MPPT OF HYBRID ENERGY SYSTEM USING MACHINE LEARNING TECHNIQUES

A PROJECT THESIS

Submitted in Partial fulfillment of the requirements for the award of the degree of

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IN

ELECTRICAL AND ELECTRONICS ENGINEERING

by

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CERTIFICATE

This is to certify that the thesis work entitled "**MPPT for Hybrid Energy Systems Using Machine Learning Techniques"** is a bonafide record of work carried out by **Mr. Aman Vaijnath Solanke,** bearing Roll No.: 520238**, Mr. Satyam Kumar** bearing Roll No.: 520235 and **Mr. Suman Kumar Verma** bearing Roll No.: 520241**,** submitted to the faculty of Electrical Engineering, in partial fulfilment of the requirements for the award of the degree of Bachelor of Technology in Electrical and Electronics Engineering at National Institute of Technology, Andhra Pradesh during the academic year 2023-24. Mr. Aman Vaijnath Solanke, Mr. Satyam Kumar and Mr. Suman Kumar Verma have worked under my guidance and supervision and have fulfilled the requirements for the submission of this thesis, which to my knowledge has reached the requisite standard. The results obtained here in have not been submitted to any other University or Institute for the award of any degree.

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ABSTRACT

With the mass scale adoption of renewable energy sources the power grid is undergoing significant changes. Microgrids, powered by hybrid energy sources are seen as the future of the power grid due to their resilience and local operation.

To maximize the energy yield we need to operate the hybrid energy sources at the maximum power point. Maximum energy yield signifies optimum utilization of the available energy and thus cheaper electricity costs, high scalability and high incentives to switch to renewable energy sources. Maximum power point tracking techniques have been used to track the maximum power point for photovoltaic system and wind energy conversion system. In modern times, with the rise of intelligent systems, the older maximum power point tracking algorithms can be updated to make them smarter and thus faster and more efficient.

In this project we used machine learning to develop an artificial neural network powered perturb and observe algorithm and compared its performance with the conventional perturb and observe algorithm. We discuss the benefits and future scope of Machine Learning based. Maximum Power Point Tracking algorithms for hybrid energy sources.

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LIST OF SYMBOLS

I_{ph}	Photovoltaic current generated (Amps)
I_D	Diode current (Amps)
I_{pv}	Current at the output terminal (Amps)
I_{sh}	Current flowing through the shunt branch (Amps)
R_s	Series resistance (Ω)
R_{ph}	Shunt resistance (Ω)
ρ	Air density (kg/m^3)
A	Swept area of the rotor blade (m^2)
v	Wind velocity (m/s)
P	Power captured by the wind turbine (W)
$C_p(\lambda, \beta)$	Power coefficient
λ	Tip speed ratio
β	Pitch angle (degrees)
ω	Turbine angular speed (rad/s)
R	Radius of the turbine (m)
V_t	Voltage at the terminal (Volts)
E_a	Back EMF (Volts)
I_a	Armature current (Amps)
R_a	Armature resistance (Ω)
L_a	Armature Inductance (H)
ϕ	Field flux (Wb/m^2)
ω_m	Angular velocity of the rotor (rad/sec)
V_o	Voltage at the output terminal (Volts)
I_o	Current at the output terminal (Amps)
V_{in}	Voltage at the input terminal (Volts)
I_{in}	Current at the input terminal (Amps)
d	Duty ratio
P_{in}	Power at the input terminal (W)
R_L	Load Resistance connected to the output terminal (Ω)
n	Number of samples
y	Actual output

$\hat{y}$	Expected output
C	Number of classes
θ_t	Parameters at iteration t
α	Learning rate
β_1	Decay rate for the moment estimates typically set to 0.9
β_2	Decay rate for the moment estimates typically set to 0.999
ϵ	Small constant to prevent division by zero
$J(\theta_t)$	Loss function

LIST OF ABBREVIATIONS

Abbreviations	Description
RES	Renewable Energy Sources
HES	Hybrid Energy Sources
PVS	Photovoltaic Systems
WECS	Wind Energy Conversion Systems
MPPT	Maximum Power Point Tracking
MPP	Maximum Power Point
ANN	Artificial Neural Network
ML	Machine Learning
AI	Artificial Intelligence
DL	Deep Learning
PSO	Particle Swarm Optimization
GA	Genetic Algorithm
P&O	Perturb and Observe
InC	Incremental Conductance
TSR	Tip Speed Ratio
AC	Alternating Current
DC	Direct Current
MSE	Mean Squared Error
MAE	Mean Absolute Error

CHAPTER 1
INTRODUCTION

1.1 General Introduction

A HES consists of two or more power generation sources [1]. For the sake of this project we have considered a hybrid system made of PVS and WECS[2]. It is known that the RES suffer from the problem of the unpredictable nature of the availability of solar or wind power. Combining these systems together reduces our exposure to only one kind of energy resource thus ensuring more reliable power supply at any given time[3][6].

Continuous tracking of the MPP is important to extract the maximum possible power from the system. Traditional algorithms like P&O, Incremental Conductance(InC), etc.[7] for PV and Tip Speed Ratio(TSR), Hill Climbing, etc.[8] for WECS take time to converge. By the time the algorithm converges, the MPP shifts to a new location, thus, operating at the MPP for a longer time becomes difficult and the energy yield is low.

We used machine learning to provide a starting point for the widely used P&O algorithm to considerably increase its speed for the real-time tracking of the MPP. By reducing the number of iterations it takes for the P&O algorithm to converge will allow us to operate at the MPP for longer durations and improve the energy efficiency of the system.

Artificial Neural Networks(ANN) were trained to predict the MPP voltage and power for the WECS and PVS. The expected duty ratios for the boost converters connected to the WECS and PVS were calculated based on the output of the respective ANNs. This duty ratio was used as a starting point for the P&O to search for the MPP, thus expecting to speed up the process of MPPT and ensure faster convergence.

1.2 State of Art

In the present scenario MPPT is not widely used for small scale operations. The adoption of MPPT techniques increases with the increasing size of the renewable energy capturing system(PVS or WECS). MPPT techniques are used more frequently in the WECS than they are for PVS. There has been a large-scale adoption of simple and easy to implement algorithms like P&O and Incremental Conductance.

These algorithms lack the element of intelligence and thus are susceptible to converging at the local maximas. This can result in losing the available power under partially shaded conditions for PVS. Poor and slower tracking of the MPP reduces the profits and thus results in increasing energy prices and lesser adoption of RES.

Due to these problems researchers are now working on developing intelligent MPPT algorithms that have higher degree of accuracy and efficiency. Some widely accepted ideas are Meta Heuristic Algorithms like Particle Swarm Optimization (PSO) and Genetic Algorithm (GA). Fuzzy Logic based techniques have also gained attention in recent times.

Artificial Intelligence, based on ANN, which is a part of the Machine Learning domain, has been considered as a powerful tool to address the present day MPPT issues. Machine Learning based algorithms have been under development and are soon expected to be the industry standard because of the ease of implementation and the ability to collect the pros of all the other algorithms.

1.3 Scope of Work:

Based on the extensive literature review on RES, HES, Conventional MPPT Techniques, and Intelligent MPPT Techniques the following research areas have been identified.

1. Fuzzy Logic Based MPPT for HES
2. Reinforcement Learning Based Online MPPT Algorithm
3. Methods to Calculate the Parameters of a PV Panel using the Datasheet
4. Methods to Calculate the Parameters of a DC Generator
5. Performance of various DC and AC Generators for WECS Applications
6. ML based MPPT Algorithms
7. AI based Weather Prediction Model Integration with MPPT Algorithms

1.4 Chapter Outline:

The contents of this thesis have been divided into the following chapters:

Chapter 1: Introduction

The problem statement under consideration is thoroughly introduced and the groundwork for the project is laid.

Chapter 2 : Literature Review

An extensive literature review has been done on Hybrid Energy Systems, Present day MPPT Techniques, Intelligent MPPT Algorithms and the drawbacks of conventional MPPT Algorithms. After a critical literature review, project areas are identified.

Chapter 3 : Modeling Photovoltaic and Wind Energy Conversion System

Mathematical modeling of Photovoltaic and Wind Energy Conversion Systems is thoroughly discussed. The characteristics of PVS and WECS have been studied.

Chapter 4 : Basics of DC Generator and Boost Converter

Mathematical modeling and operations of the DC generator and Boost Converter are discussed. A brief discussion on the use of Boost Converter for MPPT has been done.

Chapter 5 : Artificial Neural Network

An introduction to ANNs is presented. Various Loss Functions and optimizers are discussed. Steps regarding acquisition, generation and cleaning of data for training ANN have been discussed. The use of ANN for MPPT has been thoroughly presented.

Chapter 6 : Proposed Algorithm: ANN+P&O

The Machine Learning based MPPT Algorithm has been presented and its steps of operation have been elaborated. A way of integration of ML models to power conventional algorithms like P&O has been discussed.

Chapter 7 : Pseudo Codes

The pseudo codes for all the mathematical models and Machine Learning models have been shared.

Chapter 8 : Testing ANN+P&O And Conclusion

The proposed algorithm has been tested under varying circumstances and its performance has been compared with the conventional P&O Algorithm. A valid conclusion has been drawn based on the observation.

Chapter 9 : Conclusion and Future Scope

A short summary and future scope has been discussed and listed.

CHAPTER 2
LITERATURE REVIEW

2.1 Renewable Energy

The energy crisis is one of the greatest threats facing our civilization since access to electricity is a mandatory condition for socio-economic development which we cannot do without renewable energies .Renewable energy are those sources of energy that can be obtained naturally without depleting the planet's resources. The imperative for transitioning to renewable energy sources is underscored by the irrefutable scientific consensus on climate change. The Intergovernmental Panel on Climate Change (IPCC), the leading international body for the assessment of climate change, has unequivocally concluded that human activities are the dominant cause of observed warming since the mid-20th century [9].In light of these concerns, renewable energy has emerged as a beacon of hope for a sustainable future. Renewable energy sources offer a plethora of advantages over traditional fossil fuels.

Renewables have made impressive progress in the power sector. Over the past decade, renewables capacity increased by 130%, while non-renewables only grew by 24%. In 2021, the total installed capacity of renewable electricity reached 3,064 GW, generating around an estimated 8,000 terawatt-hours (TWh) of electricity[10]. This growth is further illustrated by the following graph:

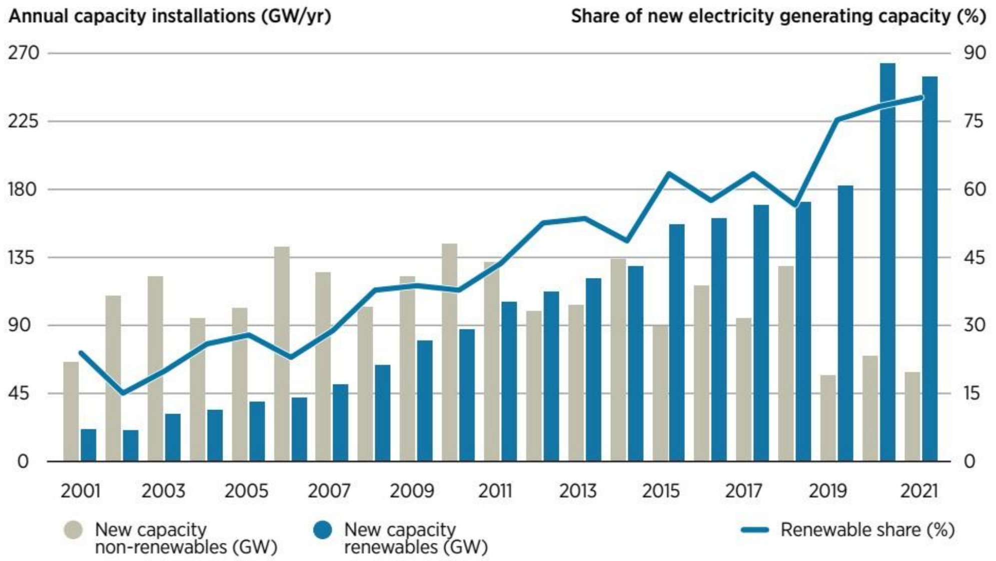

Fig 2.1 Annual capacity installations of renewables and non-renewables from 2001-2021 [10]

Additionally, the technologies to capture and utilize these energies have improved in recent years, making their use increasingly viable and economical. Renewable energies are a key solution to combating climate change and reducing dependence on fossil fuels [11]. By investing in these energy sources, jobs can be created and sustainable economic development can be promoted. In summary, renewable energies are a key alternative to ensure a cleaner and safer future for future generations.

These sources include solar, wind, hydro, geothermal, biomass, and biofuels. Unlike non-renewable energies, such as oil, gas, and coal, which are finite and emit large amounts of greenhouse gasses, renewable energies are cleaner and more sustainable.

RESs (solar energy, wind energy, ocean energy, bioenergy, geothermal energy, etc.) have been installed in many places around the world especially in the rural places .[12-14] Wind energy and solar energy are the most prevalent renewable energy sources. Because of the instability, intermittency, and high cost of the solar and wind system, the non-renewable energy sources and energy storage have been added to ensure the continuous and stable power supply.[15]

2.2 Challenges

Producing electricity with environmental concerns at an affordable price has become a key challenge[16, 17].While variable speed wind power generation offers significant advantages, making it a major area of research, its dependence on climatic conditions like solar irradiation, temperature and wind speed, presents a challenge. This intermittency can disrupt energy production and make it difficult to consistently meet load demand.[18,19].

Due to the random and varying conditions of wind speed which changes throughout the day, wind turbines can influence the stability of the electrical systems. For this reason, the energy production control strategy has a great impact on the overall operating performance. Hence, wind power generation systems need to adopt different control methods according to diverse wind speed intervals . In order to extract the maximum energy from the WECS in the MPPT interval where the WECS produces the maximum available wind power, it is necessary to design a maximum power point tracking controller (MPPT) [20]-[23].

2.3 MPPT Techniques:

In the literature, various control methods have been developed for photovoltaic (PV) and wind systems. These include the Perturb and Observe (P&O) algorithm [24] for PV systems and Hill Climbing Search (HCS) [25] for wind systems. Additionally, techniques such as Fuzzy Logic Control (FLC) [26, 27] and Sliding Mode Control (SMC) [28, 29] have been proposed. Each method has its own advantages and disadvantages [30, 31]. P&O and HCS algorithms exhibit significant oscillations around the optimal power point, leading to increased energy losses. While SMC offers good accuracy and stability at the maximum power point (MPP), it suffers from chattering, reducing its efficiency . FLC demonstrates good performance with dynamic response and stability under varying climatic conditions.

To address these limitations and enhance efficiency, hybrid approaches based on these techniques have been proposed. For the PV subsystem, a hybrid control strategy is proposed, comprising three parts [30]. Firstly, a reference voltage is calculated using the P&O algorithm to improve response time. This reference parameter is then utilized in subsequent steps employing SMC and FLC techniques. SMC enhances accuracy, while FLC improves dynamic response, reducing oscillations and chattering around the MPP.

For the Wind subsystem, a control technique is proposed based on a reference step [31]. This step calculates two parameters using the HCS algorithm and optimal wind turbine characteristics. These parameters are then used to determine input variables for a fuzzy controller, optimizing performance.

The Perturb and Observe (P&O) algorithm stands as one of the cornerstone methods employed in maximizing the power output of photovoltaic (PV) systems and Wind energy conversion systems (WECS). Its principle revolves around perturbing the operating point of the PV system and observing the resulting change in power output. By iteratively adjusting the operating voltage or current and monitoring the corresponding power response, the algorithm navigates towards the point of maximum power, known as the maximum power point (MPP)[32][33].

In the hybrid renewable energy system proposed in the literature, P&O methods are used for both sources to achieve MPPT for maximize the power output Various derivatives of P&O have also been utilized as reported in literature for wind /solar energy sources using power electronics converter mainly boost converters.[34, 35] It is simple MPPT method and only uses the current and voltage information of boost input to control by changing duty cycle of boost converter as per the information. P&O has many advantages like no need of a priori information, no need to measure wind speed and quick response in steady variations etc [36-38]

The general working sequence of P&O algorithm is depicted through below flowchart:

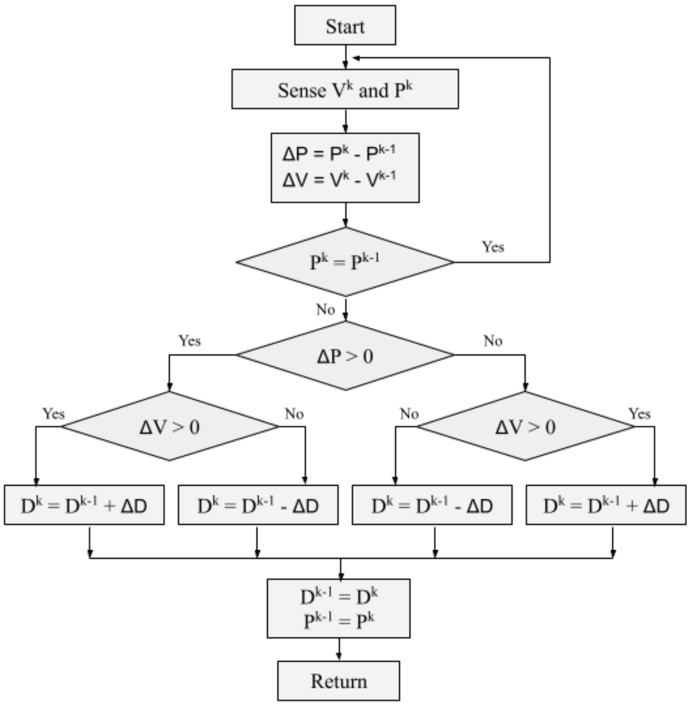

Fig 2.2 P&O Flowchart

2.4 Drawbacks of Conventional MPPT Algorithms:

The drawbacks of the MPPT techniques mentioned in the literature can be summarized as follows:

1. Perturb and Observe (P&O)/ Hill Climbing Search (HCS) algorithm: Significant oscillations around the optimal power point: The P&O algorithm, while widely used for its simplicity, exhibits oscillations around the maximum power point (MPP), leading to increased energy losses. This drawback has been noted by researchers [39-42].
2. Sliding Mode Control (SMC): Despite its accuracy and stability at the MPP, SMC is prone to chattering, characterized by high-frequency switching between control modes. This phenomenon can reduce efficiency and system lifespan [43, 44]

These drawbacks underscore the importance of ongoing research efforts aimed at improving MPPT techniques to achieve better performance in terms of efficiency, stability, and reliability.

2.5 Hybrid Energy System (HES):

Hybrid renewable energy systems are those that combine two or more renewable energy sources to generate electricity. These systems are especially useful in places where there is no access to the conventional electrical grid, or where the connection is limited or unstable [45]. An example of a hybrid system combines solar and wind energies. During the day, when the sun shines, solar panels generate electricity that is stored in batteries for later use. At night, when there is no sun, wind energy conversion systems (WECS) harness the wind to generate additional electricity and charge the batteries [46]. Another example of the hybrid system combines solar and hydro energies. During the day, solar panels generate electricity that is used to pump water from a river or lake to a dam. At night, when there is no sun, the water stored in the dam is released through a hydro turbine to generate additional electricity [47].

Hybrid renewable energy systems can be more efficient and reliable than systems that use a single energy source [48]. Additionally, they allow for a better use of available resources and reduce the cost of generated energy. For these reasons, hybrid systems are becoming increasingly popular worldwide, especially in rural or remote areas [49].By combining multiple renewable energy sources and energy storage technologies, these systems offer a transformative approach to meeting our energy needs while mitigating environmental impact.

To establish a hybrid energy system from renewable sources, standardized procedures and frameworks are crucial due to the varied operational characteristics of these sources. Such systems integrate renewable energy sources, energy storage, loads, and optionally, a grid connection for autonomous operation. Integration techniques typically fall into three categories AC, DC, and hybrid-coupled systems.[50-51]

1. AC Integration: Involves converting all energy sources to AC before combining them, simplifying integration with existing infrastructure and grid synchronization.

2. DC Integration: Maintains energy in its native DC form until reaching loads or storage, offering higher efficiency and reduced losses, particularly in low-voltage applications.
3. Hybrid-Coupled Integration: Combines elements of both AC and DC integration to leverage the advantages of each based on the operational characteristics and requirements of different renewable sources.

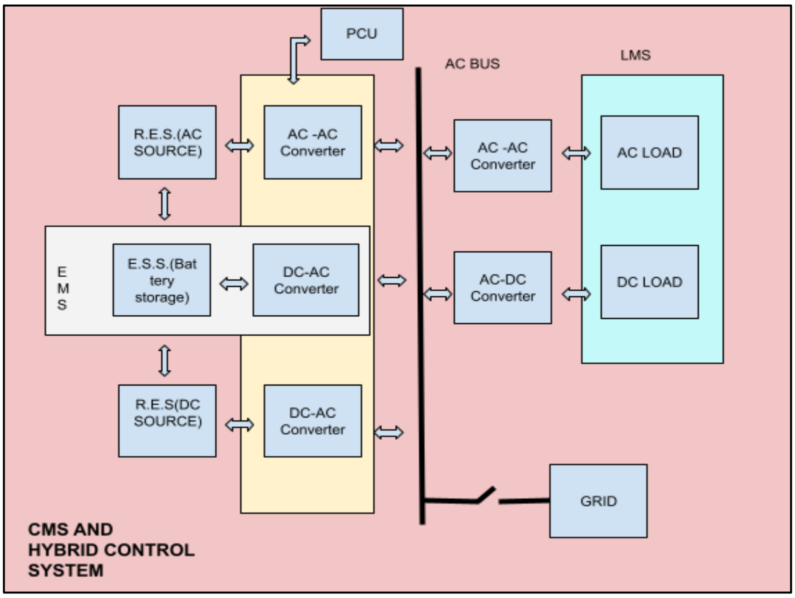

Fig 2.3: HES Configuration Block Diagram

Wind energy and solar energy are the most prevalent renewable energy sources. In the remote places, small-scale off-grid (microgrid) systems are installed rather than building the transmission line to bring the electricity from the generation stations to loads. A microgrid system is a small system that mainly contains solar and wind energy sources.[10]

2.6 Solar and Wind Trends:

Electricity generation from solar power in terawatt-hours (TWh) per year in various regions and countries. The data goes from 1983 to 2022. Here are some key points represented in the graph-1:

- Solar power generation has been increasing steadily in all the regions and countries shown over the past few decades.

- China is the world leader in solar power generation, producing over 100 TWh of electricity from solar panels in 2022. This is more than ten times the amount of solar power generated by any other country.
- The European Union (27) as a whole generated around 100 TWh of electricity from solar power in 2022.
- The United States is the third-largest producer of solar power, generating around 50 TWh of electricity from solar panels in 2022.
- India is the fourth-largest producer of solar power, generating around 20 TWh of electricity from solar panels in 2022.
- The United Kingdom is the fifth-largest producer of solar power, generating around 15 TWh of electricity from solar panels in 2022.

Overall, solar power is a rapidly growing source of electricity generation around the world. This is likely due to a number of factors, including the decreasing cost of solar panels, government incentives for solar power generation, and increasing concern about climate change.

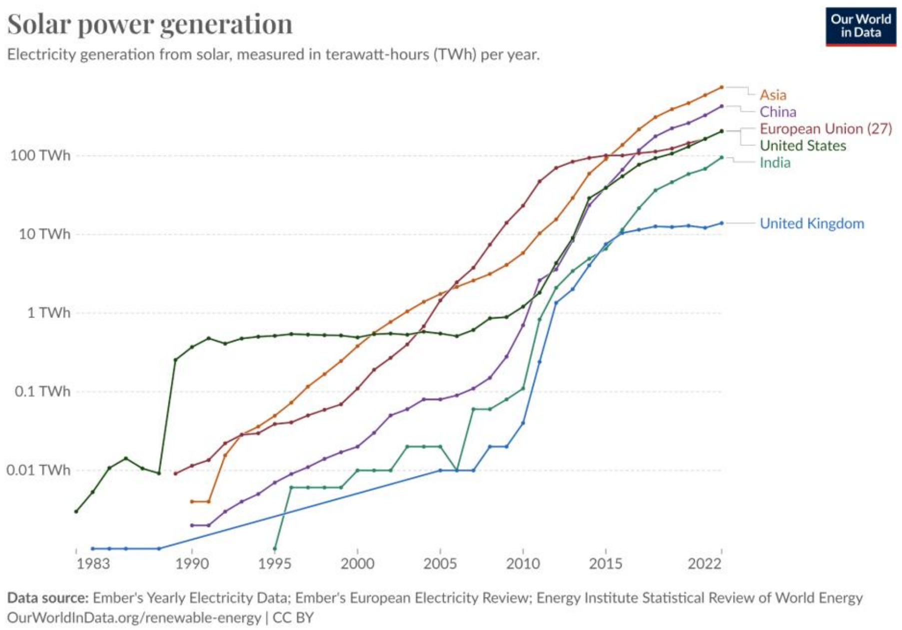

Fig 2.4 Electricity generation from solar [34]

Wind energy production has been steadily increasing over the past few decades. China is the world's largest producer of wind energy, followed by the United States and the European Union. Here are some key points represented in the graph 2:

- Wind energy production is measured in terawatt-hours (TWh) per year. This includes both onshore and offshore wind sources.
- China is the world leader in wind energy production, generating over 1,000 TWh of electricity from wind in 2021.
- The United States is the second largest producer of wind energy, generating over 400 TWh of electricity from wind in 2021.
- The European Union (27) is the third largest producer of wind energy, generating over 300 TWh of electricity from wind in 2021.
- India is the fourth largest producer of wind energy, generating over 100 TWh of electricity from wind in 2021.
- The United Kingdom is the fifth largest producer of wind energy, generating over 10 TWh of electricity from wind in 2021.

It's important to note that the rate of wind energy production is increasing much faster in some countries than in others. For example, China's wind energy production has grown by over 1,000 TWh since 2000, while the United States' wind energy production has grown by about 400 TWh over the same period. This suggests that China is likely to remain the world's leading producer of wind energy for the foreseeable future.

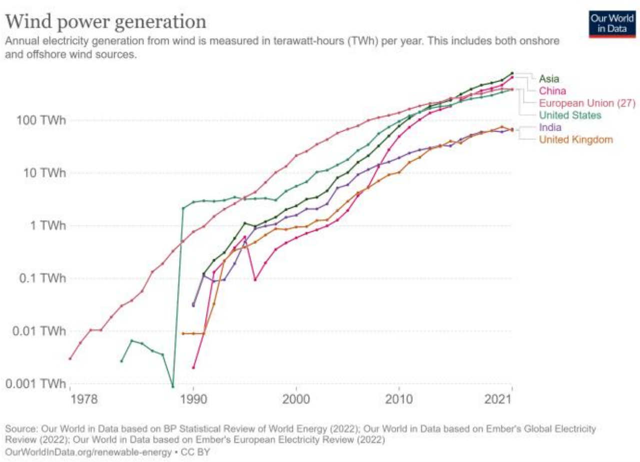

Fig 2.5 Electricity generation from wind [34]

2.7 Conclusion:

An extensive literature review was done on hybrid energy systems, MPPT techniques, PVS and WECS and research areas were identified. Based on mentioned drawbacks of the various MPPT algorithms an effort was put to develop and faster and more efficient MPPT algorithm using ML to provide a better solution for MPPT. Renewable energy sources were used to make up the HES based on the strong trend of adopting RES worldwide.

CHAPTER 3
MODELING PHOTOVOLTAIC AND WIND ENERGY CONVERSION SYSTEM

3.1 Introduction to PV System

Light coming from the sun carries energy in the form of electromagnetic radiation. Solar cells, which are made of semiconductor materials like crystalline silicon, are used to capture this energy from the sun and convert it into electrical energy. This happens when the photons carrying energy(sun light) knock off the electrons from the semiconductor material. The semiconductor material is doped. The dopants create an electromagnetic field which directs the knocked off electrons towards the metallic conductors. Thus, a DC current supply is created. The power generated by a single cell is very less, usually in the range of 1-2 Watts, and thus has no real use. When multiple cells are connected together they generate enough power to supply to electrical appliances. Multiple cells connected together make a solar panel(PV Panel).

3.2 Mathematical Modelling of PVS

The circuit diagram of a single solar cell is as given below.

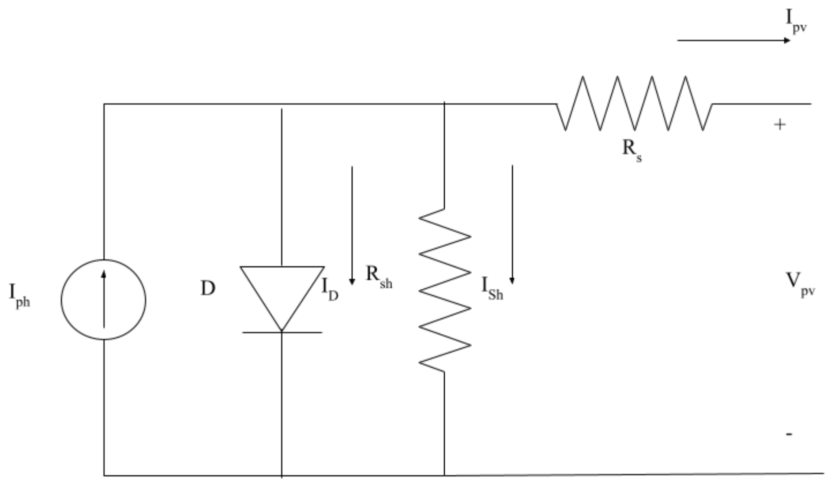

Fig 3.1: Circuit Diagram of PV Cell

The mathematical modeling of a PV cell is discussed below. [52][53]

From the circuit diagram we can say that the PV current is given by the below equation,

$$I_{pv} = I_{ph} - I_D - I_{sh} \tag{1}$$

Photovoltaic current can be calculated as follows,

$$I_{phn} = I_{scn} \tag{2}$$

$$I_{ph} = \left(I_{phn} - K_i \cdot \left(T - T_n \right) \right) \cdot \left(\frac{G}{G_n} \right) \tag{3}$$

Diode current can be calculated as follows,

$$V_t = \frac{N_s \cdot k \cdot T}{q} \tag{4}$$

$$I_{on} = \frac{I_{scn}}{e^{\left(\frac{v_{ocn}}{a \cdot V_{tn}} - 1 \right)}} \tag{5}$$

$$I_o = I_{on} \cdot \left(\frac{T}{T_n} \right)^3 \cdot e^{\left(\frac{q \cdot E_g}{a \cdot k} \right) \cdot \left(\frac{1}{T_n} - \frac{1}{T} \right)} \tag{6}$$

$$I_D = I_o \cdot e^{\left(\frac{V_{pv} + I_{pv} \cdot R_s}{\eta \cdot V_t} - 1 \right)} \tag{7}$$

Current through the shunt branch can be calculated as follows,

$$I_{sh} = \frac{V_{pv} + I_{pv} \cdot R_s}{R_{sh}} \tag{8}$$

3.3 Current-Voltage and Power-Voltage Characteristics of PV System

The Current-Voltage characteristic of the PV System is given below.

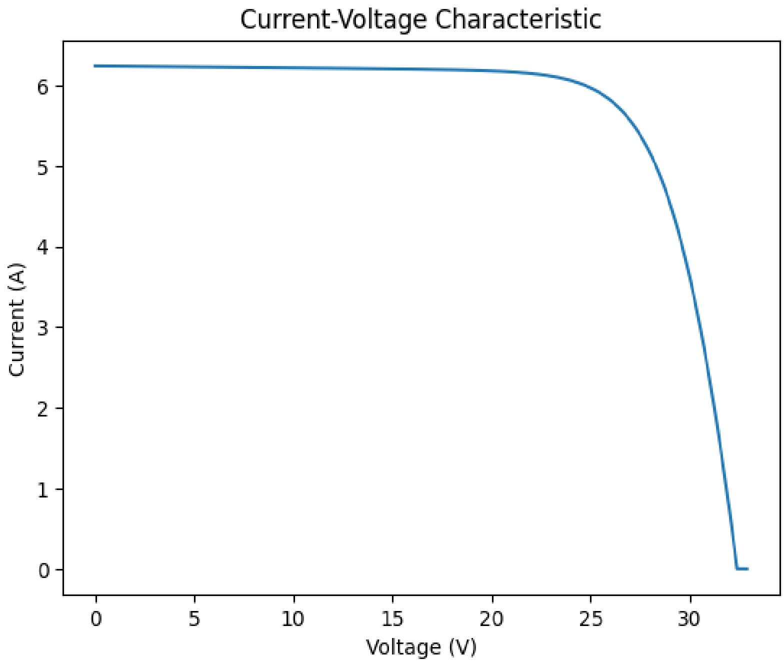

Fig 3.2: I-V Characteristics of PV Panel

The power generated by the PV panel can be calculated from the voltage and current at the output of the panel,

$$P_{pv} = V_{pv} \cdot I_{pv} \tag{9}$$

The Power-Voltage characteristic of the PV panel is given below.

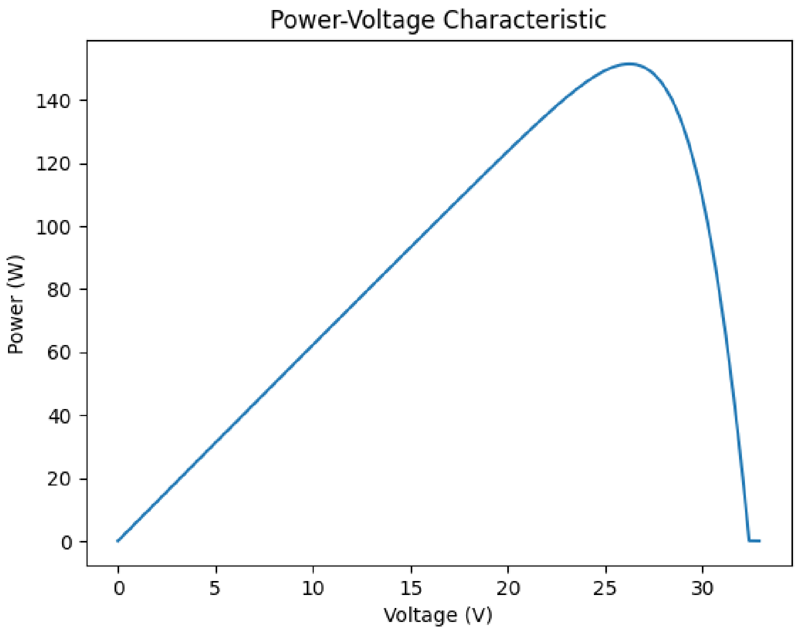

Fig 3.3: P-V Characteristics of PV Panel

It can be observed that for any given operating condition, which is the value of temperature and solar irradiance, the PV panel generates maximum power at only one point. This point is called the Maximum Power Point and the corresponding voltage is called Maximum Power Point Voltage(MPP Voltage).

The operating conditions of a PV panel keep changing every moment. These changing conditions change the maximum power that can be drawn from a PV panel. Under cloudy operating conditions the power drawn from the panel is less than what can be drawn under a clear sky. As the MPP keeps changing with respect to the surroundings it becomes necessary to search for the new MPP for optimum use of the solar panel. This process of constantly searching for the MPP is known as Maximum Power Point Tracking. Over the years various algorithms have been proposed for solving the problem of MPPT. For example, Perturb and Observe and Incremental Conductance. Intelligent algorithms like Particle Swarm Optimization, Genetic Algorithm and Artificial Neural Networks are currently being researched for MPPT applications.

In this project we use an Artificial Neural Network based algorithm to track the MPPT.

3.4 Introduction to WECS

Due to the uneven heating of the atmosphere by the sun, the geographical characteristics of the earth's surface and rotation of the earth, winds are created. The winds in different regions blow with different velocity thus some regions have abundant wind energy resources than others. A wind turbine consists of blades that capture the kinetic energy of the wind and convert it into mechanical energy. The turbine is coupled with an electrical generator through the shaft and a gearbox. The electrical generator converts the mechanical energy into electrical energy.

The wind turbines are divided into two primary categories:

- Vertical Axis Turbines
- Horizontal Axis Turbines

Horizontal axis turbines give higher efficiency as compared to the vertical axis turbines and thus have been adopted in the industry extensively. However, vertical axis turbines are more feasible for household and rooftop wind energy capturing systems. In recent years research has been made to improve the efficiency of the wind turbine by implementing various strategies like pitch angle control, height of the turbine, the radius of the blades, etc. This has resulted in a steep decline in the per unit cost of electricity generated by WECS and thus wide adoption of wind energy systems to supply electricity to our grids. Wind energy is a renewable energy source, i.e. wind is virtually a limitless and free resource. WECS plays an important role in developing a renewable energy based electrical grid and shaping a sustainable future.

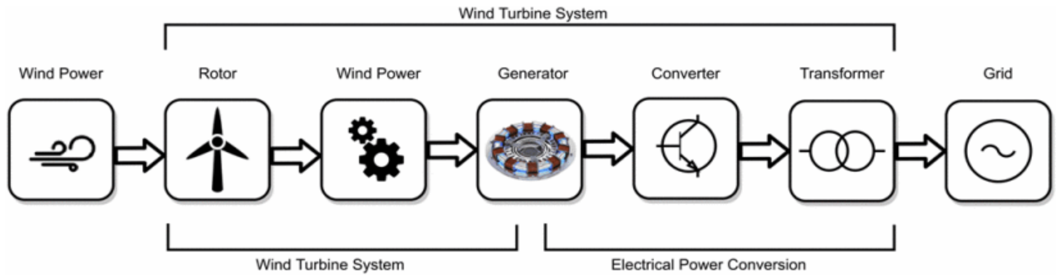

Fig 3.4: Wind Turbine System [60]

At different velocities of the wind, the output power of the wind turbine also varies. The mathematical model of a wind turbine is given by the equations given below:

3.5 Mathematical Modeling of WECS [6]

The power carried by the wind can be written as,

$$P_w = \frac{1}{2} \cdot \rho \cdot A \cdot v^3 \tag{10}$$

The power captured by the wind turbine is given as,

$$P = \frac{1}{2} \cdot C_p(\lambda, \beta) \cdot \rho \cdot A \cdot v^3 \tag{11}$$

C_p is called the power coefficient and can be calculated by the following equations,

$$C_p(\lambda, \beta) = 0.5176 \cdot \left(\left(\frac{116}{\lambda_i} - 0.4 \cdot \beta - 5 \right) \cdot e^{\frac{-21}{\lambda_i}} + 0.0068 \cdot \lambda_i \right) \tag{12}$$

$$\frac{1}{\lambda_i} = \frac{1}{\lambda + 0.08\beta} - \frac{0.035}{\beta^3 + 1} \tag{13}$$

The tip-speed ratio is calculated as follows,

$$\lambda = \frac{\omega \cdot R}{v} \tag{14}$$

Based on the equations above we can observe that by varying the rotor angular speed we can change the power generated by the WECS. The rotor angular speed depends on the velocity of the wind and thus controlling it directly will require a complex setup of gears and mechanical systems.

3.6 Power vs Angular Speed Characteristics of WECS

The turbine power is plotted against the angular speed of the rotor in the below figure:

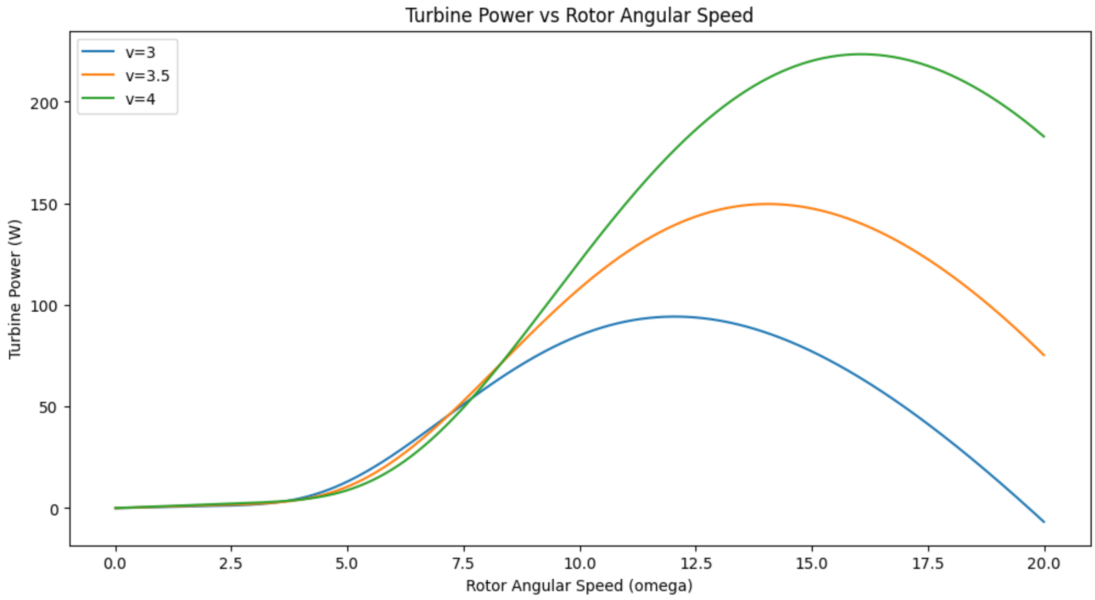

Fig 3.5: Turbine Power vs Shaft Angular Velocity

From the graph we observe that the maximum power that can be drawn from the WECS depends on the velocity of the wind. The point of maximum power is called the Maximum Power Point(MPP). There is only one MPP for the given wind speed and it occurs at only one rotor angular speed. The method to track this point is known as Maximum Power Point Tracking(MPPT). Over the years various algorithms have been developed to track the MPP of a WECS, for example, Tip-Speed Ratio, Hill Climbing, etc. By operating the WECS at the MPP we can ensure higher energy yield and optimum use of the system. This then ensures cheaper cleaner electrical power for commercial use.

As discussed earlier, changing the rotor angular speed is a complicated process. To operate at the MPP we can instead control the amount of current we draw from the generator and thus control the amount of power drawn based on the varying angular speeds which in turn change the voltage at the terminals of the generator. Hence, the

MPPT problem for a WECS boils down to controlling the amount of current drawn from the system.

3.7 Conclusion:

As discussed the MPP occurs at only one point. For optimum use of the PVS and WECS the system should be operated at this point. Thus, continuous tracking of the MPP is necessary and various algorithms have being adopted. The mathematical models behave as real world systems and thus are used to train and test the proposed algorithm.

CHAPTER 4
BASICS OF DC GENERATOR AND BOOST CONVERTER

4.1 Modeling a DC Generator

A generator is used to convert mechanical power into electrical power. A generator operates on the principle of electromagnetic induction, which was discovered by Michael Faraday in the 1830s. This principle states that a changing magnetic field induces an electromotive force (EMF) or voltage in a conductor. Generators consist of a stationary component called the stator and a rotating component called the rotor. The stator contains coils of wire. The rotor, which is mounted on a shaft, contains a magnetic field that can be either permanent magnets or electromagnets. When the rotor is turned, it creates a changing magnetic field around the stator coils. According to Faraday's law of electromagnetic induction, this changing magnetic field induces an EMF in the stator coils. If the circuit is closed, current will flow, creating electricity.

In summary, a generator operates by converting mechanical energy (rotation of the rotor) into electrical energy through the principle of electromagnetic induction. Depending upon the form of current produced the generators are characterized as DC generators or AC generators. In this project a DC generator is coupled with the wind turbine to convert the mechanical energy generated by the turbine into electrical energy.

The DC generators are further classified into

- separately excited,
- series excited and
- shunt excited DC generators.

They are also classified based upon if permanent magnets are used or not. In this project we use a separately excited DC generator. In a separately excited DC generator the current flowing through the field winding is independent of the current flowing through the generator. Thus the generator excitation control becomes easier. Also a constant flux can be produced irrespective of the load on the generator.

The circuit diagram of a DC generator is given below.

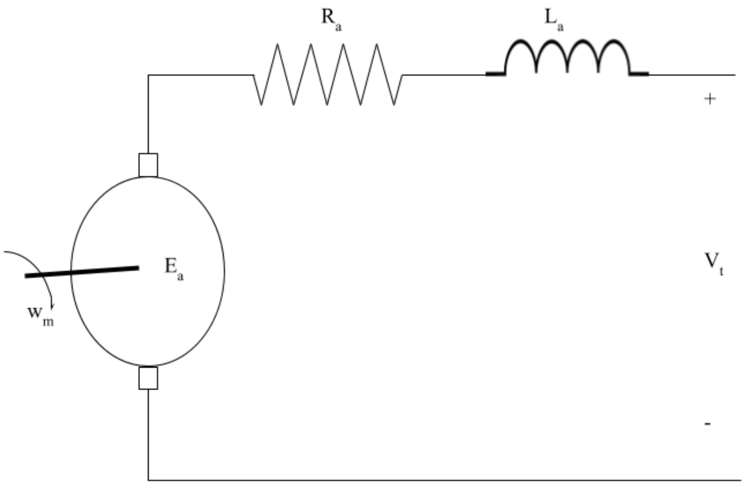

Fig 4.1: Circuit Diagram of DC Generator

From the circuit diagram we can make the following equations [54],
The voltage at the DC generator terminal can be written as,

$$V_t = E_a - I_a \cdot R_a - L_a \cdot \frac{dI_a}{dt} \tag{15}$$

Where E_a is the armature back EMF generated and is given by the following equation,

$$E_a = k_1 \cdot \phi \cdot \omega_m \tag{16}$$

k_1 depends on the construction of the generator and is calculated by the following expression,

$$k_1 = \frac{(No.\ of\ \ Poles) \cdot (No.\ of\ \ Armature\ Conductors)}{2\pi \cdot (No.\ of\ \ Parallel\ Paths)} \tag{17}$$

For negligible voltage drop in the armature winding it can be assumed that,

$$V_t \approx E_a \tag{18}$$

Thus, we can conclude that the voltage produced at the terminals of the generator depends on the angular velocity of the rotor. Varying wind speeds will vary the terminal voltage and thus the power output at the generator output terminal.

The torque produced by a generator depends on the amount of load current which in turn depends on the loading of the generator. Higher loads draw higher currents and thus produce higher torques. By increasing or decreasing the load current we can control the power extracted from the generator. Thus, controlling the loading of the generator will help in extracting maximum power from a system which is coupled with the generator.

4.2 Modeling a Boost Converter

Power electronic converters play a crucial role in modern power systems, enabling the efficient conversion, control, and conditioning of electrical power. These converters are essential for integrating renewable energy sources, such as solar and wind, into the grid, as well as for various industrial and consumer applications.

At their core, power electronic converters are devices that convert electrical energy from one form to another using semiconductor switches. These switches can be turned on and off rapidly to control the flow of power, allowing for precise regulation of voltage, current, and frequency. One of the key advantages of power electronic converters is their ability to efficiently convert power between different voltage and frequency levels. This makes them ideal for applications where variable voltage or frequency is required, such as in variable speed drives for motors or in grid-tied inverters for renewable energy systems.

Power electronic converters come in various configurations and topologies, each suited for different applications and power levels. They can range from simple diode rectifiers used in low-power applications to complex multi-level inverters used in high-power, high-voltage applications. For MPPT applications DC-DC converters have been used widely.

DC-DC converters are primarily categorized in three different types,

- Buck Converter,
- Boost Converter and
- Buck-Boost Converter.

In a Buck converter the voltage received at the output is lesser than the voltage supplied at the input, inversely, in a Boost Converter the voltage available at the output is more than the voltage supplied at the input. In a Buck-Boost Converter the voltage can range from lower to higher values. The choice of the type of DC-DC Converter depends on the application. Usually a Boost converter is widely used for the problem of MPPT.

In this project we use a Boost Converter for MPPT. The operations of the boost converter are discussed below based on [55].

Mode 1 of operation [55]:

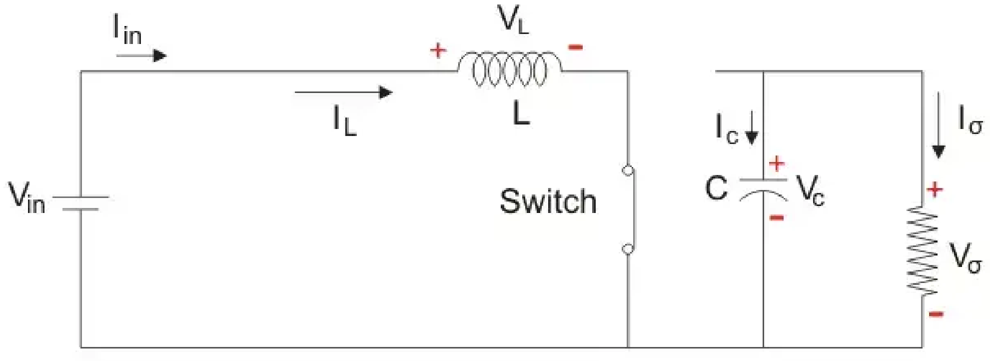

Fig 4.2: Boost Converter Mode 1 of Operation [61]

$$D = \frac{T_{on}}{T} \tag{19}$$

By using KVL we can write that,

$$V_{in} = V_L \tag{20}$$

$$V_L = L \cdot \frac{di_L}{dt} = V_{in} \tag{21}$$

$$\frac{di_L}{dt} = \frac{\Delta i_L}{\Delta t} = \frac{\Delta i_L}{DT} = \frac{V_{in}}{L} \tag{22}$$

Thus,

$$\left(\Delta i_L \right)_{closed} = \left(\frac{V_{in}}{L} \right) \cdot DT \tag{23}$$

Mode 2 of operation [61]:

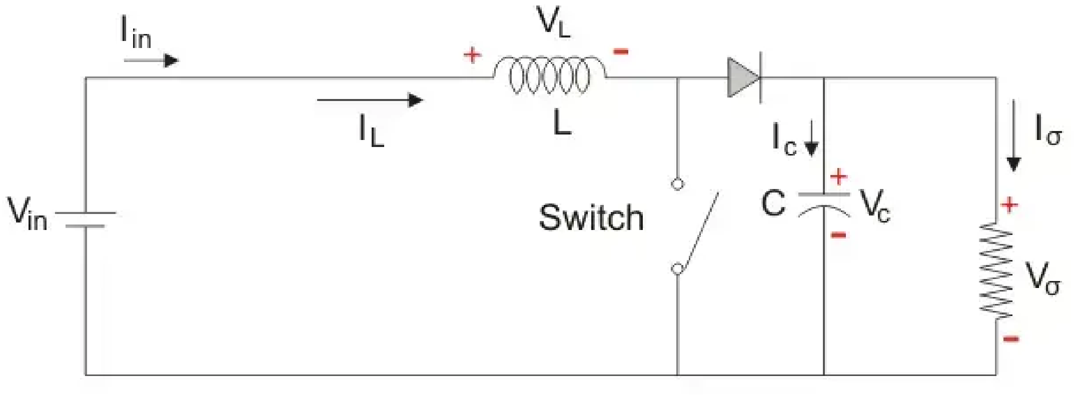

Fig 4.3 Boost Converter Mode 2 of Operation [55]

By using KVL we can say that,

$$V_{in} = V_L + V_o \tag{24}$$

$$V_L = L\frac{di}{dt} = V_{in} - V_o \tag{25}$$

$$\frac{di_L}{dt} = \frac{\Delta i_L}{\Delta t} = \frac{\Delta i_L}{(1-D)T} = \frac{V_{in} - V_o}{L} \tag{26}$$

$$(\Delta i_L)_{open} = \left(\frac{V_{in} - V_o}{L}\right) \cdot (1-D) \cdot T \tag{27}$$

Thus,

$$\left(\Delta i_L\right)_{closed} + \left(\Delta i_L\right)_{open} = 0 \tag{28}$$

$$\left(\frac{V_{in} - V_o}{L}\right)(1-D)T + \left(\frac{-V_o}{L}\right)DT = 0 \tag{29}$$

$$\frac{V_o}{V_{in}} = \frac{1}{1-D} \tag{30}$$

4.3 Boost Converter for MPPT

Consider the below given diagram of a Boost Converter.

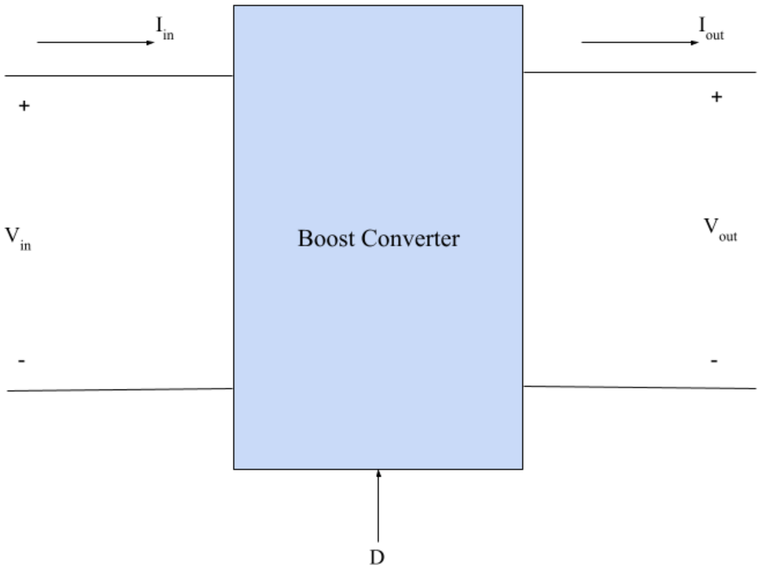

Fig 4.4: Boost Converter Input-Output Relation

The output voltage of the boost converter can be given by the following equation,

$$V_o = \frac{V_{in}}{(1 - d)} \tag{31}$$

Assuming negligible loss in the boost converter we can state that the input power will be equal to the output power.

Therefore,

$$V_{in} \cdot I_{in} = V_o \cdot I_o \tag{32}$$

$$I_o = I_{in} \cdot (1 - d) \tag{33}$$

$$P_{in} = V_o \cdot I_o = \frac{(V_o)^2}{R_L} \tag{34}$$

Hence, we can state that,

$$P_{in} = \frac{(V_{in})^2}{(1 - d)^2 \cdot R_L} \tag{35}$$

Thus, the duty cycle can be given as,

$$d = 1 - \frac{V_{in}}{\sqrt{P_{in} \cdot R_L}} \tag{36}$$

As we can see from the equations, the boost converter changes the way the system perceives the load. The load changed from R_L to $(1-d)^2R_L$. Thus by controlling the duty cycle we can control the loading of the system which in turn will control the load current flowing through the system and thus the power drawn from the energy source. In this manner any system can be operated at the MPPT by finding the optimum duty ratio. Our problem statement thus boils down to find the optimum duty ratio for any given system. The input parameters for the algorithm will be the readable quantities from the Boost converter, i.e. the current and voltage at the input terminals[56][57].

4.4 Conclusion:

The boost converter is used to track the MPPT by controlling its duty ratio. Various techniques have been used to control the duty ratio of the boost converter as discussed in the literature review. By varying the duty ratio of the boost converter the load as perceived by the system is changed. The DC generator is coupled to the turbine and used to capture the wind energy. The mathematical models of both the devices are used to mimic the real world models and thus aid in developing the algorithm.

CHAPTER 5
ARTIFICIAL NEURAL NETWORK

5.1 Basics of ANN

Artificial Neural Network(ANN) is inspired from the biological neural network such as the human brain. Biological Neurons receive signals from other neurons through dendrites, process these signals in the cell body, and transmit signals to other neurons through axons. The strength of the connections between neurons, known as synapses, can change over time based on the activity of the neurons, a process known as synaptic plasticity. In this manner, through practicing any human can gain expertise in a given task. Thus we can conclude that the biological neurons process the real world inputs to find and recognize patterns and thus help in decision making.

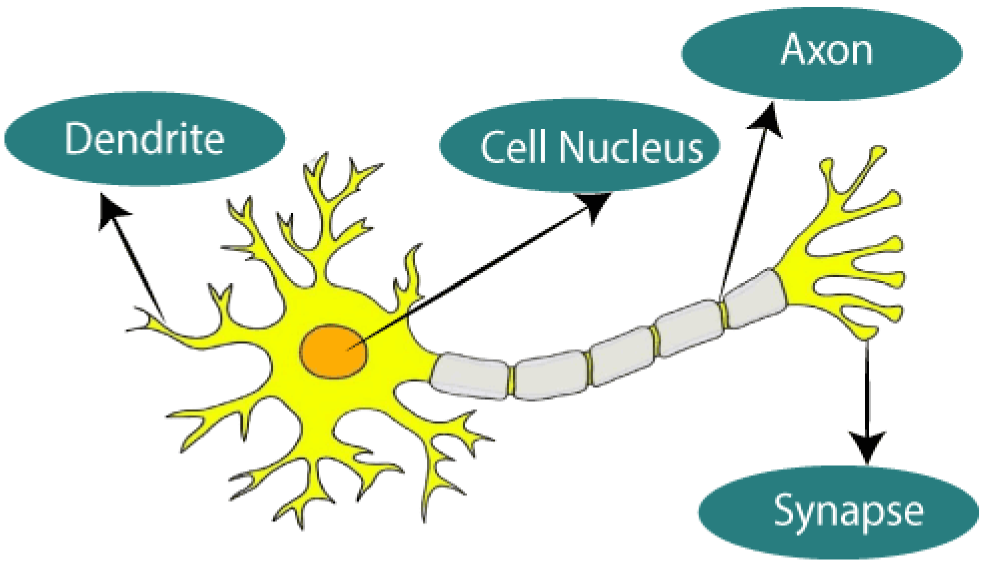

Fig 5.1: Biological Neuron [58]

This same framework was used to develop the Artificial Neural Network. ANNs are the backbone of Deep Learning(DL) which is a subfield of Artificial Intelligence and Machine Learning(AI/ML). In ANNs, artificial neurons, or nodes, are interconnected in layers. Each neuron receives input signals, processes them using an activation function, and passes the output to other neurons. The connections between neurons, known as weights, are adjusted during the learning process to improve the network's performance on a given task [59].

5.2 Loss Functions

The performance of the ANN for a given task is evaluated using the loss function. A loss function is a mathematical equation that quantifies the difference between the predicted output of the ANN and the expected output(actual output).

There are several loss functions available and the selection depends on the type of problem that is being addressed. Few commonly used loss functions are listed below:

- Mean Squared Error

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(y_i - \widehat{y_i}\right)^2 \tag{37}$$

- Binary Cross-Entropy

$$Binary\ Cross\ Entropy = \frac{-1}{n}\sum_{i=1}^{n}\left(y_i \cdot \log(\hat{y}_i) + (1 - y_i)\cdot \log\left(1 - \widehat{y_i}\right)\right) \tag{38}$$

- Categorical Cross-Entropy

$$Categorical\ Cross\ Entropy = \frac{-1}{n}\sum_{i=1}^{n}\sum_{c=1}^{C} y_{i,c} \cdot \log\left(\widehat{y_{i,c}}\right) \tag{39}$$

- Mean Absolute Error

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|y_i - \widehat{y_i}\right| \tag{40}$$

The goal during training the ANN is to minimize the loss function and thus the algorithm achieves convergence. The training process consists of forward pass, loss computation, backpropagation, and weight updation. In the forward pass step the input is fed into the ANN and an output is received. In the loss computation step the loss is calculated from the loss function. In the backpropagation and weight updation step the slope of the loss is used to update the weights and biases of the neurons moving from the output layer towards the hidden layers.

5.3 Weight Updation and Optimizers

This weight updation, also known as optimization, is responsible for the convergence of the ANN and is done by optimizers. There are several optimizers and the selection of an optimizer depends on the type of problem. The most commonly used optimizers are listed below:

- Stochastic Gradient Descent(SGD)
- Momentum
- AdaGrad(Adaptive Gradient Algorithm)
- RMSProp(Root Mean Squared Propagation)
- Adam(Adaptive Moment Estimation)

In this project we used the Adam optimizer to train the ANN. It combines the ideas of momentum and RMSprop into a single algorithm, offering both speed and stability during training. The key idea behind Adam is to maintain two moving averages of the gradients. The first moment m is the exponentially decaying average of past gradients, similar to momentum. The second moment v is the exponentially decaying average of past squared gradients, similar to RMSprop. These moving averages are used to adaptively adjust the learning rate for each parameter.

The following steps explain how the Adam optimizer works:

Step 1: Initialize the first (m) and second (v) moment estimates to zero.

Step 2: Compute the gradient of the loss function with respect to the parameters.

Step 3: Update the first moment estimate:

$$m_t = \beta_1 m_{t-1} + \left(1-\beta_1\right) \nabla J\left(\theta_t\right) \tag{41}$$

Step 4: Update the second moment estimate:

$$v_t = \beta_2 v_{t-1} + \left(1-\beta_2\right)\left(\nabla J\left(\theta_t\right)\right)^2 \tag{42}$$

Step 5: Compute the bias-corrected first and second moment estimates:

$$\widehat{m}_t = \frac{m_t}{1 - \beta_1^t} \tag{43}$$

$$\widehat{v}_t = \frac{v_t}{1 - \beta_2^t} \tag{44}$$

Step 6: Update the parameters:

$$\theta_{t+1} = \theta_t - \frac{\alpha}{\sqrt{\widehat{v}_t} + \varepsilon}\widehat{m}_t \tag{45}$$

5.4 Epochs and Batch Size

An epoch refers to one complete pass of the entire training dataset through the neural network. During one epoch, the model receives all the training samples, computes the loss, and updates the weights of the network using an optimization algorithm (e.g., SGD, Adam). The number of epochs is a hyperparameter that determines how many times the model will see the entire dataset during training. Training for more epochs allows the model to learn more from the data, but there is a risk of overfitting if the model learns to memorize the training examples instead of generalizing to new examples.

The batch size refers to the number of training examples processed in one iteration (or batch) before the model's weights are updated. Instead of updating the weights after processing each individual example (which would be computationally inefficient), we update the weights after processing a batch of examples. The batch size can significantly affect the training process. A larger batch size typically leads to faster training because it exploits parallelism in modern hardware, but it may result in less noisy updates and a less stable convergence. On the other hand, a smaller batch size may lead to slower training but could result in a more stable convergence and better generalization.

In summary, epochs and batch size are essential parameters in training neural networks. The number of epochs determines how many times the model will see the entire dataset, while the batch size determines how many examples are processed before updating the weights.

5.5 ANN for PVS

Number of Layers: 5 (3 Hidden Layers)

Layer 1: Input Layer; 2 Perceptrons

Layer 2: Hidden Layer; 100 Perceptrons; ReLU Activation

Layer 3: Hidden Layer; 100 Perceptrons; ReLU Activation

Layer 4: Hidden Layer; 100 Perceptrons; ReLU Activation

Layer 5: Output Layer; 2 Perceptrons; Linear Activation

Optimizer: Adam

Loss Function: Mean Absolute Error(MAE)

Epochs: 100

Batch Size: 50

Diagram:

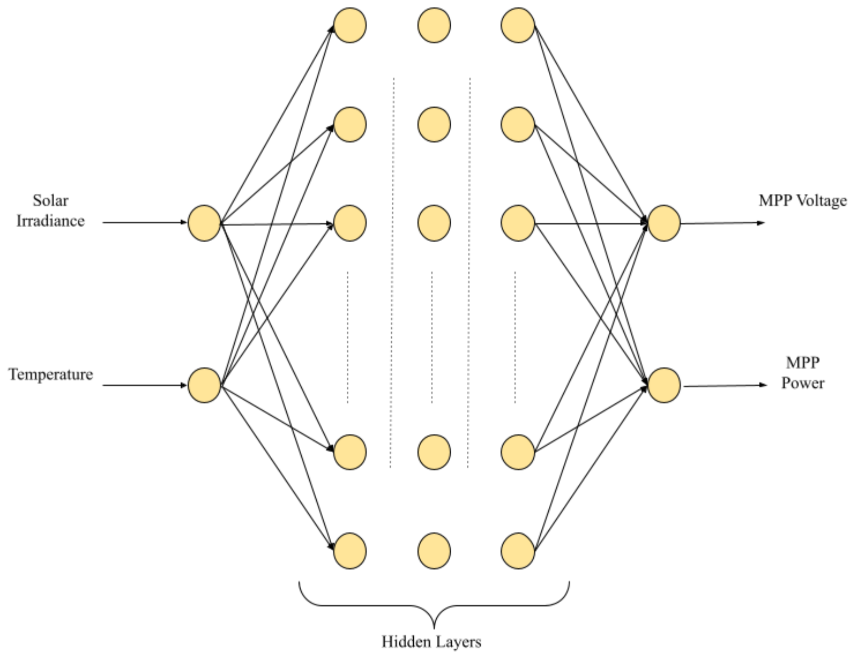

Fig 5.2: ANN for PVS

5.6 ANN for WECS

Number of Layers: 5 (2 Hidden Layers, 1 Dropout Layer)

Layer 1: Input Layer; 1 Perceptron

Layer 2: Hidden Layer; 50 Perceptrons; ReLU Activation

Layer 3: Hidden Layer; 50 Perceptrons; ReLU Activation

Layer 4: Dropout Layer; 25% Dropout

Layer 5: Output Layer; 2 Perceptrons; Linear Activation

Optimizer: Adam

Loss Function: Mean Squared Error(MSE)

Epochs: 100

Batch Size: 50

Diagram:

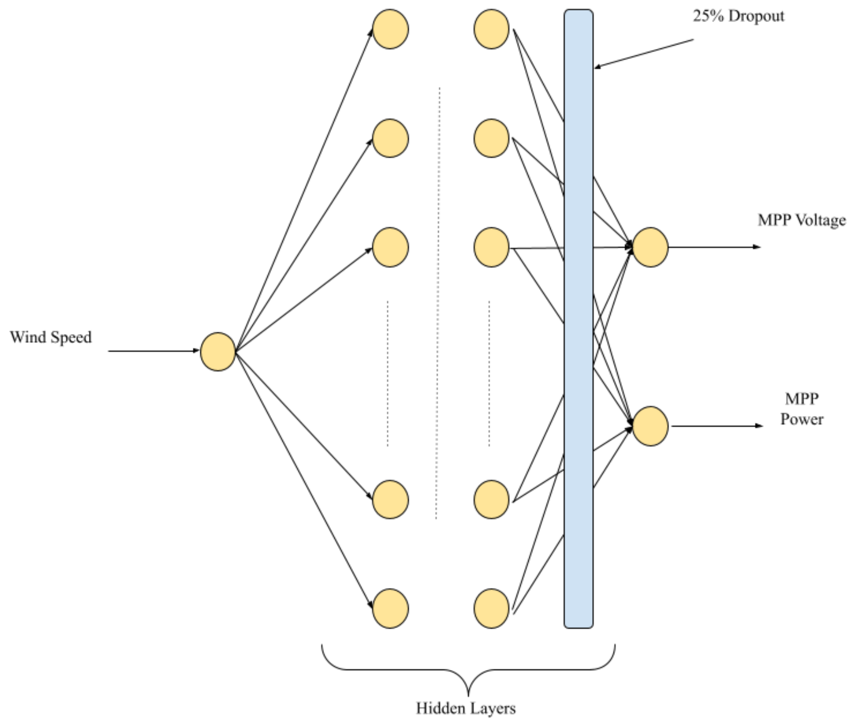

Fig 5.3: ANN for WECS

5.7 Acquiring, Creating and Cleaning Data

Artificial Neural Networks require a huge amount of data to train on and data also plays a crucial role in evaluating the performance of ANN. The quality, quantity, and preprocessing of data significantly impact the effectiveness of the model. High-quality data that is accurate, relevant, and representative of the problem domain leads to better-trained models. Conversely, low-quality or noisy data can negatively affect performance. The quantity of data is also important. In general, more data leads to better generalization and performance, especially for complex tasks. However, collecting and labeling large amounts of data is challenging and expensive. Data preprocessing is often necessary before training an ANN. Tasks such as normalization, scaling, handling missing values, and encoding categorical variables can improve the performance and training efficiency of the model. Proper data splitting is essential. The dataset is typically split into training, validation, and test sets. The training set is used to train the model, the validation set is used to tune hyperparameters and monitor performance, and the test set is used to evaluate the final performance of the model. It's also important to consider data bias and fairness. Biases in the data can lead to biased predictions, which can have negative real-world consequences.

To train the ANNs in helping predict the MPP of the HES we needed the data of the operating conditions of the PVS and WECS, which includes the surrounding temperature, irradiance and wind speed. The temperature and irradiance data was collected from the Indian Meteorological Department(IMD) Climate Data Service Portal(CDSP) [63]. The wind speed data was collected from the NASA POWER Data Access Viewer [64] and wind speeds at a height of 10 meters were considered.

The ANNs were trained through supervised learning, thus, the data was to be labeled. The mathematical models for PVS and WECS designed in Chapter III were used to calculate the MPP Voltage for PVS and MPP Angular Speed for WECS and MPP Power for both the systems for all the data points.

Thus the ANN for PVS was trained on 1,02,588 data points and the ANN for WECS was trained on 2,00,953 data points. The data set was split into two parts, the training set and the validation set. The training set was 75% of the original data set. The validation set was 25% of the original data set.

The training and testing performance for both the ANNs is given below.

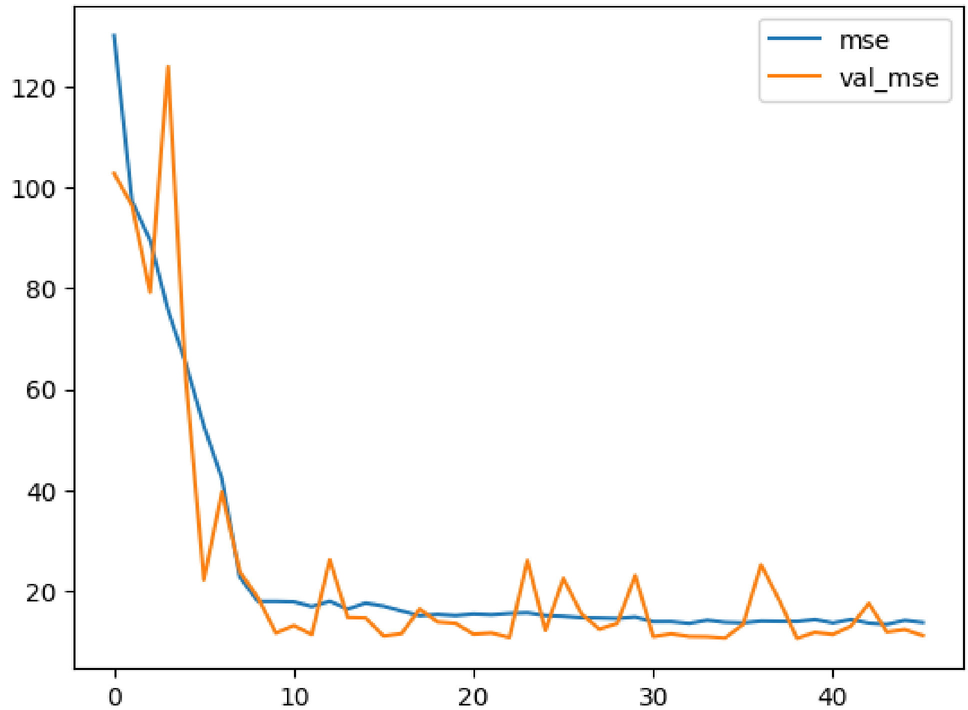

Fig 5.4: ANN Training vs Testing Performance for PVS

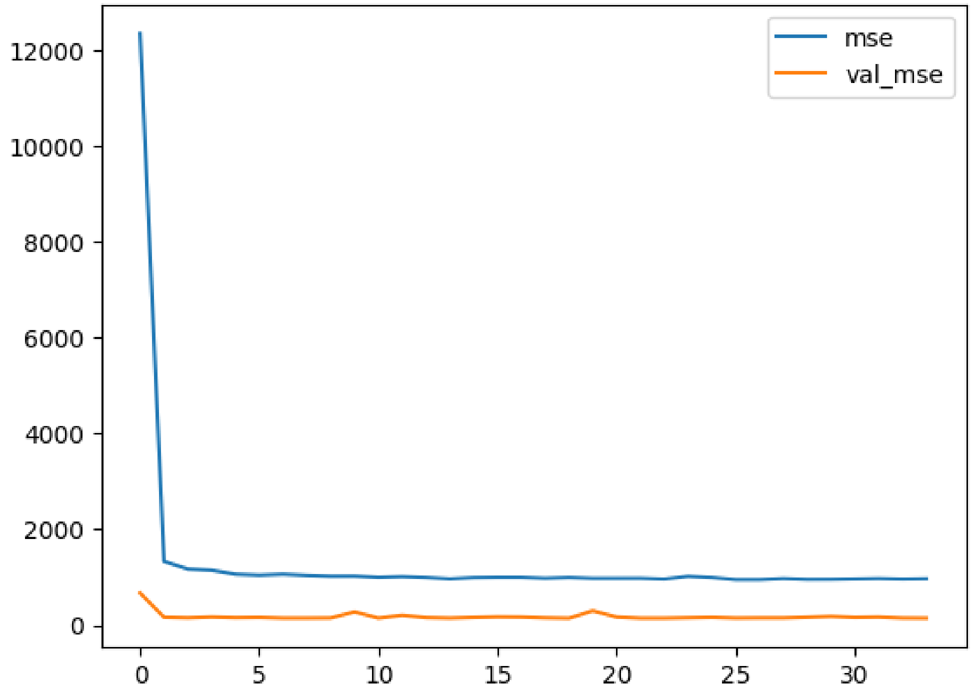

Fig 5.5: ANN Training vs Testing Performance for WECS

5.8 Conclusion:

Two ANNs, one for PVS and one for WECS each were trained to predict the MPP points and thus the duty cycle. ANNs were trained using MSE and MAE as the loss function respectively and the performance was evaluated with the help of training and validation set as shown in Fig 5.4 and Fig 5.5.

CHAPTER 6
PROPOSED ALGORITHM: ANN+P&O

6.1 ANN+P&O

As discussed earlier, the P&O algorithm does not always converge to the global optima. Depending upon the step size the time required for convergence can be more or less. A smaller step size reaches the local maxima with less error however takes very long until convergence. A larger step size tracks the local maxima with a very large error but takes less time until convergence. A tradeoff between accuracy and convergence time has to be made.

The MPP keeps changing as the surrounding conditions change. If the algorithm takes a long time to track the MPP it will never be able to converge to any point as the MPP will change location before the algorithm converges. This is a problem faced by the conventional P&O algorithm. Thus, real-time tracking of the MPP becomes difficult resulting in losing the available power.

To maximize the energy yield by addressing the problems faced by the conventional algorithms like P&O we have proposed a Machine Learning based algorithm that gives faster convergence and is highly likely to converge at the global maxima. In this algorithm we use Artificial Neural Networks to act as a support for the conventional P&O algorithm by providing the starting point for the P&O.

The ANN for PVS takes the solar irradiance and temperature as input and predicts the MPP for the given operating conditions and the given solar panel model. An expected duty ratio is then calculated. The optimum duty ratio will be present very close to the predicted duty ratio. The predicted duty ratio is given as a starting point for the conventional P&O. This helps the conventional P&O to not start from a point that might be far from the optimum duty ratio and rather start looking for the global optima from a point very close to it. This will thus improve the speed of tracking and reduce the time until convergence. Reduction in convergence time will result in the possibility of real-time tracking of the MPP and increased energy yield.

The ANN for WECS takes the wind speed as input and predicts the MPP for the WECS. This prediction is used to determine a duty ratio corresponding to the MPP. The predicted duty ratio, as for the PVS, is very close to the optimum duty ratio and is thus provided as a starting point for the P&O. Similar to the PVS, the convergence time will reduce considerably and improve the energy yield.

The ANN+P&O algorithm tries to use the human-like decision making ability of the ANN to guide the conventional P&O to select a point from which to start looking for the optimum solution. Conventional P&O is not an intelligent algorithm and thus follows a set of predetermined rules which slow down the process of MPP tracking as it has to always start looking for the maxima from the duty ratio corresponding to the previous maxima. ANN is an intelligent model, i.e. it makes decisions based on the operating situation. However, ANN is a predictive model, i.e. its output is the most probable solution but not the optimum solution. ANN makes decisions based on the probability of attaining the desired outcome. By combining both ANN and P&O we can eliminate most of the cons of both the algorithms and take advantage of the pros of both the algorithms. ANN+P&O uses the element of intelligence of the ANN and the ability to track the optima of the P&O. Thus both algorithms help each other and provide a faster and better MPPT solution.

6.2 Block Diagram of the Complete System

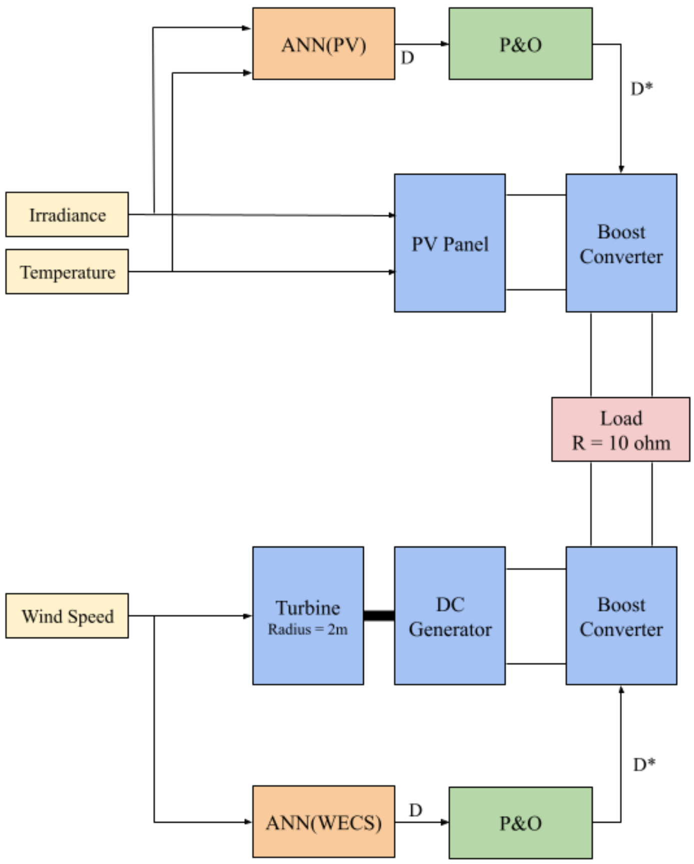

Fig 6.1: Complete System Block Diagram

CHAPTER 7
PSEUDO CODES

The pseudo codes for all the working codes in the project have been shared below. The pseudo codes shed light on the logical working of the codes in the project and their integration with each other to mimic the much complex real-world system which were studied in this project.

7.1 Calculating the I-V Characteristics of PVS:

The inputs taken are the temperature and irradiance. This code mimics the PV Panel operations in the real world with the help of the I-V characteristic equation.

PV Characteristic Equation(Calculating V and I)

$j \leftarrow 0;$
for $i \leftarrow 0$ **to** Isc steps of 0.001 **do**
  $j \leftarrow 0;$
  $I_{pvc}(j,1) \leftarrow I;$
  $V_c(j,1) \leftarrow 0;$
  if $I < (I_{ph} - I_o)$ **then**
    $V_{pv}(j,1) = \left[V_{tcs} \cdot \log\left(\frac{I_{ph}-I-I_o}{I_o}\right) - I_{R_s}\right] \cdot N_s;$
  else
    $V_{pv}(j,1) \leftarrow 0;$
  end if
  if $V_{pv}(j,1) < 0$ **then**
    $V_{pv}(j,1) \leftarrow 0;$
  end if
end for

7.2 Training ANN for predicting MPP for PVS:

This pseudo code presents the underlying structure of the ANN trained to predict the MPP of a PVS.

Training ANN for PVS

```
Input: Xpv_train, Ypv_train, Xpv_test, Ypv_test        ▷ Training and testing data
Output: model                                          ▷ Trained neural network model
model ← Sequential()
model.add(Dense(units=100, activation='relu', input_shape=[2]))
model.add(Dense(units=100, activation='relu'))
model.add(Dense(units=100, activation='relu'))
model.add(Dense(units=2, activation='linear'))
early_stopping ←
        EarlyStopping(min_delta=0.001,
        patience=15, restore_best_weights=True)
model.compile(optimizer='adam', loss='mae', metrics=['mse'])
history ← model.fit(Xpv_train, Ypv_train,
            validation_data = (Xpv_test, Ypv_test),
            batch_size = 50, epochs = 100, callbacks = [early_stopping])
```

7.3 Calculating Power vs Angular Speed for WECS:

The pseudo code to mimic the real world WECS is presented below. It is based on the characteristic equation of the wind turbine.

Wind Characteristic Equation (Calculating P and W)

```
function CALCULATE_LAMBDA(ω, R, v)
    return ω·R / v
end function
function INVERSE_LAMBDA_I(β, λ)
    return 1/(λ+0.08·β) − 0.035/(β^3+1)
end function
function CP(inverse_lambda_i, λ, β)
    term1 ← (116 · inverse_lambda_i − 0.4 · β − 5)
        · exp(−21 · inverse_lambda_i)
    term2 ← 0.0068 · λ
    return 0.5176 · (term1 + term2)
end function
function CALCULATE_ACTUAL_POWER(v, A, ρ, Cp, β)
    return 0.5 · ρ · A · v^3 · Cp
end function
beta_range ← [0, 2, 4, 6, 8, 10, 12, 14]                ▷ Range of beta values
v_values ← [3, 3.5, 4]                                   ▷ Wind speed values
for each β in beta_range do
    for each v in v_values do
        omega_vals ← [0, 0.01, 0.02, . . . , 24.99]      ▷ Range of omega values
        lambda_vals ← [calculate_lambda(ω, R, v) for ω in omega_vals]
```

```
        inverse_lambda_vals ← [inverse_lambda_i(β, λ) for λ in lambda_vals]
        Cp_vals ← [Cp(inv_lambda, λ, β) for inv_lambda,
         λ in zip(inverse_lambda_vals, lambda_vals)]
        actual_power_vals ← [calculate_actual_power(v, A, ρ, Cp, β)
          for Cp in Cp_vals]
                                    ▷ Plot omega_vals vs actual_power_vals for each v
    end for
end for
if Wind_speed is not NaN and is finite then
    omega_vals ← [1, 1.01, 1.02, . . . , 24.99]            ▷ Range of omega values
    lambda_vals ← [calculate_lambda(ω, R, Wind_speed) for ω in omega_vals]
    inverse_lambda_vals ← [inverse_lambda_i(β, λ) for λ in lambda_vals]
    Cp_vals ← [Cp(inv_lambda, λ, β) for inv_lambda,
         λ in zip(inverse_lambda_vals, lambda_vals)]
    actual_power_vals ← [calculate_actual_power(Wind_speed, A, ρ, Cp, β)
          for Cp in Cp_vals]
    if actual_power_vals is not empty then
        max_power_index ← index of max(actual_power_vals)
        Pmax ← actual_power_vals[max_power_index]
        omega_for_Pmax ← omega_vals[max_power_index]
    else
        Pmax ← 0
        omega_for_Pmax ← 0
    end if
else
    Pmax ← 0
    omega_for_Pmax ← 0
end if
```

7.4 Training ANN for predicting MPP for WECS:

This pseudo code presents the underlying structure of the ANN trained to predict the MPP of a WECS.

Training ANN for WECS

```
Input: Xwind_train, Ywind_train, Xwind_test, Ywind_test      ▷ Training and
testing data
Output: modelwind                                           ▷ Trained wind model
modelwind ← Sequential()
modelwind.add(Dense(units=50, activation='relu', input_shape=[1]))
modelwind.add(Dense(units=50, activation='relu'))
modelwind.add(Dropout(0.25))
modelwind.add(Dense(units=2, activation='linear'))
```

```
modelwind.compile(optimizer='adam', loss='mse', metrics=['mse'])
early_stopping ← EarlyStopping(min_delta=0.001,
                    patience=15, restore_best_weights=True)
history ← modelwind.fit(Xwind_train, Ywind_train,
                  validation_data = (Xwind_test, Ywind_test),
                  batch_size = 50, epochs = 100, callbacks = [early_stopping])
```

7.5 P&O for PVS:

The conventional P&O Algorithm for tracking the MPP of the PVS is presented below.

P&O for PV

```
function PANDOPV(d_prev, iter_max)
    iter ← iter_max, deld ← 0.0001
    ind ← index of the min abs difference between dpv and d_prev
    P_prev ← V[ind] × I[ind], V_prev ← V[ind]
    d ← d_prev + 0.001
    Create arrays P_array and count_array of size max_iter, initialized with
zeros
    count ← 0
    for i ← 0 to iter do
        count ← count + 1,
index ← index of the min abs difference between dpv and d
        P_new ← V[index] × I[index], V_new ← V[index]
        delP ← P_new − P_prev, delV ← V_new − V_prev
        if delP ≠ 0 then
            if delP > 0 then
                if delV > 0 then
                    d ← d − deld
                else
                    d ← d + deld
                end if
            else
                if delV > 0 then
                    d ← d + deld
                else
                    d ← d − deld
                end if
            end if
        else
            d ← d_prev
        end if
```

```
            d_prev ← d, P_prev ← P_new, V_prev ← V_new
            Store P_new in P_array at index i, Store count in count_array at index i
        end for
        return P_array, count_array, d
    end function
```

7.6 P&O for WECS:

The conventional P&O Algorithm for tracking the MPP of the WECS is presented below.

P&O for WIND

```
    function PANDOWIND(wprev, iter_max)
        iter ← iter_max
        delw ← 0.1
        ind ← index of the minimum absolute difference between omega_vals and wprev
        Pprev ← actual_power_vals[ind]
        Omegaprev ← omega_vals[ind]
        w ← wprev + 0.3
        Create arrays Parray and countarray of size iter, initialized with zeros
        count ← 0
        for i ← 0 to iter − 1 do
            count ← count + 1
            index ← index of the minimum absolute difference between omega_vals and w
            Pnew ← actual_power_vals[index]
            omeganew ← omega_vals[index]
            delP ← Pnew − Pprev
            delomega ← omeganew − Omegaprev
            if delP ≠ 0 then
                if delP > 0 then
                    if delomega > 0 then
                        w ← w + delw
                    else
                        w ← w − delw
                    end if
                else
                    if delomega > 0 then
                        w ← w − delw
                    else
                        w ← w + delw
                    end if
```

```
            end if
        else
            w ← Omegaprev
        end if
        Pprev ← Pnew
        Omegaprev ← omeganew
        Store Pnew in Parray at index i
        Store count in countarray at index i
    end for
    return Parray, countarray, w
end function
```

CHAPTER 8
TESTING ANN+P&O

8.1 Comparing ANN+P&O with Conventional P&O

As discussed earlier, the starting point for the P&O is provided by the ANN. This ANN+P&O algorithm converges in fewer iterations as compared to the conventional P&O algorithm.

To test the hypothesis an initial operating point of duty ratio 0.20 for PVS and 0.3647 for WECS is considered. First the operating conditions change to 30.29^{o}Celsius, 692.09 W/m^2 and 5m/s wind speed(Operating Condition 1). The operating conditions then change to 24.93^{o}Celsius, 760.78W/m^2 and 4m/s wind speed(Operating Condition 2). Under all the changing conditions both the algorithms are made to track the MPP and the performance in terms of number of iterations until convergence is noted in the table along with the details of the operating conditions.

Operating Conditions for hypothesis testing:

	Temperature (^{o}C)	**Irradiance (W/m^2)**	**Wind Speed(m/s)**
Initialization(Duty Ratio)	PVS: 0.20 ; WECS: 0.3647		
Operating Condition 1	30.29	692.09	5
Operating Condition 2	24.93	760.78	4

Table 8.1: Operating Conditions for Testing ANN+P&O Algorithm

The table below summarizes the changing conditions for PVS and compares the performance of Conventional P&O with the proposed ANN+P&O:

T (ºC)	**G (W/m²)**	**D_Previous for P&O**	**D_Predicted for ANN+P&O**	**D_Actual**	**No. of Iterations until convergence for Conventional P&O**	**No. of Iterations until convergence for ANN+P&O**
Initialization at previous duty ratio = 0.2						
30.29	692.09	0.2	0.2267	0.3015	1100	800
24.93	760.78	0.3015	0.3123	0.3253	250	130

Table 8.2: Performance of ANN+P&O for PVS

The table below summarizes the changing conditions for WECS and compares the performance of Conventional P&O with the proposed ANN+P&O:

v (m/s)	**D_Previous for P&O**	**D_Predicted for ANN+P&O**	**D_Actual**	**No. of Iterations for ConventionalP&O**	**No. of Iterations for ANN+P&O**
Initialization at previous duty ratio = 0.3647(v = 3m/s)					
5	0.3647	0.5852	0.5053	60	30
4	0.5053	0.4665	0.4496	50	10

Table 8.3: Performance of ANN+P&O for WECS

The convergence graphs for both ANN+P&O and conventional P&O are shown below along with the number of iterations required until convergence for operating condition-1.

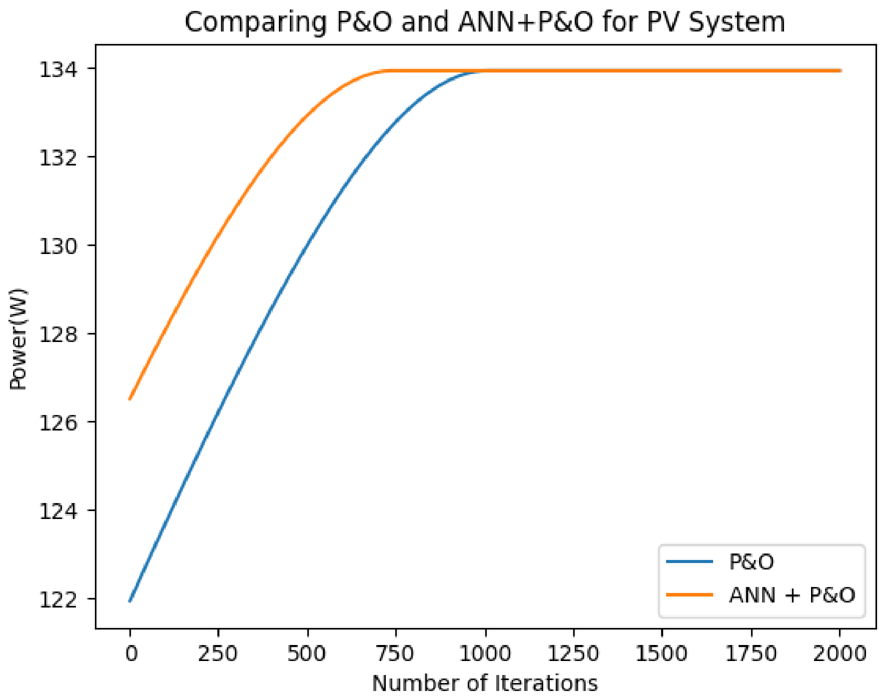

Fig 8.1: Comparing ANN+P&O with P&O for Operating Condition 1(PVS)

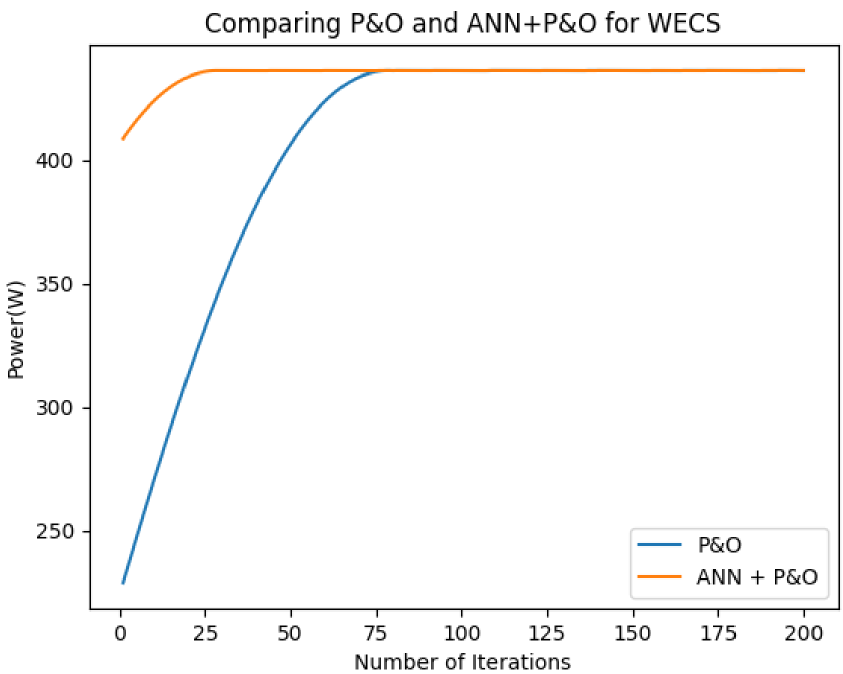

Fig 8.2: Comparing ANN+P&O with P&O for Operating Condition 1(WECS)

The convergence graphs for both ANN+P&O and conventional P&O are shown below along with the number of iterations required until convergence for operating condition-2.

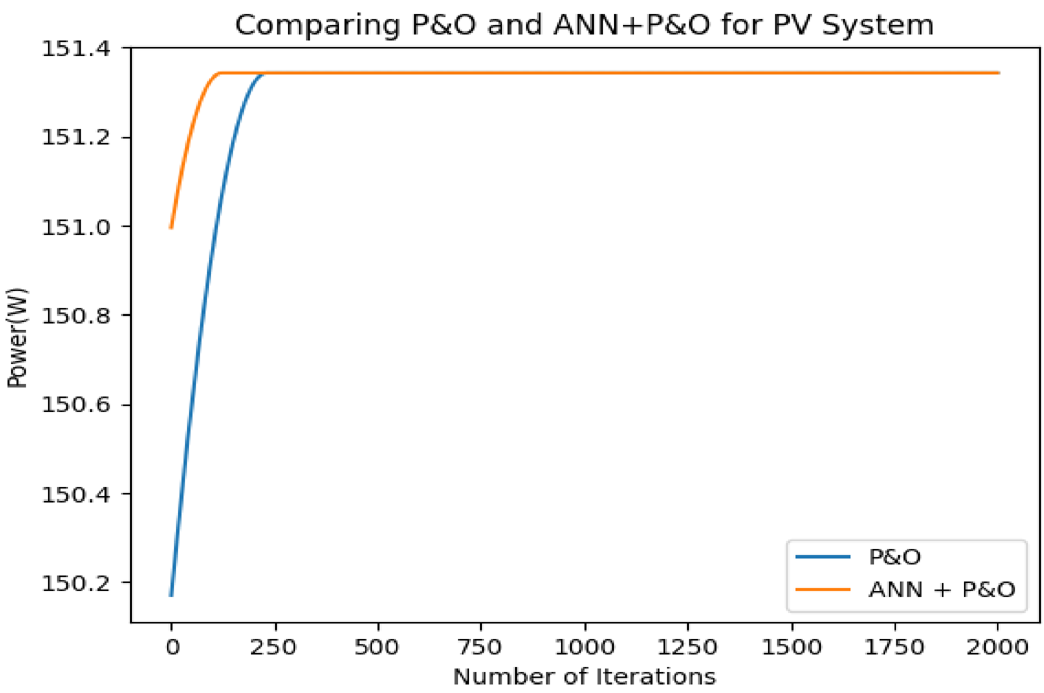

Fig 8.3: Comparing ANN+P&O with P&O for Operating Condition 2(PVS)

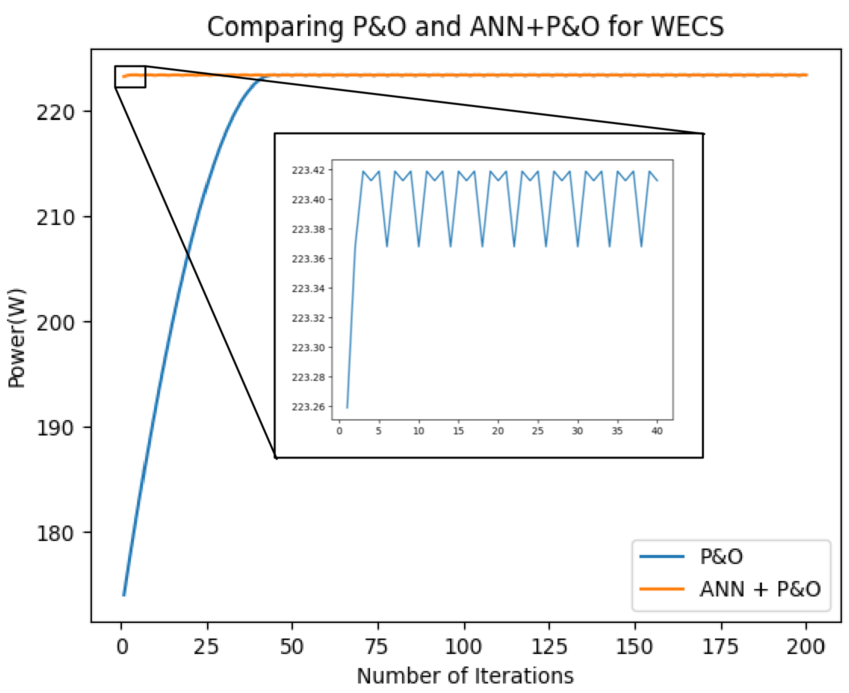

Fig 8.4: Comparing ANN+P&O with P&O for Operating Condition 2(WECS)

It can be seen that the ML powered P&O algorithm converges in fewer iterations as compared to the conventional P&O algorithm. In both cases the number of iterations required for the ANN+P&O algorithm are less than half of what the conventional algorithm requires. After the conditions changed the ANN+P&O algorithm jumped to the point closer to the MPP and then converged towards the MPP unlike the conventional P&O which continuously took small steps towards the MPP. Thus, saving time and maximizing the energy yield.

The scatter plots given below compare the predicted MPP with the actual MPP.

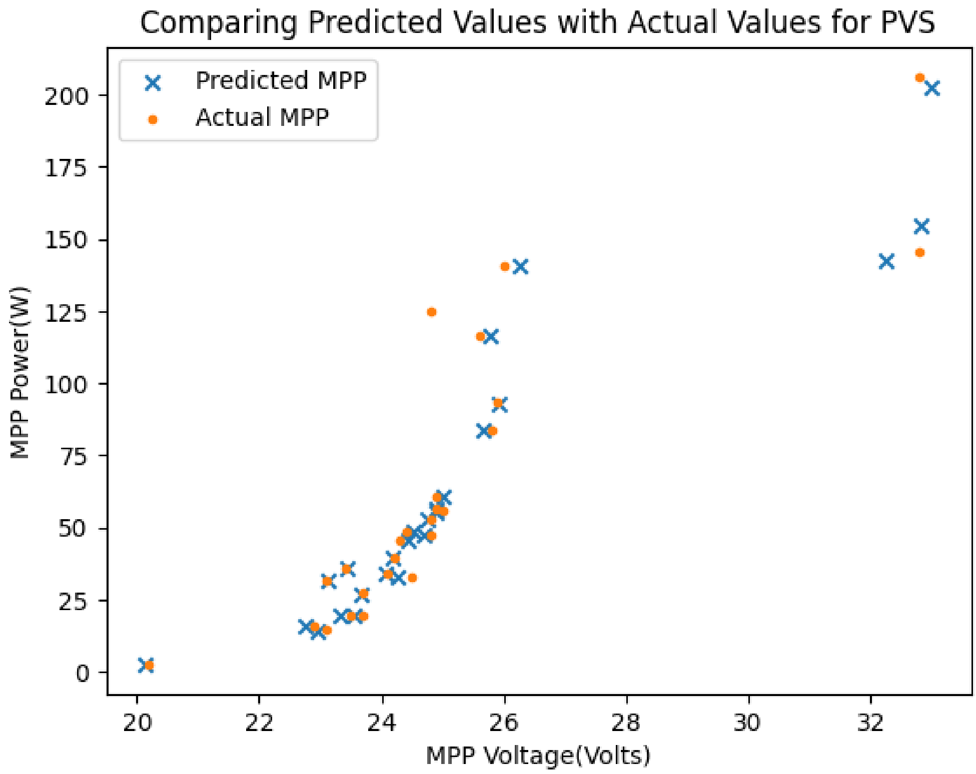

Fig 8.5: Predicted Value vs Actual Values (PVS)

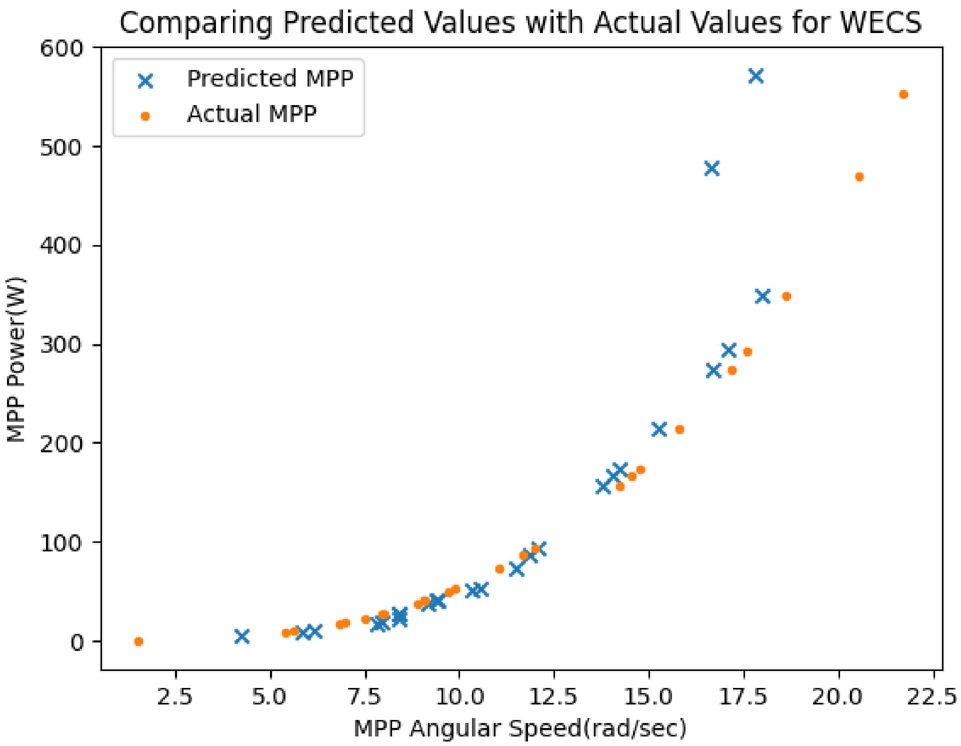

Fig 8.6: Predicted Value vs Actual Values (WECS)

We can observe that the predicted MPP is very close to the actual MPP. Thus, giving the P&O algorithm a starting point which is very close to the actual MPP and speeding up the MPPT process with greater accuracy.

CHAPTER 9
CONCLUSION AND FUTURE SCOPE

9.1 Conclusion:

In this project a ML powered P&O algorithm, ANN+P&O, was proposed. It was observed that the ML model added an element of intelligence to the conventional P&O algorithm by predicting the duty ratio for the current operating conditions. The conventional P&O algorithm then jumps to the predicted MPP point and starts converging. Without the ML model the P&O would have started looking for the new MPP from the previous MPP thus requiring more time, resulting in lower energy yield. The proposed algorithm converges in fewer iterations as compared to the traditional P&O and is therefore more reliable for real-time MPP tracking. It also increases the probability of converging at the global maxima instead of converging at the local maxima, a problem faced by conventional P&O. This ensures higher energy yield and optimum use of the HES.

9.2 Future Scope of Project:

1. The ANN models can be generalized to any PV Panel or Wind Turbine or Generator by using an online learning method such a Deep Reinforcement Learning.
2. The ANN models can be combined with other conventional algorithms and the performance can be compared.
3. A model can be designed to integrate energy storage systems like batteries, etc. with the RES in the HES.

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APPENDIX A

All the codes have been uploaded on Github Code Repository and the link for the same has been given below.

ANNpv.ipynb and ANNwind.ipynb contains the code for training ANNs for PVS and WECS applications respectively. The MajorProject.ipynb ties all files together and contains the final results.

Link - https://github.com/amansolanke/mppt-for-hes-using-ml

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