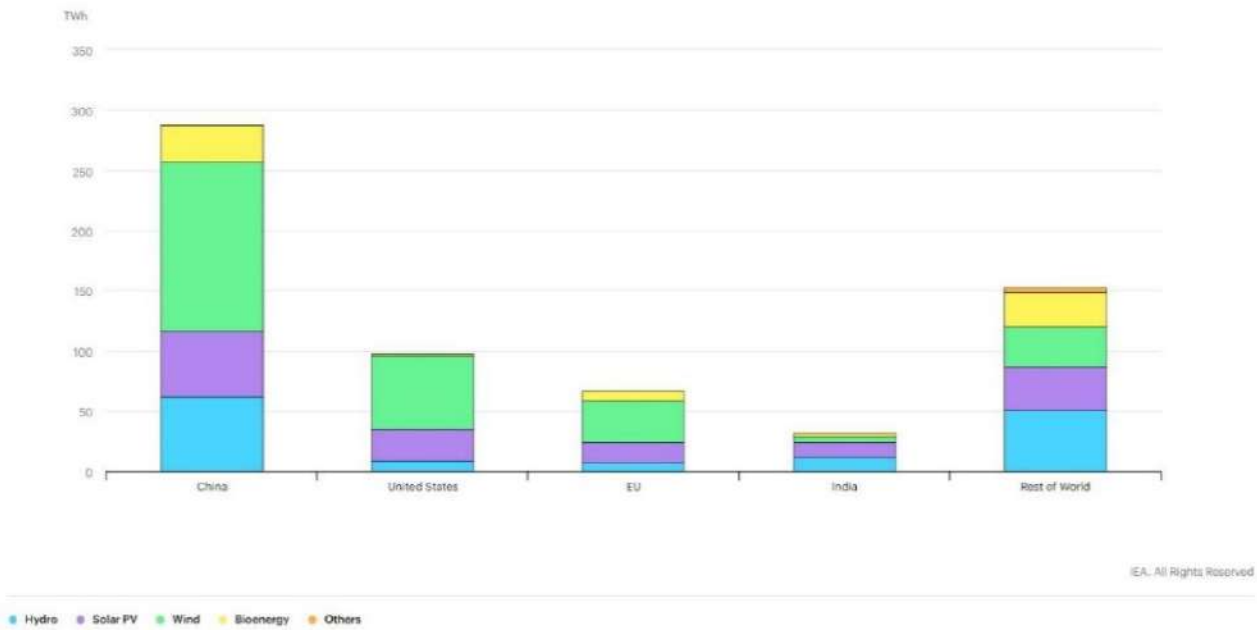

Fig. 1.1.2. Renewable electricity generation increase by country, 2020-2021

In Pakistan, the interest of the government has tilted toward renewable energy sources in recent years. According to National Electric Power Regulatory Authority's (NEPRA) 2019 yearly report, Pakistan's total installed power generation capacity is 39000 MW, of which 66% of energy comes from thermal (fossil fuels), 24% from hydro, and 6% from renewable (wind, solar and bagasse) and 4% from nuclear [2]. This installed capacity of energy resources has increased from around 40000MW in 2021 to 45000MW in 2022 as shown in Fig. 1.3 and the contribution of renewable energy sources in this increment is mainly due to wind energy as depicted by the plot. [2].

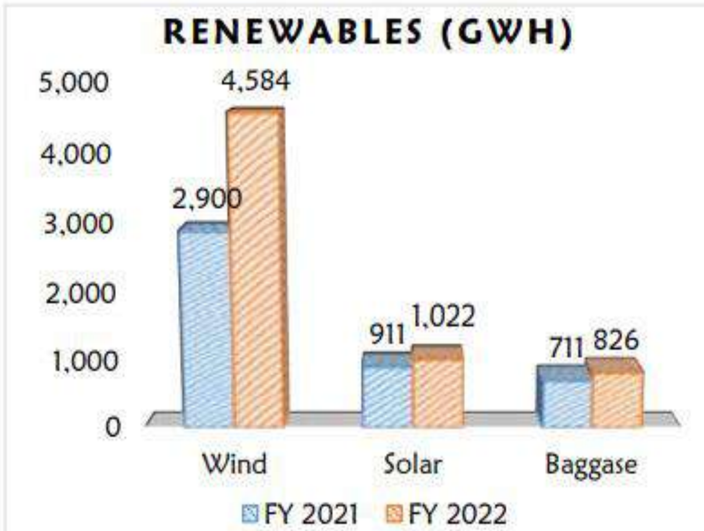

Fig. 1.1.3. Generation capacity of renewable energy sources in Pakistan in 2021 and 2022

Wind energy has emerged as one of the most promising sources of sustainable energy among the numerous renewable energy sources. Wind turbines are commonly utilized in this regard to harness the kinetic energy of the wind and transform it into electrical energy.

In this regard, wind turbines are widely used to harness the kinetic energy of the wind and convert it into electrical energy. However, conventional wind turbines suffer from various limitations, such as poor performance at low wind speeds and high maintenance costs.

To overcome these limitations, researchers have developed an innovative wind turbine design known as the Omni-directional Anemocone (ODA) wind turbine (Fig. 1.4). It is an omnidirectional wind turbine that captures wind from all directions and accelerates it through a funnel-shaped shroud. The shroud consists of a venturi section that compresses the wind, increasing its velocity. This accelerated wind is then used to turn the blades of the turbine and generate electricity by driving the generator installed at ground level and a diffuser section that decelerates the wind, extracting energy to generate electricity. Being omnidirectional, the technology does not require an active yaw control mechanism and thus eliminates the chances of environmental or damage.

Fig. 1.1.4. Omni-Directional Anemocone

1.1.2. ODA and Conventional Wind Turbine

In comparison to conventional wind turbines, ODA has several benefits such as.

- ***Smaller size:*** Traditional wind turbines have heightened towers with a rotor that captures the kinetic energy of the wind. The generator generates electricity when this rotor spins. The velocity of the incoming wind plays a huge role in determining the power output of the turbine. In the case of ODA, the funnel-like structure accelerates the flow and its size is much smaller as compared to traditional turbines.
- ***Low Cut-in speed:*** For conventional turbines the incoming speed velocity is used to rotate the rotor. In case of low velocity, the blades don't spin and power is not produced. This doesn't happen in ODA, it takes the low-velocity wind, accelerates it, and then turns the turbine.
- ***Efficiency:*** ODA is more efficient due to higher power output even in low wind regions while it is almost impossible to operate traditional turbines in such areas.

- ***Environmental Impact:*** Both traditional and ODA wind turbines have the benefits that they don't emit greenhouse gases or any other harmful emissions, but traditional wind turbines have proved to be a threat to birds and bats. Thousands of birds are killed due to these turbines. The modest design of ODA eliminates this threat as well. It is lower in height and doesn't have exposed blades that may hurt any species.

1.1.3. Parameters Affecting the Working of ODA

Fig. 1.5. shows different parts of an ODA. Air enters the system through the space between the flanges. These flanges act as a support for the funnel and as a wind collector for the turbine. The upper funnel guides air toward the inner parts of the ODA. Wind enters the system from all directions and the shroud concentrates on the collected wind. The concentrated wind then travels to a nozzle where it is accelerated to attain maximum velocity at the venturi. The turbine is mounted in the venturi section. A diffuser connected with the venturi section then decelerates the wind as it passes into the atmosphere.

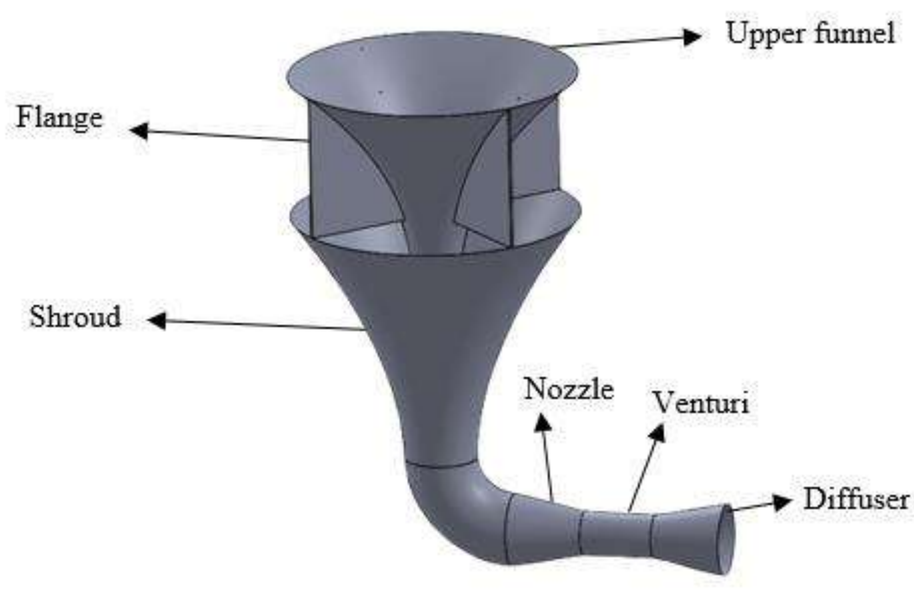

Fig. 1.1.5. Components of ODA

Each part of the ODA affects its working differently. Some of these parts or design parameters and their possible effects are discussed in Table 1.1.

Table 1.1.1. Parameters Influencing the Working of ODA

S. No.	***Affecting parameters***	***Possible results***
1	Inlet height	An increase in inlet height would increase the flow of wind through the ODA, which would possibly increase power output for the same input.
2	Overall height	An increase in the overall height of the turbine will increase the produced output; however, environmental constraints limit the maximum feasible height for the ODA.
3	Venturi diameter	A reduction in venture diameter will accelerate the wind flowing through it, thus, possibly enhancing the amount of electrical energy produced.
4	Funnel diameter	A funnel with greater diameter will enhance the flow of wind through the inlet and this might directly increase power generation.
5	Wind speed	An increase in wind speed will certainly enhance the working of the turbine as high-velocity wind will rotate the turbine blades at a greater speed, resulting in greater power generation.
6	Two-storey funnel	Two-storey funnel will increase the inlet area for incoming wind; however, due to an open environment, the incoming air from the upper funnel will exit the ODA system through the gap between the system’s body and the lower funnel.

1.2. Statement of the Problem

The development of any country can be assessed by its energy production and power consumption. Unfortunately, the energy production of Pakistan is not only low, in fact it doesn't even fulfill the needs of the society. From the last few decades, the demand of energy has increased whereas the production of energy has remained the same. Keeping all this in view, Government of Pakistan (GOP) has set a milestone of attaining over 30% power generation through renewable energy resources till 2030, which is currently less than 4% [2]. To achieve this goal several solutions are being considered and one of those solutions is an Omnidirectional Anemocone which can capture the wind from all directions and produce power at velocity as low as 2m/s. To obtain maximum output with minimum air velocity is necessary to obtain an optimized shape of the shroud of ODA. This study focuses on optimizing the shape of an ODA to upgrade wind velocity using the principles of aerodynamics.

In this regard, multi-objective optimization has been performed based on Genetic Algorithm for designs generation and the implementation of Machine Learning (Neural Network) to predict performance parameters of the designs. Achieving maximum velocity of air at the throat of venturi and minimum drag coefficient on the surface of the shroud are the two core objectives behind the optimization. The optimized design will have the capability to produce up to 5KW of power and will help in achieving the goal set by the Pakistani Govt.

1.3. Objectives

The project aims.

i. To optimize the shape of the ODA to maximize power extraction by maximizing the velocity of air at the throat and minimizing the drag coefficient on the surface of the shroud.
ii. To develop and implement a tool that can produce optimized designs using Artificial Intelligence.

1.4. Motivation (Research Gap)

The design of the ODA's shroud is the key component that surrounds the turbine and helps in harnessing maximum wind energy. In the past, the design of the shroud has been optimized using Parametric optimization techniques. Parametric optimization involves varying a set of predefined design parameters within specified ranges to find the optimal solution. However, this approach has its limitations. As a limitation, it may not always produce the best possible solution, especially when dealing with complex or non-linear problems.

In this project, Global optimization techniques will be used to produce new designs for the shape of the Anemocone. Global optimization involves searching the entire design space to find the best possible solutions without being limited by predefined design parameters. This approach can produce a greater number of unique and diverse designs, which may lead to better performance and efficiency compared to Parametric optimization.

Another advantage of Global optimization techniques is that they typically require lower computational cost than Parametric optimization since they can simultaneously evaluate multiple solutions and explore the design space more efficiently. This can be particularly beneficial when dealing with complex optimization problems that require many design iterations.

The ability of ODA to produce power at low wind velocity and the benefits of Global optimization for obtaining the best possible shape of the ODA's shroud are the main motivation for carrying out this project.

1.5. Methods

This project aimed to optimize the shape of the shroud of the ODA to improve its performance. Specifically, the goal was to optimize the shape based on two parameters i.e., drag coefficient on the surface of the shroud and speed ratio at the throat of the shroud. For this purpose, a multi-objective optimization tool was developed implementing ANNs, GA, and Pareto-Optimal Curves. This tool can generate several unique designs, predict the values of drag coefficients and speed ratios for those models, and provide the best models among the newly generated models.

For designing of new and unique model from a single parent model, a genetic algorithm has been used and then an artificial neural network model has been designed for the prediction of drag coefficients and speed ratio. The ANN model has been trained using a dataset generated by CFD analysis performed on sample ODA models. The tool optimizes the shroud shape with the help of Pareto-Optimal Curves by selecting the models with the least drag coefficients at the surface and maximum speed ratio at the throat.

A description of the technological tools that were used during project implementation is added below.

1.5.1. Computational Fluid Dynamics

Computational Fluid Dynamics is a branch of fluid mechanics that uses numerical methods and algorithms to analyze and solve problems related to the behavior of fluids, such as liquids and gases. Fluid flow and its related physical parameters, such as velocity, pressure, viscosity, density, and temperature, are computed using CFD software under specified operating circumstances. These quantities are calculated concurrently in order to arrive at an accurate, physical solution [25]

To anticipate the desired flow physics, every CFD program, commercial and/or open source, employs a mathematical model and numerical approach. The Navier-Stokes (N-S) equations underpin the majority of CFD technologies. While the majority of the terms in the Navier-Stokes equations remain constant, physics allows for new terms to be added or removed. More terms will be incorporated into the governing equations, for example, if heat transport, phase change, or chemical reactions must be considered. The main structure of thermo-fluids investigation is directed by governing equations based on the physical property conservation law of fluids. According to these concepts, mass, momentum, and energy are stable constants within a closed system and they all may remain conserved. The fundamental equations are the three conservation laws:

- The Continuity Equation and Mass Conservation
- Newton's Second Law of Momentum Conservation

- Energy Conservation Law: First Law of Thermodynamics or Energy Equation

CFD is widely used in many industries, including aerospace, automotive, energy, and biomedical engineering, to optimize designs, reduce costs, and improve performance. It allows engineers and scientists to simulate and analyze fluid behavior in a virtual environment, without the need for physical testing, which can be time-consuming, expensive, and sometimes impossible to perform.

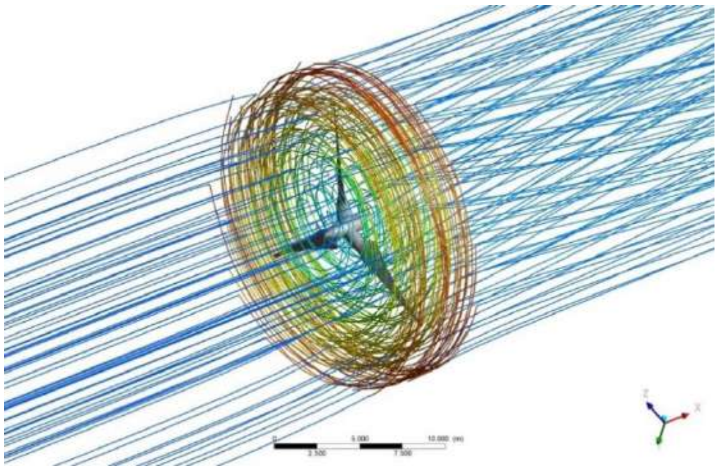

Fig.1.6. Computational fluid dynamic analysis of a turbine

There are many software that are used for carrying out CFD analysis to simulate real-time scenarios in order to save time and cost on the experimental setup. Fig. 1.6 shows a CFD analysis of a shrouded turbine performed using one of these software. In this project, *ANSYS* has been used to compute the drag coefficient on the surface and speed ratio at the throat of ODA models.

ANSYS, developed by *ANSYS* Inc., is a robust and extensively used engineering simulation software suite. It provides extensive modeling, simulation, and analysis tools and capabilities for a wide range of physical phenomena in a variety of sectors. Engineers, researchers, and designers rely on *ANSYS* software because of its adaptability and capacity to handle complex engineering challenges. Users of *ANSYS* can simulate and analyze a wide range of engineering disciplines, such as structural mechanics, fluid dynamics, electromagnetics, and Multiphysics interactions. The program provides a solid basis for virtual prototyping, allowing engineers to optimize designs, test performance, and forecast behavior before building actual prototypes. This helps to reduce development costs, improve product reliability, and shorten time to market.

ANSYS provides a wide number of modules and solvers for specialized engineering domains, such as *ANSYS* Mechanical for structural analysis, *ANSYS Fluent* for computational fluid dynamics, *ANSYS* HFSS for electromagnetic simulations, and *ANSYS* Maxwell for electrical machine design. To keep up with evolving industry trends and technical breakthroughs, the software's capabilities are constantly updated and increased [26].

In this project, all the CFD analyses have been carried out using *ANSYS Fluent* which is a general-purpose CFD software used to model fluid flow, heat and mass transfer, chemical reactions etc. Fluent incorporates modern, robust, and user-friendly features that enable users to simulate any problem with no difficulty.

1.5.2. Artificial Neural Network

An artificial neural network (ANN) is a machine-learning technique that is designed to mimic the structure and function of the human brain. ANNs are meant to recognize complicated patterns in data by processing information through layers of interconnected nodes or neurons.

A neuron is the fundamental building component of an ANN; it accepts input from other neurons or external sources, processes the information, and then delivers an output to other neurons. Fig. 1.7 shows the structure of an ANN model. The connections between neurons are weighted, which means that some inputs have a greater influence than others in deciding a neuron's output. An ANN's input layer accepts data from the external world or other sources, while the output layer provides the network's ultimate outcome. One or more hidden layers of neurons provide intermediary processing between the input and output layers.

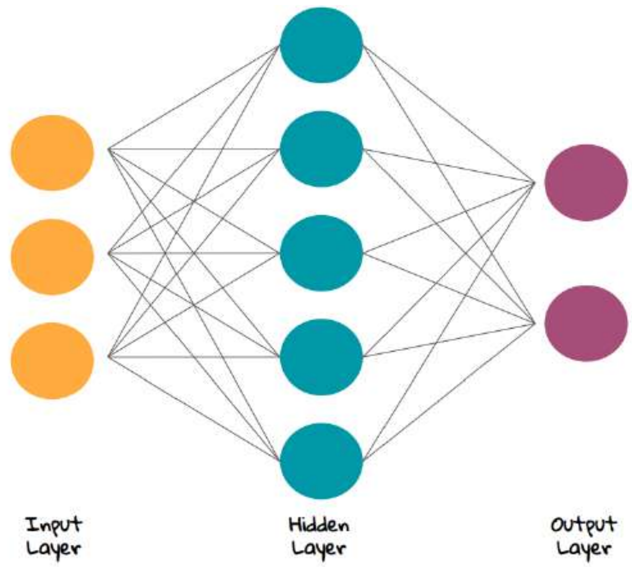

Fig.1.7. Structure of ANN Model

An ANN learns to recognize patterns in data throughout the training process by altering the weights of its connections using a technique known as backpropagation. The network is given examples of input data as well as the desired output, and the weights are changed to minimize the discrepancy between the network's actual output and the desired output. Image and audio recognition, natural language processing, financial forecasting, and robotics are just a few of the uses for ANNs. They excel at tasks that require complicated, non-linear interactions between inputs and outcomes, and they can generalize from examples to anticipate new data.

1.5.3. Genetic Algorithm

A genetic algorithm is a sort of optimization algorithm influenced by natural selection and evolution processes. It is a search-based optimization technique that mimics the natural processes of selection, reproduction, and mutation to identify the best solution to a problem. It is a strategy based on natural selection, the process that drives biological evolution, for tackling both limited and unconstrained optimization issues.

The algorithm works by generating a population of potential problem solutions known as individuals, which are represented as strings of bits or genes. These individuals are then evaluated using a fitness function that measures how successfully they solve the task. Individuals with the greatest fitness scores are then chosen for reproduction, in which their genes are combined to form new individuals in a manner like how genetic material is mixed in biological reproduction. The fitness function is then used to evaluate the new people, and the procedure is repeated until a good solution is discovered. Some individuals are randomly modified in each iteration of the algorithm to introduce new variants in the population, which helps to prevent getting stuck in local optima and improves the overall variety of the population. Fig. 1.8 shows the schematic of the working of a genetic algorithm.

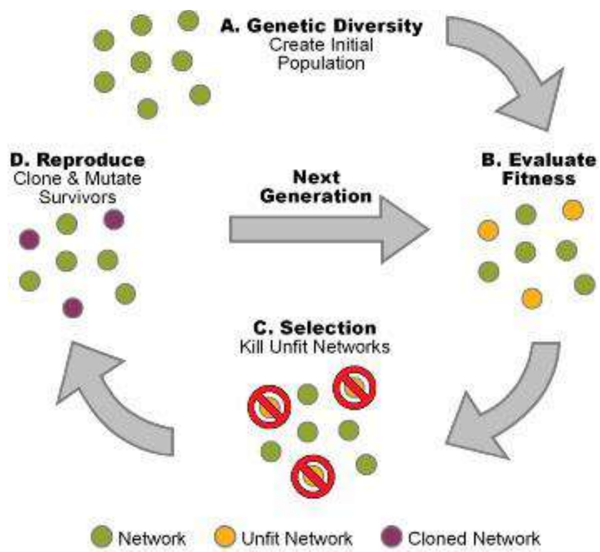

Fig.1.8. Schematic of the working of a genetic algorithm

Genetic algorithms have been widely employed in a variety of industries, including engineering, finance, and computer science, to tackle complex optimization issues. They are especially beneficial in problems with a high number of variables, non-linear connections, and several conflicting objectives, where typical optimization methods may fail.

1.5.4. Pareto Optimal-based Optimization

Pareto optimum-based optimization, also known as multi-objective optimization, is an optimization technique that aims to identify a collection of optimal solutions that optimize numerous, often conflicting, objectives at the same time. The purpose of single-objective optimization is to identify a single solution that maximizes or minimizes a single objective.

function. However, in many real-world challenges, many objectives must be considered at the same time, such as maximizing profit while limiting cost or optimizing efficiency while minimizing environmental effects.

This difficulty is addressed by Pareto optimum-based optimization, which identifies the set of optimal solutions that cannot be improved in one objective without compromising another. These are referred to as Pareto optimum or non-dominated solutions. The Pareto-optimal curves formed based on multi-objective optimization are as shown in Fig. 1.9.

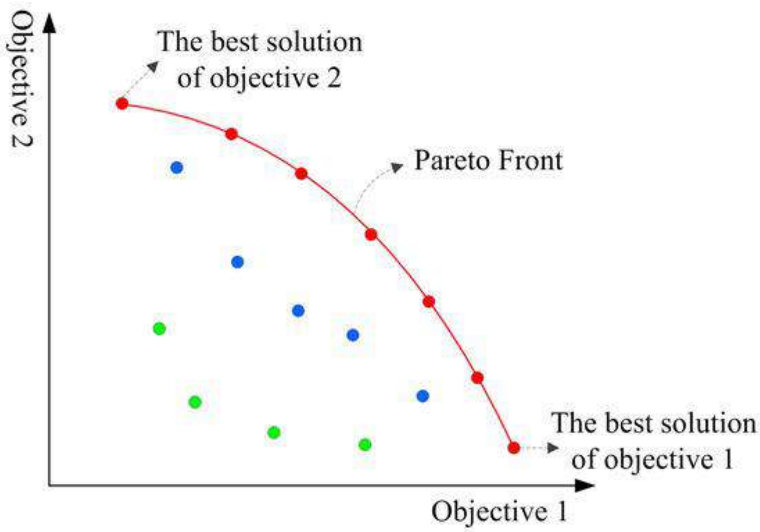

Fig.1.9. Pareto-optimal curve for multi-objective optimization

The optimization algorithm assesses a group of alternative solutions and ranks them based on their dominance relationships in order to identify the Pareto optimal answers. A solution is considered to dominate another solution if it outperforms it in at least one objective while performing no worse in any other. Pareto optimum solutions are those that are not dominated by any other solution. The Pareto optimal solutions indicate a trade-off between the various objectives and the final decision on which solution to adopt is determined by the decision maker's preferences or the problem's restrictions.

Pareto optimal-based optimization has various applications in engineering, finance, and other industries where multiple competing objectives must be evaluated at the same time. It assists decision-makers in exploring the trade-offs between various objectives and identifying the best solutions that best satisfy their demands.

1.6. Sustainable Development Goals

The Sustainable Development Goals (SDGs) were enacted by the United Nations in 2015 as a global call to action to eradicate poverty, safeguard the environment, and guarantee that by the year 2030, peace and prosperity will be experienced by everyone. The 17 SDGs recognize that development must balance social, economic, and environmental sustainability and that actions in one area will have an impact on results in others. This research work targets 4 of these sustainable goals;

- Affordable and clean energy (07)
- Industry, Innovation and Infrastructure (09)
- Climate action (13)
- Life on land (15)

1.7. Outline

Chapter 1 discusses the design and parameters of an ODA as well as its benefits over conventional wind turbines which became the main motivation of this project. The objectives, methods that were implemented, target SDGs and a brief outline of the research work have also been specified.

Chapter 2 briefs out all the literature review carried out before and during the research work.

Chapter 3 shares the complete framework of the carried-out research work. It presents how all the discussed tools have been implemented during the project. The steps involving the generation of dataset using CFD, training and implementation of ANN, utilization of GA and optimization using pareto optimization has been thoroughly discussed.

A GUI has been designed to make the developed tool user-friendly. Chapter 4 presents the layout of the developed GUI application.

Chapter 5 summarizes and explains the obtained results. The obtained plots and tables have been presented.

The entire research work has been concluded in Chapter 6.

Chapter 2

2.1. Literature Survey

To harness maximum power through an Invelox system, a variety of research projects are in progress. Work has been and will continue to be carried out to improve, optimize and enhance the use of this unique system.

In 2014, Daryoush Allaei and Yiannis Andreopoulos presented a new design for harnessing wind energy; an INVELOX wind turbine which provided solutions to all the major problems related to conventional wind turbines like reliability, intermittency issues, and wildlife hazards. The Omni-directionality of the system resulted in a significant increase in power output [3]. The concept underwent further research when Daryoush Allaei *et al.* analyzed the effect of multiple turbines in the Venturi section. Multiple turbines significantly increased the performance as compared to single turbines [4].

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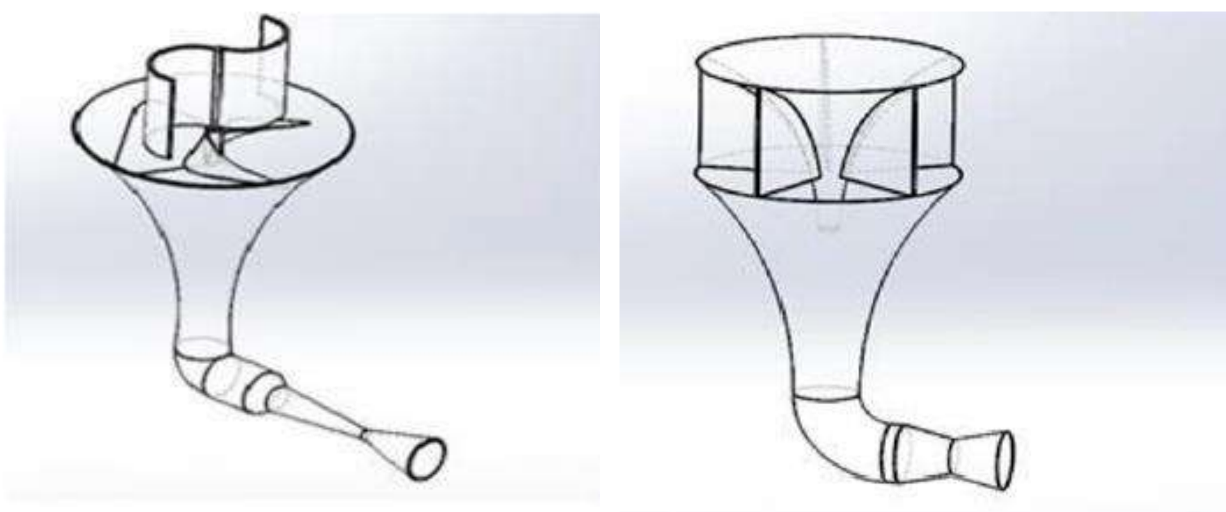

Fig. 2.1.1. Models compared in [5].

Gohar *et al.* also performed a comparative study for two models of Invelox; Model 1 having a typical funnel and venturi and Model 2 with a combination of Vertical Axis Wind Turbine (VAWT) blades and propeller fan (consider Fig. 2.1). CFD analysis showed that Model 2 can generate more power by optimizing the mass flow rate of air and pressure drop across the turbine. The wind velocity increased from 10.42 to 45.5 m/s at the venture section of Model 2, and the pressure drop decreased from -1.7223 x 10^1 to -6.9383 x 10^2 Pa. The total power output was calculated as 1825.52 W for Model 1 and 93.153 x 10^3 W for Model 2. The effect of adding multiple turbines at the venturi section was also studied during the study. For both models, the speed ratio decreased as the number of turbines increased from one to three [5].

It was noted that changes in the geometrical parameters also influenced the working of the system. Anbarsooz *et al.* studied the impact of main geometrical parameters on the performance of the turbine. The speed ratio at the venturi was significantly affected by increasing inlet area. Increasing the dimensionless inlet height leads to a 15% increase in the speed ratio. Increasing both parameters increases the pressure drop, directing wind directly across the shroud which prevents air from escaping from the opposite side of the incoming wind. The resultant Speed ratio changes weakly. Wind speed has a negligible effect on the speed ratio [6]. Freshteh Sotoudeh *et al.* also increased the assembled height from 10m to 40m which produced an 87.5% increase in output power and a 39.3% increase in power acoustic level. To increase the efficiency of IWT, a new structure has also been suggested. As shown in Fig. 2.2, the results indicated that by using a two-storey Invelox turbine, the output power increases up to 44% [7].

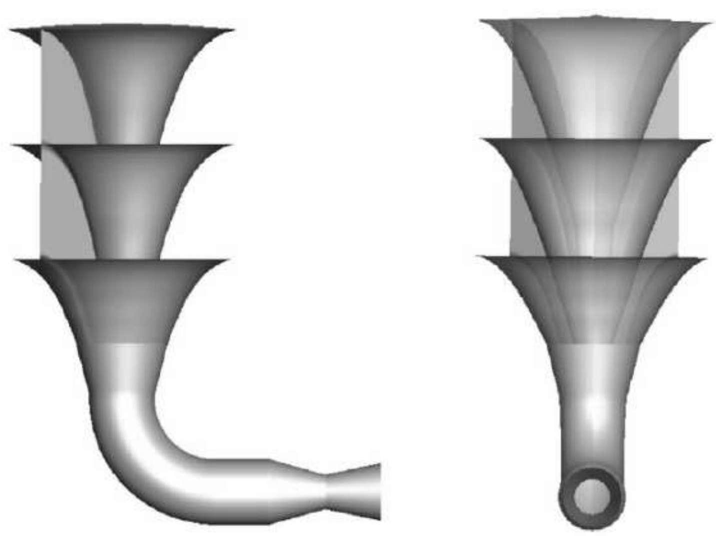

Fig. 2.1.2. Two Story model proposed in [7].

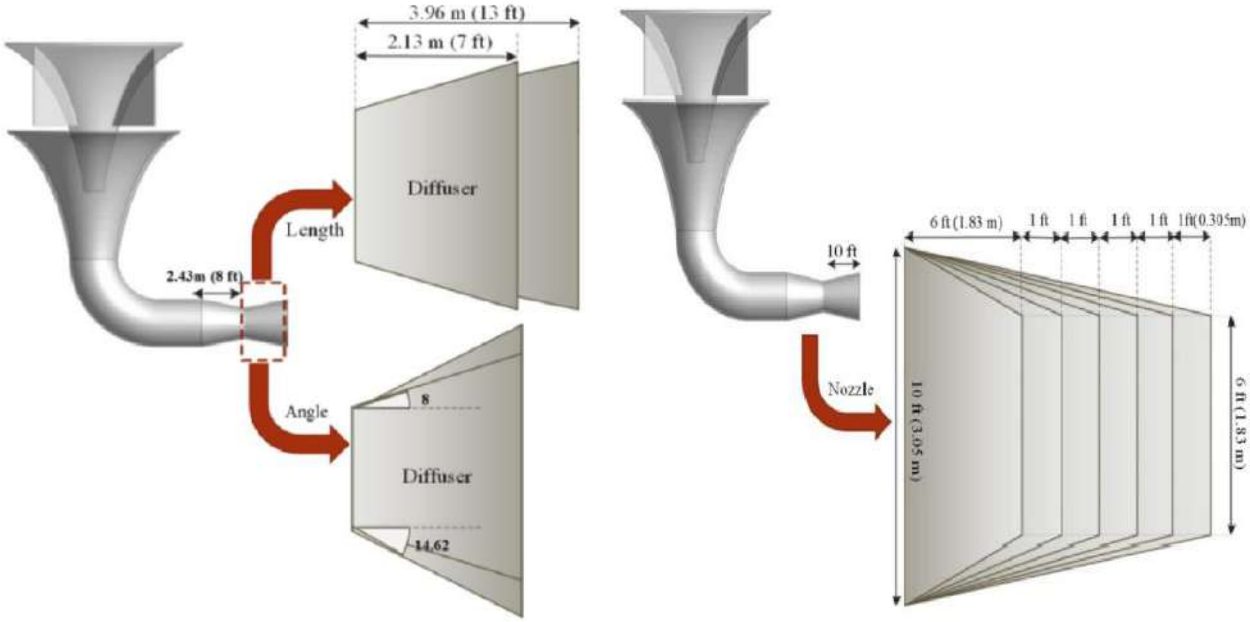

Fig. 2.1.3. Variations discussed in [8]

S. Rasoul Hosseini and Davoud Domiri Ganji analyzed the nozzle-diffuser section of the Invelox system; the varying dimensions are shown in Fig. 2.3. As long as the channel flow is not separated, increasing the nozzle and diffuser length or diffuser angle was found to boost channel efficiency. The flow rate through the channel was significantly increased by the addition of the exit flange; however, adjusting the angle of the flange has only a little effect on the flow rate increase [8].

Another key factor influencing the performance of the turbine is its orientation. Keeping this in view, Patel Snehal Narendrabhai and T.S. Desmukh, studied the effect by positioning the shroud at different angles concerning incoming air. With regard to the turbine axis, wind flows from 8 different directions (0, 45, 90, 135, 180, 225, 270, 315, and 360) were analyzed. Except for 135° and 225° angles, higher speed ratios were obtained in every scenario. The 45° and 315° angles produced the maximum wind speed ratio. The Invelox wind turbine system, according to the results, may produce between 6 and 8 times as much energy as conventional wind turbine systems with a similar size turbine [9]. According to the numerical results of the study performed by Li Ding and Tongqing Guo, the speed ratio drops sharply when an Invelox exit is facing the incoming wind. To solve this problem, a straight-through layout with a windshield was presented as shown in Fig. 2.4. The windshield increased the speed ratio by about 42% [10].

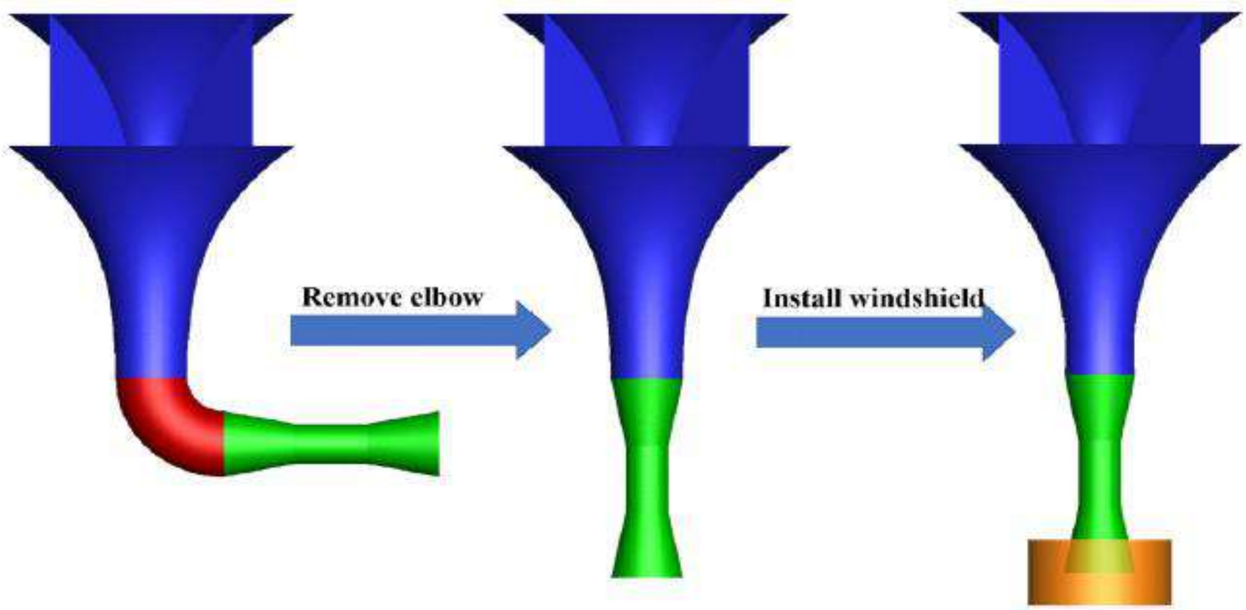

Fig. 2.1.2. Model proposed in [10]

Three modifications to the actual model of IWT have been proposed and numerically tested by M. Anbersooz *et al.* consider Fig. 2.5. Extending the guiding curtains reduces the volumetric flow rate while the second modification eliminates escaping air without changing pressure drop and increased wind velocity by 25% in the venturi section for 3m/s to 12m/s inlet wind velocities. The modifications increased the average velocity in the Venturi section by 5.4%, 25.9%, and 6.1%, respectively [11].

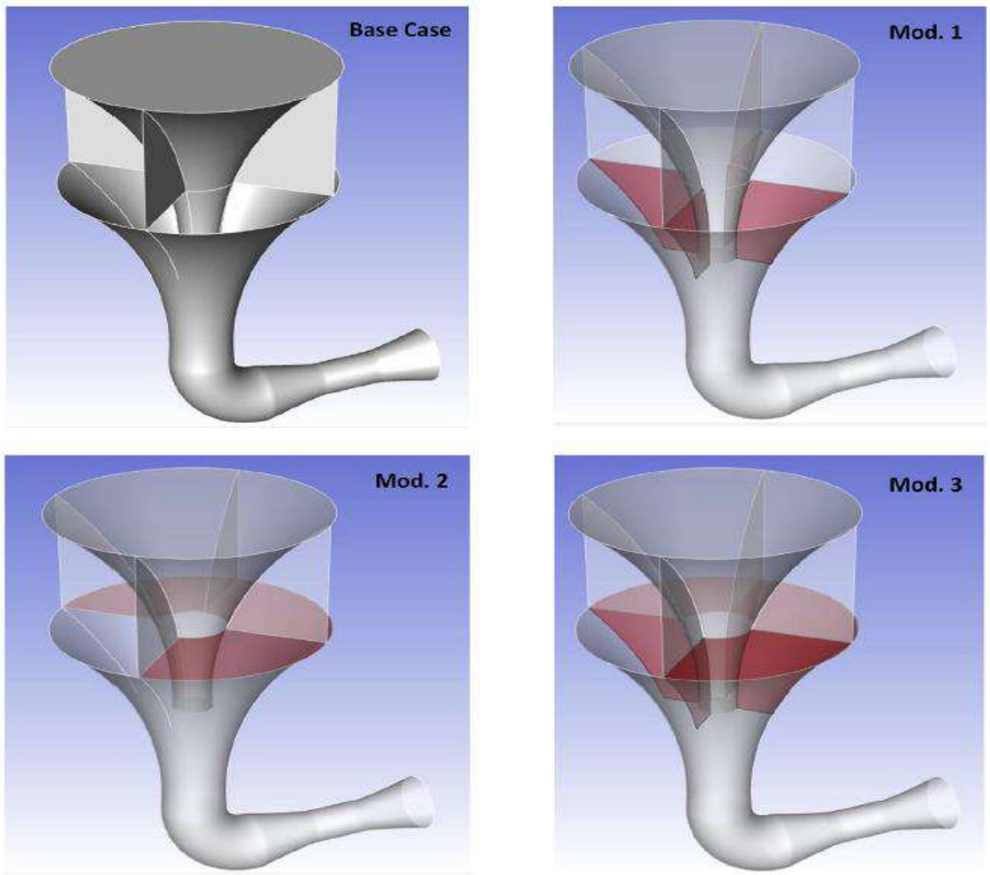

Fig. 0.1. Modification proposed in [11]

Furthermore, a piezoelectric vibration energy harvester (PVEH) with a bluff splitter, was introduced by Zhi Chao Ong *et al.* The modified model achieved 2.7 times the wind speed amplification. Moreover, it had the potential to harvest a maximum power output of 0.82 MW at 20m/s wind velocity [12]. The ability of the wind turbine to generate energy at different conditions in different areas had an impact on the results. To analyze this effect Mousa Meratizaman and Mojtaba Nateqi performed a comparative study based on technical and economical properties, conducted in 2021 in 5 major cities in Iran. It showed that IWT is more economical and generates more than a conventional Horizontal axis wind turbine (HAWT) [13]. A mini-ducted wind turbine, as shown in Fig. 2.6 was analyzed numerically and experimentally at six different configurations by Fabio Nardecchia *et al.* and obtained less than a 1 % relative percentage difference between the numerical and experimental results [14].

Fig. 0.2. Mini Ducted Wind Turbine [14]

In recent studies, machine learning and optimization techniques are used to improve energy output and operational efficiency by optimizing power curves, detecting faults, improving wind predictions, controlling, and optimizing wind turbine layout. Marugán studied the benefits and drawbacks of Artificial Neural Network (ANN) applications. Significant challenges and technological constraints of deploying ANN in wind power-producing systems were discussed [15]. For modeling the power curve of a wind turbine, Pelliter employed an ANN technique that incorporated six parameters [16]. A study conducted by Haiying Sun *et al.* proposed an ANN model for predicting wind turbine power generation. The proposed model was found to have less computational cost and could be applied to complex wind turbine problems[17]. Mashhadimoslem *et al.* compared conventional prediction models to ANN and deduced ANN is a useful forecasting technique that offers several benefits [18]. Taghinezhad *et al.* proposed an ANN model for the prediction of power curves of ducted wind turbine using the Levenberg-Marquardt training algorithm [19]. By utilizing a dataset containing over 700,000 empirical raw sequence data, Yan developed an ANN capable of simulating the power generation of a wind farm [20][20]. Farhad Elyasichamazkoti and Abolhasan Khajehpoor studied the use of ANN for wind energy systems and highlighted their advantages for the efficient and optimal design of wind turbines and wind farms [21].

For reducing computational cost and time as well as generating robust several algorithms and optimization techniques have been implemented in the past. The use of genetic algorithms for searching for optimal solutions has been in practice for a very long time
now; a study has proposed Aesthetic-Generative Design Technique (A-GDT), for generating optimal and aesthetically convincing designs for provided CAD model. A-GDT outperformed the existing modeling techniques [22]. Fig. 2.7 shows the outcome an A-GDT.

R. Asfour *et al.* conducted a study on Wind Farm Layout Optimization (WFLO) and used a Genetic Approach to determine the optimal wind turbine locations. The aim was to maximize net energy production while minimizing the Cost of Energy (COE) using a

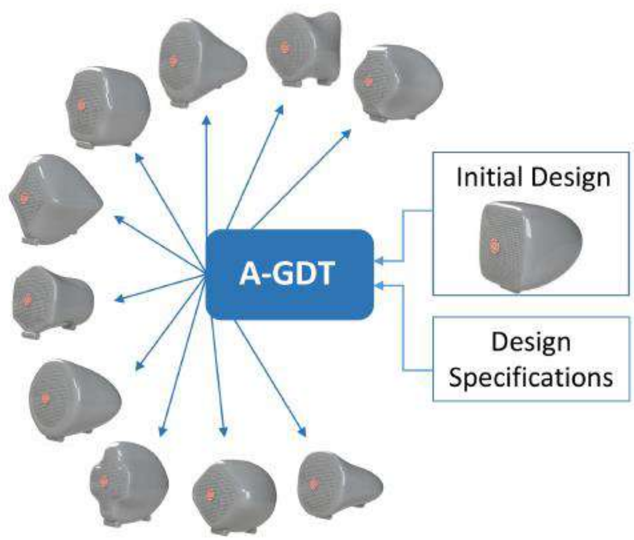

Fig. 0.3. Illustration of the outcomes of A-GDT

complex optimization approach influenced by upstream turbine inflow wind. The study conducted WFLO for 500, 1000, and 1500 iterations and found that the best output was achieved at 1500 iterations with the lowest value for the objective function [23].

The geometry of IWT was optimized using Multi-Objective Particle Swarm Optimization (MOPSO) based on the surrogate-based method by Mohammad Mahdi Ghorani *et al.* In comparison with the original model of IWT, the maximum net mass flow rate (M_{net}), maximum wind power (P_{max}), and speed ratio increased significantly. The backflow was eliminated through the optimized model [24].

Chapter 3

3.1. Research Framework

3.1.1. Complete Methodology

A brief layout of the procedures to be followed during the research is provided in Fig. 3.1. The optimization process is started with the Computer-Aided Design (CAD) modeling of the ODA wind delivery system. The CAD model for the ODA system was modeled in *Solidworks.* Fig. 3.2 shows the geometry of the created model with dimensions.

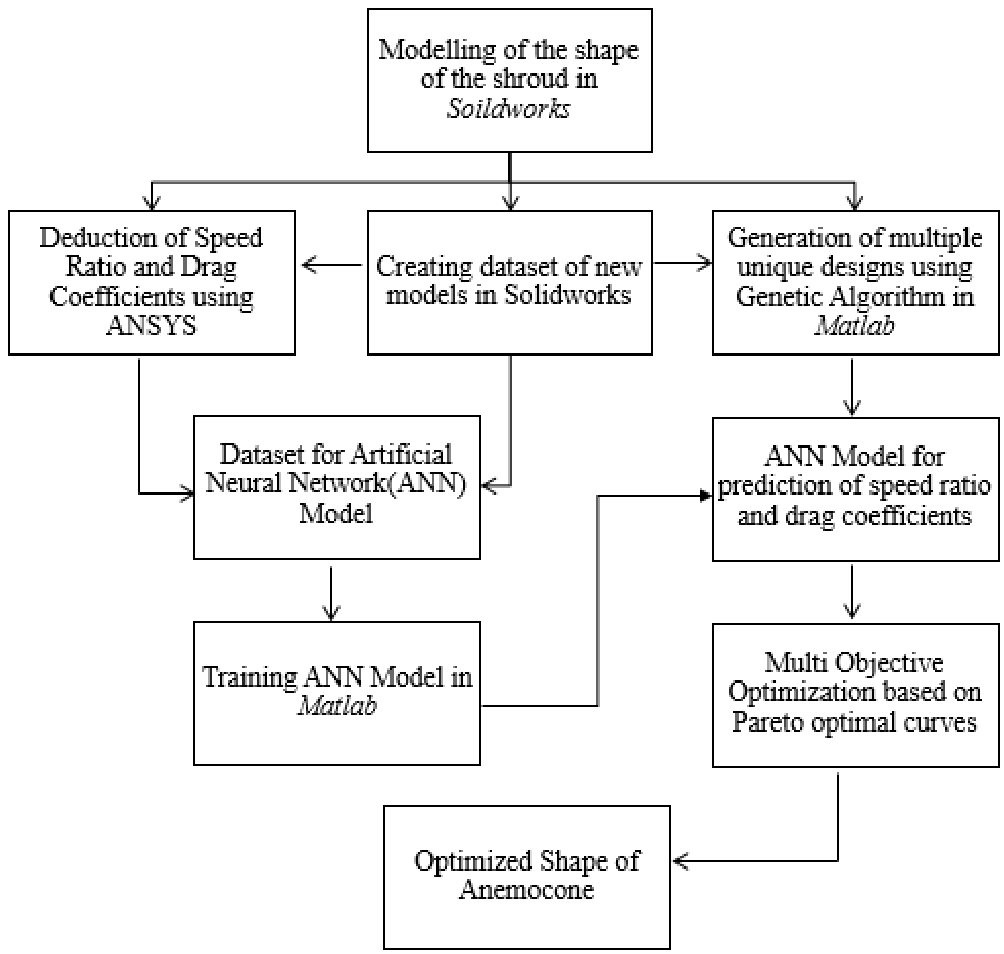

Fig. 3.1. Research Framework

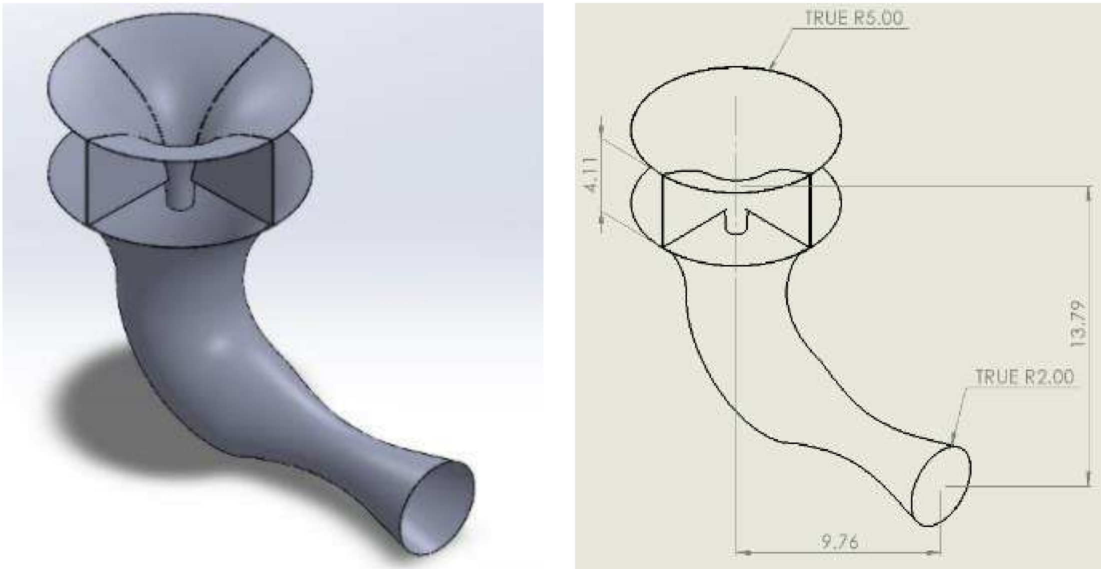

Fig. 3.2. CAD Model of ODA

The geometry presented in existing literature [10] was used to validate the CFD approach. The validated approach was then applied to the originally modeled ODA. The geometrical parameters of the model including funnel height, shroud height, shroud diameter, venturi length and venturi diameter, etc., were varied to create a large number of unique models. The variation was brought about by adjusting the coordinates that define the shape of the shroud. The validated CFD approach was implemented on these models to obtain the value of the drag coefficient and velocity for each model. The results, coordinates of all the models, and their corresponding drag coefficients and velocities were compiled to build a dataset used to train an Artificial Neural Network (ANN). The developed ANN tool can predict the values of velocity and drag coefficient for any input coordinates. A Genetic Algorithm (GA) has been developed to create thousands of new designs using the initially created unique designs. The trained ANN was integrated with the GA to predict the velocities and drag coefficients for all the new models. In the end, Pareto-curve optimization was implemented to optimize the shape of the ODA based on the two defining parameters.

3.2. Numerical Method

3.2.1. Governing equations

The velocity of air at the venturi section and the drag coefficient of air at the surface of the ODA were to be deduced using Computational Fluid Dynamics (CFD). This study has utilized *ANSYS Fluent*, a commercial software, as the tool to perform aerodynamic analysis on the ODA wind turbine system. Three possible approaches to solving turbulent flows are used commonly. Among these approaches, three-dimensional incompressible Reynolds-Averaged Navier-Stokes (RANS) equations were employed in this study as it reaches the maximum degree of approximation with minimum computational requirements. There existed no need to solve the energy equations for the flow as no heat transfer occurred. In Cartesian coordinates, the mass and momentum conservation equations for the steady RANS system can be written as;
Continuity;

$$\frac{\partial \overline{u'}_{\mathrm{i}}}{\partial x_{\mathrm{i}}} = 0 \tag{3.1}$$

Momentum;

$$\rho \bar{u}_{\mathrm{j}} \frac{\partial}{\partial x_{\mathrm{j}}} \overline{(u_{\mathrm{i}})} = -\frac{\partial \bar{p}}{\partial x_{\mathrm{i}}} + \frac{\partial}{\partial x_{\mathrm{j}}}\left(\mu \frac{\partial \overline{u'}_{\mathrm{i}}}{\partial x_{\mathrm{j}}} - \rho \overline{u'_{\mathrm{i}} u'_{\mathrm{j}}}\right) + S_{\mathrm{i}} \tag{3.2}$$

where u_i is the velocity of air in *i* direction (m/s), u'_i is a fluctuating component of velocity of air in *i* direction (m/s), ρ is the density of air (kg/m^3), p is pressure applied by fluid in *i* direction (Pa), μ is the viscosity of air (kg/ms), S_i is the source term and $-\rho\overline{u'_{\mathrm{i}} u'_{\mathrm{j}}}$ is Reynolds stress term: an apposite turbulence model is used to tailor this term.

Prominent RANS turbulence models include k-omega (k-ω), k-epsilon (k-ε), and Shear Stress transport (SST) models. Two transport equations are used in the k-ε model: one for the kinetic energy of turbulent flow (k) and another for the rate at which kinetic energy is lost (ε).

Since anisotropic effects and flow separation are not included in the model, it assumes isotropic turbulence. *k-ω* also employs two transport equations: turbulent kinetic energy (*k*) equation and dissipation rate equation (ω). For flows with negative pressure gradients, boundary layer flows, and near-wall flows, the *k-ω* turbulence model works well. The *k-ω* and *k-ε* models' components are combined to create the SST model. It accurately predicts boundary layer behavior in the region close to the walls using the *k-ω* model and switches to the *k-ε* model to simulate flow in the regions away from the wall.

3.2.2. Solution methodology

The simulation employed a pressure-based solver, implementing Semi-Implicit Method for Pressure Linked Equations (SIMPLE) algorithm. The upwind scheme in second order was used to discretize the pressure and momentum equations. To model turbulence, an enhanced wall function was employed with the *k-ε* turbulence model. The realizable *k-ε* model was established as the most suitable one for modeling flows in wind turbines. This model was claimed to be more accurate for predicting the spreading rate of jets][27] and, thus, this study uses the same model. At the order of 10^{-5} for the scaled residuals, the calculation results were obtained for the two monitored variables i.e. velocity and drag coefficient.

3.2.3. Mesh Sizing and boundary conditions

The accuracy and stability of a numerical simulation are significantly affected by the quality of the mesh. The computational mesh created in this analysis is composed of tetrahedral cells as shown in Fig. 3.3. The addition of a wind turbine can greatly increase the complexity and computational cost of the numerical problem and as the aerodynamic analysis performed in this study revolves around the performance of the wind-gathering device itself, no turbine has been involved in the simulation.

Other than the inlet, outlet, and symmetry, the remaining faces of the domain (top, bottom, and sides) are the slip boundary walls as shown in Fig. 3.4. Analysis has been performed at an inlet velocity of 5m/s. For uniform incoming velocity, 5% turbulence intensity and a 1m length scale is applied. Symmetry has been applied to reduce the computational cost of the analyses.

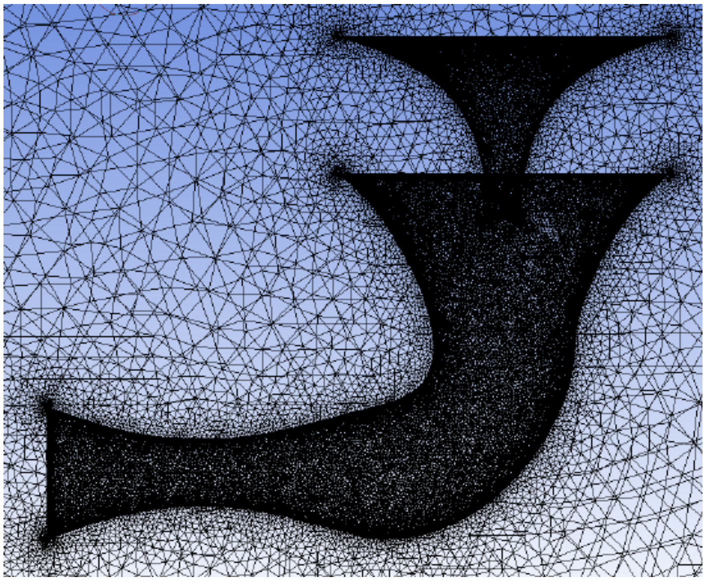

Fig. 3.1. Unstructured Mesh of ODA.

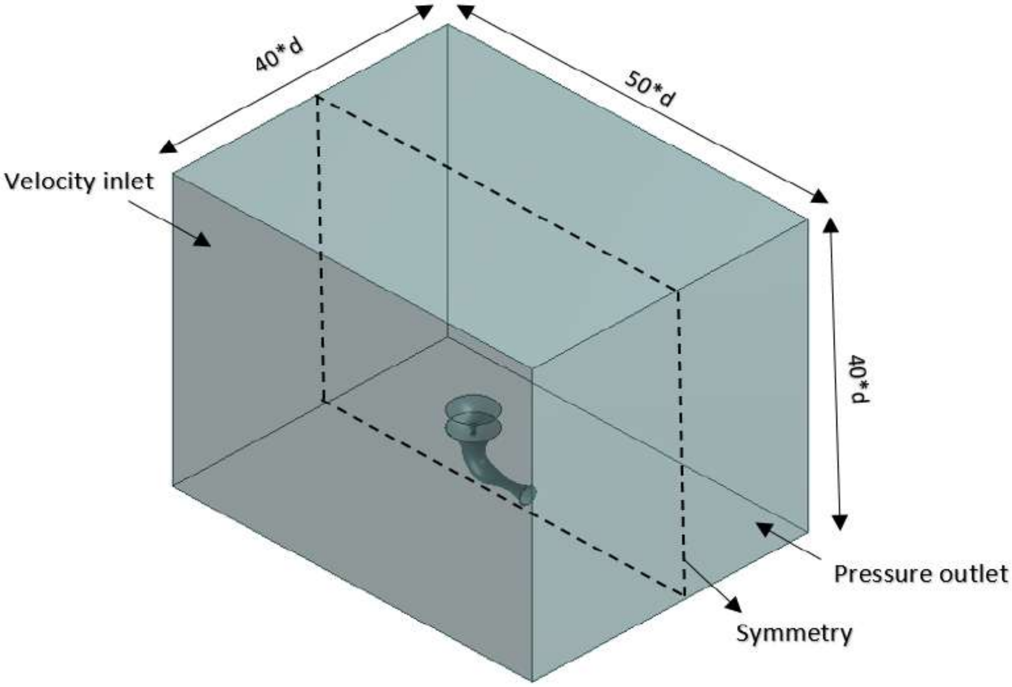

Fig. 3.2. Fluid domain and boundary conditions.

3.2.4. Validation of the approach

The approach for the flow analysis is validated from existing literature [10]. Fig. 3.5 shows the velocity contour for the validated CFD approach. The results were in concurrence with the reference paper [10], with a maximum error of 1.5% between them. For comparison, the results of the validation study are presented in Fig. 3.6.

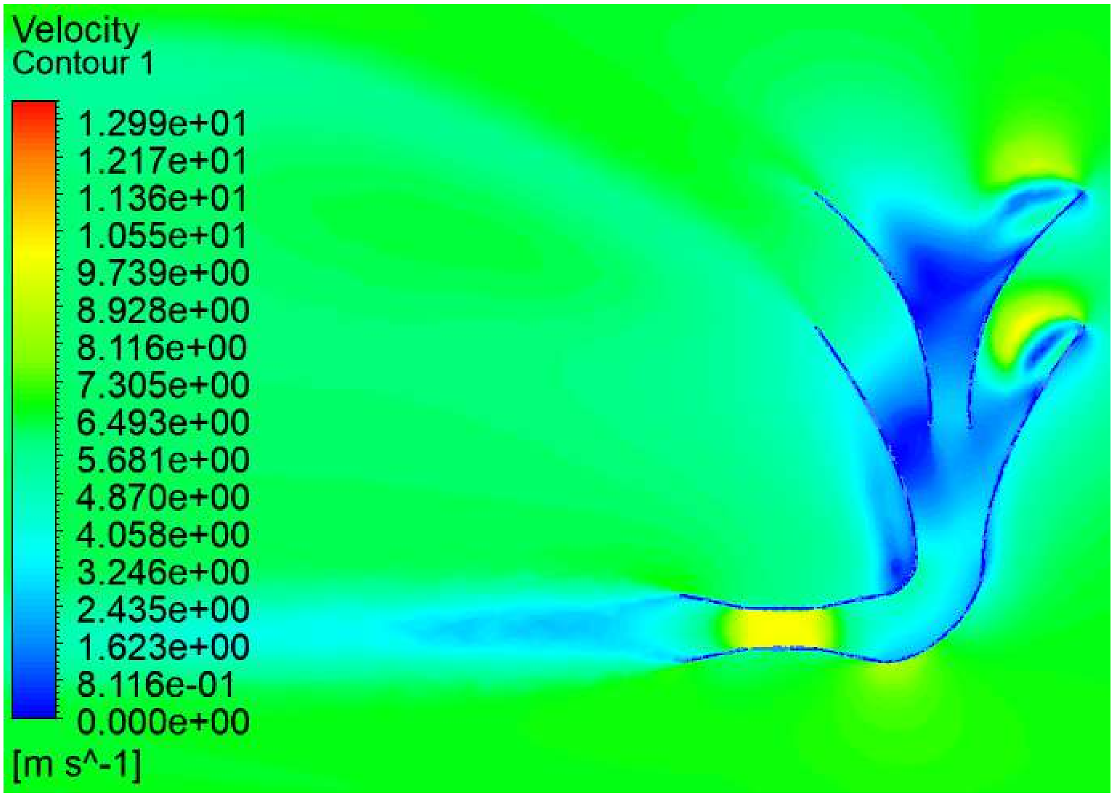

Fig. 3.3. Velocity contour for the validation study.

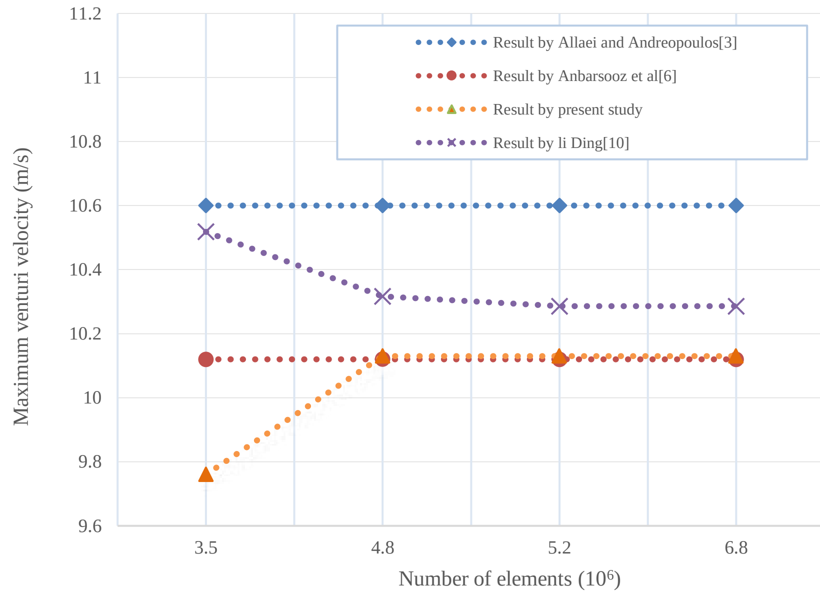

Fig. 3.4. Validation of numerical results.

3.2.5. Mesh independent study

A Mesh independent study was conducted to reduce the cost associated with computing the simulation and attaining accuracy. With a fine mesh closer to the surface of the system and a coarse mesh in regions away from the system, three different meshes were obtained with cell numbers of 3.5, 4.8, and 5.2 million, respectively. Table. 3.1 shows the average velocity in the venturi section for all three grid sizes.

Table 3.1. Mesh Independence study.

S. no.	***Number of elements (10^6)***	***Venturi velocity (m/s)***
1	3.5	9.76
2	4.8	10.13
3	5.2	10.13

3.3. Optimization

3.3.1. Shape of Spline

The shape of the shroud used in the optimization of ODA is designed using the spline feature of *Solidworks*. It was defined by 11 points, each with its own *x* and *y* coordinates, as shown in Fig. 3.7. The coordinates of the models created in *Solidworks* along with the corresponding velocities and drag coefficients, obtained through CFD, act as the dataset for the training of an Artificial Neural Network.

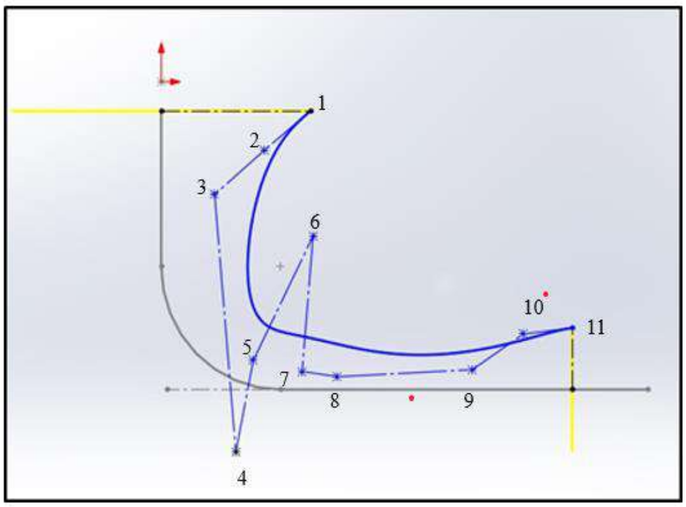

Fig. 3.1. Spline with x and y co-ordinates.

The coordinates of the models generated by the Genetic Algorithm were fed to the trained Artificial Neural Network model, which predicted the drag coefficients and speed ratio of the new models.

3.3.2. Artificial Neural Network Model

The model for machine learning was developed using *MATLAB* with a supervised learning approach. The model had 22 input parameters (coordinates of the shroud) and 2 output parameters (Drag Coefficients and Speed Ratio). The training dataset was split up into three sets at random with 70% of the data selected for learning, 15% for validation, and 15% for testing. The performance of the network was assessed using the dataset extracted for testing. The network's operation during the learning process was verified using the data separated for validation and the dataset separated for learning was used for adjusting weights as required. The model was trained using the Levenberg Marquardt Training algorithm.

The model's framework consists of an Input layer, a Hidden layer, and an Output layer. There were 22 nodes in the input layer and 2 nodes in the output layer. Tansig activation function or a hyperbolic tangent function was applied to the hidden layer which allowed the model to learn and represent the complex relationship between inputs and outputs. For the output layer linear transfer function was used. The performance of an ANN model is greatly influenced by the number of nodes that form the hidden layer. The empirical formula of hidden layer design states that,

$$l < (m + n)^{1/2} + a \tag{1}$$

where *l* represents the number of nodes in the hidden layer, n is the number of nodes in the input layer, m is the number of nodes in the output layer, a is a constant and can vary between 0 and 10 [28]. Based on this formula, it was established that the number of nodes in the hidden layer must range between 5 and 15. The number of nodes was varied to obtain the best results with less prediction error and training time. The best performance was observed with 12 nodes in the hidden layer, as shown in Fig. 3.8.

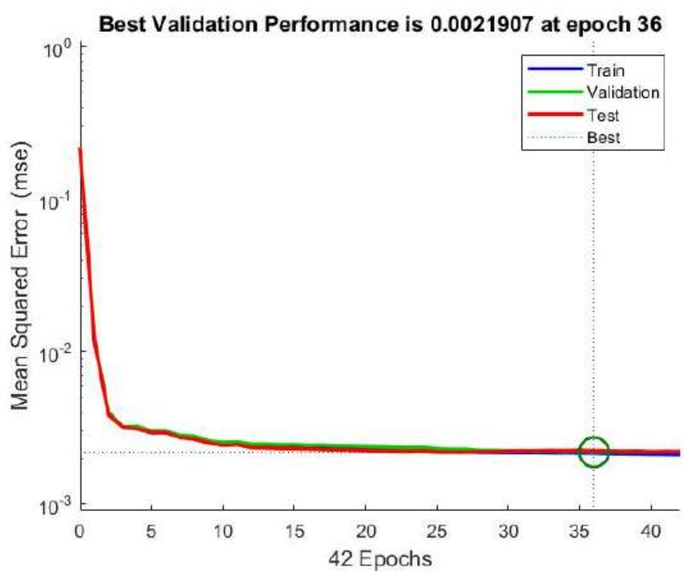

Fig. 3.2. Performance graph of the ANN model

3.3.3. Multi-Objective Optimization

The multi-objective optimization aims to optimize the shape of the shroud of the ODA by maximizing the speed ratio and minimizing drag coefficients. To achieve this goal, the initial step was the generation of new models. For this purpose, Genetic Algorithm was used which is a search heuristic that mimics natural selection processes and uses biological operators like crossover and mutation. The initial population as shown in Fig. 3.9 was generated randomly, and it served as a parent population for the next generations.

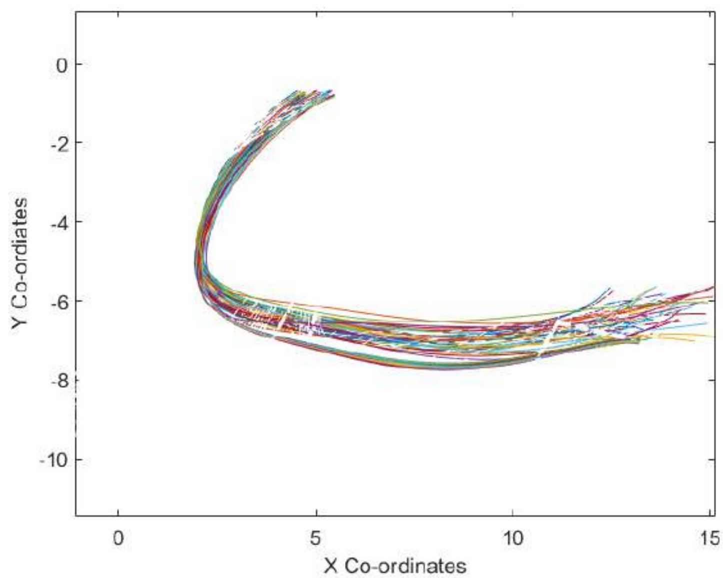

Fig. 3.3. Randomly generated initial population

The Artificial Neural Network model predicted the values of the speed ratio and drag coefficients of this parent population. These values were also plotted for Pareto fronts for each generation as shown in the figures below; Fig. 3.10 and Fig. 3.11. In the initial generations, the results were quite scattered and as the iterations were processed the results got better and led towards convergence. The Pareto front graph denotes the 1/speed ratio as abscissa because the aim was to obtain maximum velocity. Pareto optimal minimizes both its ordinate and abscissa in order to achieve minimum drag coefficient and maximum speed ratio at the throat.

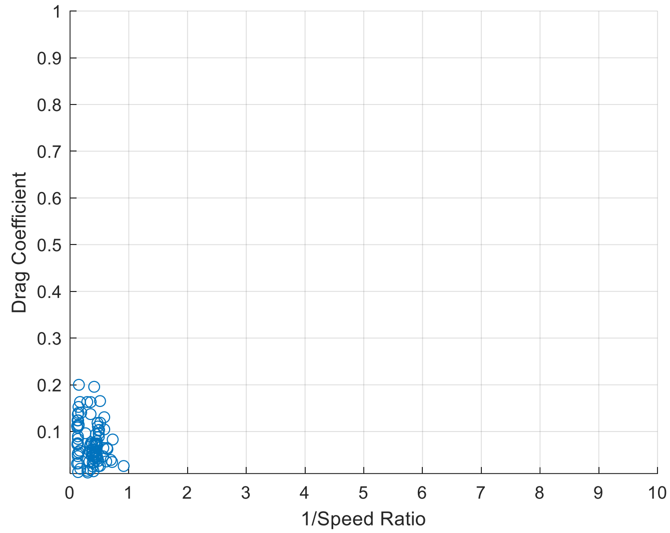

Fig. 3.4. Pareto plot of generation.

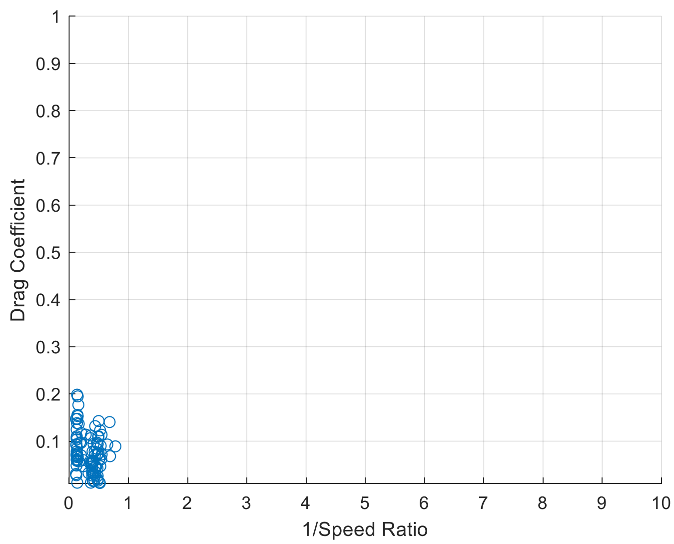

Fig. 3.5. Another Pareto plot of generation.

The next step involved assigning a fitness function to the population. In this study, Euclidean distance is used as the fitness function and chromosomes with the least fitness function were selected for further generation of new offspring. After that, the crossover was applied to generate new offspring having the combined information of the two fittest chromosomes. To introduce diversity, the mutation was applied to this new generation. Further sorting among the new generation was carried out through crowding distance. At the end, a population with a maximum speed ratio and minimum drag coefficient was selected. Fig. 3.12 presents the flowchart of Multi-Objective Optimization.

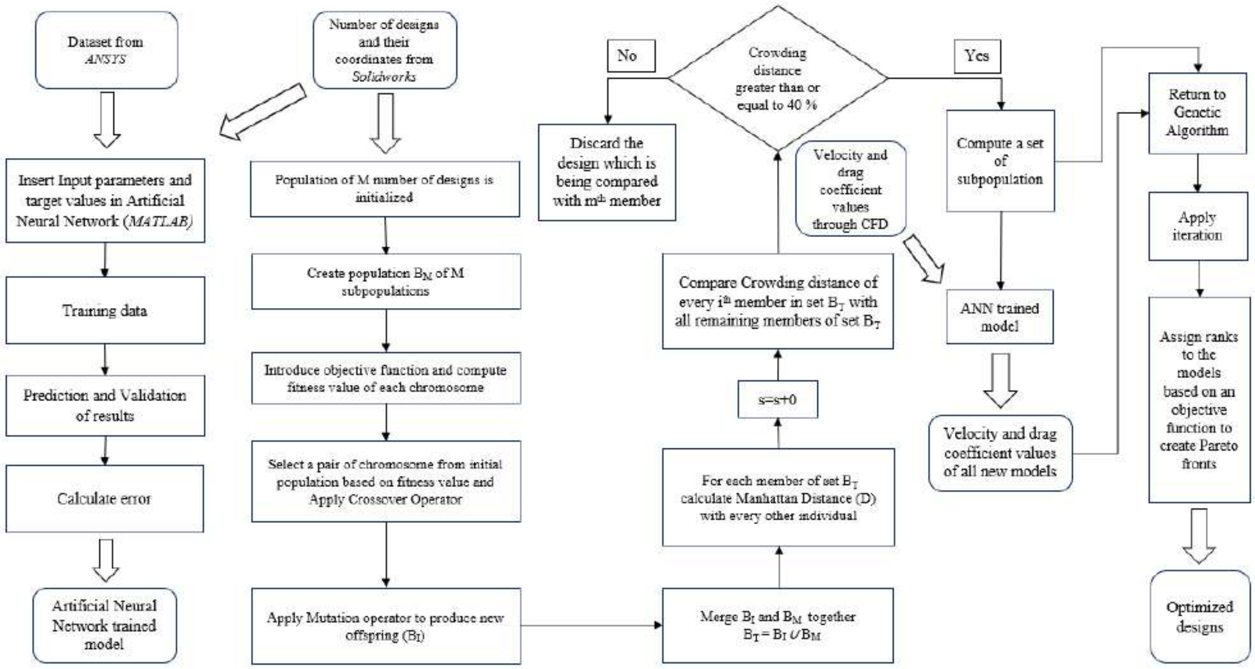

Fig. 3.6. Flowchart of Multi-Objective Optimization.

Chapter 4

4.1. Graphical User Interface

The graphical user interface (GUI) plays an essential role in modern computing because it allows users to interact with software programs in a visually appealing and user-friendly manner. The significance arises from its ability to simplify complex functionality, allowing users to easily explore and control software without requiring any technical understanding. By providing information and alternatives through visual components like menus, buttons, icons, and windows, the GUI increases usability, productivity, and accessibility. GUIs enable users to finish tasks more quickly by offering a familiar and intuitive interface, reducing learning curves, and allowing for a more enjoyable and efficient computer experience.

Keeping in view, these benefits a GUI was developed for this tool. This GUI takes input from users by reading their provided data that is the coordinates of the user model and then performs optimization on it to yield a better result. Another feature was introduced in this GUI which enhanced the tool's appeal and provided users with more control, making it more engaging and user-friendly. Using this feature, the user can control the new models being produced.

Fig. 4.1. Graphical User Interface.

The GUI has been designed in several tabs. Fig. 4.1 shows the basic layout of the GUI. The tab displays the name of the designed application i.e. ‘Anemo Shape Optimizer’. The user can then proceed to the next tab. In the next tab, the tool introduces itself as displayed in Fig. 4.2.

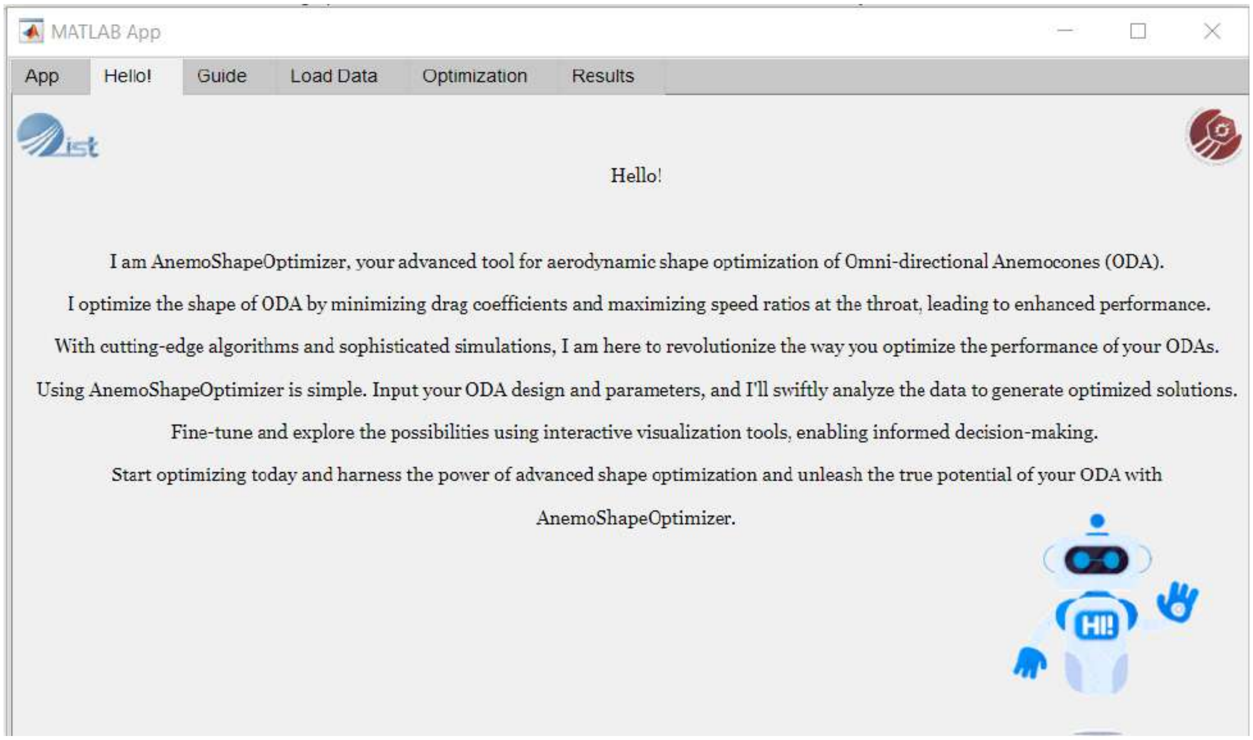

Fig. 4.2. Introduction Tab

As shown in Fig. 4.3, the GUI also provides a flowchart in which all the steps have been explained which are required to run the application.

Then comes the Load Data Tab in which the user-controlled parameters such as initial population size, percentage variation, selection pressure, termination criteria, rate of crossover, and rate of mutation are added which are needed to optimize the models; consider Fig. 4.4. The user model is entered through an Excel file and then it is plotted on the screen.

The next step includes the optimization step, in this step, the user starts optimization of the model and new generations begin to display on the screen as shown in Fig. 4.5.

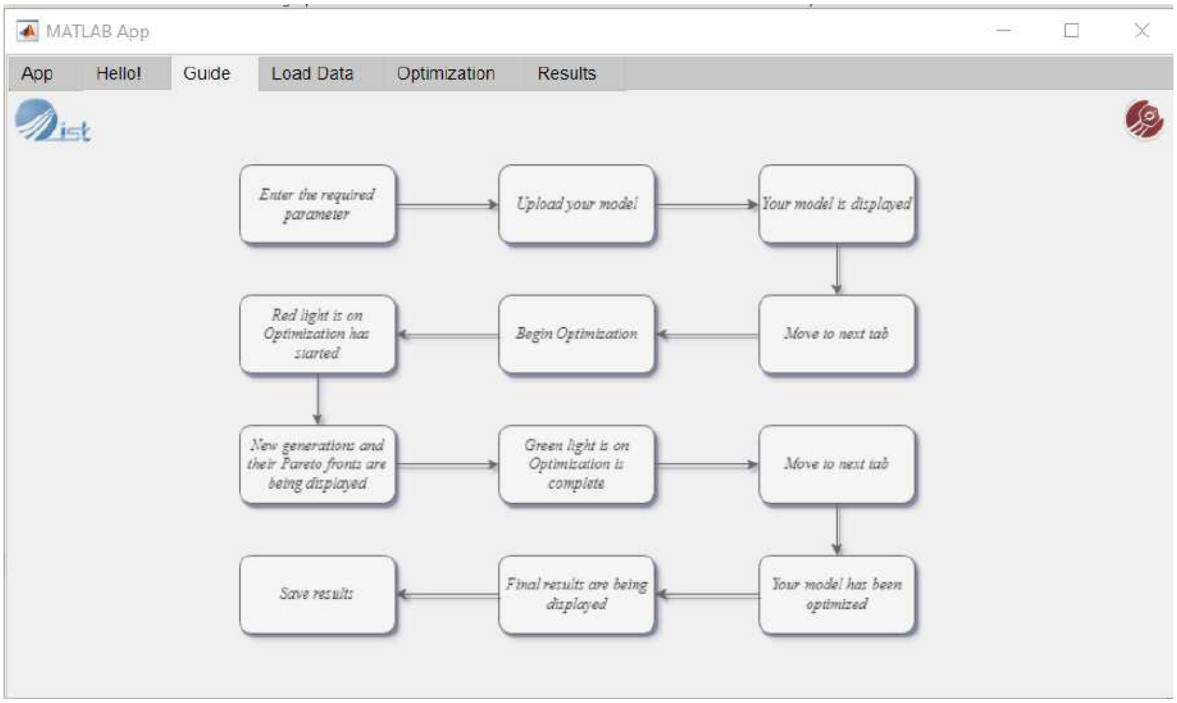

Fig. 4.3. Flowchart of the app

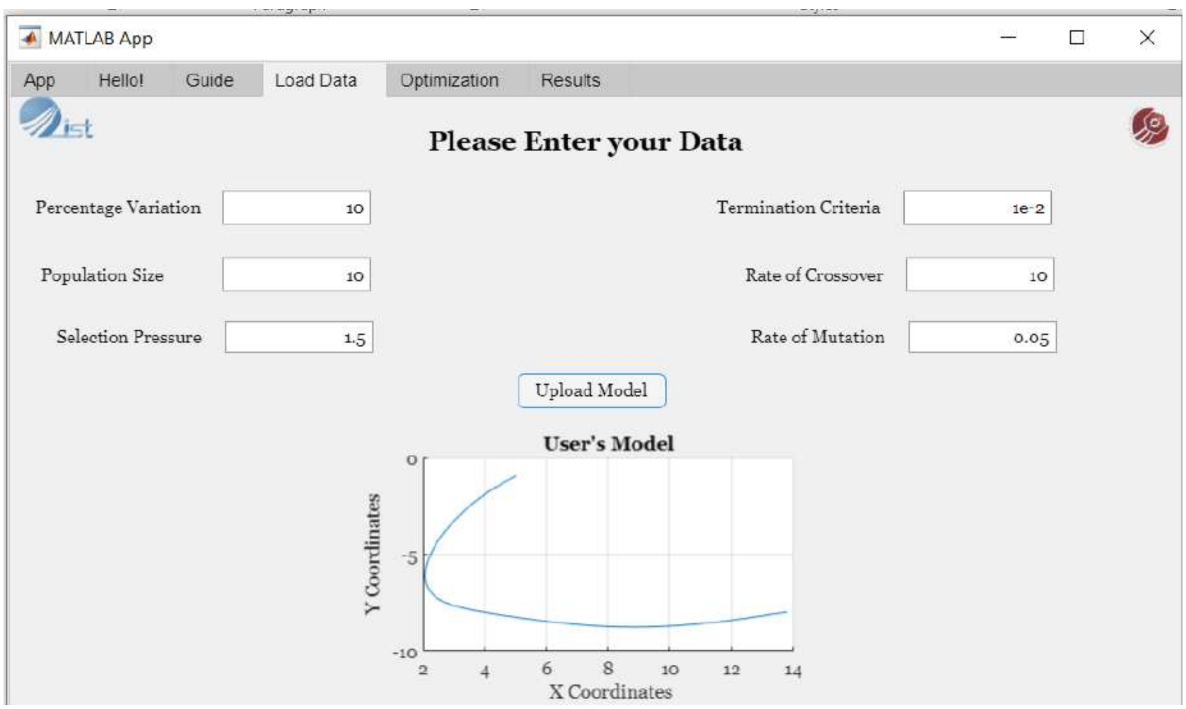

Fig. 4.4. User Input Tab

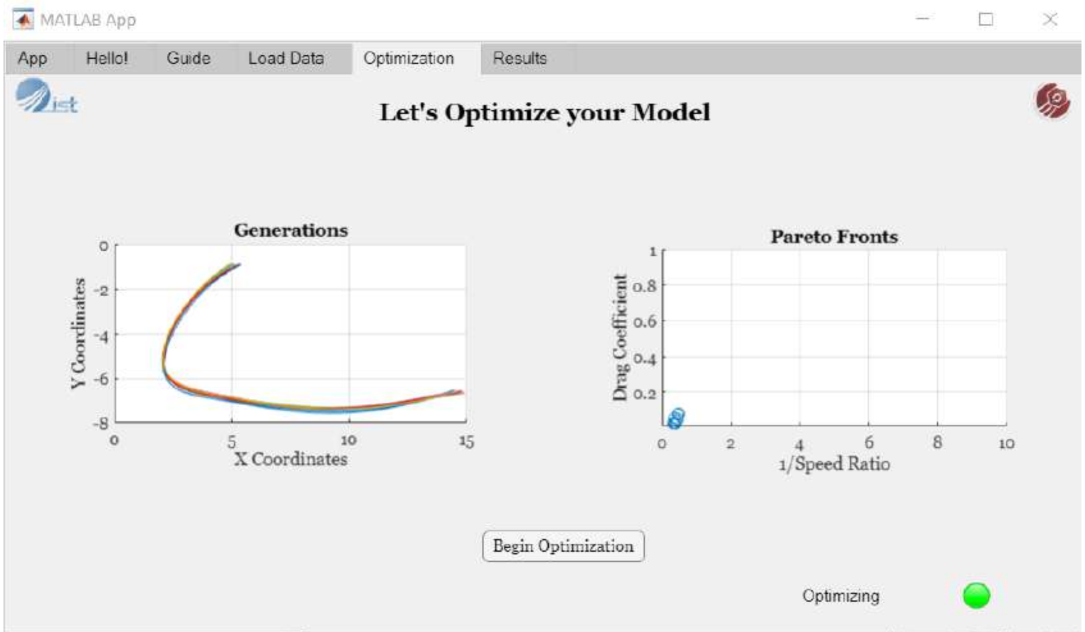

Fig. 4.5. Optimization Tab

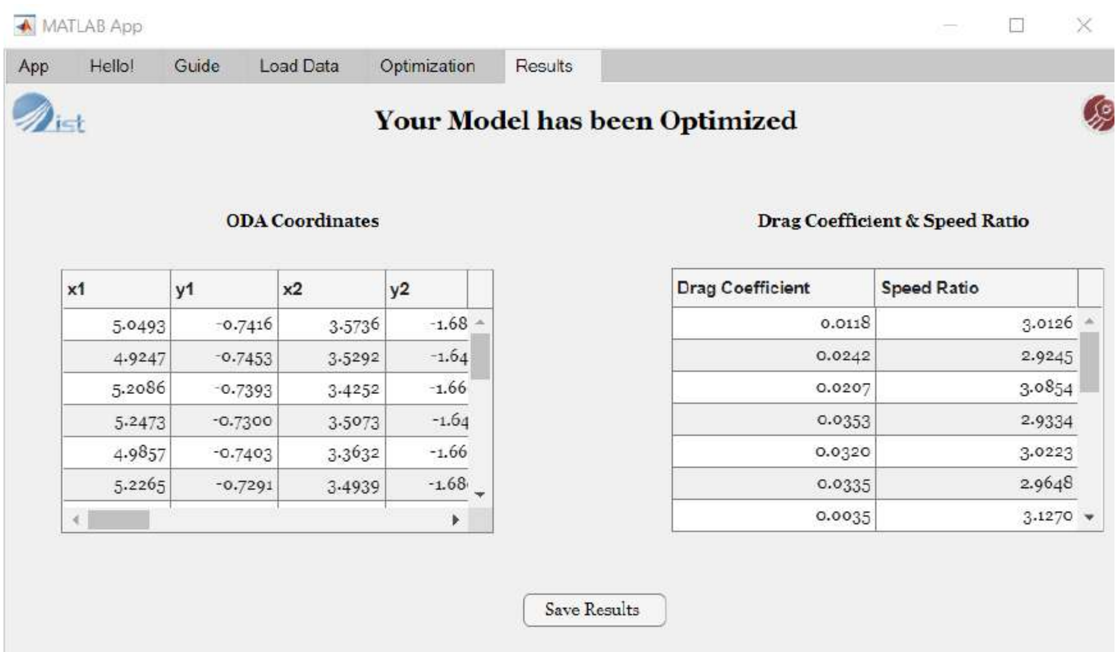

Fig. 4.6. Results Tab

After the optimization is complete, the final results can be seen on the Results tab which is shown in Fig. 4.6.

Chapter 5

5.1. Results And Discussion

The result of the multi-objective optimization was a population consisting of numerous unique designs, consider Fig. 5.1. The values of the speed ratio and drag coefficients of this population were predicted using the ANN model, and the convergence of results, shown in Fig. 5.2 proved that the best offspring generation has been generated. Among all these models the best shape was selected based on the highest speed ratio and least drag coefficient. The 3-D model of the obtained optimized shape is shown in Fig. 5.3.

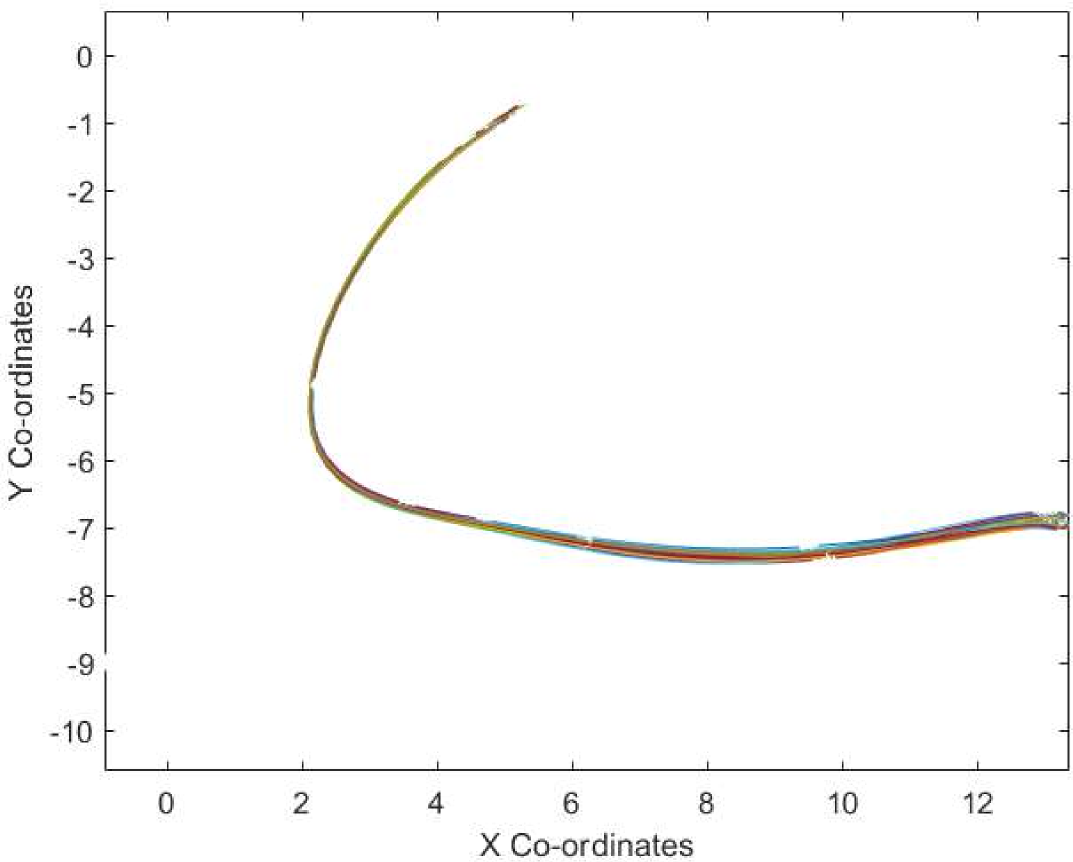

Fig. 5.1. Optimized ODA Models

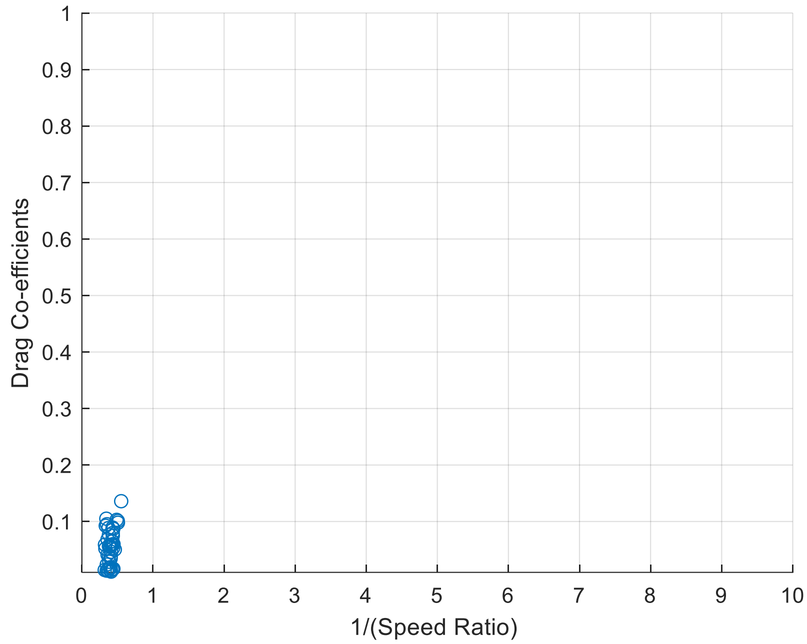

Fig. 5.2. Converged Pareto Results

Fig. 5.3. 3-D model of optimized shape

To validate the developed ANN model, the velocity and drag coefficient for the optimized model were obtained using two means: prediction by ANN tool and CFD analysis. For this purpose, a validated CFD approach was implemented on the obtained optimized shape of the ODA. The velocity contour obtained is shown in Fig. 5.4. Maximum wind velocity is obtained at the venturi section with a magnitude of 10.29m/s.

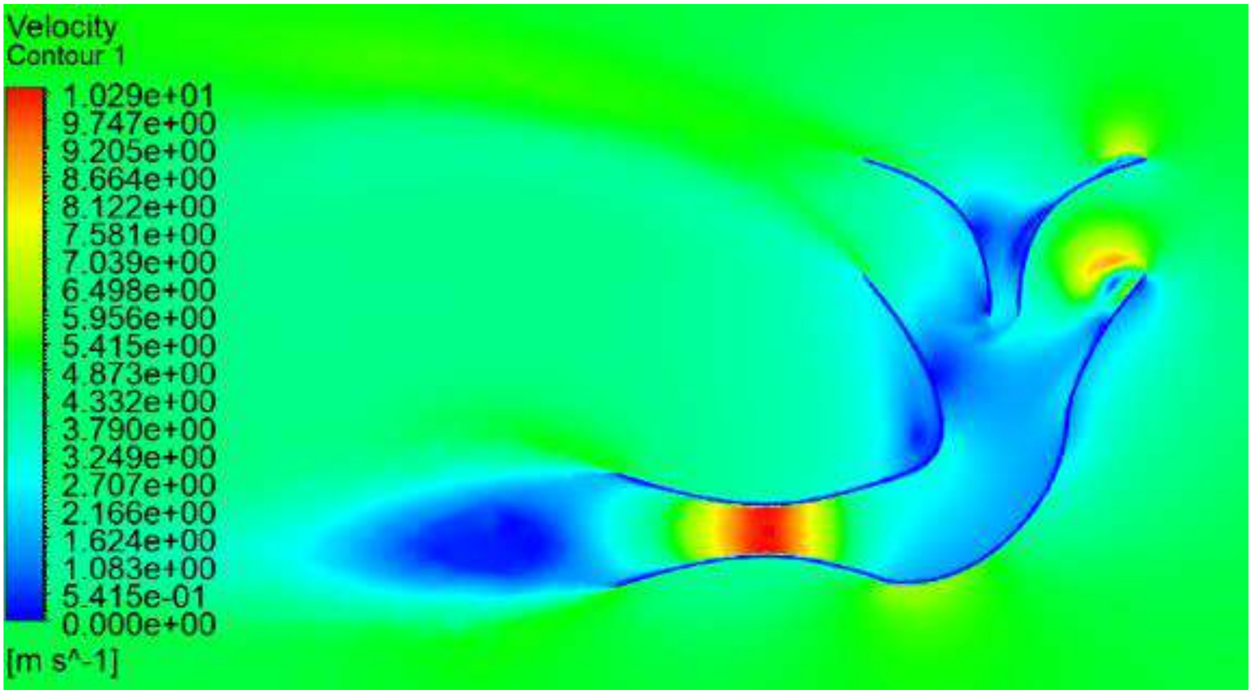

Fig. 5.4. Velocity contour for the optimized geometry

Fig. 5.5 shows streamlines across the same model. Flow separation occurs as the wind enters the shroud through the inlet. Flow develops as the wind passes through the shroud and it attains maximum value as it reaches the throat section. Fig. 5.6 shows the drag plot obtained for the optimized model; an average drag coefficient of 0.0358 is obtained on the surface of the ODA.

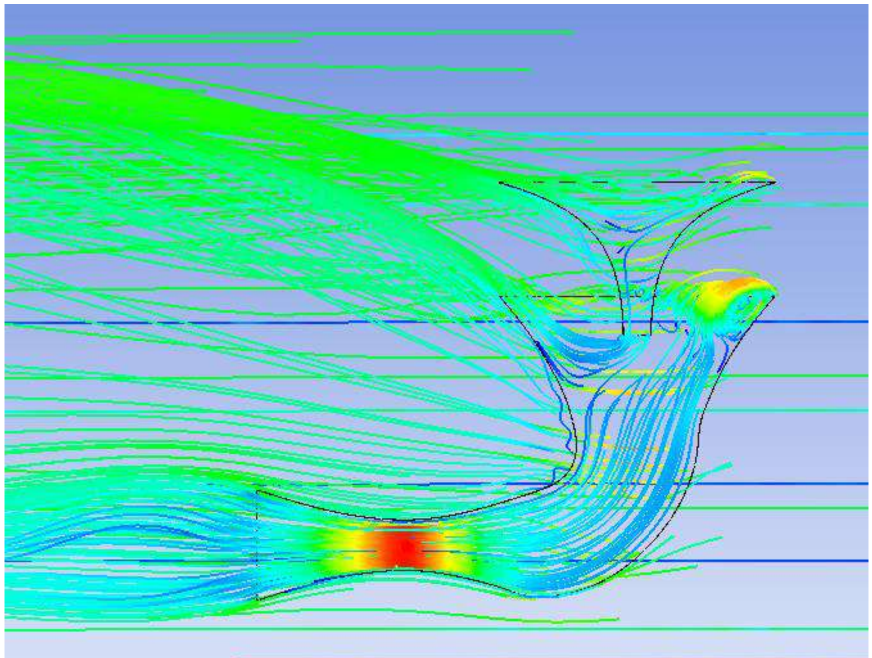

Fig. 5.5. Streamlines across the optimized model

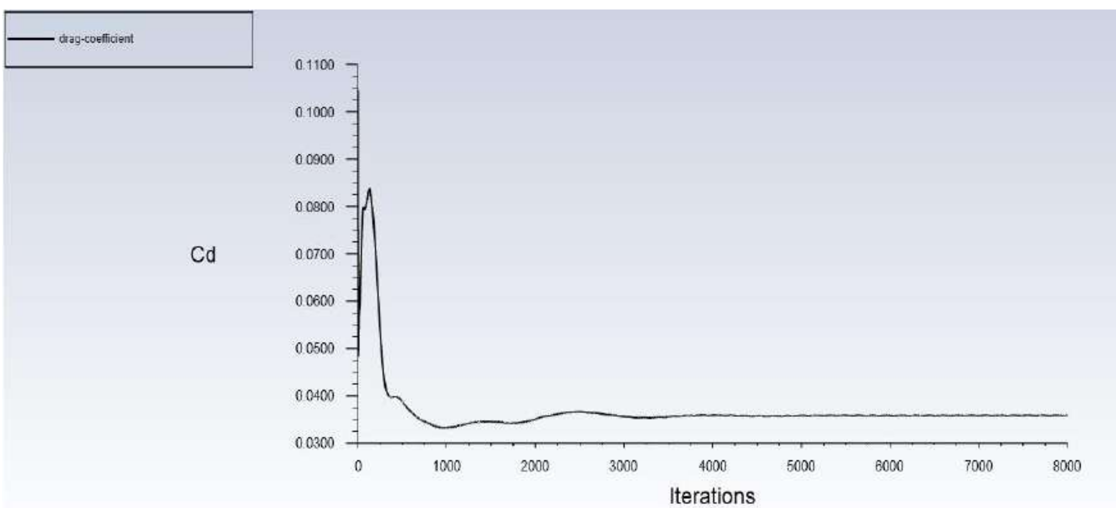

Fig. 5.6. Drag plot for the optimized model

Table. 5.1 summarizes the comparative study between the results obtained from both approaches.

Table 5.1. Validation of ANN Model

Approach	***Speed Ratio***	***Drag Coefficient***
ANN Model	2.231	0.0391
CFD Analysis	2.0580	0.0358
Percentage Error	8.4%	9.21%

Chapter 6

6.1. Conclusion

In this study, the shape of an Omni-directional Anemocone was optimized through Multi-Objective Optimization which employs Artificial Neural Networks, Genetic Algorithm, and Pareto optimal curves. The goal was to maximize the speed ratio at the throat and minimize the drag coefficient at the surface of the shroud. At first, a dataset was created containing the results of the speed ratio and drag coefficients of different ODA models. An ANN model was then trained using this dataset which aided in the prediction of speed ratios and drag coefficients for new models. To enhance the uniqueness and diversity of the results genetic algorithm was implemented and multi-objective optimization was carried out through Pareto optimum curves. This methodology not only lowered the overall time required but also eliminated the requirement for any computationally expensive software commonly used for aerodynamic analyses. The accuracy and efficiency of the developed tool was validated by comparing them to real-time simulations. This comparison yielded a percentage error of less than 5%. The errors can be reduced by improving the quality of the dataset by including a wide and diverse range of ODA designs, exploring different architectures and network configurations of artificial neural networks, and experimenting with the mutation rate, crossover rate, or population size of a genetic algorithm that may lead to better results. Overall, this methodology has proven to be an effective method for optimizing the shape of the ODA and the study's findings contribute to the improvement of wind power technology by offering significant insights for future renewable energy research and development.

Chapter 7

7.1. Environment And Sustainability

Power generation through Omni-directional Anemocone is vital to environmental sustainability and preservation. These turbines use wind energy, a renewable resource that never runs out, making it an environmentally friendly way to produce electricity. The wind energy-based project can dramatically lower greenhouse gas emissions, which contribute to air pollution and climate change. Because wind turbines don't emit dangerous pollutants into the environment like conventional power plants do, air quality and public health will also be enhanced. Countries can increase their energy independence and decrease their reliance on imported fossil fuels by embracing wind energy, fostering a steady and secure energy supply.

The project complies with Sustainable Development Goal (SDG) 7, which aims to ensure that everyone has access to affordable, dependable, sustainable, and contemporary energy. It makes a direct contribution to raising the proportion of renewable energy in the world's energy mix, which is essential for halting climate change and fostering sustainable energy consumption practices. The initiative also relates to SDG 9, which is concerned with developing resilient infrastructure, encouraging inclusive and sustainable industry, and encouraging innovation. Innovation and technology developments in the renewable energy sector are necessary to implement cutting-edge wind turbine technologies like Omni-directional Anemocones. The establishment of this infrastructure may open doors for regional economic expansion and job creation, which would support an industrialization that is more equitable and sustainable. The initiative is essential to addressing climate change and its effects in relation to SDG 13. It lessens the carbon footprint of power generation and aids in reducing the negative effects of climate change by producing clean energy from wind. This is in line with international initiatives to slow global warming and increase resiliency to climate-related dangers. Additionally, the project is strongly related to SDG 15, which focuses on protecting, restoring, and managing terrestrial ecosystems sustainably. To prevent or reduce potential negative effects on biodiversity and natural habitats, proper siting and environmental impact evaluations are crucial for wind turbine deployments. When used wisely, wind energy technology may coexist peacefully with the environment and support sustainable land use techniques.

Technology breakthroughs in energy storage and renewable energy are accelerated by wind power, paving the way for a cleaner and more sustainable future.

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